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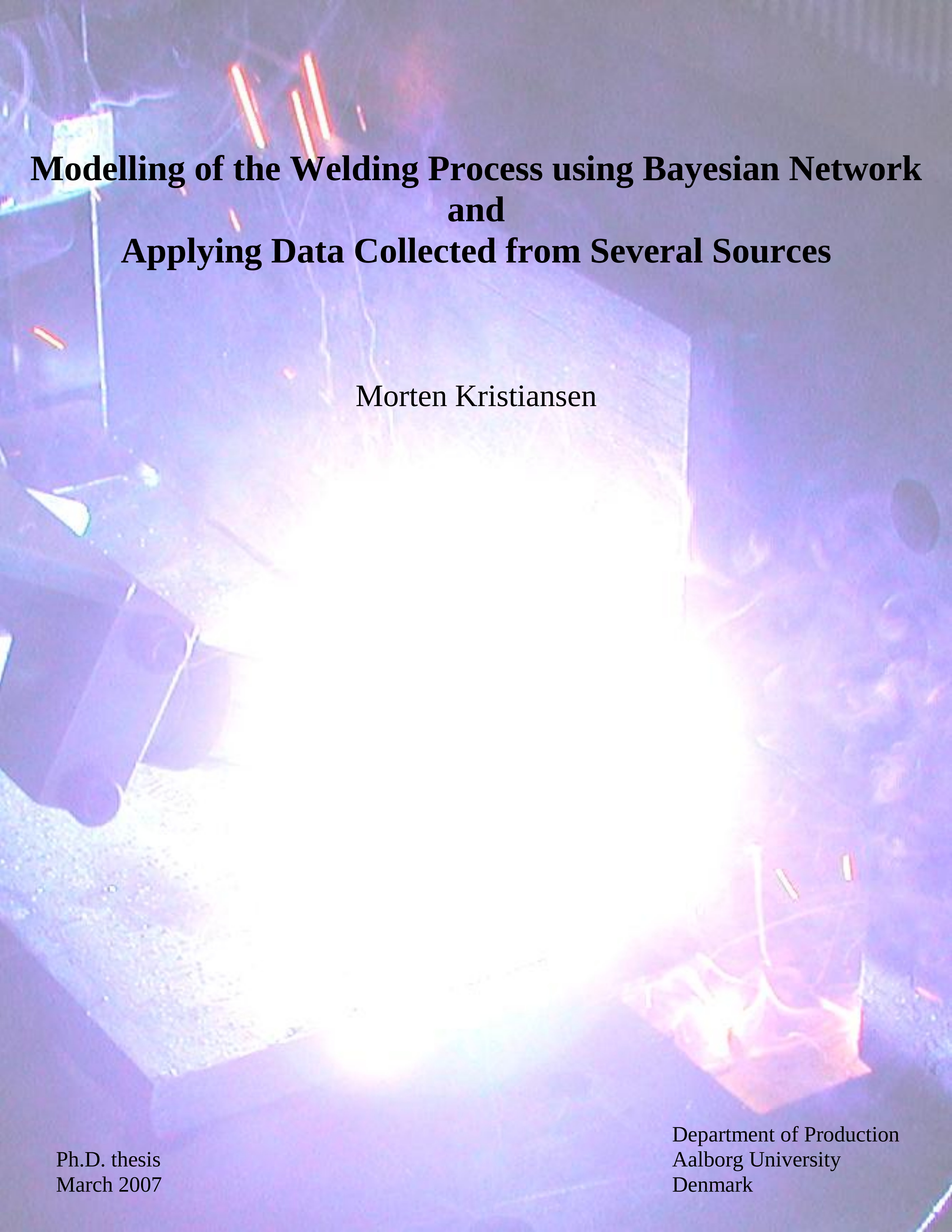

Modelling of the Welding Process using Bayesian Network and Applying Data Collected from Several Sources

Morten Kristiansen

Ph.D. thesis
March 2007

Department of Production
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and
Applying Data Collected from Several Sources

Ph.D. Thesis

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Preface

This thesis presents the results of the research for the Ph.D. scholarship AAU no. 562/06-9-22560 with the title:

Application of automatic learning methods for modelling and control of industrial processes

The work was carried out at Department of Production at Aalborg University and the thesis is submitted as one of the requirements to fulfil the Ph.D. degree in Mechanical Engineering. The project was carried out from August 2002 to August 2005 and financed by Department of Production at Aalborg University.

Formalities

The thesis is divided into five parts where the Part I to IV is the main thesis and part V is the appendices. The main thesis is subdivided into eight chapters and the appendices are from A to L.

Throughout the thesis references are given in square brackets. The references are divided into three categories. The first category includes books, thesis and articles and they are specified by a name and a publication year. The second category includes standards and they are specified by the number of the standard. The third category includes software and products and they are specified by a name of the software or product.

Abbreviations used throughout the thesis are written in full length in the list with abbreviations and in some cases explained.

Acknowledgements

First I would like to thank my supervisor, Ole Madsen, for his support and suggestions during the entire project. I also have thanks to my colleagues from Department of Production, who have participated in interesting discussions and gave inspiring help. Furthermore, I would like to thank Erling Rask for his help with the experimental work.

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Finally I would like to thank my girlfriend Ewa and my family for their patience, interest and support during the project period.

English summary

This thesis was launched because a lack of reliable process models in industry was identified. The process models required are to perform automatic planning and control of the processes in order to automate these. Furthermore, the field of automatic learning methods was developing with promising approaches to fill the lack of producing reliable process models. As a consequence of this it was selected to use the Bayesian network to produce inverse process-planning models for welding and make use of analytical, empirical and operator knowledge sources.

The work reported in the thesis is presented by the following three contributions.
Empirical knowledge is found troublesome to use because the description of parameters and variables from different experiments are not in a general and unique description, which makes them difficult to reuse. A taxonomy of a generic information model is proposed, which is able to represent dynamic welding data from experiments. An architecture of a system to produce empirical data, as specified in the generic information model, is proposed and implemented. The system makes welding experiments and afterwards it analyses the collected experimental data and produces empirical data sets.
Operator knowledge is a relatively unused knowledge source for producing process-planning models. Reasons for the little use are that it is mainly a silent knowledge source and operators are imprecise and do not always agree with each other. A methodology is developed for collecting process knowledge from operators and produce formalised knowledge from it.
A methodology to create a process-planning model based on Bayesian network, which makes use of empirical, analytical and operator knowledge is proposed. To combine these knowledge sources the existing methods for building Bayesian network is further developed. The proposed methodology is applied to produce a process-planning model for a T-Joint with a square groove. In a benchmark the Bayesian network based process-planning model showed a significantly higher reliability than a process-planning model based on artificial neural network. Benchmarked with a regression based process-planning model the Bayesian network based process-planning model had the same level of reliability but was able to use more kinds of knowledge sources and was presumed to be extended to other workpiece geometries and welding parameters.

The perspective and recommendation of continuous development is to extend the Bayesian network based process-planning model to more workpiece geometries, welding parameters and other welding processes. Further research is also to produce dynamic process-planning models based on Bayesian network and to include data from sensors to make a closed loop control. Finally, application of the methodologies described in the three contributions in the thesis would also be a research on other processes, which has a similar lack of process-planning models.

Dansk resume

Denne afhandling blev lanceret, da der i industrien var identificeret en mangel på pålidelige procesmodeller. Procesmodeller er nødvendige for at udføre automatisk planlægning og styring af processer for at kunne automatisere disse. Endvidere har fagområdet med automatisk selvlærende metoder udviklet sig med lovende fremgangsmåder til at udfylde mangler i at producere pålidelige procesmodeller. Som en konsekvens af dette, blev Bayesianske netværk udvalgt til at producere inverse procesplanlægningsmodeller for svejsning, hvor der gøres brug af kilderne analytisk, empirisk og operatør viden.

Arbejdet som afrapporteres i denne afhandling kan præsenteres med de følgende bidrag.
Empirisk viden er fundet vanskelig at anvende pga. at beskrivelsen af parametre og variable fra forskellige eksperimenter ikke er i en general og entydig beskrivelse, hvilket gør dem vanskelige at genanvende. En taksonomi for en general informationsmodel blev foreslået, som er i stand til at angive dynamiske svejsedata fra eksperimenter. En arkitektur af et system til at producere empiriske data, som specificeret i den generiske informations model, blev foreslået og implementeret. Systemet er i stand til at lave svejse eksperimenter, efterfølgende at analysere opsamlede data og producere empiriske data set.
Operatør viden er en relativ ubenyttet videns ressource til at producere procesplanlægnings-modeller. Grunde til den ringe anvendelse er, at det hovedsageligt er en tavs videns ressource, og operatører er upræcise og ikke altid enige med hinanden. En metodik blev udviklet til opsamling af proces viden fra operatører og producere formaliseret viden herfra.
En metodik til at skabe en procesplanlægningsmodel baseret på Bayesianske netværk, som gør brug af empirisk, analytisk og operatør viden, blev foreslået. Til at kombinerer disse videns ressourcer blev de eksisterende metodikker for at bygge et Baysianske netværk yderligere udviklet. Den foreslåede metodik blev anvendt på en T-samling med en I-søm. Som et sammenligningsgrundlag har den Baysianske netværk baserede procesplanlægningsmodel en signifikant større pålidelighed end en procesplanlægningsmodel baseret på kunstige neurale netværk. Som sammenlignings-grundlag med en regressions baseret procesplanlægningsmodel har et Bayesian netværk baseret proces-planlægningsmodel den samme grad af pålidelighed, men var i stand til at bruge flere slags videns ressourcer og formodes at kunne udvides til andre emne-geometrier og svejse-parametre.

Perspektivet og anbefalingen for videre forskning er at udvide det Bayesianske netværk baserede procesplanlægningsmodel til flere emne-geometrier, svejse-parametre og andre svejse-processer. En videre forskningsmulighed er også at producere dynamiske procesplanlægningsmodeller baseret på Baysianske netværk og at inkludere data fra sensorer til at lave en lukket sløjfe styring. Slutteligt ville anvendelsen af de metodikker beskrevet i de tre bidrag i afhandlingen også involvere forskning, som kan anvendes på andre processer, som har tilsvarende mangel på pålidelige procesplanlægningsmodeller.

Table of contents

Chapter 1

Introduction

The introductory chapter describes the background and motivation of the work presented in this thesis and defines briefly the field of automatic learning, modelling and control of industrial processes, which are the main topics of the thesis. A current state of the art analysis of making process-planning models for welding and the use of learning methods in a production system are presented. Furthermore, a problem statement is outlined and the research objectives of the thesis are defined. This leads to the research methodology and structure of the present thesis work.

1.1 Background and motivation

This thesis is based on the Ph.D. scholarship entitled “Application of Automatic Learning Methods for Modelling and Control of Industrial Processes”. It was launched because there is a lack of reliable models for process-planning and control for many industrial processes. Models are required to perform automatic planning and control in an industrial production system using robots, e.g. models of the robot, models of the workpiece and models of the process. Models of the robots are available in commercially off-line programming systems, models of the workpiece can be designed in CAD-systems, whereas reliable models of the process are rarely available.

The reasons why models of processes are rarely available are that many industrial processes are non-linear and the physics of the processes are not completely understood. It involves the production of both empirical and analytical process models. The large number of empirical experiments required makes the empirical based models hard and time consuming to construct. Furthermore, the capability of the analytically based models to predict the states of a process is not sufficiently good.

The investigation of the thesis focuses on how automatic learning methodologies can be built into industrial manufacturing systems in order to introduce automation. Different methods for automatic learning will be examined to select suitable ones, and it will be investigated how these methods will fit into an industrial manufacturing system. Requirements and sources of knowledge for learning the different methods are investigated.

1.1.1 Automatic learning

Automatic learning methods were selected to produce a model for process-planning and control of industrial processes because these methods were expected to be powerful compared to more traditional methods used so far. More traditional methods are empirical methods with mathematical models based on empirical data and analytical methods with analytical models. The empirical and analytical models are described in appendix A section A.4 “Modelling process knowledge” and their usability is demonstrated by examples from the literature.
Automatic learning originates from the field of machine learning, data mining and artificial intelligence. This field has grown rapidly since the computational power and storage of large amounts of data have dropped in cost, and data collection over computer networks has increased in ease. [Mitchell, 1999] states that a first generation of algorithms in the field of machine learning and data mining is limited to data described by numeric or symbolic features, while an expected second

generation can handle more sources of data. These sources could be numeric, symbolic, text and image features and even human hypotheses.
The field of automatic learning of industrial processes is an interdisciplinary field between the artificial intelligence area of computer science, mechanical engineering and control engineering. In this thesis it is defined as follows:

Definition of automatic learning

Automatic learning is the process of acquiring knowledge, values or skills through a self-operating machine.

Many tools for automatic learning are developed and in appendix A section A.3 “Machine learning”, the most applied tool in the literature and those with a big potential are reviewed, these are:

- Decision trees
- Bayesian network
- Decision graphs
- Artificial neural network
- Instance-Based learning
- Genetic algorithms

1.1.2 Welding

To focus, the thesis is pointed towards the arc-welding process because this process demonstrates the difficulties in process-planning and process-control. Furthermore, in welding there is a big demand for process-planning and process-control models. This is shown in the literature survey in appendix A section A.4 “Modelling process knowledge”, where the state of the art shows a lack of reliable and flexible models compared to the industrial requirements. In the area of welding a lot of different methods are available such as the electrical arc welding, oxyfuel gas welding, laser welding and friction stir welding. MIG/MAG welding is a successful welding process, widely used in industry today. This is the main reason why it is on the welding processes this thesis focuses. However, the welding process is also chosen continues the research about this process that has already been carried out at Department of Production, Aalborg University, Denmark.

1.2 Models for process-planning and process-control

When modelling a real process a number of parameters and variables are involved. A process-model describes the process by the relations between the parameters and variables and their influence at each other. These interactions of parameters and variables are illustrated in a process-model, shown in figure 1.1, and the involved parameters and variables are described as follows:

- Control variables are characterised as being changeable during process execution.
- Equipment parameters are chosen according to the specific equipment used, they are changeable before process execution, but fixed during process execution.
- Workpiece parameters are results of the design and manufacture of the workpiece and they describe and specify the workpiece. Workpiece parameters are constant or they vary during process execution if the process can have an impact on them, e.g. the heat can cause distortion.
- Quality parameters denote the quality to be achieved from the process execution.

- Process state variables define the states of the process during process execution. The process state variables are a function of control variables, equipment parameters and workpiece parameters.

A model of the process is required to make planning and control of the process. The better the model predictions fit to the real process behaviour, the more reliable is the model. A model of the process is required both for process-planning and process-control, where the difference is: Process-planning works as an open-loop control and can be done off-line. Process-control works as a closed-loop control and gets a feedback from the real process. Process-planning and process-control are more thoroughly explained in appendix A section A.4 “Modelling process knowledge”.

Process-planning model

A process-planning model is used before process execution to determine the control variables necessary for achieving the required quality parameters. Figure 1.1 shows a direct process-planning model. The reversed direct process-planning model is an inverse process-planning model, shown in figure 1.1. In most cases the inverse process-planning model is required.

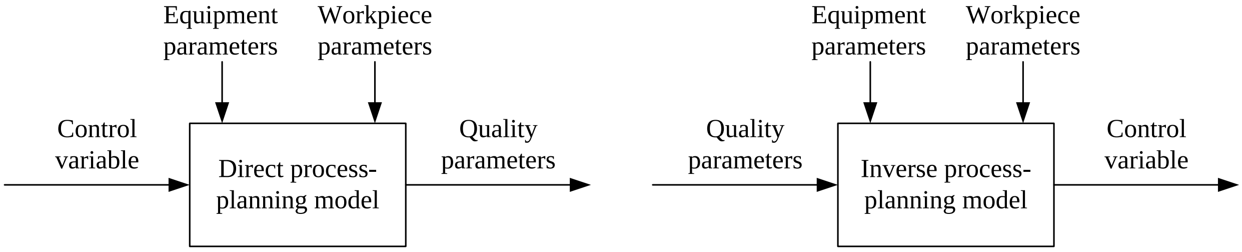


Figure 1.1: Input and output for a direct process-planning model to the right and inverse process model to the left [Madsen, 1992].

A process-planning model can be described as a functional relation. The direct process-planning model gives one set of quality parameters for one set of control variables, whereas for the inverse process-planning model one set of quality parameters can give zero, one and up to infinite sets of control variables. Figure 1.2 illustrates this with one control variable and one quality parameter.

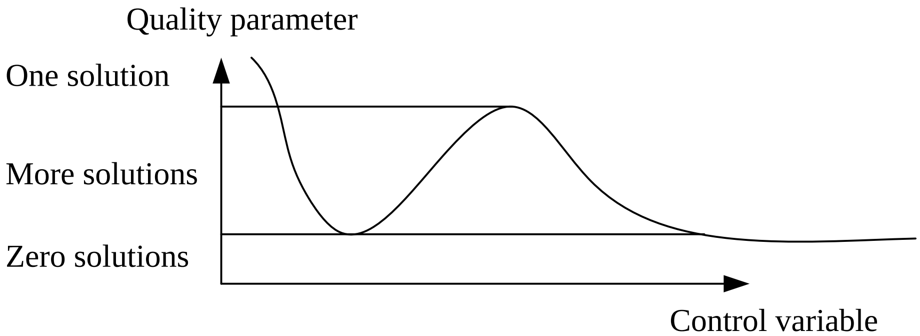


Figure 1.2: A continuous function relating a control variable with quality parameter. For one control variable setting there is one quality parameter. For one quality parameter setting there is zero, one and up to infinite solutions of control variable.

A process-planning model does not have any feedback from the process and for this reason an identical behaviour between the model behaviour and the real process behaviour is important. Furthermore, it is important that disturbances are minimised to avoid a difference between the input to the model and the real process.

Process-control model

A process-control model is used during process execution to determine the control variables to achieve the required quality parameters. The process-control model includes a process-planning model to determine the control variables, and it contains a control-loop to update the control variables when obtaining measurements made during the process execution. Construction of process-control models can be made with the process-planning part running on-line or off-line. Some of the process-planning models are too time-consuming to run on-line, shown in the review in appendix A section A.4 "Modelling process knowledge". The requirement for using process-control models is that measurements of the real process behaviour can be obtained on-line. Because the process behaviour is measured and fed back, the benefit of using a process-control model is a higher tolerance to disturbances.

Constructing process-planning and process-control models

Process models for both planning and control can be constructed from different modelling techniques and they can use different knowledge sources. The models can be characterised according to their cohesion with physical modelling to be in one of the following three groups:

- White-box model. It is constructed from physical insight and prior knowledge, and the model is perfectly known.
- Grey-box model: It is constructed from some physical insight and prior knowledge. However, some models are also constructed from empirical sources. The model is not perfectly known.
- Black-box model: It is constructed without physical insight and prior knowledge but rely on empirical sources, and the model is unknown.

All models are practically between white- and black-box models.

1.3 State of the art

The field of constructing models for process-planning and process-control of the welding process is scientifically investigated and has been developed for more than a decade as shown in appendix A section A.4 "Modelling process knowledge". The developed models are still not as flexible, reliable and cheap to produce as it is required in many cases for industrial use. The literature survey is summarised in table 1.1 and shows state of the art methods for making process-models for open and closed loop control.

Table 1.1: Classification of the work in the area of making process-planning models.

Model / Control	Empirical process-planning models	Analytical process-planning models
Open loop control	**Raw data** [Madsen et al., 2002]: Experimental results or operator experience entered in database. **Mathematical models** [Juang et al., 2002]: Taguchi and optimization. [Tarng et al., 2002]: Taguchi and optimization. [Moon et al., 1997]: Regression model and optimization.	[De et al., 2004] and [Kumar et al., 2004]: Heat transfer model and optimization. Uses process state variables instead of welding control variables for optimization. [Jeberg et al., 2006] and [Jeberg, 2005]: Finite element model and simulation with control loop. Iterative learning control used to improve the iterative process. [Mahrle et al., 2000]: Heat transfer model and simulations. Talks about

	[Murray, 2002]: Regression model and dimensional analysis. [Maul et al., 1996]: Control charts avoiding defective welds by making settings and rules. [Kim et al., 1996b]: Regression model inverted. **Machine learning** [Dilthey et al., 1999]: Artificial neural network, genetic algorithms for modelling and optimization. [Tay et al., 1997]: Artificial neural network and simulations used to manual find inverse solutions. [Moon et al., 1997]: Artificial neural network. [Chan et al., 1999]: Artificial neural network. [Cook et al., 1995]: Artificial neural network. [Moon et al., 1996]: Artificial neural network and fuzzy logic. [Yanhong et al., 1994]: Decision tree and learning sets of rules. [Peng et al., 2000]: Rule based reasoning, case based reasoning and artificial neural network. [Smartt et al., 2003] and [Smartt et al., 2006]: Agent and fuzzy logic to make control with welding knowledge.	how to use it for an inverse model. [Holm et al., 2002]: Finite element model and simulation with control loop. [Holm et al., 2003a]: Finite element model and simulation with control loop using PI control and iterative learning control.
Closed loop control	**Machine learning** [Di et al., 2001]: Artificial neural network, fuzzy logic and control with measurements of parameters used to estimate the welded seam. [Christensen, 2003] and [Christensen et al., 2003]: Artificial neural network and control with measurement of the welded seam shape.	[Orye, 2005], [Kjeldsen et al., 2003] and [Holm et al., 2003b]: Finite element model with simulation and offline control. Online thermal vision measurements are used for control. [Andersen et al., 1997]: Model of the weld pool. Measurements of the pool size is made from oscillations and used to control the pool size.

In the following the work and the approaches from table 1.1 are summarised and commented on.

1.3.1 Open and closed loop control

In most of the literature survey an open loop control is applied. The work in the literature survey with closed loop control utilises sensors to measure the size of the weld pool, the heat distribution on the workpiece surface or the shape of the welded seam. The environment in and around the welding process makes the use of sensing complicated, but as it is shown there are feasible methods available, however most of them need to be brought from the lab to industrial use. The development using an open loop control illustrates a lot of different approaches, but the hurdle is to control the disturbances from the surroundings, which can be problematic in industrial use. Approaches in the literature show different kinds of vision and through the arc sensing, which are used to determine workpiece parameters.

1.3.2 Empirical and analytical process-planning models

In the literature survey the process-planning models are divided depending on whether the models are based on empirical knowledge or analytical knowledge. In most of the literature survey there are empirical based process-planning models, but the development in the area of using finite element models to model the welding process is progressing. The reason for this progress is development of modelling capabilities and increase of computational power. The different modelling techniques described in the literature survey are categorised according to the following three groups:

- White-box model: Finite element models and other models built from knowledge from physics.
- Grey-box model: Fuzzy logic and rule based reasoning.
- Black-box model: Artificial neural network, regression and case based reasoning.

The different modelling techniques are mainly based on one knowledge source where the white-box models use analytical knowledge, and the black- and grey-box models use empirical knowledge. Process knowledge from humans is restrictively applied for some of the grey box models. It is possible because to some extend the grey box models are understandable by humans.

1.3.3 Knowledge sources for machine learning

From the literature survey it can be concluded that the knowledge sources, applied to make process-planning models based on machine learning, are restricted sources. The knowledge used is empirical, analytical and operator knowledge; and the last two knowledge source are only applied in a few cases. Looking at the methods from machine learning, artificial neural network is used in most cases. Furthermore, the machine learning methods are only using a single kind of knowledge source.

1.4 Industrial use of process-planning models

The industrial interest of process-planning models is especially from the companies which will introduce automation in their production. One of today's main reasons for automation is to reduce personnel costs as a precaution against moving wage-intensive production to low labour cost areas. Industry with a small batch size production requires a process-planning model to program the machinery when new products have to be manufactured. This topic is discussed in the following sub section together with the discussion on the challenges in programming an industrial production with small batch sizes compared to large batch sizes. In the second sub section a model of an industrial production system is presented, and it is proposed how the production and use of process-planning models for welding can be incorporated into that system.

1.4.1 Industrial production system with small batch sizes

When changing from manual to automated production in an industrial production the programming of tasks is different for production with small batch sizes than for productions with large batch sizes. Figure 1.3 is an illustration of how manual operations are carried out by different kinds of programming in order to make automation. Automation of industrial processes with large batch sizes can be carried out using either on-line or off-line programming. On-line programming is when the process is manually programmed by teaching in the production line. Off-line programming is also when the process is manually programmed, but the teaching and a possible simulation are made outside the production line, so the production is not disturbed. Industrial processes with small batch sizes and manually operated processes are automatically programmed by using a computer, illustrated in figure 1.3. This is because manual programming, which is made by on-line or off-line programming, is not beneficial for parts in small batch sizes. It is because today's methods for programming of the processes take longer time than the manual operations for carrying out the process. This is stated based on experience achieved from different projects at Department of Production, Aalborg University. For welding it takes between 40 minutes for a simple task to 480 minutes for a complex task to programme one minute of a robot programme manually.

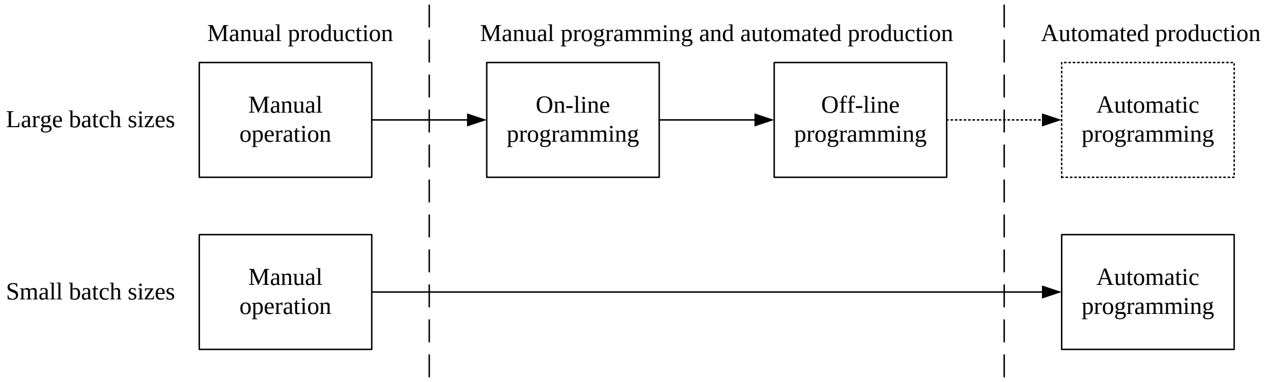


Figure 1.3: When going from manual production to automated production it is not necessary to automate the programming for large batch sizes, but it is necessary for small batch sizes.

Going from manual operation, on-line and off-line programming to automatic programming causes that the knowledge required to carry out the operation is moved from a person to a computer.
When automation involves numerically controlled equipment instead of human workers, process-planning and control are required. Especially there is a high demand for flexibility and reliability for models in an automatic production system for one-of-a-kind and small batch sizes compared to productions with large batch sizes. It is because an individual fabrication is required for each part. The high demand for flexibility and reliability occurs because the model should handle every part, and almost every part is unique and has never been produced before. The parts are unique when changing e.g. geometric shape, material, tolerances and quality requirements. There is often a short delivery time and it is not beneficial to make prototypes. Possible ways to reduce the production costs for small batch sizes and one-of-a-kind productions is through automation of the manual processes in the production system. The problem of automating these productions is in the fact that the tasks in the production system have never been made before in exactly the same way and therefore it is not possible to make repetitions. When using humans in a production system it is not required to make repetitions because humans are able to adapt to new conditions by using knowledge and skills from other similar parts and tasks they have made before.

1.4.2 Architecture for production and use of process-planning models for welding

In appendix A section A.1 "Architecture of a production system" a model of an industrial production system is presented. It is done to identify places where process knowledge is used or can be used. Many places were identified and in appendix A section A.2 "Identification of places to model process knowledge using machine learning" it is described how different tasks could make use of process knowledge. Examples from the literature describe how the machine learning methods have been applied to model process knowledge. Most of the examples are in the function "Prepare production" to make process models and in the function "Control production" to detect error and record the quality.

The focus of this thesis is on making process models for planning. They need to fit into the industrial production system where the models are made and used. Therefore the making of process-planning models is incorporated into the generic system architecture for an automatic production system, described in appendix A section A.1 "Architecture of a production system".
The functional model, in appendix A section A.1 "Architecture of a production system", describes both the making of process-planning models for welding and their use in an industrial production. The making of a process-planning model for welding, shown at the top in figure 1.4, is a part of the task in node A31 in the functional model. The use of a process-planning model to compute control variables for a given welding production task, shown at the bottom in figure 1.4, is simplified compared to the description in node A32 in the functional model.

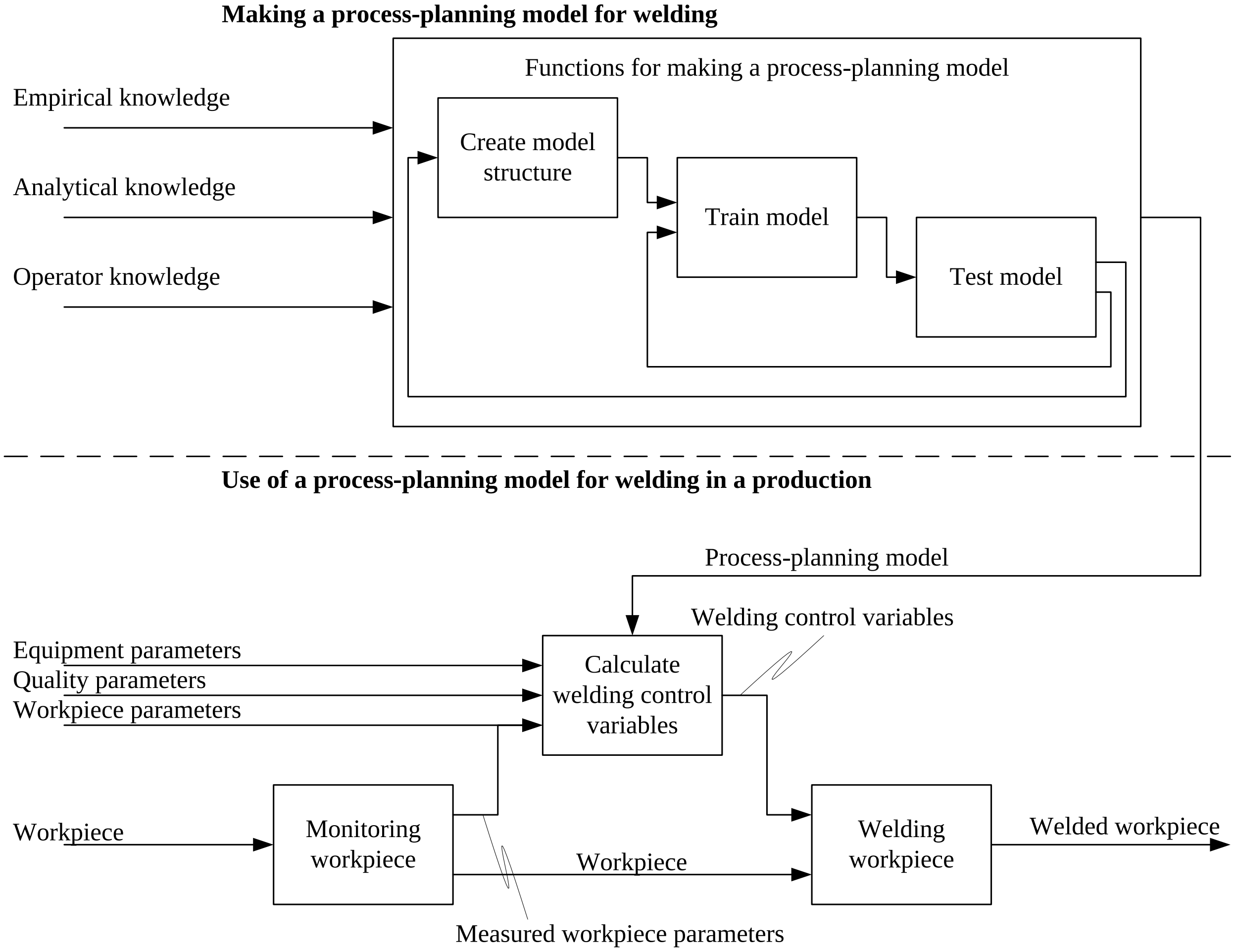


Figure 1.4: Making a process-planning model for welding and its industrial use in a production.

Making a process-planning models for welding

Knowledge sources were identified in appendix A section A.4 “Modelling process knowledge”. From these sources welding knowledge for production of process models can be formalised. Three sources could be classified and these are:

- Empirical knowledge gained form welding experiments, which are described in a database as related datasets of workpiece parameters, equipment parameters, quality parameters and welding control variables.
- Analytical knowledge found in the literature and described by physical laws, rules and equations.
- Welding operator knowledge, which the operators possess from years of welding experience. The knowledge can be formalised for making process-planning models and it is investigated in this thesis.

The task of making process-planning models can be carried out by different tools, each using one or more knowledge sources. Making the process-planning models is separated into two functions: creating the model structure and training the model. Before using a process-planning model it is necessary to test it in order to decide whether the model is sufficiently accurate or whether it should be retrained or remade. The common way to verify a model is to use some untested empirical datasets. The workpiece, equipment and quality parameters should be inserted into the inverse process-planning model and then the welding control vector could be calculated from the inverse process-planning model and afterwards compared with the welding control vector from the dataset. The output is a process-planning model for use in a production.

Use of process-planning model for welding in a production

The process-planning model made is for planning the welding process in an industrial production. The bottom of figure 1.4 illustrates the general principle of using a process-planning model.

The input to the process-planning model is the workpiece, equipment and quality parameters. It is specified in the information system of the company. Beside that, some measurements of the workpiece can be made to give additional information, shown in figure 1.4. Based on the workpiece, measured and given workpiece, equipment, and quality parameters the process-planning model calculates the welding control variables. They are sent to a welding robot and a welding machine that carry out the welding of the workpiece.

1.5 Problem formulation

A lot of work is carried out in the field of making models for process-planning and control, as identified in section 1.3 “State of the art”. But still, producing the models is time consuming and expensive and they are often created for a specific application.

The contribution of this thesis is in the field of the automatic learning methods, black and grey box models, as it was stated in the background of the thesis. The dominant methods in this field were reviewed and compared in appendix A section A.3 “Machine learning”. Bayesian network stands out as an interesting method because it was found flexible for making use of different knowledge sources and showed a potential because the graphically represented model can be changed graphically. Although the Bayesian network is untested for making process-planning models for welding it has been successfully implemented other places in a production system, see appendix A section A.2 “Identification of places to model process knowledge using machine learning”. Artificial neural network is selected for benchmarking; because it compared with other learning

methods is the most often used method in the field of welding. Regression is also selected for benchmarking, because it is used often and it is a standard modelling method.
The problem that the models are time consuming and expensive to produce appears for most of the grey- and black box models. This is caused by the fact that the main knowledge sources are datasets from experiments. Furthermore, reusability of the knowledge sources is also troublesome because no standard representation is used and in most of the articles in the literature survey, in appendix A section A.4 “Modelling process knowledge”, experiments are made to produce empirical data. For this reason the focus of this thesis is also on producing cheaper and reusable knowledge sources.

Process-models with a closed loop control are out of the focus of this thesis, because application of sensing for welding is demonstrated and application of new kinds of sensors is a topic for an entire project.

The problem to be investigated in this thesis is formulated in the following two points:

- Investigate how to create reliable and reusable knowledge sources from empirical experiments and operators to make process-planning models.
- Make a process-planning model based on a Bayesian network and compare its capabilities to use and combine different knowledge sources with other frequently used techniques for making process-planning models.

Based on the formulated problems the research objectives are formulated in the next sections.

1.5.1 Research objectives

Building a process-planning model requires knowledge about the process. Different types of knowledge as e.g. operator knowledge, analytical knowledge and empirical knowledge can be used. Getting the knowledge and formalising it in a way that can be used by a computer is a difficult and expensive task.

- Operator knowledge is hard to formalise in a way that is understandable by a computer.
- Analytical knowledge for the welding process is rarely available and it often requires calibration from empirical data.
- Empirical knowledge is very expensive to create because the experiments and analyses are very time consuming. It is also very difficult to save for later use and to communicate.

Most of the process-planning models are built from one knowledge source. In those cases when two sources are combined, it is usually the empirical data, which is used to calibrate models made from analytical data.

Based on the discussion above the research objectives of the thesis are formulated as follows:

1. How can empirical knowledge be formalised so it can be saved, reused and communicated?
2. How can operator knowledge be formalised so it can be saved, reused and communicated?
3. How can the creation of empirically knowledge be automated and used as input for training a process-planning model based on learning?
4. How and to what extend can different types of knowledge be combined and used for training a process-planning model based on automatic learning?
5. How can a reliable process-planning model be created by using a Bayesian network?
6. How good is the performance of a process-planning model based on a Bayesian network compared with a process-planning model based on regression analysis and artificial neural networks?

1.6 Thesis structure

The thesis is divided into 5 main parts: Part I describe the motivation and background of the research conducted and presented in this thesis. Part II outlines the data collection for different available sources and methods to collect and represent them. Part III describes methodologies for building of process-planning models. The main emphasis is on a method using Bayesian networks and the performance of the Bayesian network-model is benchmarked. Part VI concludes and discusses the results presented in the thesis with a proposal for further work. Part V consists of appendices for the thesis.

Each chapter is included in a main part. The contest of each chapter is presented below. The numbers in the parenthesises corresponds to the number(s) from the research objective(s).

The 5 main parts in the thesis are:

Part I: Motivation and background

Chapter 1 – Introduction.
The background and motivation of the thesis is presented. It leads to a description of the research field and analysis of a current state of the art. The problem statement, research objectives are formulated and the thesis structure along with the research methodology are presented.

Part II: Data collection

Chapter 2 – Data collection of knowledge to create a process-planning model (1 and 2).
Data collection of operator, empirical and analytical knowledge sources for making process-planning models for welding are investigated. The investigation makes an overview of the three knowledge sources and describes how the knowledge sources are collected and formalised.

Chapter 3 – A data model for production of empirical data (1).
A taxonomy for formalising and saving empirical welding data from different welding experiments is presented. The taxonomy assures that the empirical data can be communicated and reused by others.

Chapter 4 – A system for automating production of empirical welding data (3).
To make empirical data in the form described in chapter 3 a system is specified and built, which automates the production of empirical welding data. It is done to reduce the time consumption of producing empirical welding data compared to the manual production.

Chapter 5 – Formalising operator knowledge (2).
Process knowledge from operators is found to be a valuable source for making process-planning models, because it is cheap and fast to produce compared to empirical knowledge from experiments and analytical knowledge. The hurdle of using operator knowledge is to formalise the knowledge in a way that can be used in a process-planning model. In this chapter methods for formalising operator knowledge are described.

Part III: Modelling and results

Chapter 6 – Building Bayesian network based process-planning models (4, 5).
The creation and training of Bayesian network based process-planning models for welding is described. Methods for making use of different knowledge sources are developed. An artificial neural network model and a regression model are also made for benchmarking purposes. It is

clarified which knowledge sources are useful and to what extend they are useful for creating and training different models.

Chapter 7 – Test results (6).
The reliability of a process-planning model for welding based on a Bayesian network is investigated for the direct and inverse solution. It is benchmarked with a process-planning model based on artificial neural networks and one based on regression. The benchmarked is illustrated in figure 1.5.

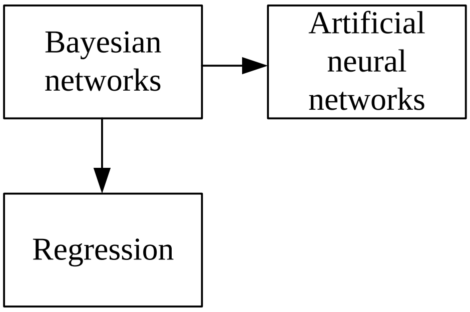


Figure 1.5: A Bayesian network is benchmarked with artificial neural networks and with regression.

Part IV: Discussion and conclusion

Chapter 8 – Conclusion.
This chapter concludes the research objectives and the results obtained in the research. The contribution of this research is stated and discussed. Finally further research areas are presented and the aspects of future work are discussed.

Part V: Appendices

This part includes all the appendices, and they give in depth information to support the chapters in the thesis.

Chapter 2

Data collection of knowledge to create a process-planning model

This chapter defines welding process knowledge and specifies different sources of welding process knowledge. The task of obtaining and collecting welding knowledge from the real welding process and of formalising it is illustrated in figure 2.1. The real welding process requires formalising to a language from which process-planning models can be created. Different ways to procure real welding knowledge are reviewed. The most promising of the available quantitative and qualitative knowledge sources for formalising knowledge about the welding process is analysed and it is presented how they can be represented.

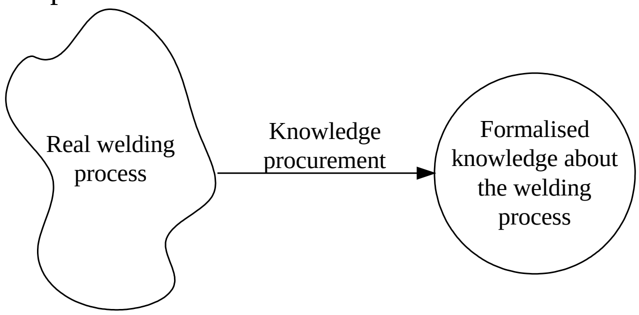


Figure 2.1: Procuring formalised knowledge of the real welding process requires an extraction of the process knowledge to a description in a formalised language, represented in the circle.

2.1 Knowledge collection from welding process

To create process-planning models for welding, knowledge about the process is required. The welding process knowledge has to be created or collected before it can be transferred and utilized in a process-planning model. In this section the meaning of knowledge and different sources of knowledge is specified to make a clear distinction between them.

In the literature [Nonaka, 2001] distinguishes between information and knowledge, where information is data and knowledge involves understanding. Understanding could for example be of interrelationships and behaviour according to [Nonaka, 2001]. Knowledge can be categorised as:

- Scientific knowledge: E.g. the physical laws which are well documented and approved.
- Process/industrial knowledge: E.g. skills which are learned by using or doing.

Another way of looking at knowledge is the availability which can be categorised as:

- Formalised knowledge also referred to as explicit knowledge: Knowledge which has a formal and systematic representation and it is e.g. data, scientific formulas, specifications and manuals.
- Silent knowledge also referred to as tacit knowledge: Personal knowledge and it is e.g. actions, procedures, routines, commitment, ideals, values and emotions.

To categorise the knowledge contained in the three knowledge sources used in this thesis after this distinction is illustrated in figure 2.2 and elaborated in the following.

Knowledge categories \ Availability	Formalised knowledge	Silent knowledge
Scientific knowledge	Analytical knowledge	
Process/industrial knowledge	Empirical knowledge	Operator knowledge

Figure 2.2: A systemisation of the three knowledge sources after their availability and knowledge categories.

Operator knowledge

Process/industrial knowledge which the operator has learned by doing and it is a silent knowledge which is embedded in operator actions, procedures and routines for welding. In figure 2.2 the delimitation of operator knowledge should not be seen sharply, because the knowledge source can be mowed in the direction of both formalised and scientific knowledge.

Empirical knowledge

Empirical data is not only considered as information in this thesis but as a knowledge source because data comes from well documented experiments.

Analytical knowledge

Scientific knowledge which has an explicit representation and it is for welding often in formulas and specifications.

The three knowledge sources are reviewed in the following three sections where the knowledge creation and collection is described such that knowledge can be transferred and utilized in a process-planning model.

2.2 Operator knowledge

Welding operators often have a large source of welding knowledge and practical expertise which is rarely used for creating process-planning models. Acquisition and formalising of the knowledge is a big hurdle for using this source. Identified methods to capture and use operator knowledge are for instance fuzzy logic and expert systems.

In the fuzzy logic system vague, uncertain and imprecise knowledge is captured by making a rule base and making the terms descriptive. Using welding terms can a rule be e.g. IF travel speed is low AND wire feed speed is high THEN weld face width is high.

Expert systems can use different machine learning methods to capture the operator knowledge. In appendix A are given some examples of fuzzy logic and machine learning methods to capture operator knowledge for welding.

In this section it is investigated how to read off the operator skills and how to transfer the knowledge laying behind the skills to process-planning model creation.

2.2.1 Analysis of operator knowledge source

This thesis refers to the welding operator either as a craftsman who carries out practical welding and has expertise in selecting equipment parameters and welding control variables or a welding expert who can formalise welding knowledge into analysed knowledge.

Through education and years of welding experience, welding operators have achieved skills in selecting welding control variables and equipment parameters for a given task. The welding operator selects the welding control variables to achieve the required quality performance. This is not only for one type of welding but also for changing workpiece parameters, workpiece variables, equipment parameters and quality parameters. When a change is made to a new workpiece or equipment, the welding operator in some cases requires one or few welding experiments to adjust the welding control variables in order to achieve the required quality performance. The skills and knowledge, that the operator has, are mainly a silent knowledge which is hard to formalise and communicate/transfer to other people. The welding operator knows for a given task the settings on the welding machine but does not know exact values of welding control variables as travel speed, oscillation pattern, work angle, travel angle and contact tube to workpiece distance (CTWD). Without knowing the value of the welding control variables the welding operator can still carry out the task and it makes the operator knowledge source difficult to use.

The welding operator can have different roles for carrying out the welding process according to if the welding is manual or automated. Depending on how the welding is carried out different sources of knowledge are required from the operator as illustrated in figure 2.3. In the figure a fixed equipment and workpiece setup is used for a welding task.

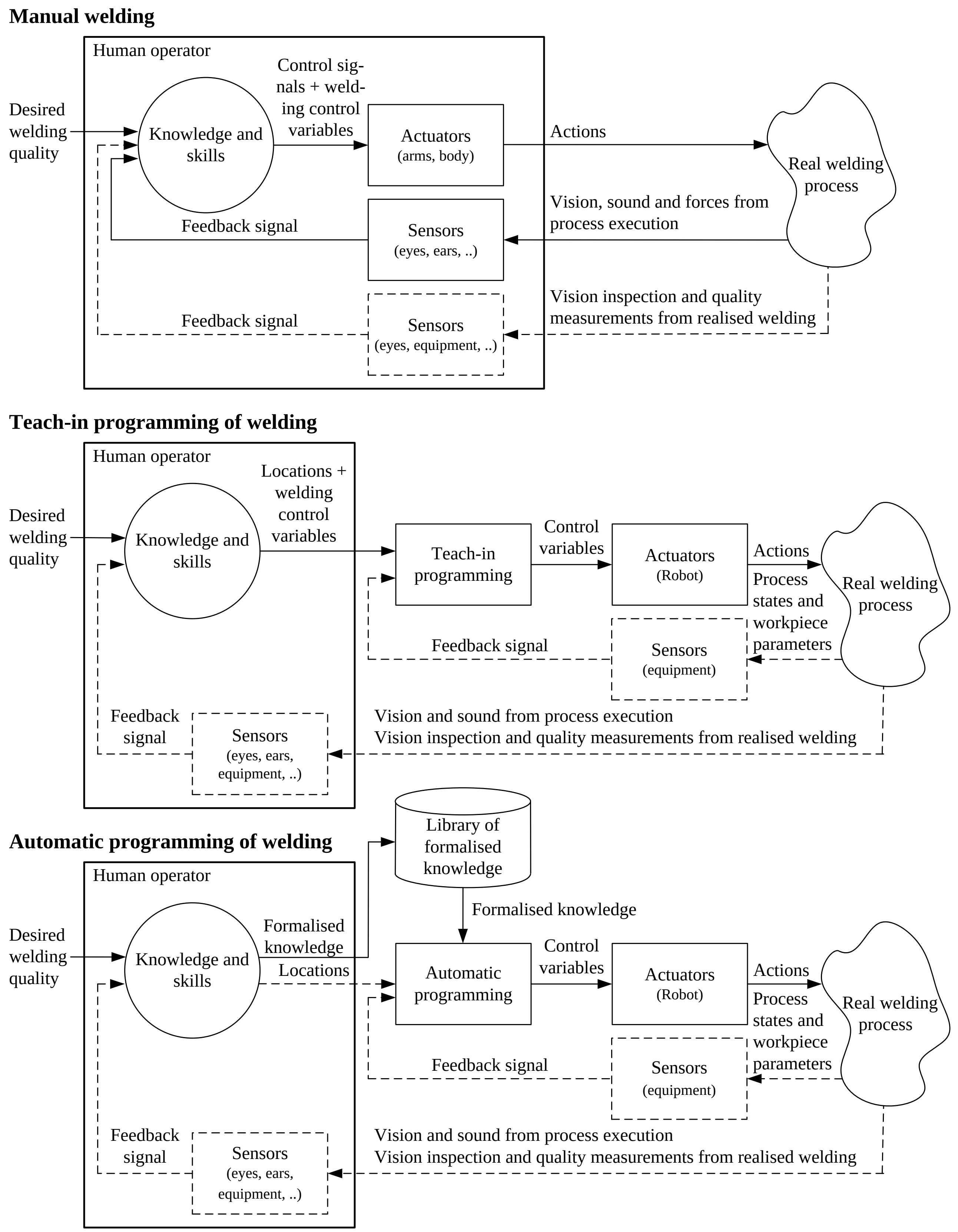


Figure 2.3: Three main categories when using human operator knowledge and skills to carry out welding. Dashed lines in the figure illustrate operations and tasks which can be carried out.

Operators' knowledge and skills used for different ways of carrying out the welding process are described below:

Manual welding

Operator knowledge and skills for manual welding are used before welding to select good welding control variables of voltage and wire feed speed on the welding machine. During welding the operator continuously uses knowledge and skills to determine how to produce the decided quality. To produce the decided quality the operator sends control signals to the actuators, which in physiologic terminology is nerve signals giving action to the operators' body, arm and hand for manipulating the welding torch. During welding the operator uses different senses such as vision, and hearing, to observe the welding process. The operator interprets the sensor signals to a feedback signal, which with use of knowledge and skills produces a new control signal. This can be described as closed loop controller, illustrated in figure 2.3. For the human operator only the voltage and wire feed speed are set explicitly while the description about moving the welding torch is implicit knowledge and skills. The implicit knowledge is normally difficult to explain for the operator. Besides improving the knowledge and skills during welding from the feedback signal, the operator can also make vision inspection and measurements of the realised quality after the welding task is finished giving a feedback signal also to improve knowledge and skills.

Teach-in programming of welding

Teach-in programming is carried out when the operator either in an on-line or off-line programming system is teaching a robot. The operator teaches the robot locations along the weld seam and the operator sets explicitly the welding control variables which are voltage, wire feed speed, travel speed and oscillation pattern. Based on the resulting robot program a robot controller computes control variables which are send to the robot actuators and the welding machine. Different sensors, e.g. profile sensor or arc sensor, can be applied to give information about the workpiece shape or the process states. Applying sensors gives a feedback signal which can modify the robot program taught by the operator. When the operator teaches the robot some of the welding control variables are given implicitly such as e.g. travel and work angel, CTWD, position of torch according to workpiece. The operator can improve the performance during and after welding. During welding the operator can use vision and hearing to observe the robotised welding process, and after the welding task has finished the operator can use vision inspection and measurements of realised quality. This gives a feedback signal which can improve knowledge and skills of the operator to produce welding control variables. The operators knowledge is not only silent knowledge but becoming more formalised because is can be formulated as welding control variables.

Automatic programming of welding

Automatic programming is carried out when the operator types formalised knowledge into a knowledge library in an automatic programming system. The knowledge is typical formalised as rules which are of more systematic and general character as analytical knowledge. The library of formalised knowledge is used to calculate welding control variables instead of using the welding control variables typed in by the operator. Furthermore, locations for start and end of the task are maybe required from the operator to specify physical location of the welding tasks. The automatic programming generates a robot program and it is executed in the same way as for teach-in programming. Feedback signals from sensors can be fed backwards to the automatic programming system to improve knowledge and skills of the operator as for teach-in programming.

Welding knowledge and skills for manual welding and robotic programming of welding are compared in table 2.1. The operator is required to formulate the welding knowledge and skills more explicitly going from manual welding to automatic programming of welding. For the manual welding the low degree of explicit knowledge is a result of that the operator is incorporated in the real time closed loop control system. While for the teach-in programming and the automated programming of welding the operator has to describe the knowledge more explicitly in order to feed it to a programming system. This description is made outside the real time control of the welding process.

Table 2.1: Explicit welding knowledge and skills which the operator provides for different ways of carrying out welding.

	Explicit welding control variables set by the operator
Manual welding	Voltage and wire feed speed
Teach-in programming of welding	Voltage, wire feed speed, travel speed and oscillation pattern
Automatic programming of welding	Formalised knowledge of analytical character to compute the welding control variables

To use the operator knowledge in the creation of process-planning models for automatic programming of welding a change from the implicit knowledge and skills of the operator to explicit knowledge is required. Furthermore, a formalisation of the explicit knowledge is required.

2.2.2 Formalisation and use of operator knowledge

Two usable strategies to extract and formalise the knowledge of welding operators are following discussed in details.

Observe and analyse operators behaviour

The first strategy is to observe and analyse how operator behaves to carry out the manual welding process and then imitate the execution. It can be made manually or automatic.

Manually, it is measured how operator behaves to carry out the process and then it is formalised to be used for programming the robot and welding machine. It can be done by recording the welding control variables as e.g. settings of voltage and wire feed speed, measuring of travel speed, work angle, travel angle, CTWD, oscillation width and oscillation frequency. Some of these measurements are complicated to perform during the welding process. It can be further complicated because some variables can be coupled, e.g. the CTWD can be dependent on the welding torch position in the oscillation pattern.

Automatic measurement of operator behaviour can be made during the welding task. It is expected that it can be made by a sensing system measuring the operator's hand moving the welding torch and recording the voltage and wire feed speed settings. Examples of systems to imitate human skills are described in [Lee et al., 1998] and [Yeasin et al., 2000] who use a cyperglove and a vision system, respectively. Both systems are used for learning and transferring of human grasping skills for programming of grasping with a robotic hand. [Jiang et al., 2004] is another example of tracking human motions and transferring them to a robot using a vision system. For all systems considerable setups are required to perform the task. Furthermore, they are experimental systems and only for a simple task compared to carrying out welding.

The operator formulate the welding knowledge

The second strategy is to ask operators to formulate their welding knowledge either through an interview or by writing down the knowledge. It requires tools for formalising the knowledge. The formalisation can be in a written language or graphical language which can be used in a computer. This strategy is in the literature not found investigated for the welding process.

In this thesis, only the second strategy will be used because it has not previously been systematically investigated. Furthermore, the second strategy is expected to be much less resource demanding to prepare and carry out. The strategy is illustrated in figure 2.4.

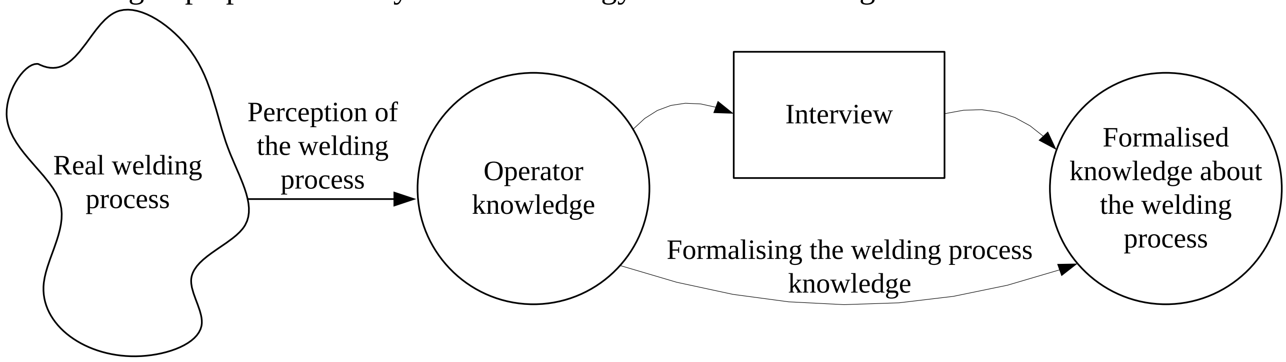


Figure 2.4: The operator has achieved a lot of knowledge about the welding process by perception of the process. Formalising the operator knowledge can be done with and without the use of an interviewer.

2.2.3 Features of operator knowledge

As discovered in the analysis of the operator knowledge sources and described in table 2.1 the operator has to deliver explicit knowledge which has to be formalised to make automatic programming of welding. Through interviews it was discovered, that the way operator expresses knowledge is mainly by describing which relations and interactions occur between parameters and variables of the process. Formalising the relations and the interactions was found to be a very useful way to gather the operator knowledge and skills. Through interviews it was discovered, that it is very difficult for the operator to give a high level of details in estimating exact numbers and values. The operator has only a rough feeling about numbers and values and they require experiments to be precise. For this reason, the method for formalising the operator knowledge is selected to be through relations and interactions. This method for formalising operator knowledge from operator interviews for production of explicit operator knowledge is described in chapter 5.

Features of the operator knowledge are characterised by the following points.

- Operator knowledge about welding is mainly implicit and not described precisely but giving rough values and numbers.
- Operators working with teaching and automatic programming of welding are required being more or completely explicit about their knowledge and the formalising of it.
- The knowledge from the operator can be noisy because the operator can misunderstand the physical relations of the process and different operators can have different opinions when describing the welding process.
- It is discovered that operators from interviews can describe and formalise welding knowledge as relations and interactions.
- Operator knowledge is potentially a cheap knowledge source to produce.

2.3 Empirical knowledge

Knowledge from empirical experiments is a commonly used source of gathering welding knowledge.

2.3.1 Analysis of empirical knowledge

Empirical knowledge is defined as knowledge based on scientific testing or practical experience, [Longman, 1995]. The empirical knowledge from practical experience is in this thesis considered as operator knowledge described in the previous section. This section only deals with the empirical knowledge from scientific testing. Empirical knowledge is based on observations or measurements from practical experiments, from which inter-related datasets are produced. For the experiments a test setup is required where the relevant parameters are measured and observed. These measurements and observations have to be analysed and formalised into datasets of commonly known terms.
For welding, an operator can carry out the welding experiments with measurements and observations of the welding process. The process of making formalised empirical knowledge of the welding process is illustrated in figure 2.5.

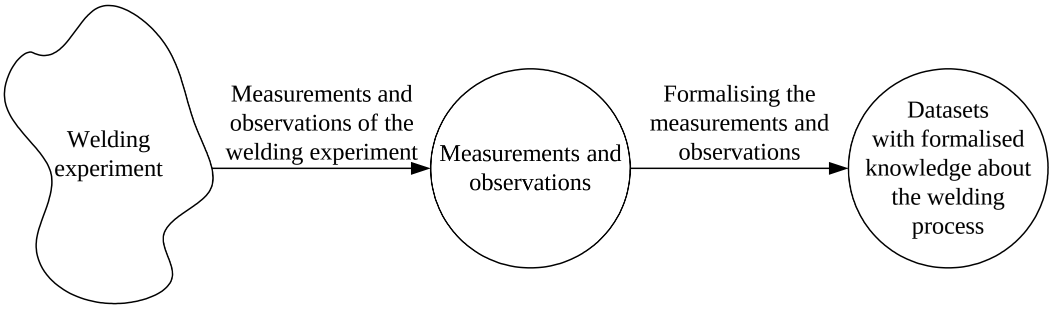


Figure 2.5: Formalising knowledge from welding experiments.

The empirical datasets are often hard to reuse from other empirical experiments. The most important causes for this are:

- Not well defined boundary conditions. The information about parameters and variables is missing or not uniquely defined so repeatable experiments cannot be made.
- No standardised documentation. The datasets are written in different formats so they require conversion before they are in the same format and can be merged together.

Another issue about using empirical data is in case of many parameters and variables which requires a lot of experiments to produce the empirical data.

2.3.2 Generation and use of empirical data

Before describing the generation of empirical data is two definitions required.

Definition of tolerance box

The tolerance box is the area stretched out where the output parameters with a defined probability are inside.

Definition of process window

The process window is the area stretched out where the input variables result in output parameters inside the tolerance box.

The procedure of making datasets to an empirical process-planning model is based on [Ropohl, 1975]. The procedure is divided into four tasks:

1. Determine the input variables and the output parameters of the system.
2. Define for the output parameters their allowed tolerance box according to the determined performance.
3. Make screening experiments to determine which input variables have effect at the output parameters and to determine the selected input variables process window.
   - Stochastic search (trial and error).
   - Systematic search.
4. Make experiments inside the process window to create empirical data.
   - Stochastic search (trial and error).
   - Systematic search.
   - Factorial design: Full factorial, fractional factorial, orthogonal array, one factor at a time.

Going through the four tasks require for the two last tasks a selection of one of the sub method for each of the tasks.

In the third task are made experiments adjusting the welding control variables to determine the process window. At the same time it is also investigated, which welding control variables affect the welding process and the quality, and in which direction the quality is affected. It results in experiments both inside and outside the process window as illustrated in figure 2.6.

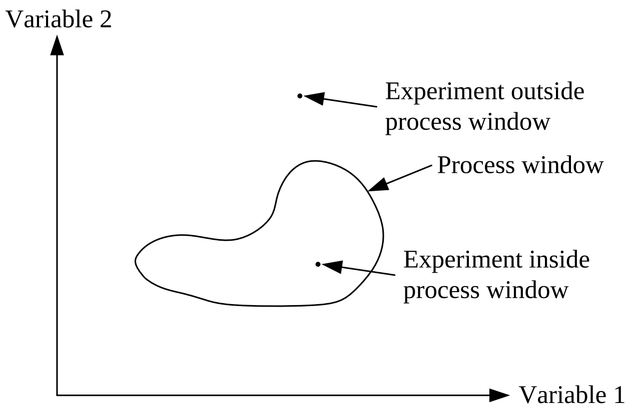


Figure 2.6: Illustration of the process window for two variables.

The number of required experiments for task three and four is very much dependent on the size of the process window, the number of welding control variables and the welding experience of the person carrying out the experiments.

Stochastic search (trial and error)

The stochastic search method for carrying out the experiments is by trying the most likely settings of the welding control variables. The experiments are carried out iteratively using knowledge from the previous experiments. There is no plan for the experiments so the settings of the welding control variables are decided by the operator before carrying out each experiment. For task three these experiments leads to find the welding control vectors to control the process and adjust them to determine the process window shown in figure 2.7. For task four the purpose of the experiments is to investigate the process window area and each welding control variable impact on the quality parameters. It is done to produce distributed datasets spread around inside the process window shown in figure 2.7.

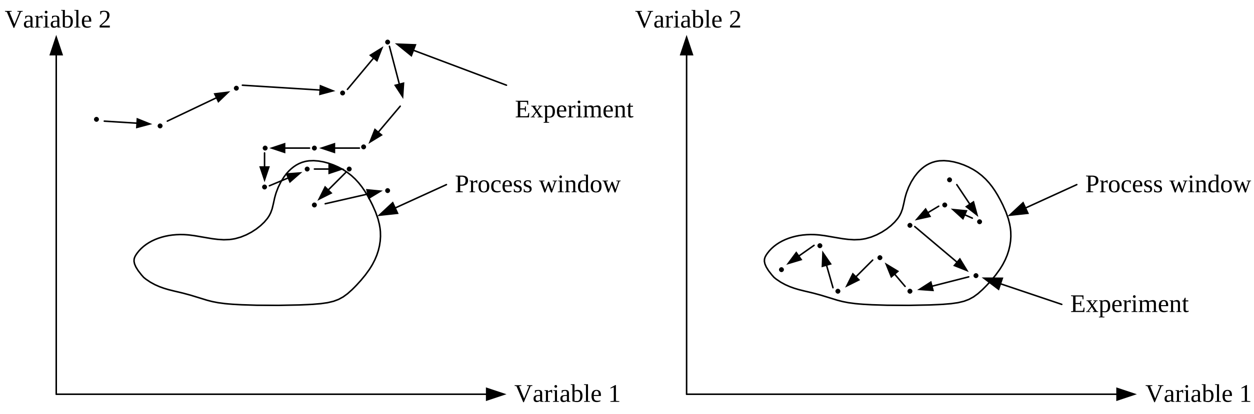


Figure 2.7: To the left is a part of the process window determined by a series of stochastic planned experiments and to the right is the inside of the process window investigated by a series of stochastic planned experiments.

The unordered empirical datasets produced by stochastic search are useful for creating process-planning models which are based on learning methods. Within the field of learning methods different learning approaches are developed as reviewed in appendix A. The amount of empirical datasets required for these methods is dependent on factors, such as how accurate and reliable the process-planning model should be and how complicated it is to model the process. The amount of required datasets is also dependent on factors as the shape and size of the process window, skills of the operator to explorer the process window and the number of welding control variables.

Systematic search

The systematic search method for carrying out the experiments is trying the settings of the welding control variables after a certain pattern. The benefit of the systematic search compared to the stochastic search is to maintain the control of the experiments. Systematic search can be used for both determining the process window and to produce distributed datasets spread around inside the process as illustrated in figure 2.8.

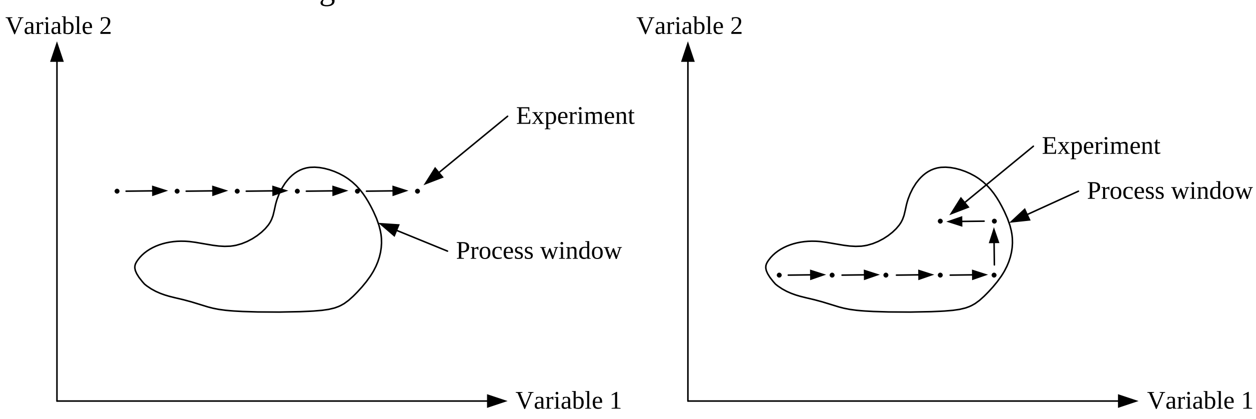


Figure 2.8: To the left is a part of the process window determined by a series of systematic planned experiments and to the right is the inside of the process window investigated by a series of systematic planned experiments.

The dataset produced from systematic search can be used in a similar way as it was described for the stochastic search.

Factorial design

Factorial design is a systematic and often used method, based on statistics, to produce an experimental plan for carrying out experiments and for further analysis of the experiments. The statistical plan lay out the factor levels in a series of experiments to explore the system's behaviour, shown in figure 2.9. By factor is meant the variables to vary for the different experiments and if possible also the noise factors if they can be measured. Factorial design is described in [Montgomery, 2001] and [Walpole et al., 2002]. From the factorial design's experimental results, a function can be constructed and optimum settings of the factors can be found. For a large number of factors and for a system with a complex and interconnected relationship, the number of required experiments is large and the analysis needs to be made with great care. Different plans for factorial design can be deployed depending on the number of factors and the system. Four of the most important factorial designs are listed below:

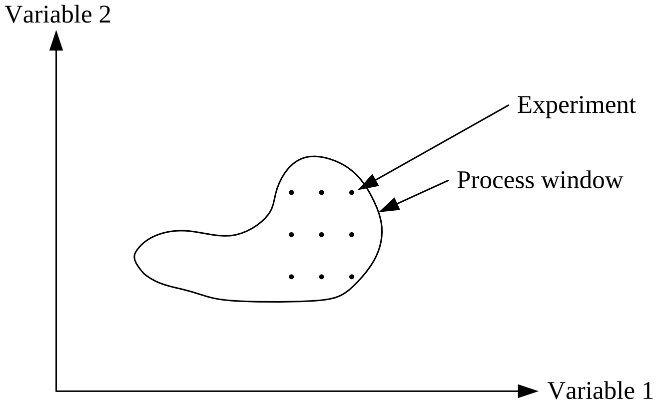


Figure 2.9: Example of a factorial plan for two variables to determine the systems behaviour within the area of experiments.

Full factorial

The full factorial design explores systematically every combination of levels of each factor. Besides identifying the main effect, multifactor interactions can also be identified. A full factorial design is experimental resource demanding because investigating k factors at n levels requires n^k experiments.

Fractional factorial

The fractional factorial design minimizes the number of required experiments to a fraction of a full factorial design. A disadvantage is the ability to compute all effects from interactions is sacrificed. To make the fractional factorial design knowledge about the process is required in order to eliminate some of the interacting effects. For welding a 2^{5-1} fractional factorial design is used by [Moon et al., 1997] for making a model for process-planning reducing the number of experiments to the half.

Orthogonal array

The orthogonal array design is also often referred to as the Taguchi method. This design makes the smallest fractional factorial plan where the main effects from each factor can be identified. The identification of the main effect can be made even though many interacting effects confound the main effect. The design is used in [Juang et al., 2002] for making a model to optimize the weld pool geometry for TIG welding.

One factor at a time
The design with one factor at a time is an unbalanced experimental plan which is generally an inefficient way to explorer all the factors. This is even though the number of trial for each factor is small with $1 + k\ (n - 1)$ experiments for the first factor.

2.3.3 Features of empirical knowledge

The representation of the formalised empirical knowledge from experiments is stored as interrelated datasets in a database. A generic structure of datasets and a database is proposed in chapter 3.

Features of the empirical knowledge are characterised by the following points.

- An unknown number of experiments are carried out and cannot be used before the area of the process window is found where a useful quality is produced.
- Each empirical dataset tells only about the process in this point.
- It is very expensive and time consuming to produce datasets because an experimental setup is required and each experiment requires preparation, execution and analysis.
- The knowledge source is hard to reuse because of defective documentation.

2.4 Analytical knowledge

Analytical knowledge is found in the literature and it describes very well defined and approved physics. For the welding process, analytical knowledge is used to describe the process is limited, but because welding is a very complex and chaotic process with high temperatures, electricity, gases and melted metal.

2.4.1 Analysis of analytical knowledge

A substantial amount of research is going on in the area of creating analytical based models for welding.
The origin of the analytical knowledge is experiments and observations which have been formalised as for the empirical knowledge. The formalised knowledge has been approved, generalised and formalised to a general usable form. Figure 2.10 illustrates the creation of analytical knowledge.

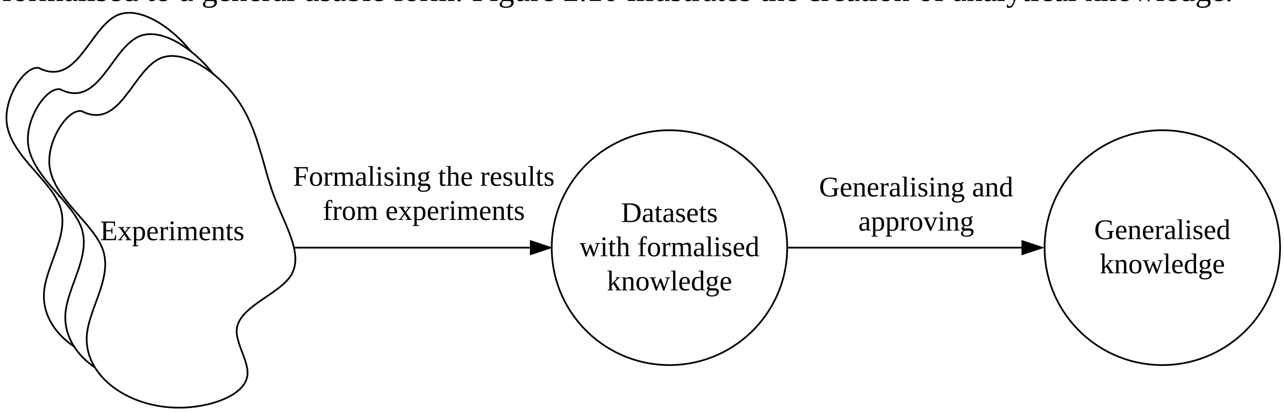


Figure 2.10: Illustration of how analytical knowledge is constructed to described the welding process properties. Several experiments are formalised, generalised and approved to make analytical knowledge.

Analytical knowledge within the welding area is mainly described by equations and rules. For welding, the complex and chaotic characteristics of the process limits the amount of available rules and equations. To make general rules for welding, it is often necessary to use elementary cases. The approach is then to decompose the task to a model of elementary cases and use a FEM program to solve the task. The analytical knowledge source for welding can then be distinguished between either an overall model or an elementary model.

2.4.2 Generation and use of analytical data

The analytical equations and rules found in the literature can have a general character that can be used as general relations or an elementary character that can be used in more specific models as finite element models and thermal models.

General relations

Few examples of equations and rules to use for the general relation are given below.

- Mass conservation from the law of mass conservation [Serway, 1996] states that mass is neither created nor destroyed. That induces the mass before the process equals the mass after the process.
- Energy conservation from the first law of thermodynamics [Serway, 1996] says that the total inflow of energy to a system must be equal to the total outflow of energy from the system, plus the change in the energy contained within the system.
- The power P is in [Serway, 1996] calculated from voltage U and current I as:

  $$P = U \cdot I$$

  Q is the energy disposed from electrical power P dissipated over a resistor, [Serway, 1996]. For welding the absolute largest resistance in the welding circuit, illustrated in appendix B, is over the arc and the electrode sticking out of the contact nozzle. The energy disposed Q is on different forms as heat, radiation of light and heat, chemical conversion and electromagnetic field. The energy is calculated as:

  $$Q = (U_e + U_a) \cdot I$$

  The energy input is calculated as the voltage drop, U_e and U_a, between the contact tube and the weld pool multiplied by the current I. Depending on the welding process the amount of energy disposed Q converted to heat energy Q_h is different.

  $$Q_h = k \cdot (U_e + U_a) \cdot I$$

  The amount of energy transferred to heat energy in the workpiece is from [DS/EN 1011-1] determined by efficiency constant k, which is 0.6 for TIG, 0.8 for MIG/MAG and 0.9-1.0 for submerged arc welding.

- Heat input Q_i is the energy from the equation above divided with the travel speed v_t, which is described by [DS/EN 1011-1]:

  $$Q_i = \frac{k \cdot (U_e + U_a) \cdot I}{v_t}$$

- Relation between wire feed speed v_e, current I and CTWD l_c is described by [Bolmsjö, 2001]:

  $$v_e = k_1 I + k_2 l_c I^2$$

When the wire feed speed is increased the current is also increased. The constants k_1 and k_2 need to be determined from empirical experiments. Over a small region the equation can be approximated as a linear relation without the second order term [Bolmsjö, 2001].

- Relation between terminal voltage U_t and current I is used for type testing of welding machines and is specified in the international standard for arc welding equipment [IEC 60974-1]:

  $$U_t = k_5 I + k_6$$

  It is a static model and it does not describe phenomena of the arc with shift between globular and spray transfer. The constants k_5 and k_6 are determined from empirical experience to be 0.05 and 14 respectively. The relation can be explained in appendix B with the welding machine characteristic, where the machine characteristic line can be parallel-displaced up and down for different levels of matching pairs of voltage and current.
- Welding standards for classifying the quality and for welding are [ISO 5817] for geometrical weld quality, and [DS/EN 1011-2], [DS/EN 1011-3] and [DS/EN 1011-4] for metallurgical weld quality.

Finite element and thermal models

An overview of the area and phenomena for welding process modelling using finite element and thermal model is given. The overview is based on [Goldak et al., 2006], [Jeberg, 2005] and [Lindgren, 2001d] who give a more detailed description.

- Heat source models of the arc with heat conduction to the workpiece and within the workpiece with temperature distribution in each time step.
- Material addition from the electrode for MIG/MAG welding, where drops of metal are added to the weld pool.
- Weld pool model, where impact from gravity, surface tension and arc pressure affects the weld pool shape.
- Stress and strain model, where the distribution of stress and strain is affected by thermal expansion of the material and the thermal history.
- Microstructure evolution model, where the distribution of the microstructure is determined by the thermal history and the alloy.

Making an elementary model and solving the model using FEM is an approved method, it is described in appendix A. However, making the inverse solution for the same model is not a trivial task because the inverse problem has to be solved as it is reviewed in appendix A. The inverse modelling makes the use of analytical knowledge for the elementary model less interesting.

2.4.3 Features of analytical knowledge

Features of the analytical knowledge are characterised by the following points.

- The welding process is not fully describable by analytical knowledge because the physics of the welding process are not fully understood.
- Empirical experiments are often required to calibrate empirically based constants in the equations.
- For the overall model the amount of analytical knowledge is limited.
- The elementary model, solved by FEM, requires modelling of the workpiece and the boundary. The same is in the case of the inverse problem because it is computational demanding and it is not a trivial task.

2.5 Summery

The presentation of the welding process, in appendix B, illustrates that many parameters and variables affect the process and should be included for building process-planning models. Knowledge is required for building a process-planning model. The analysis of the operator knowledge, empirical knowledge and analytical knowledge leads to the following characteristics:

- The cost of the empirical data is high compared to operator data is found by interviews and analytical data is found from the literature, because expensive experiments are required.
- The accessibility of the empirical data is a matter of making enough experiments while the operator data and analytical data cannot describe the welding process completely.
- The level of details describes how accurate the knowledge source description is. The empirical and analytical data both have a high detail level because they come from certain repeatable, documented experiment and a general documented description. The operator data is less detailed because the operator generally has less precise description of the data.

About the different sources of data the following can be stated:

- Even though empirical data has a high cost it is unavoidable because both operator data and also several equations from analytical data cannot stand alone but requires empirical data for calibration.
- The reliability of the empirical data and the operator data is dependent on the people involved in creating the data, whereas the analytical data is well approved and verified. The analytical data and the operator knowledge are not more reliable than the empirical data used for calibration.
- The accessibility and level of detail for the operator data is very dependent on the abstraction level of the operator.
- The empirical and operator data cannot be used directly, but requires data processing or application in modelling for constructing a process-planning model.

Chapter 3

A data model for production of empirical data

In chapter 2 it was identified that use of empirical welding data from different sources is difficult for production of process-planning models. It is difficult because there are no standardised descriptions of the data. Hence in this thesis, a generic information model for describing empirical data has been developed. The information model taxonomy and data representation are described.

This chapter is structured as follows; the generic information model is described first. Afterwards the presented model is applied in two examples: one with a T-Joint with a square groove, and one with a corner-Joint with a bevel groove.

3.1 Generic information model

Expenses and time consumption for production and analysis of empirical welding data make empirical data a restricted source. Furthermore documentation of empirical data does in many cases not follow a standardised data representation and is not sufficiently documented for repeatability. These factors make reuse of the data awkward or impossible. The work by [Lauridsen, 1991] proposes a standardised way to measure and to represent empirical welding data for multi-pass welding. [Rippey, 2004] proposes a welding data dictionary to gather welding data in a single document with a dedicated format. The welding data dictionary is based on standards from the American Welding Society, and it is a static database describing workpiece parameters, quality parameters and describing jointly equipment parameters and welding control variables. Also [Kojima, 2002] proposes a structure to represent manufacturing data and he uses welding as a case. In this thesis the information model is developed consistent with the work of [Rippey, 2004] but it differs on the following points:

- The model can represent dynamic welding data and not only steady state data. It is useful for start and stop of the welding process and for changing of welding control variables and workpiece parameters.
- It divides equipment parameters and welding control variables according to [Madsen, 1992] to separate parameters from variables.
- Process variables collected during welding execution are stored in the database.
- Groove orientation is described according to [Lauridsen, 1991] to give the exact grove orientation.
- The representation of the geometry is changed in the database to include bounds specifying only valid configurations of joints and grooves.

The information model was developed for generic use, but in this thesis the model is not made complete for any kind of workpiece and equipment. Furthermore, the model is not complete covering all possible parameters and variables.

The generic information model has been developed so that it can store empirical welding process data in a database thus the welding process data can be exchanged between different users. It is achieved by defining and standardising the representation of the data and the access to enter and extract empirical welding data. Furthermore, the generic information model is designed to structure empirical welding data, which is collected from different sources, and stored in the same database.

It is illustrated in figure 3.1 and the different sources producing empirical welding data could be e.g. experiments and industrial production.

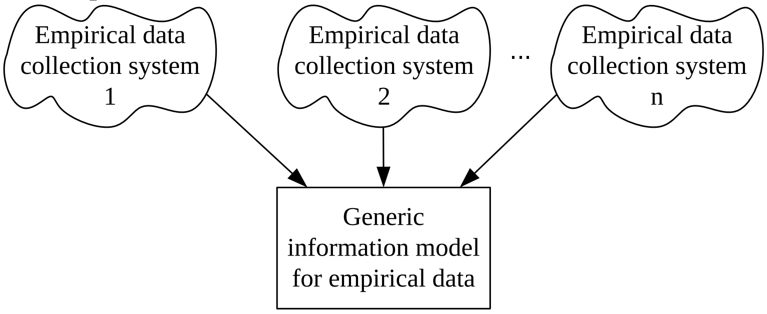


Figure 3.1: A generic information model is used to store empirical data collected from different welding systems.

The idea of the generic information model was to make a model with a clearly defined description of all the parameters and variables in a standardised and systematic way which is not dependent on the workpiece, equipment and sensors used.
In the generic information model it is not sufficient to define workpiece and quality parameters found in standards. Other parameters specifying e.g. unaligned plates have to be defined. It is because real workpieces are not ideal and if they are considered as ideal, information that may be important for later modelling will be lost.
A systematic database was important for later reuse of the datasets and for entering more datasets to the database. To describe the database object oriented taxonomy is used.

The delimitations of the proposed generic information model are:

- A limited amount of the most common workpiece geometries used for welding are included.
- Only welding processes which can be automated are included.
- Parameters and variables for pulsed welding are not included.

The overall structure of the information model is shown in figure 3.2. The developed information model has two parts, a specific part and a general part. The specific part contains raw empirical data and is specific for the welding setup and empirical data collection system used. The general part contains the analysed data from different empirical data collection systems. The generic information model was constructed so that every time welding data is produced it is stored in the specific part. Afterwards the welding data in the specific part can be analysed and described in a standardised and systematic way and then transferred to the generic information model in the general part as illustrated in figure 3.2. The specific part is not part of the generic information model, because it is for a specific welding setup and empirical data collection system. For this reason, the specific part is described later, in chapter 4.

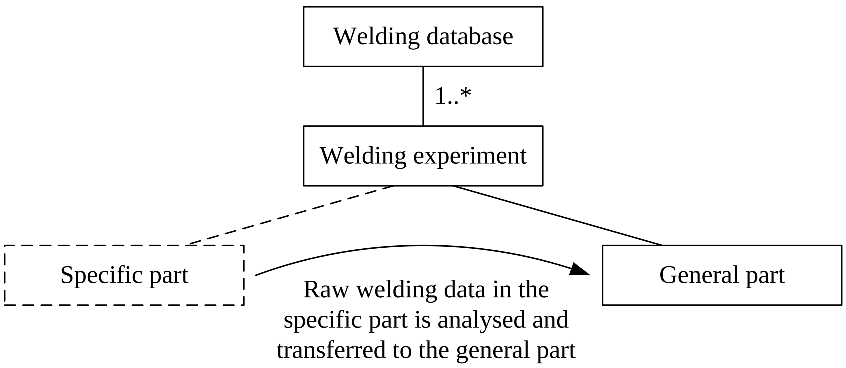


Figure 3.2: The generic information model is a specification of a welding database which consists of data from several welding experiments. Each welding experiment is described in the specific and general part. The specific part is not a part of the generic information model, which is in the general part, but is used for delivering data.

The taxonomy of the general part of the generic information model is shown in figure 3.4. As it can be seen each welding experiment consists of a number of welding experiment samples which are analysed data from measurements along the weld seam illustrated in figure 3.3. During a welding experiment parameters and variables can vary along the weld seam. Hence, for each welding experiment the sample contains the time of the sample and the distance from the start of the welding. Since both the distance and time are stored then the data can be used for both static and dynamic models.

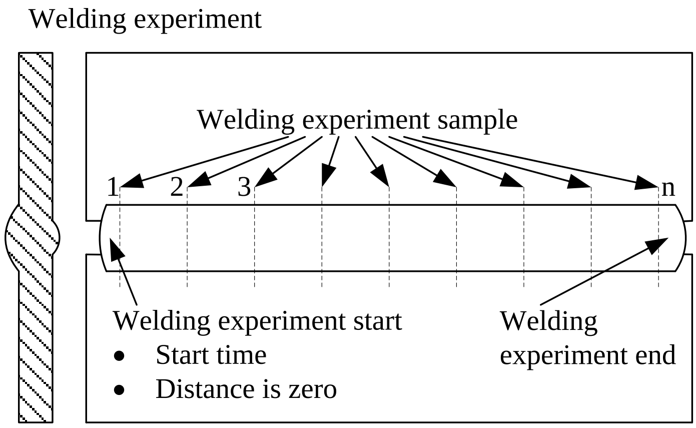


Figure 3.3: Each welding experiment contains a number of welding experiment samples obtained from measurements along the weld seam.

A welding experiment consists of a number of welding experiment samples, as explained before, and fixed parameters, which are further explained below.

Each welding experiment has two child classes “Workpiece parameters” and “Equipment parameters”, which cannot be changed during an experiment.
Each of the welding experiment samples has zero or one of the following four child classes for storing data: “Process variables”, “Workpiece variables”, “Welding control variables” and “Quality parameters”. It can be zero if the child class does not have any data measured for the particular welding experiment sample.
The altogether six child classes correspond to the four kinds of variable and parameter types defined in chapter 1 and shown in figure 1.1. The four kinds have an extra child class “Process variables”, for measurements of process states made during process execution. Furthermore “Workpiece parameters”, illustrated in figure 1.1, is divided into two child classes.

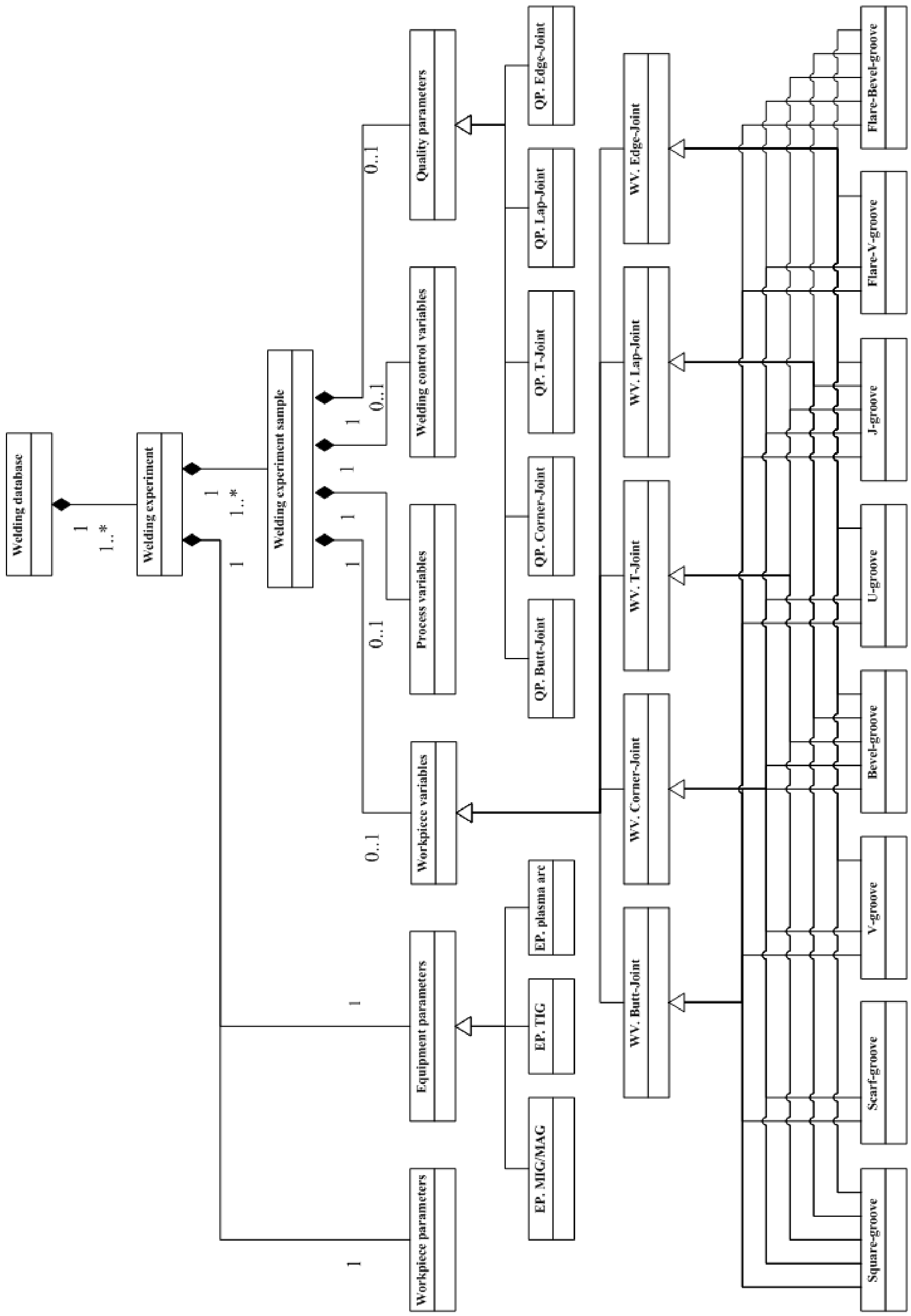


Figure 3.4: Taxonomy of the generic information model. The model is illustrated with attributes in appendix L.

“Workpiece parameters” class

This class describes the general parameters of the workpiece, which do not change for the workpiece. It is e.g. the type of material for the plates.

“Equipment parameters” class

The equipment parameters for the general description of the equipment used are described in attributes. Different welding methods can be applied, and attributes for a specific welding method are described in child classes. In the generic information model in figure 3.4 MIG/MAG, TIG and plasma-arc welding are included, but the model can be extended with other welding methods as e.g. laser welding and hybrid welding processes.

“Workpiece variables” class

This class describes the variables of the workpiece, which change along the seam e.g. the geometrical shape. The geometrical shape can be further specified in child notes by a joint and groove as it is done in the systematic description in [Welding Encyclopedia, 1997]. Not all combinations of grooves and joints are possible due to geometrical reasons described later in section 3.1.1 “Workpiece variables” and possible combinations are shown in figure 3.4.

“Process variables” class

The process variables are stored as attributes from measurements carried out during the process execution and they are e.g. measurements of voltage and current from the welding machine. The measurements are made at the time and distance specified in the class “Welding experiment sample” and as illustrated in figure 3.3.

“Welding control variables” class

Variables for the general description of the welding control variables used are described in attributes. As for the “Equipment parameters” class, different welding methods can be applied, which require adjustment of specific welding control variables for the particular welding method. The attributes for the specific welding control variables are described in child classes.

“Quality parameters” class

The quality parameters for the general description of the quality are described in attributes. For different types of weld joints, shown in figure 3.4, different quality requirements and quality parameters are to be measured so attributes specific for a type of weld joint are described in child classes.

In figure 3.4 not all attributes are included in the taxonomy, but only those important for e.g. describing the workpiece geometry and equipment control variables. Thus, it can be denoted that some classes do not have any attributes.

3.1.1 Workpiece parameters

The workpiece parameters describe the parameters of the workpiece which are not changeable during process execution. The workpiece parameters are as follows:

- Material plate 1 [type] the types is given using the norm EN 10025 (1993).
- Material plate 2 [type] as above.
- Start temperature [degrees Celsius] is usually between 0 and 300 degrees Celsius

3.1.2 Equipment parameters

The equipment parameters describe the parameters of the equipment which are not changeable during process execution. This description is limited to three process types used as example. The three processes are MIG/MAG, TIG and plasma arc and they are illustrated in figure 3.5 and explained in [Welding Encyclopedia, 1997]. The processes have the following common parameters:

- Gas mixture [type] describes the percentage of the different gas components in the mixture.
- Gas flow rate [l/min] is usually between 12 and 18 litres per minute.
- Gas nozzle diameter [mm] is measured as inner diameter of the nozzle and is usually with a diameter between 12 and 25 millimetres.
- Wire type [type] is specified by the name of the wire from the producer and when changing between different producers the producers have tables with specifications converting the wire type to the wire name for another producer.
- Wire diameter [mm] is between 0.6 and 2.4 millimetres.

MIG/MAG:

- Contact tube setback [mm] is the distance the contact tube is sticking out of the gas nozzle and it is usually between -5 and 5 millimetres.

TIG:

- Electrode type [type] is specified by the name of the electrode from the producer in the same way as for the wire for GMAW.

Plasma arc:

- Electrode type [type] is specified by the name of the electrode from the producer in the same way as for the wire for GMAW.
- Plasma gas mixture [type] describes the percentage of the different gas components in the mixture.
- Plasma gas flow [l/min] is usually between 12 and 18 litres per minute.
- Transferred [transferred/nontransferred].

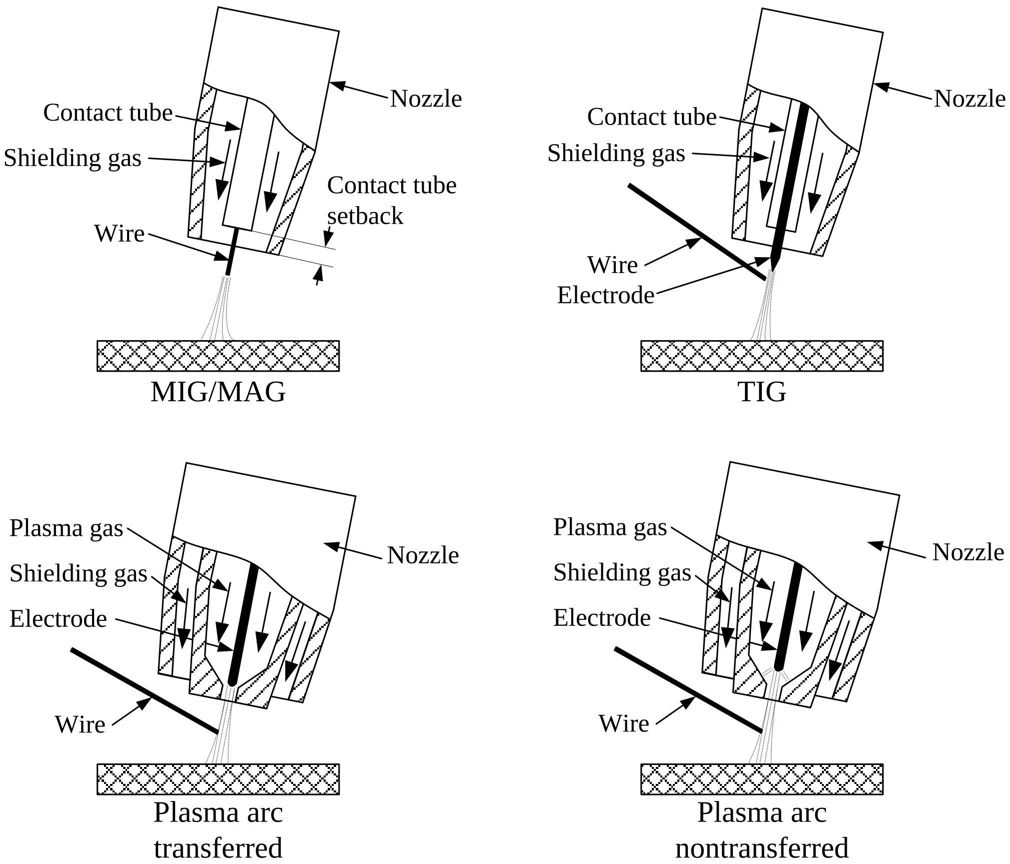


Figure 3.5: Equipment for MIG/MAG, TIG and plasma arc welding. Two methods exist for plasma arc welding: Transferred arc where the arc is between the electrode and the workpiece. Nontransferred arc where the arc is between the electrode and the nozzle, and the hot plasma gas carries the heat to the workpiece.

3.1.3 Workpiece variables

To define the workpiece variables it was first required to define workpiece related terms.
Before defining the workpiece variables a number of definitions will be introduced. The definitions represent a supplement and a modification of the work of [Lauridsen, 1991].

Definition of joints and grooves

The types of weld joints and weld grooves, illustrated in figure 3.6, are defined using the systematic description in [Welding Encyclopedia, 1997]. For each type of weld joint some or all types of the specified weld grooves are applicable and the possible combinations are shown in figure 3.4. The definition of the joint and groove for the workpieces is taken from [Welding Encyclopedia, 1997]:

Joint:
The opening provided between two members to be joined by a weld.

Groove:
The junction of members or the edges of members that are to be joined or have been joined.

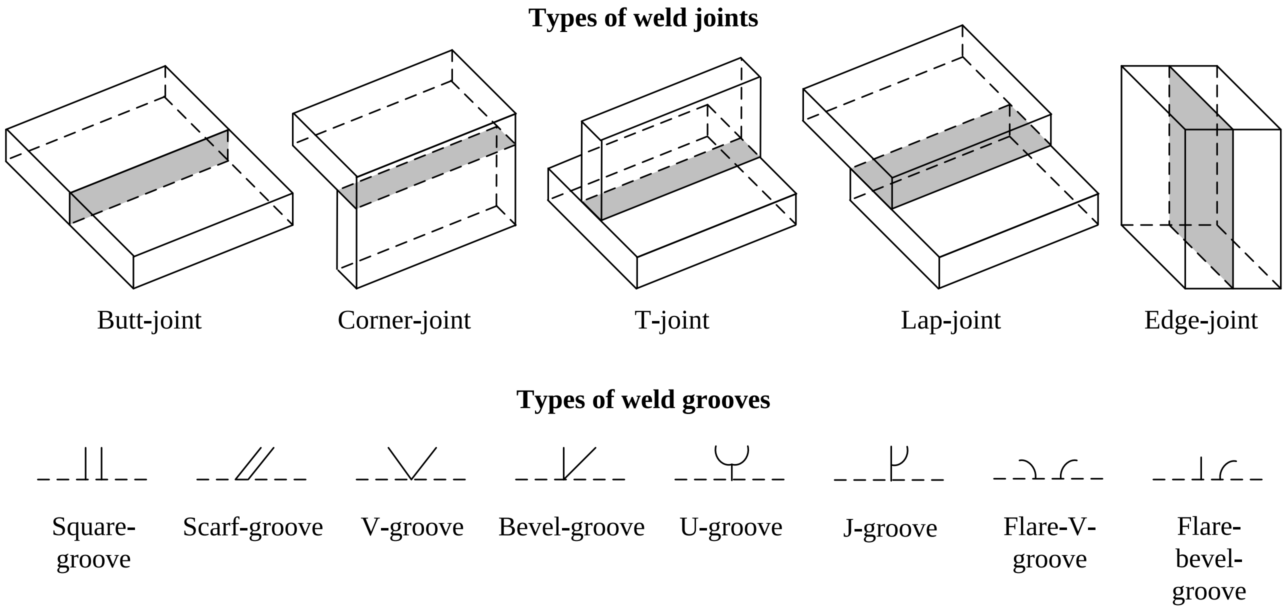


Figure 3.6: Overview of types of weld joints and weld grooves from [Welding Encyclopedia, 1997].

Definition of aligned, offset and angling

Two workpieces to be joined can either be aligned or unaligned. In cases where workpieces are unaligned the un-alignment can be an offset and/or an angling between the workpieces. Figure 3.7 illustrates the four cases.

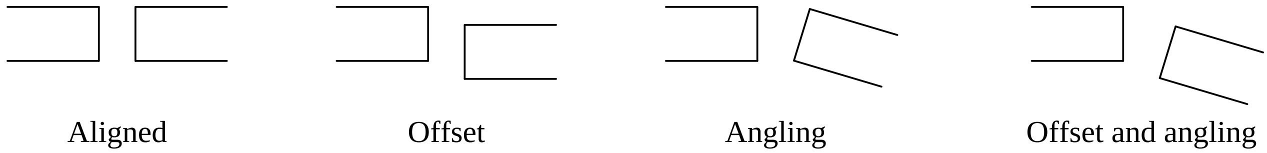


Figure 3.7: For a butt-joint with a root gap an aligned workpiece and un-aligned workpieces shown with an offset and angling are illustrated.

In the following definitions the aligned is case used, but the definitions also apply for the unaligned cases. Un-alignment is not possible for all weld joints.

Definition of pass and bead

The definition of pass and bead is taken from [Welding Encyclopedia, 1997]:

Pass:
A pass is a single progression of welding along a joint, resulting in a weld bead or layer.

Bead:
A weld resulting from a pass.

Definition of weld axis and fix points

A weld axis is placed according to the groove geometry by the following definition and illustrated in figures 3.8 and 3.9:

For all grooves the weld axis is through the length of the weld. It makes the cross section of the groove perpendicular to the weld axis.

Unwelded grooves:
For grooves without bevel (square- and scarf-groove): Fix points are positioned at the groove corner at the weld face side and the weld axis is placed at the midpoint of the line spanned between the fix points.

For grooves with one bevel (bevel-, J- and flare-bevel-groove): A fix point is positioned at the bottom corner of the bevel and from that fix point a perpendicular line is drawn to the groove edge of the other workpiece. The weld axis is placed at the midpoint of the line spanned

For grooves with two bevels (V-, U- and flare-V-groove): A fix point is positioned at the bottom corner of the two bevels and the weld axis is placed at the midpoint of the line spanned between the fix points.

Welded grooves with at least one previous pass:
The weld axis is placed at the intersection between two weld beads or at the intersection between groove edge and weld bead.

The direction of the weld axis vector is in the welding direction.

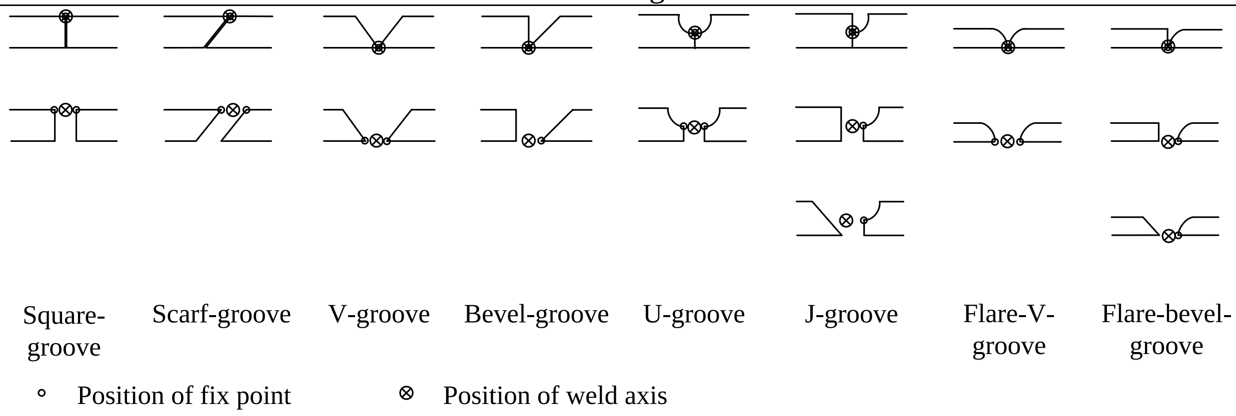


Figure 3.8: Weld axis position in the plane perpendicular to the weld groove. Top row: without a root gap. Middle and bottom row: with a root gap.

For multi pass welding the groove is in most cases best represented by a J-, flare-V- or flare-bevel groove which are illustrated in figure 3.8.

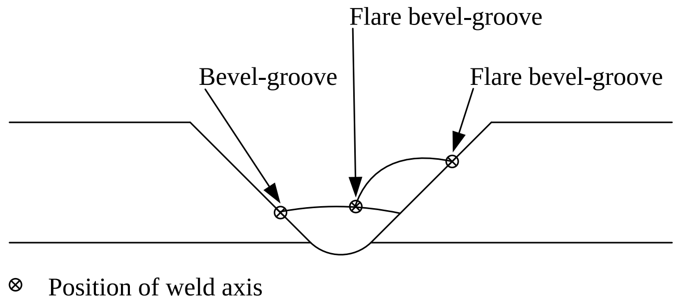


Figure 3.9: For a butt-joint with two weld beads three weld axes are defined as illustrated. The root bead is considered as plane on the weld face side.

Definition of bisector plane

A bisector plane is defined, as illustrated for different groves in figure 3.10, to give an orientation of the groove:

The bisector plane divides the groove in half between the groove legs, defined below, from the weld face side and intersects the weld axis.

For square-, scarf-, V- and bevel-grooves the groove legs are straight edges of the groove.

For U-, J- and flare-grooves the groove legs are tangent to the start of groove edges.

Determination of the tangent for the U-, J- and flare-grooves is not trivial to measure, but in this thesis this measurement is applied to suggest an applicable definition.

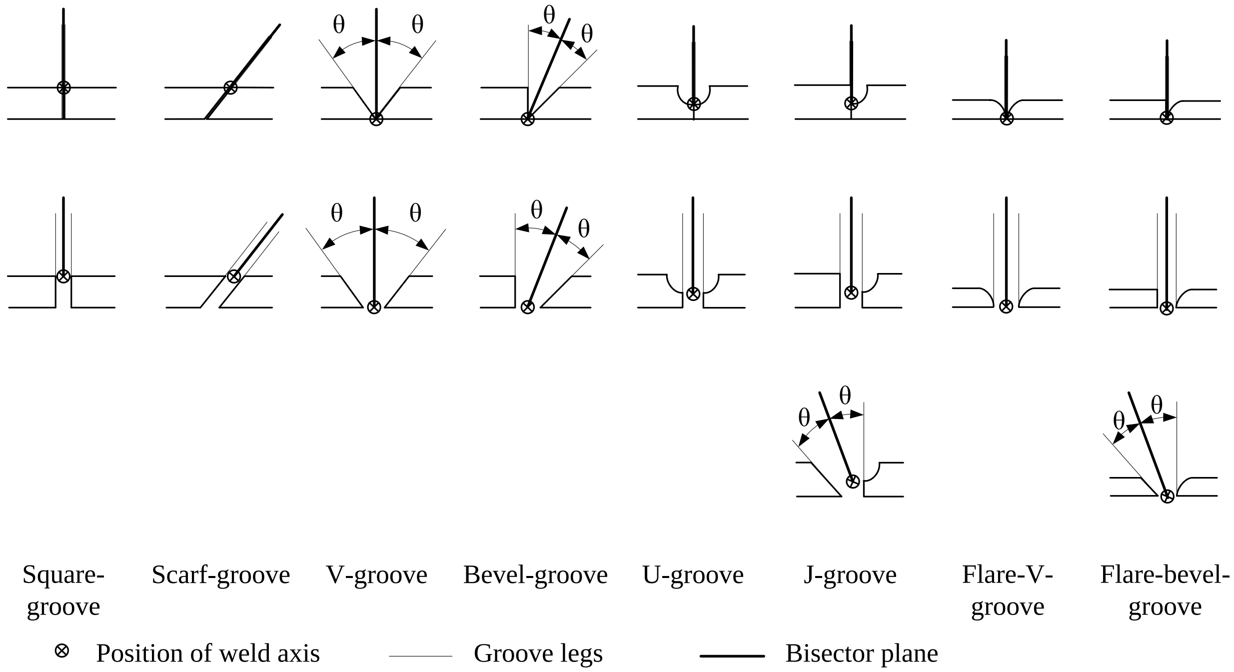


Figure 3.10: The bisector plane is located according to groove geometry where θ is half of the angle between the groove legs.

Definition of bisector vector

From the bisector plane a bisector vector is defined:

The bisector vector is within the bisector plane and perpendicular to the weld axis pointing out of the groove.

Definition of groove vertical and groove horizontal angle

The bisector vector and the weld axis specified on the workpiece can be used to describe the orientation of the weld bead with respect to the direction of gravity by two angles. For this purpose two angles Ψ and Φ are defined and illustrated in figure 3.11:

The groove vertical angle, Ψ, is the angle between the bisector vector and the gravity vector. Ψ is positive if projection of the bisector vector is in the direction of the gravity vector, i.e. the vector product of the bisector vector × weld axis vector is positive.
The groove horizontal angle, Φ, is the angle between weld axis and a horizontal plane. Φ is positive if the projection of the weld axis vector on the gravity vector is in the direction of the gravity vector.

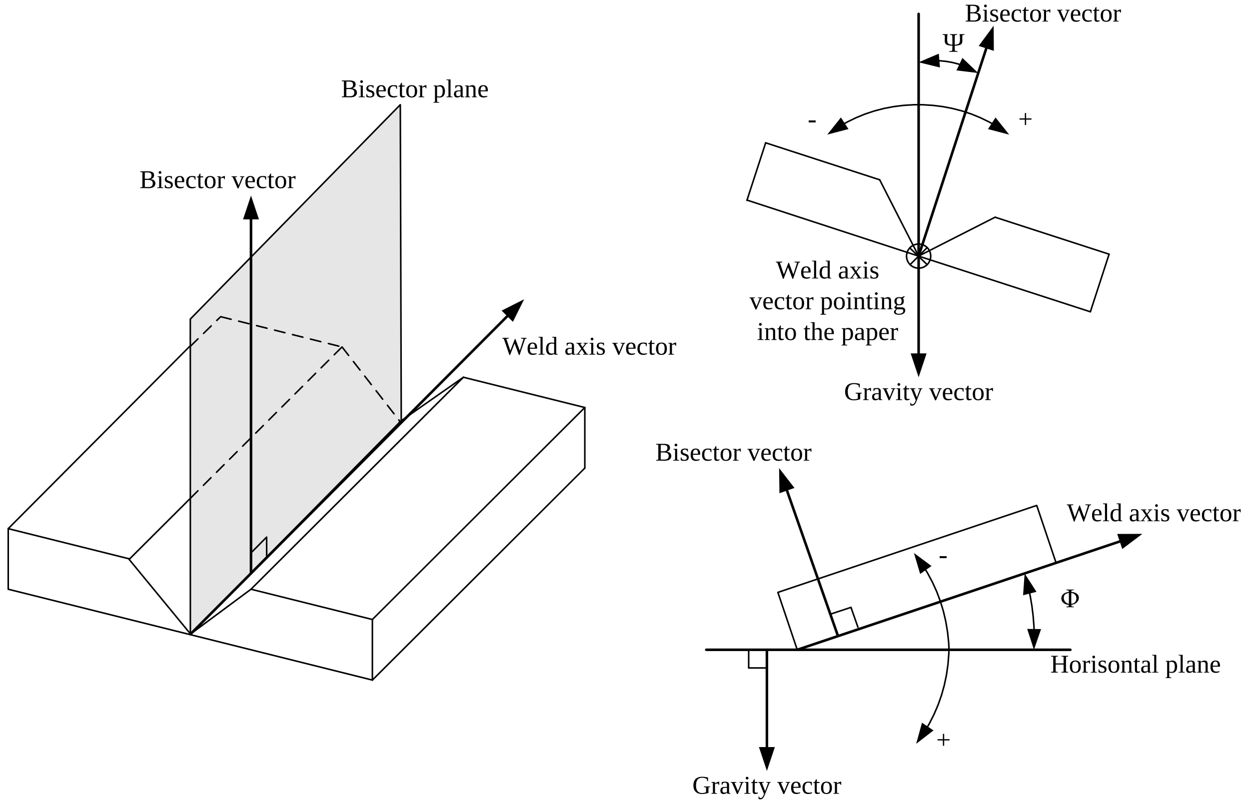


Figure 3.11: The workpiece rotation around the weld axis defines Ψ, and the workpiece rotation around the vector product of the bisector vector × weld axis vector defines Φ. Positive and negative rotational direction is shown.

Definition of groove-frame

A groove-frame is defined to represent the weld groove position and orientation at the pass. The groove-frame follows the welding torch so when the welding proceeds the groove-frame moves along the welding axis. The motion of the tool is determined by the transformation ${}^{groove}T_{tool}$ is defined in section 3.1.5 "Welding control variables". The groove-frame is defined as:

O_{groove}	= origin at the weld axis following the tool frame with the transformation ${}^{groove}T_{tool}$.
X_{groove}	= coincides with the weld axis vector.
Z_{groove}	= coincides with the bisector vector.
Y_{groove}	= $Z_{groove} \times X_{groove}$ to fulfil the frame is a right hand coordinate system.

Definition of workpiece plate 1 and plate 2

The definition of the workpiece plate 1 and plate 2 below and with an illustration in figure 3.12:

Plate 1 is for symmetrical joints, as butt- and edge- joints, in the direction of the Y_{groove} vector.
Plate 1 is for unsymmetrical joints, that is the plate where the leg length, on a drawing, is unaffected by an increasing root gap.
Plate 2 is the opposite plate of plate 1.

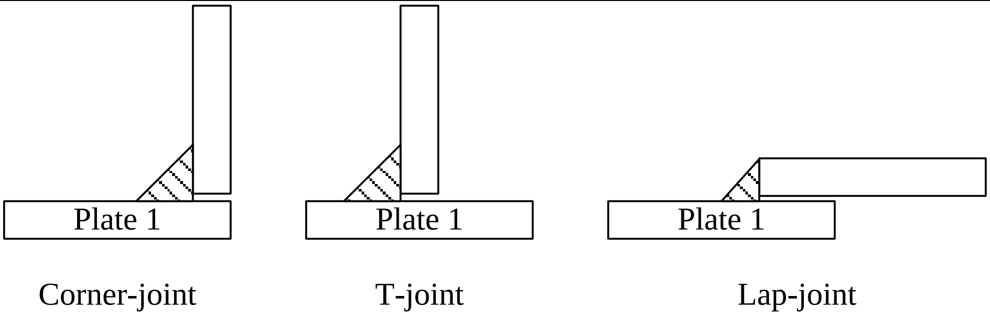


Figure 3.12: Plate 1 illustrates different unsymmetrical joints shown according to the above definition.

The common workpiece variables for the weld joints are the following (see also figure 3.13):

- Root gap [mm] is ≥ 0.
- Thickness plate 1 [mm] is > 0.
- Thickness plate 2 [mm] is > 0.
- Surface plate 1 [type] the types are e.g. untreated with oxide scale or blank.
- Surface plate 2 [type] as above.
- Φ (groove horizontal angle) [degrees] is between -180 and 180 degrees.
- Ψ (groove vertical angle) [degrees] is between -180 and 180 degrees.

The specific workpiece variables for the weld joints are the following and they are illustrated in figure 3.13:

Butt-joint:

- Plate angle [degrees] is between 135 and 225 degrees.
- Offset [mm] has no defined limits.

Corner-joint:

- Plate angle [degrees] is > 0 and < 135 degrees.
- Offset [mm] has no defined limits.
- Plate 2 in direction of Y_{groove} vector [yes/no].

T-joint:

- Plate angle [degrees] is > 0 and < 180 degrees.
- Plate 2 in direction of Y_{groove} vector [yes/no].

Lap-joint:

- Overlap [mm] has no defined limits.
- Plate 2 in direction of Y_{groove} vector [yes/no].

The offset is zero if the plate corner at the backside of plate 1 is aligned with the line spanned from the backside of plate 2. The positive direction of the offset is if plate 1 is moved in the direction of the y-axis of the groove frame.

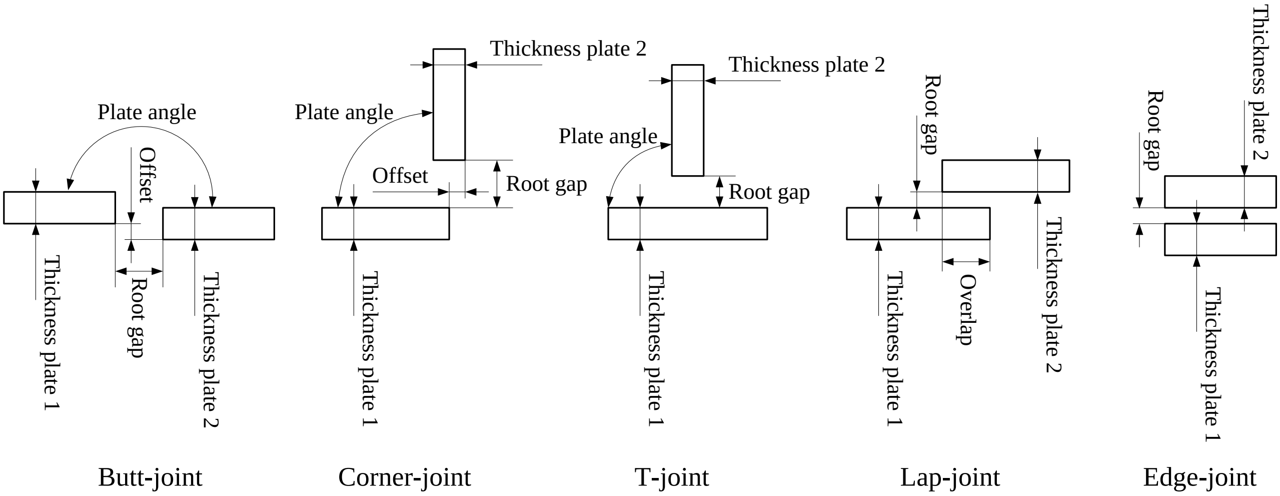


Figure 3.13: Workpiece geometry for weld joints.

For each weld joint a weld groove is defined and the possible combinations are illustrated in figure 3.4. The workpiece variables for the weld grooves are the following (see also figure 3.14):
Scarf-groove:

- Scarf angle [degrees] measured from plate 1 is > 0 and < 180 degrees.

V-groove:

- Bevel angle plate 1 [degrees] > 0 and < 90 degrees.
- Bevel angle plate 2 [degrees] > 0 and < 90 degrees.
- Depth of bevel plate 1 [mm] has no defined limits.
- Depth of bevel plate 2 [mm] has no defined limits.

Bevel-groove:

- Bevel angle [degrees] > 0 and < 90 degrees.
- Depth of bevel [mm] has no defined limits.
- Bevel plate [1 or 2].

U-groove:

- Bevel angle plate 1 [degrees] > 0 and < 90 degrees.
- Bevel angle plate 2 [degrees] > 0 and < 90 degrees.
- Groove radius plate 1 [degrees] > 0 degrees.
- Groove radius plate 2 [degrees] > 0 degrees.
- Depth of bevel plate 1 [mm] has no defined limits.
- Depth of bevel plate 2 [mm] has no defined limits.

J-groove:

- J-bevel angle [degrees] > 0 and < 90 degrees.
- Groove radius [degrees] > 0 degrees.
- Depth of bevel [mm] has no defined limits.
- J-bevel plate [1 or 2] is the plate number.

- Bevel angle [degrees] > 0 and < 90 degrees.

Flare-V-groove:
- Flare radius plate 1 [degrees] > 0 degrees.
- Flare radius plate 2 [degrees] > 0 degrees.
- Depth of flare plate 1 [mm] has no defined limits.
- Depth of flare plate 2 [mm] has no defined limits.

Flare-bevel-groove:
- Flare radius [degrees] > 0 degrees.
- Depth of flare [mm] has no defined limits.
- Flare plate [1 or 2] is the plate number.
- Bevel angle [degrees] > 0 and < 90 degrees.

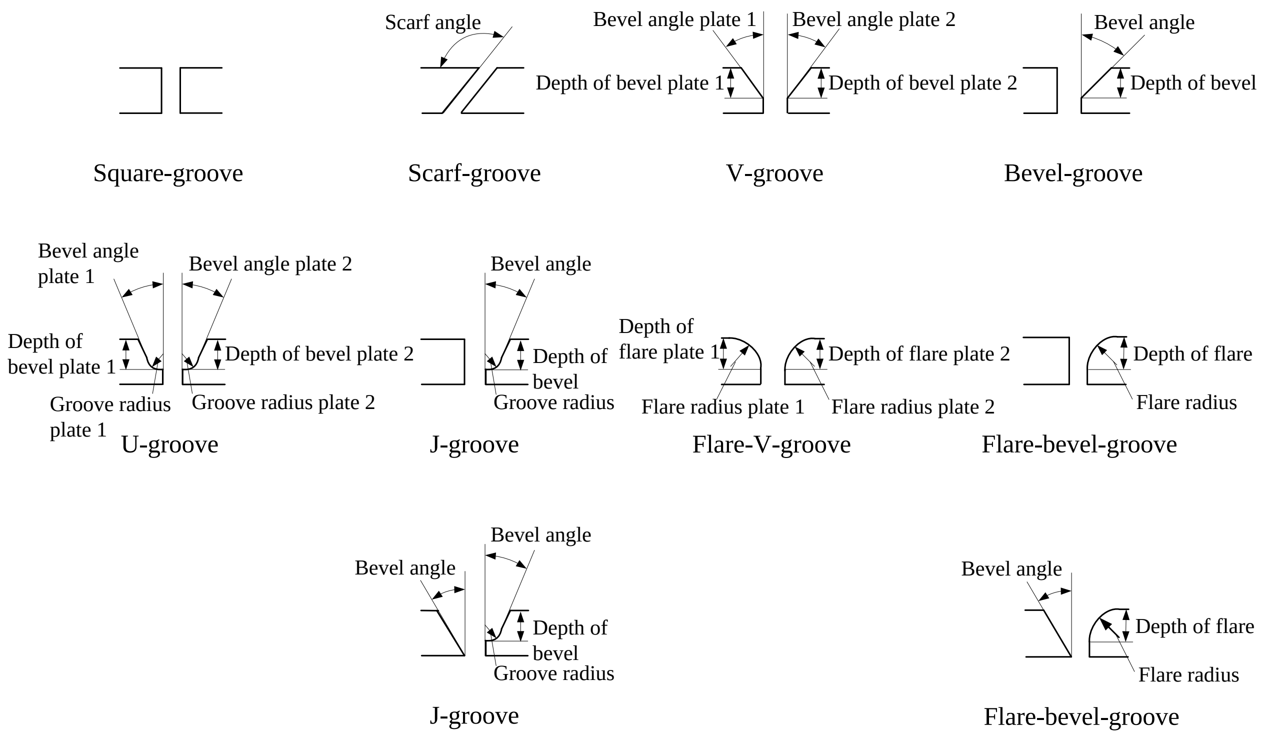


Figure 3.14: Workpiece geometry for weld grooves.

3.1.4 Process variables

The process variables are measurements of variables from the real welding process during process execution.

Process variables are:
- Voltage [volt] is usually between 14 and 40 volt.
- Current [ampere] is usually between 30 and 550 amps.
- Oscillation distance [mm] is from 0 and usually up to 5 millimetres.

The oscillation distance is the distance from the weld axis to the tool centre point, defined in section 3.1.5 “Welding control variables”. Figure 3.15 shows an example of an oscillation pattern.

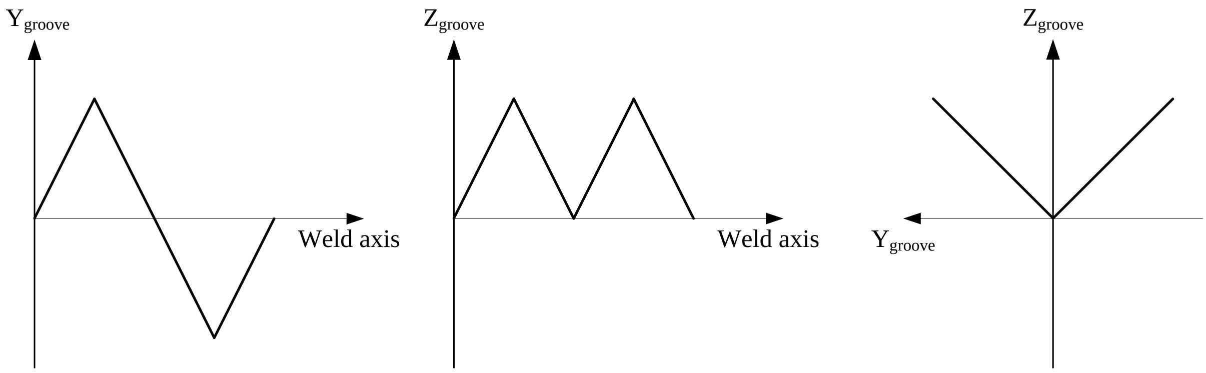


Figure 3.15: An example of an oscillation pattern shown in the Y and Z direction of the groove-frame and along the weld axis. For the oscillation pattern the tool centre point is defined in section 3.1.5 "Welding control variables", following the drawn line during one oscillation cycle.

3.1.5 Welding control variables

To define the welding control variables it is required first to define the welding control variable related terms.

Definition of tool-frame

For the torch a tool-frame is defined:

O_{tool}	= origin of the tool at the tip of contact tube for MIG/MAG welding, tip of electrode for TIG welding and tip of the nozzle for plasma arc welding.
X_{tool}	= extension of the centre-axis of the contact nozzle or electrode.
Z_{tool}	= in the plane of the welding direction and perpendicular to X_{tool}.
Y_{tool}	= $Z_{tool} \times X_{tool}$ to fulfil the frame is a right hand coordinate system.

Definition of contact tube to workpiece distance (CTWD)

The definition CTWD uses the tool-frame and groove-frame definition. It is a distance which is user specified and the definition is:

CTWD is the distance from O_{tool} to the O_{groove} frame without oscillation.

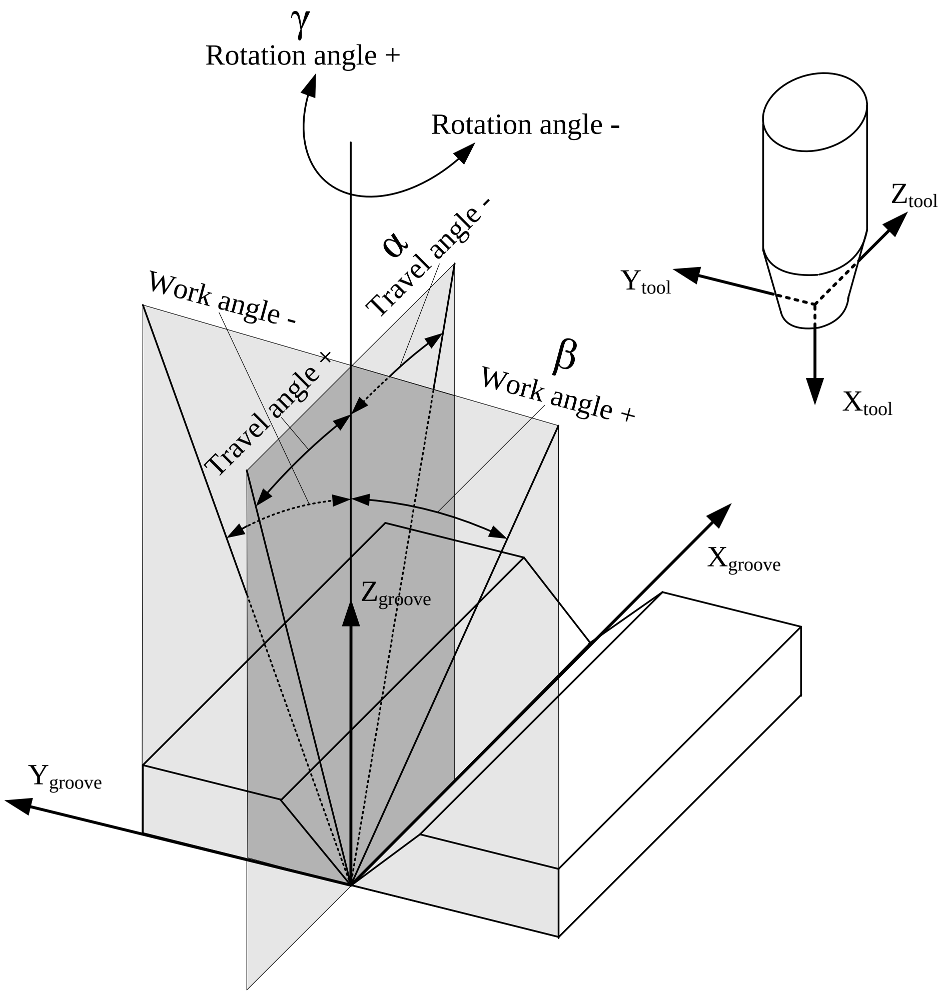
Definition of tool centre point

The tool centre point, abbreviated TCP, is defined:

The tool centre point is the position of O_{tool} projected CTWD in the direction of the X_{tool}.

Definition of groove frame to tool frame transformation

Several welding control variables are used for specifying the transformation from the groove frame to the tool frame as illustrated in figure 3.16.



For
work angle = 0,
travel angle = 0 and
rotation angle = 0
is
$X_{groove} = Z_{tool}$
$Y_{groove} = Y_{tool}$
$Z_{groove} = -X_{tool}$

Figure 3.16: The groove and tool frame are illustrated together with the travel, work and rotational angle and the defined positive and negative directions and orientations.

To define the ${}^{groove}T_{tool}$ the work of [Lauridsen, 1991] which is further developed by [Boelskifte et al., 1994] is used. Travel angle α, work angle β, and rotational angle γ, CTWD, sideway (see figure 3.17) and groove rotation ε (see figure 3.17) are used for calculating the transformation from the groove frame to the tool frame. The equation below keeps the travel-, work- and rotational angles independent so when one angle is changed then others are kept constant.

$$
{}^{groove}T_{tool} = \begin{bmatrix} s\alpha & c\alpha s\gamma & c\alpha c\gamma & -CTWD\cdot s\alpha \\ s\beta c\alpha & c\beta c\gamma - s\beta s\alpha s\gamma & -c\beta s\gamma - s\beta s\alpha c\gamma & CTWD\cdot c\alpha s\beta - c\varepsilon\cdot sideway \\ -c\beta c\alpha & s\beta c\gamma + c\beta s\alpha s\gamma & -s\beta s\gamma + c\beta s\alpha c\gamma & CTWD\cdot c\alpha c\beta + s\varepsilon\cdot sideway \\ 0 & 0 & 0 & 1 \end{bmatrix}
$$

The groove rotation ε is a part of the equations, to define the direction of the sideway displacement to follow the joint. ε is the angle between the bisector line determined by the groove and the joint orientation. The joint orientation is for the butt-joint determined by a vector perpendicular to plate 1 and for corner-, T-, lap- and edge-joint determined by a vector along plate 1. Figure 3.17 shows how ε is established.

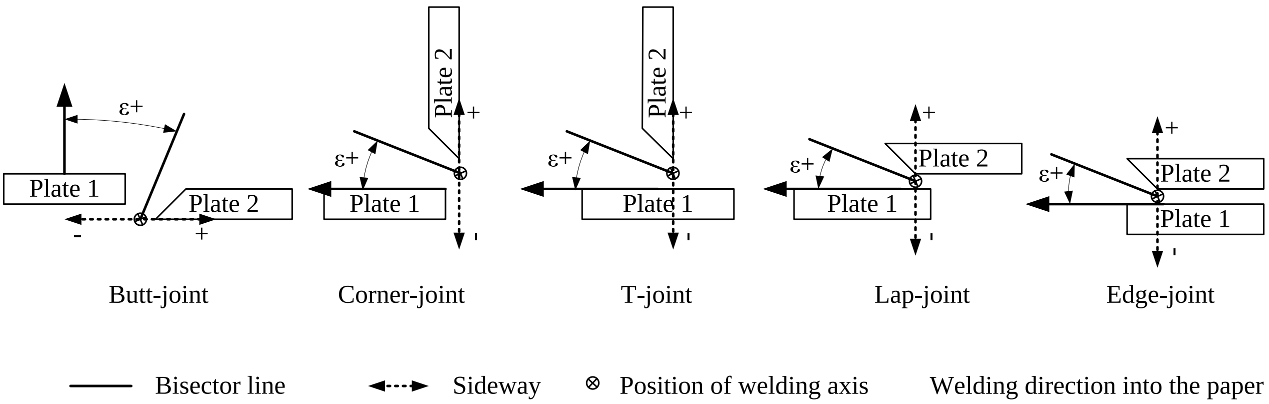


Figure 3.17: Groove rotation ε between a joint vector and bisector line. For all the shown joints ε is positive, marked by a +, when the welding direction is into the paper. The sideway displacement is angular to the joint vector and the positive and negative directions are shown.

The welding control variables are the following and they are decomposed into kinematic-, welding machine- and oscillation variables:
Kinematic variables

- Work angle [degrees] is usually between -45 and 45 degrees.
- Travel angle [degrees] is usually between -45 and 45 degrees.
- CTWD [mm] is usually between 10 and 25 millimetres.
- Sideway [mm] has no defined limits.
- Travel speed [mm/sec] is > 0 and usually between 2 and 20 millimetres per second.

Welding machine variables

- Voltage [volt] is usually between 14 and 40 volt.
- Wire feed speed [m/min] is usually between 2 and 18 m/min.

Oscillation variables

- Oscillation on [Boolean] 0 for off and 1 for on. If off then the nine variables below are not used.
- Oscillation vector X [unit] is between -1 and 1.
- Oscillation vector Y [unit] as above.
- Oscillation vector Z [unit] as above.
- Oscillation width [mm] is > 0 and usually up to 5 millimetres.
- Oscillation frequency [Hz] is > 0 and usually between ½ and 4 Hz.
- Oscillation holding 1 [%] is between 0 and < 100 but is usually between 5 and 50 per cent.
- Oscillation holding 2 [%] is between 0 and < 100 but is usually between 5 and 50 per cent.
- Oscillation holding centre [%] is between 0 and < 100 but is usually between 5 and 50 per cent.
- Oscillation pattern [type] is linear or circular where the circular type has a radius given in millimetres.

The rotational angle is not within the list because it does not affect the process as welding is a rotational symmetric process. It is still required because it is used to orient the equipment to avoid collisions. The rotational angle [degrees] is between -180 and 180 degrees.

Sideway moves the aiming point of X_{tool} in the direction of Y_{groove} with negative direction in the direction of the Y_{groove} vector.

Travel speed is the speed of the welding motion along the X_{groove}.

Voltage states the voltage the welding machine is set to deliver.

Wire feed speed states the speed of the welding wire the wire feed system is set to deliver.

Oscillation parameters for specifying an oscillation pattern are explained in the following and examples are given in figure 3.18:
The oscillation is specified relative to the groove frame, shown in figure 3.16, because specifying the oscillation relative to the tool frame would change the orientation and position depending on the values of the variables calculating the ${}^{groove}T_{tool}$ transformation. The oscillation vector has an x, y and z component where the y and z components specify the oscillation perpendicular to the welding direction and the x component specifies the oscillation in the welding direction. The vector is made into a unit vector. Oscillation width is the double distance of the amplitude. Oscillation frequency is the inverse period time. Oscillation holding 1 is the percentage of the cycle time where the oscillation is kept steady at the maximum amplitude at side 1. Oscillation holding 2 is the percentage of the cycle time where the oscillation is kept steady at the maximum amplitude at side 2. Oscillation holding centre is the percentage of the cycle time where the oscillation is kept steady at the centre of the amplitude. It applies that: oscillation holding 1 + oscillation holding 2 + oscillation holding centre < 100 and when the value comes close to hundred it will be difficult for the manipulator to fulfil the required patter because high accelerations are required. Oscillation pattern can be linear or a circle cut with a diameter larger than the oscillation width.

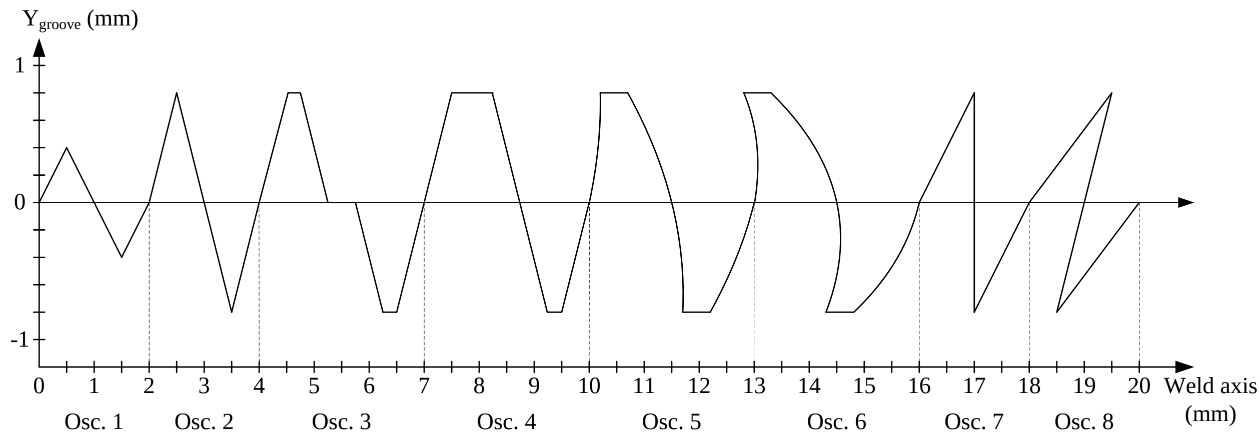


Figure 3.18: Examples of oscillation in the X_{groove}-Y_{groove} plane moving along the weld axis, which coincides with the X_{groove}. Osc. 1-6 oscillate with the oscillation vector Y and where Osc. 7 and 8 oscillate with both oscillation vectors Y and X. Osc. 1 has a width of 0.8 mm while the rest has a width of 1.6 mm. Osc. 1, 2, 7 and 8 have a frequency of 3 Hz and Osc. 4-6 have a frequency of 2 Hz with a travel speed of 6 mm/sec. Osc. 3 has an oscillation holding 1 and holding 2 at 8.3 % and an oscillation holding centre at 16.7 %. Osc. 4 has an oscillation holding 1 at 25 % and an oscillation holding 2 at 8.3 %. Osc. 5 and 6 have a circle cut pattern while the rest of the patterns are linear. Osc. 5 has a circle cut radius at 60 mm and Osc. 6 has a circle cut radius of 30 mm.

3.1.6 Quality parameters

The common quality parameters for specifying welding quality are the following:

- Leg length plate 1 [mm] is ≥ 0.
- Leg length plate 2 [mm] is ≥ 0.
- Depth of fusion plate 1 [mm] is ≥ 0.

- Depth of fusion plate 2 [mm] is ≥ 0.
- Weld face undercut plate 1 [mm] is ≥ 0.
- Weld face undercut plate 2 [mm] is ≥ 0.
- Cracks [grade] the grade is between B and E.
- Holes [grade] the grade is between B and E.

The leg length plate 1 and plate 2, depth of fusion plate 1 and plate 2 and weld face undercut plate 1 and plate 2 are defined as illustrated in figure 3.19. Weld face undercut plate 1 and plate 2 are defined in the ISO standard [ISO 5817] number 1.7. Cracks and holes were both for external and internal welding defects and were defined according to ISO standard [ISO 5817] numbers 1.1 and 1.2 for external defects and numbers 2.1, 2.2 and 2.3 for internal defects. The grades are given from B (highest quality) to E (lowest quality), according to the ISO standard. The ISO standard has only the categories B, C and D, but if it goes below the limit of grade D, grade E is given.

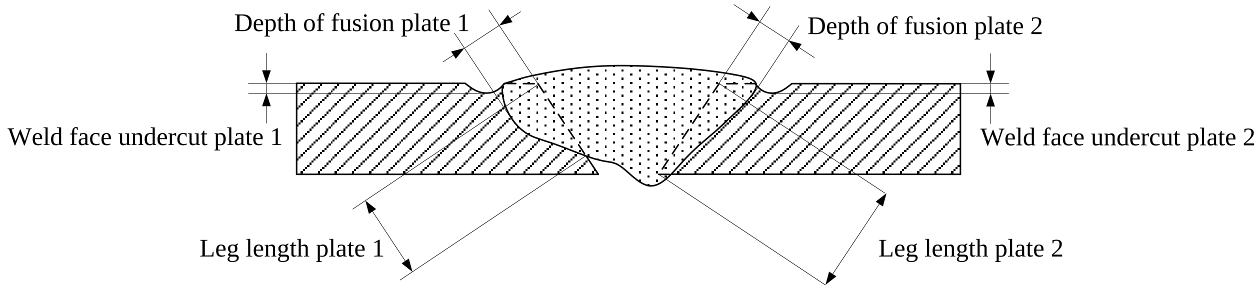


Figure 3.19: Leg length is the distance on the groove edge with interfusions. Depth of fusion is the maximum distance from the groove edge and perpendicular to where the fusion zone stops. Welding direction on the illustration is into the paper.

The joint specific parameters are the following and shown in figure 3.20:

Butt-joint:

- Weld face width [mm] is ≥ 0.
- Weld face height [mm] has no defined limits.
- Back bead width [mm] is ≥ 0.
- Back bead height [mm] has no defined limits.

Corner-joint:

- Back bead width [mm] is ≥ 0.
- Back bead height [mm] has no defined limits.
- Theoretical throat [mm] is ≥ 0.
- Equal legs [grade] the grade is between B and E.
- Convexity [grade] the grade is between B and E

T-joint:

- Theoretical throat [mm] is ≥ 0.
- Equal legs [grade] the grade is between B and E.
- Convexity [grade] the grade is between B and E.

Lap-joint:
- Theoretical throat [mm] is ≥ 0.
- Equal legs [grade] the grade is between B and E.
- Convexity [grade] the grade is between B and E.

Edge-joint:
- Weld face width [mm] is ≥ 0.
- Weld face height [mm] has no defined limits.

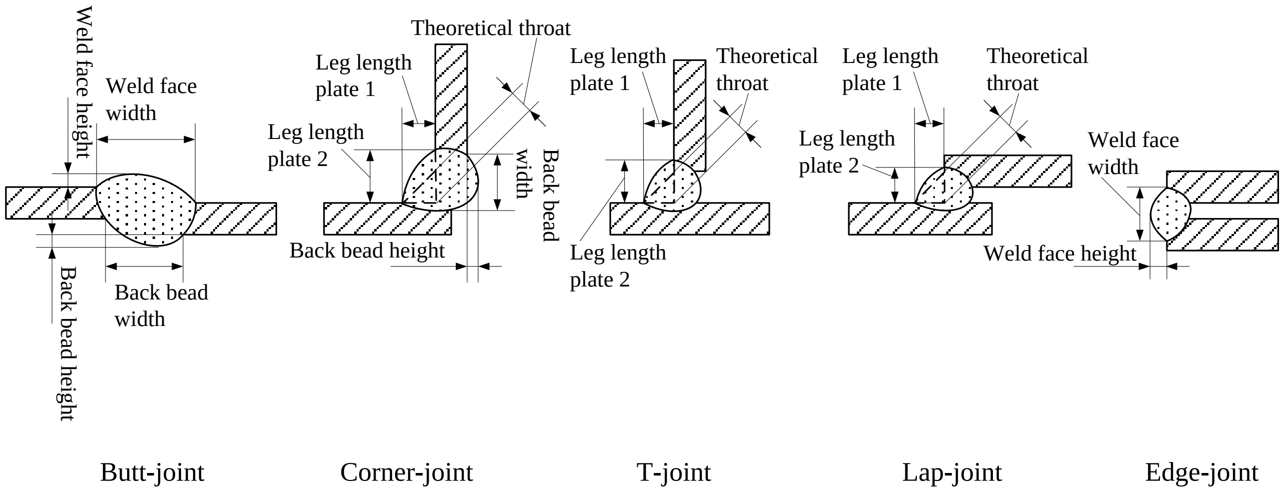


Figure 3.20: Dimensions of quality parameters on the weld, the dotted area, are shown for the five different joint types.

Theoretical throat definition is taken from ISO standard [ISO 5817] number 1.16. Weld face width and weld face height is taken from ISO standard [ISO 5817] numbers 1.9 and 1.10. Back bead width and back bead height are taken from ISO standard [ISO 5817] number 1.11. Equal legs and convexity are taken in the ISO standard [ISO 5817] numbers 1.16 and 1.10, respectively.

3.2 Examples of using the generic information model

In this section the application of the generic information model from section 3.1 is demonstrated. The generic information model was applied for two different workpiece types and one welding method. The applied workpieces were a T-Joint with a square groove and a corner-Joint with a bevel-groove. In the thesis the two parts are referred to as respectively a T-Joint and a HalfV-Joint. The applied welding method was MIG/MAG welding. In chapter 4 these workpieces and the welding method will be referred to because they are used for experiments.

T-Joint

The T-Joint with a fillet weld was used as example because it is often used industrially in e.g. shipbuilding for hull plates and for production of steel rafter for roof constructions, shown in figure 3.21. A varying root gap occurs. The purpose of important quality parameters for this joint is to achieve the specified size and geometrical shape to obtain a decided strength, obtain interfusion and then avoid weld defects.

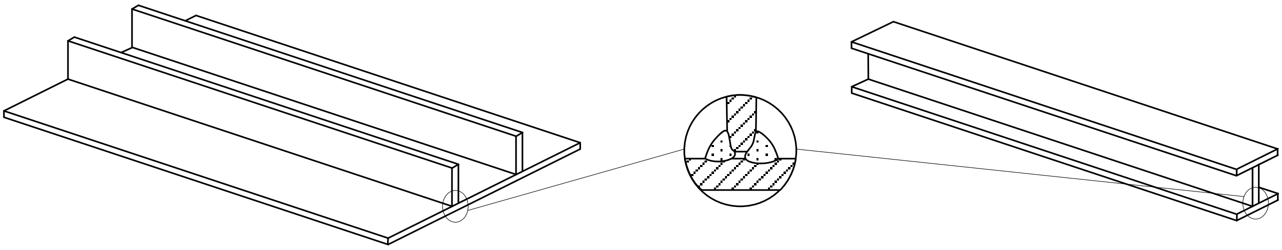


Figure 3.21: To the left: Example of hull plates. To the right: example of steel raft.

The actual experimental parts have the dimensions (T x L x W) at 12 x 200 x 100 mm for plate 1 and 10 x 200 x 100 mm for plate 2.

HalfV-Joint

The HalfV-Joint with a root gap and no backing was used as an example as it is a more difficult weld joint to manufacture than the T-Joint because of the varying root gap and the different thickness of the plates to join. The HalfV-Joint is used industrially for welding of pipe branches, as illustrated in figure 3.22, where the HalfV-Joint is a part of the weld seam. The pipes used industrially in general were seldom completely round because higher tolerances on the roundness are more expensive and the preceding cutting operation can cause distortions. These factors cause a varying root gap and a miss alignment between the plates.

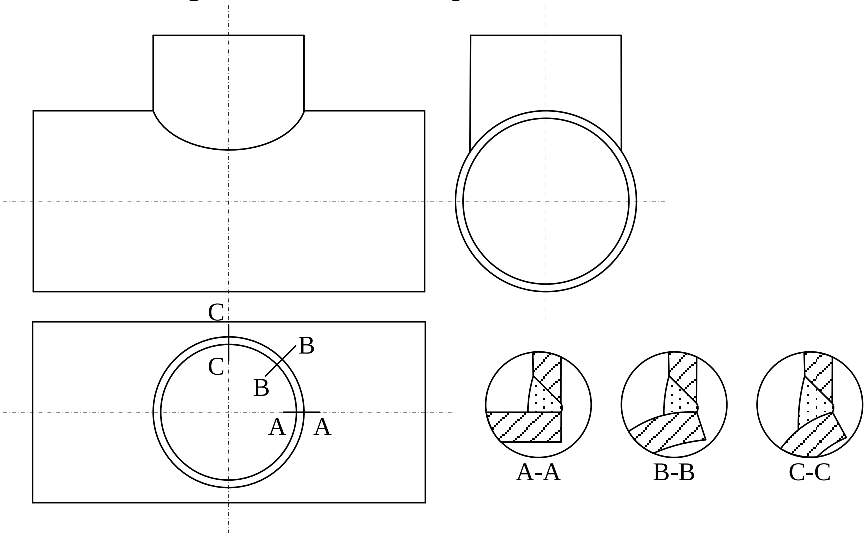


Figure 3.22: Pipe branch where the weld seam is changing from a HalfV-Joint in cut A-A to a V-Joint in cut C-C [Madsen, 1992].

The important quality parameters for the process is to secure a back bead with a geometrical shape e.g. to obtain certain grades according to the ISO standard [ISO 5817] numbers 1.8, 1.11 and 1.17, obtain interfusion and then avoid weld defects. On the weld face side the geometrical shape is not so important because more weld seam would be made to fill the weld groove.

The actual experimental parts have the dimensions (T x L x W) at 10 x 200 x 100 mm for plate 1 and 8 x 200 x 100 mm with 45° bevel for plate 2.

3.2.1 Workpiece parameters

Specification of the workpiece parameters is demonstrated for the two workpieces.

T-Joint

The workpiece parameters defining the material and the material temperature before welding of the specimen are in figure 3.23.

Workpiece parameters
-Material plate 1 = S235JRG2 -Material plate 2 = S235JRG2 -Start temperature = 19

Figure 3.23: Workpiece parameters for the T-Joint.

HalfV-Joint

In a similar manner the workpiece parameters are defined for the HalfV-Joint in figure 3.24.

Workpiece parameters
-Material plate 1 = S235JRG2 -Material plate 2 = S235JRG2 -Start temperature = 20

Figure 3.24: Workpiece parameters for the HalfV-Joint.

3.2.2 Equipment parameters

The equipment parameters specified for the MIG/MAG welding method are demonstrated for a specific setup and shown in figure 3.25.

Equipment parameters
-Gas mixture = Argon 82 and CO2 18 -Gas flow rate = 14 -Gas nozzle diameter = 15 -Wire type = OK Autrod 12.51 -Wire diameter = 1.0

EP. MIG/MAG
-Contact tube setback = 3

Figure 3.25: Equipment parameters for the MIG/MAG welding process.

3.2.3 Workpiece variables

Specification of the workpiece variables is demonstrated for the two workpieces in figures 3.27 and 3.29.

T-Joint

The workpiece variables of the T-Joint specimen are shown in figure 3.26. The root gap can vary within the interval of 0-3 millimetres and must be measured to obtain the specific measurement.

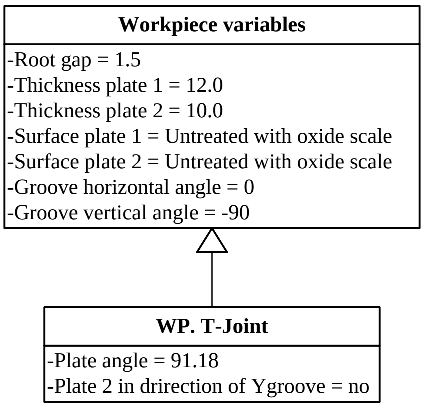


Figure 3.26: Workpiece variables for the T-Joint and the geometrical variables are illustrated in figure 3.27.

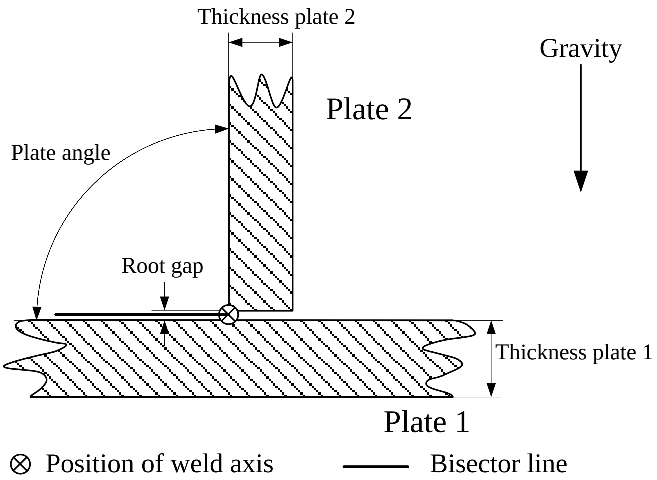


Figure 3.27: Geometric workpiece variables for T-Joint.

HalfV-Joint

In a similar fashion, the workpiece variables for the HalfV-Joint are shown in figure 3.28. The root gap can vary within the interval of 2-5 millimetres and must be measured to obtain the specific measurement as exemplified.

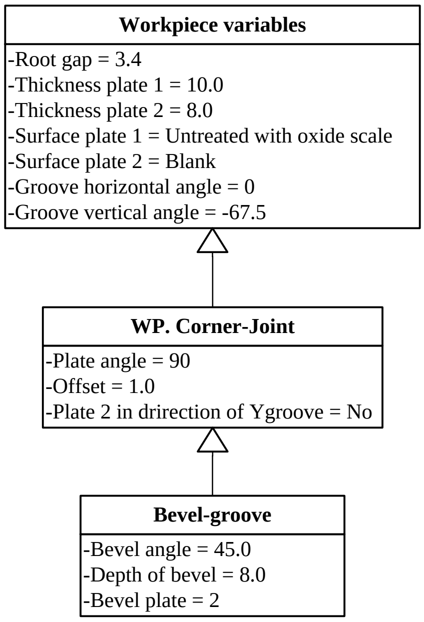


Figure 3.28: Workpiece variables for the HalfV-Joint, the geometrical variables are illustrated in figure 3.29.

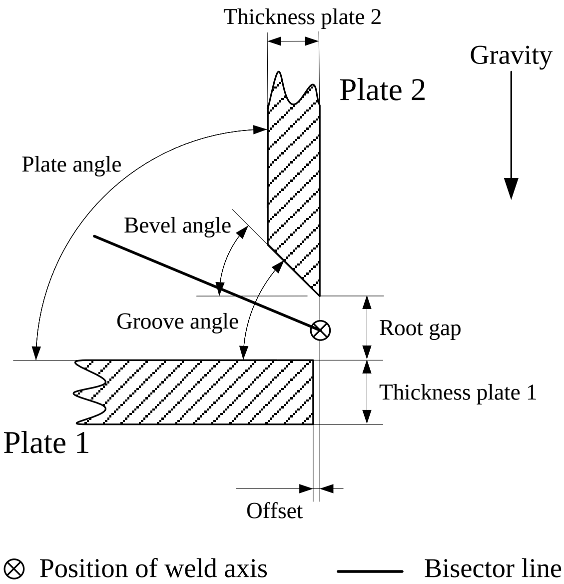


Figure 3.29: Geometric workpiece variables for HalfV-Joint.

3.2.4 Process variables

The process variables are measured during the experiment and an example is demonstrated in figure 3.30.

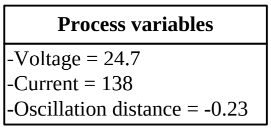


Figure 3.30: Example of process variables.

3.2.5 Welding control variables

Welding control variables, which as an example could be used for welding of the T-Joint, are shown in figure 3.31.

Welding control variables
-Work angle = 45.0
-Travel angle = 0.0
-Rotational angle = 0.0
-CTWD = 15.0
-Sideway = 0.5
-Travel speed = 8.0
-Voltage = 28.0
-Wire feed speed = 10.0
-Oscillation on = 1
-Oscillation vector X = 0.0
-Oscillation vector Y = 0.7
-Oscillation vector Z = 0.7
-Oscillation width = 1.0
-Oscillation frequency = 1.0
-Oscillation holding 1 = 25
-Oscillation holding 2 = 25
-Oscillation holding centre = 0
-Oscillation pattern = linear

Figure 3.31: Example of welding control variables.

3.2.6 Quality parameters

Quality parameters are measured for the two examples in figures 3.33 and 3.35 to demonstrate the principle.

T-Joint

The quality parameters for the T-Joint specimen are shown in figure 3.32. The grades are determined based on the measurement and the standards specified in section 3.1.6 "Quality parameters".

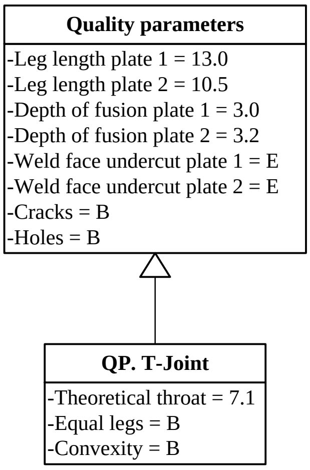


Figure 3.32: Quality parameters (QP) apply to the T-Joint illustrated in figure 3.33.

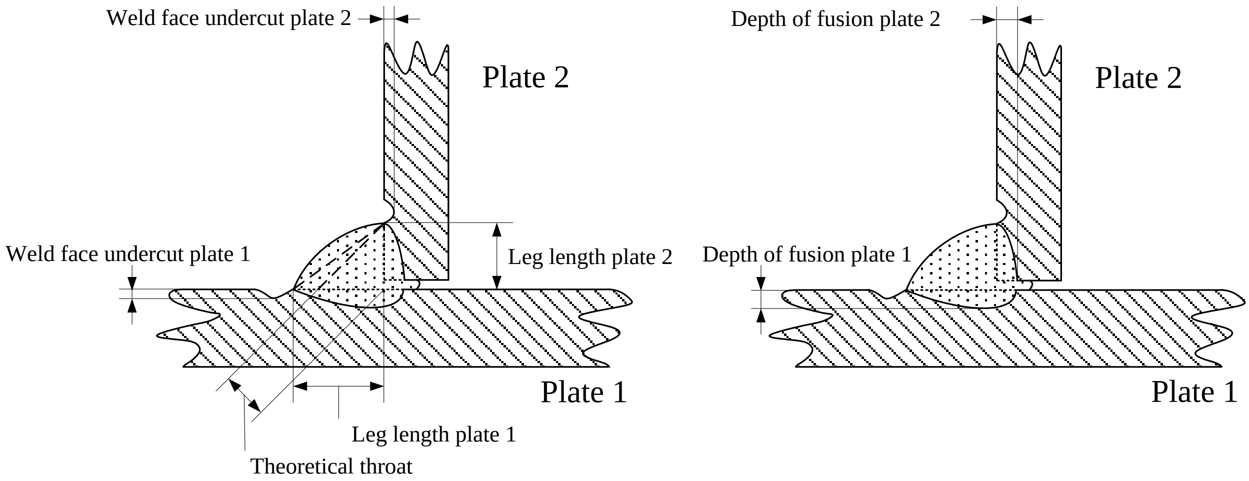


Figure 3.33: T-Joint with external geometrical weld quality parameters on the left figure and internal geometrical weld quality on the right figure.

HalfV-Joint

In a similar fashion as for the T-Joint, the quality parameters for the HalfV-Joint specimen are shown in figure 3.34.

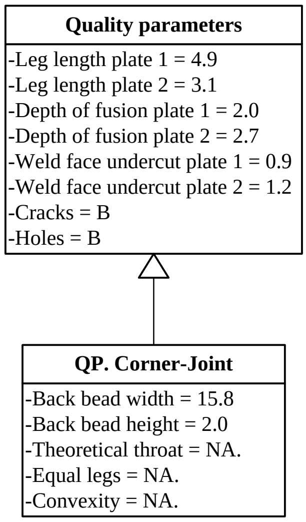


Figure 3.34: Quality parameters (QP) apply to the HalfV-Joint illustrated in figure 3.35.

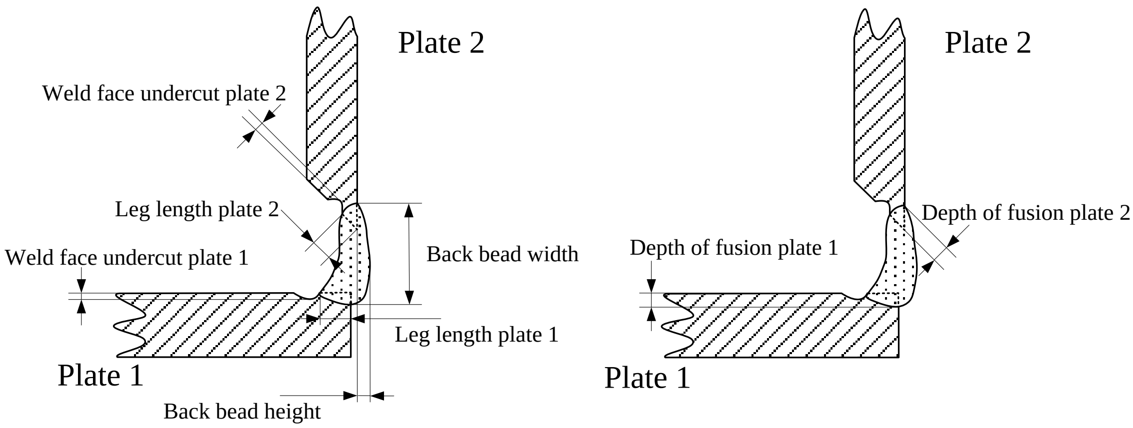


Figure 3.35: HalfV-Joint with external geometrical weld quality parameters on the left figure and internal geometrical weld quality on the right figure.

3.3 Summery

In section 3.1 a developed generic information model to store recorded empirical welding data is presented. The result is an information model which is generic because it is not fixed to a specific workpiece geometry or equipment, but can be used for different workpieces and equipment. The generic information model has specifications of all parameters and variables in the model to secure reliable and well documented empirical welding data. It makes the data in the generic information model reusable and possible to expand. In section 3.2 the generic information model was applied to the two workpiece cases T- and halfV-Joint and the equipment case MIG/MAG welding. It demonstrated the practical use of the generic information model.

Chapter 4

A system for automating production of empirical welding data

Production of empirical welding data is a time consuming and thereby an expensive process, which makes the empirical data to a restricted source. Furthermore, it is time consuming to analyse and document empirical experiments to produce data. A system was constructed, which to a higher extend automates the process of creating empirical data and produces it in a standardised and documented form so that it is ready to fill into the generic information model. The system developed was constructed flexible to include welding experiments for experimental parts specified in the generic information model shown in section 3.1 “Generic information model”, only by changing setup variables. The system is applied on two example cases. Finally the experimental results are shown from using the system for automating production of empirical welding data and from storing the data in the generic information model.

This chapter is divided into two parts. The first part is the general part. It is a specification of the system for generating experiments in section 4.1, and a specification of an architecture of the system in section 4.2 and a specification of an architecture of making and analysing experiments in section 4.3. The second part is the specific part. It gives an example of the implementation of the system in section 4.4 and the results of the experiments, which were designed and carried out, in section 4.5.

4.1 Specification of the system

The specification of the system for automating production of empirical welding data is as follows:

- Automatic motion of the torch.
- Automatic welding experiment. It includes automatic motion of the torch (kinematic and oscillation variables) and execution of welding machine variables, which all are specified in the welding control variables.
- Measurement of process variables from welding experiment.
- Automatic measurements of the groove by profile sensing to determine the groove-frame.
- Measurement of geometrical workpiece and quality variable by profile sensing.

The level of automation is chosen to produce data in the form specified in section 3.1 “Generic information model”. Furthermore, a trade-off exists between the saved manual operation time and the achievement of applying more sensors. Moreover, the period of the thesis limits the possible work. The automation level can be upgraded by e.g. an automatic ultra sonic or x-ray detection of defects.

Other research in the field of automating creation of empirical welding data is made by [Rippey, 1997] who presents an architecture of a real system to for controlling the welding process and log welding data. Compared to the specifications above a touch sensor is used to determine the position of the groove so only the measured data during welding are the process variables. The architecture of the system makes it possible to add additional sensors.

4.2 Architecture of an experiment generator system

The system to make experiments was constructed in a general way so it is usable for making experiments for workpieces with different geometrical shapes. The system was constructed such that the control of the experiments was carried out by the process control and data collection tool which communicates to neutral interfaces as shown in figure 4.1. This system architecture is general and it is independent of the equipment used. The neutral interfaces handle the communication to the specific equipment and they give the flexibility that the specific equipment can be exchanged or improved with other types of equipment.

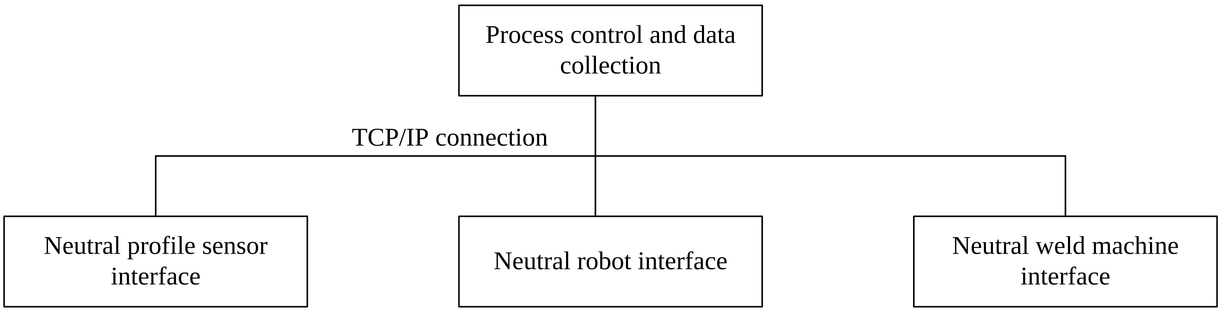


Figure 4.1: The process control and data collection tool communicates using a TCP/IP connection to neutral interfaces and using a protocol independent of the specific equipment.

The overall principle is that the process control and data collection system can require tasks to be made at the specific equipment through the neutral interfaces connections. The tasks can be:

- Execution of physical task, e.g. motion of the torch and weld as specified in welding control variables.
- Collection of data, e.g. to measure process variables and the workpiece geometry.

4.2.1 Specification of an experiment

A given experiment consists of a sequence of elementary tasks:

- Inter task motion: Moves the torch through a number of defined locations.
- Profile sensing: Makes sensing profiles of geometry along a line between two points and store the sensed profiles.
- Welding experiment: Weld a specified distance using specified welding control variables and measure and store process variables.

The process control and data collection tool can be setup to control sequential execution of inter task motion, profile sensing and welding experiment in different orders. The taxonomy for the setup of a sequence is illustrated in figure 4.2.

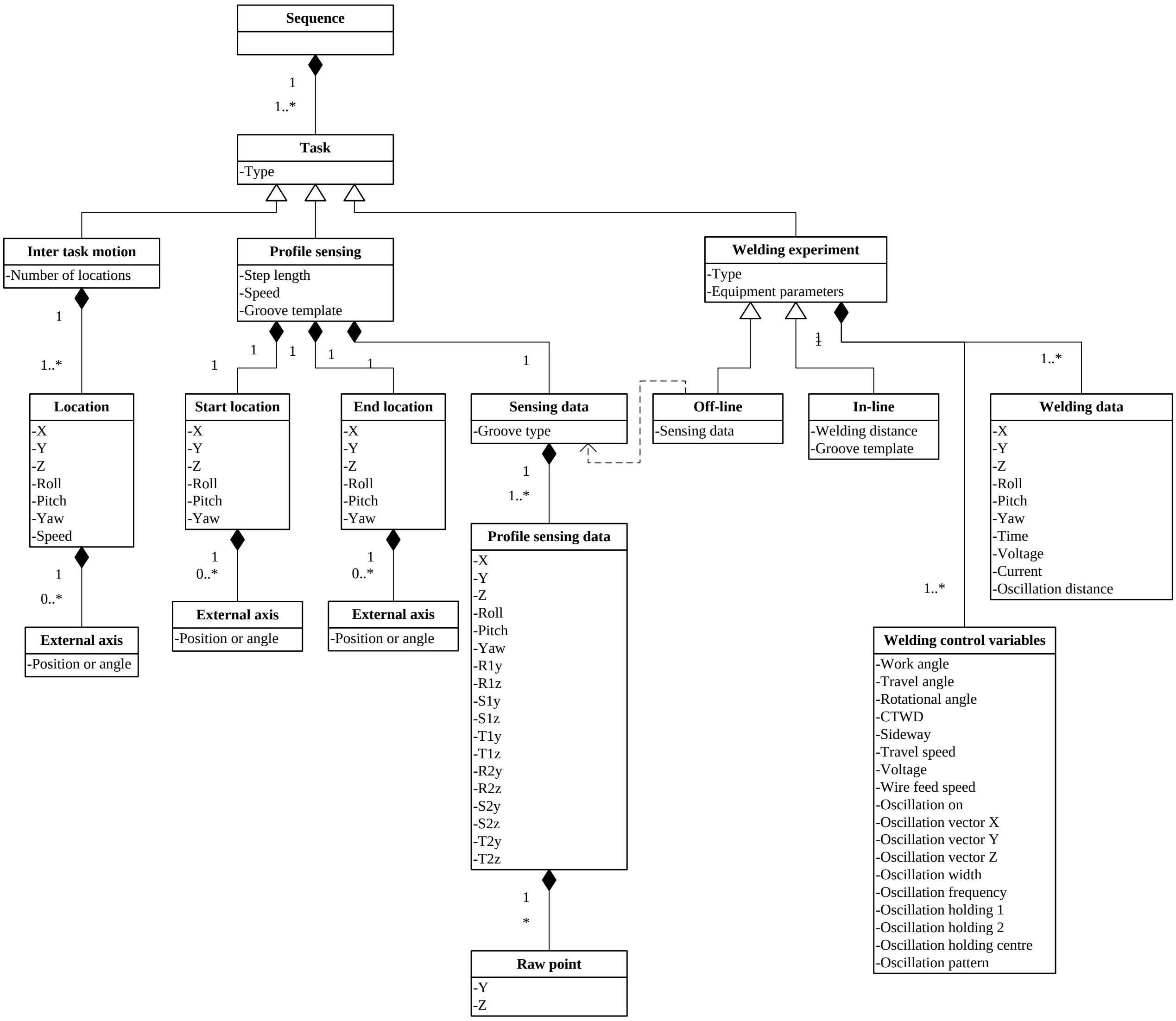


Figure 4.2: A sequence consists of a number of tasks. Each task is described by a type which either can be an inter task motion, profile sensing or welding experiment. Other types of tasks can be made and implemented in the sequence.

For the setup a determination of a number of frames is required, which is illustrated in figure 4.3. The tool-frame is defined in section 3.1.5 “Welding control variables” and the groove-frame is defined in section 3.1.3 “Workpiece variables”. A reference-frame is defined by being attached to the workpiece. A sensor-frame is located for the specific sensor and is defined in the following way.

Definition of sensor-frame

A sensor-frame is required for the particular sensor. The sensor-frame is dependent on the sensor calibration and is defined in the following way.

O_{sensor}	= origin affixed in the principal point (centre of the sensors coordinate system) of the sensor.
X_{sensor}	= perpendicular to the plane of sensing and pointing in the direction of the welding torch.
Z_{sensor}	= extending the direction of the centre of the sensor view.
Y_{sensor}	= $Z_{sensor} \times X_{sensor}$ to fulfil the frame is a right hand coordinate system.

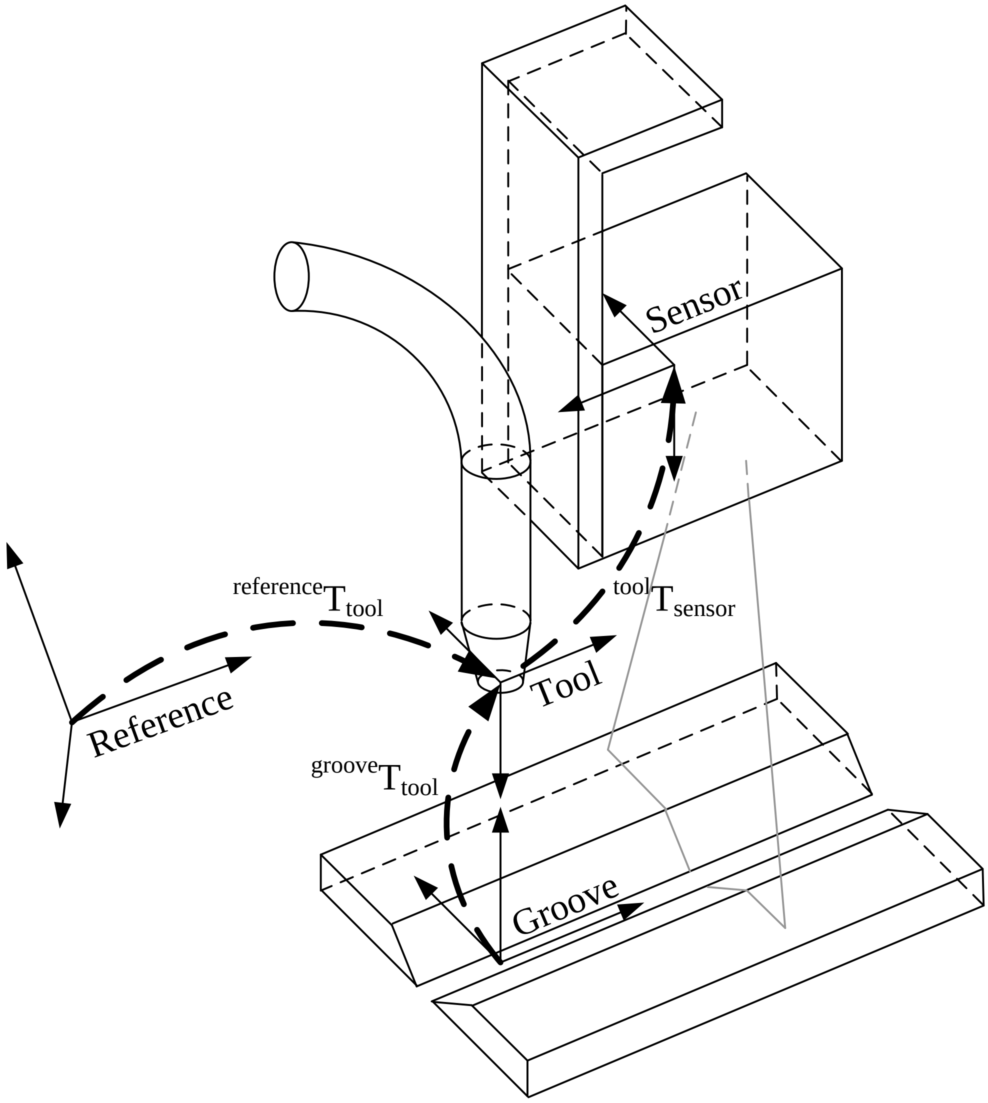


Figure 4.3: The definition of the reference frame, entail ${}^{reference}T_{tool}$ is determined by the robot and manipulating system. A sensor frame is located for the specific sensor and the ${}^{tool}T_{sensor}$ is found by calibration of the tool and sensor. The ${}^{groove}T_{tool}$ is determined from the welding control variables and it is specified in section 3.1.5 "Welding control variables.

The three kinds of elementary tasks defined are specified in the following subsections.

4.2.2 Inter task motion

Inter task motion is used to prepare and combine other tasks by manipulating and positioning equipment, e.g. tool or sensor, according to the workpiece. Instructions to do that are given from experimental parameters for inter task motion, the taxonomy is shown in figure 4.4. A number of locations can be put in a sequence to form a trajectory, where the tool frame location is given by a position of x, y and z in millimetres, roll, pitch and yaw in degrees and speed to reach the location specified in millimetres per second. If external axes are used the motion of each of them is determined by a position or angle in millimetres or degrees respectively.

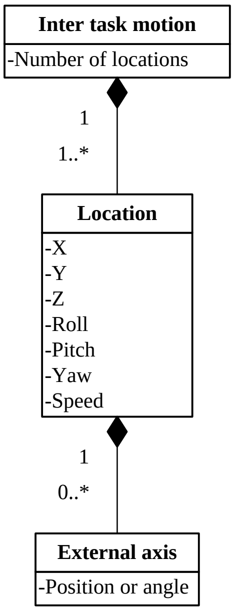


Figure 4.4: Taxonomy for experimental parameters for inter task motion.

4.2.3 Profile sensing

The purpose of the profile sensing is to measure the workpiece geometry in the area of the weld seam and welded seam. Measurements are employed to determine workpiece and quality parameters and location of grove frame. The profile sensing is two dimensional measurements, and by joining measurements when the sensor or workpiece is manipulated, a three dimensional model can be made. Experimental parameters for profile sensing, illustrated in the taxonomy in figure 4.5, specify a profile sensing task by a start and end location where the sensor location is given by a position, orientation and external axis similar to the specification of the inter task motion specification. Furthermore the step length is specified, which is the distance in millimetres between each profile sensing and the speed to reach each location measured in millimetres per second. Moreover, a specification of groove template determines which type of weld groove to measure, illustrated in figure 3.6.

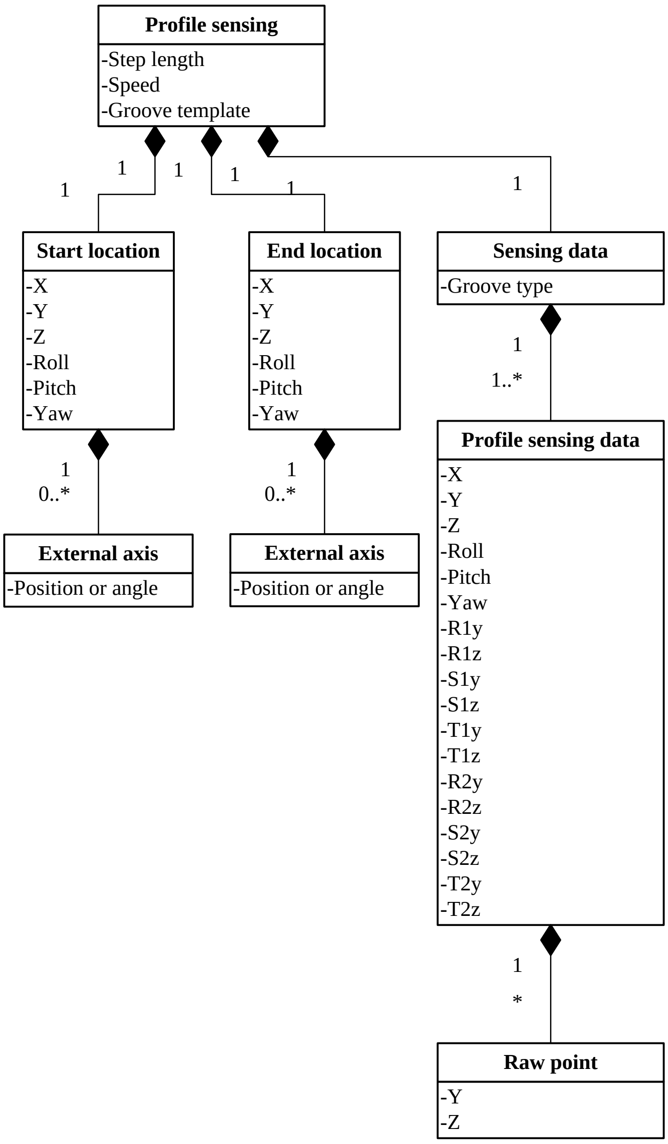


Figure 4.5: Taxonomy for experimental parameters for profile sensing and sensing data.

The output of the profile sensing task, shown in figure 4.5, is sensing data which contains the measured type of weld groove, illustrated in figure 3.6. Sensing data consists of a number of profile sensing data, where the sensor-frame location is given relatively to the reference-frame, as shown in figure 4.3. Furthermore, six breakpoints are determined as it is enough to represent the grooves defined in section 3.1.3 “Workpiece variables”.

Definition of breakpoints

Breakpoints are used to approximate the geometrical shape of the groove, shown in figure 4.6, and are defined as:

Three breakpoints are fixed on each of the two workpiece plates and are named R, S and T together with the plate number. For each plate the R, S and T points are positioned:

T: For grooves without bevel (square and scarf groove) the T points are positioned in the groove corner on the weld face side. For grooves with a bevel the T points are positioned in the bottom corner of the bevel.

R: The R points are placed on the workpiece plate outside the groove.

S: For grooves without bevel the S points are positioned on the plate surface between the T and R points. For grooves with a bevel the S points are positioned on the break/edge of the plate surface between the T and R points.

For each profile sensing data the raw points are given as y and z in millimetres for the 2 dimensional profiles.

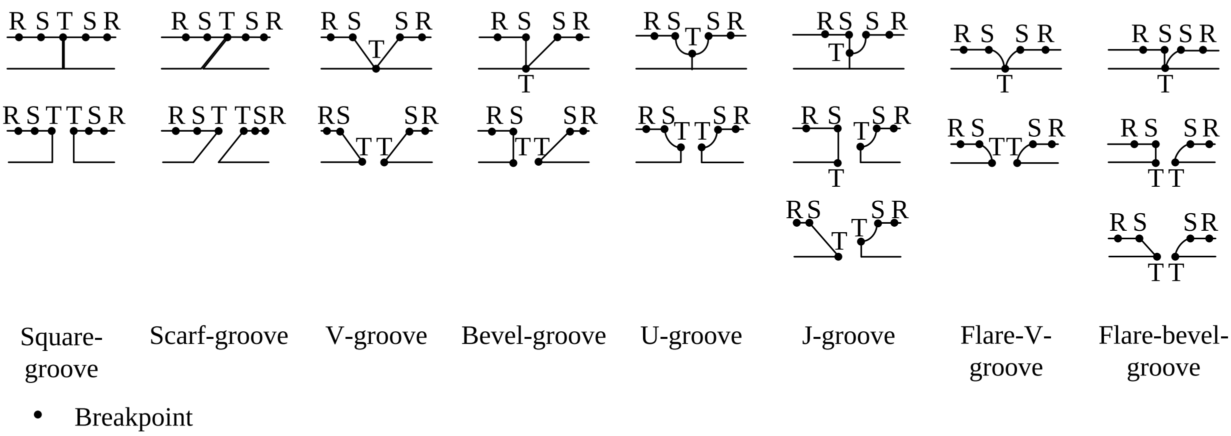


Figure 4.6: Position of the breakpoints for different groove types according to the definition.

4.2.4 Welding experiment

The welding experiment task has the purpose to carry out a welding specified by the welding control variables. The groove template is used for interpretation of the profile sensing in the same way as for profile sensing. The type specifies if either an off-line or an in-line sensing is to be used. For off-line sensing, the sensing data is made beforehand in a profile sensing task and referred to during welding, illustrated in figure 4.7. For in-line sensing, the sensing and welding are preformed simultaneously with the profile sensing ahead of the welding, shown in figure 4.7. The in-line welding is preformed for a specified welding distance or as long valid sensing data is produced. The groove template is required to determine the weld groove in the same way as for profile sensing. The equipment parameters describe the necessary settings of the equipment before the welding experiment starts. The welding control variables specify the tool motion and the equipment settings to be applied as described in section 3.1.5 “Welding control variables”, and location states a position x, y and z, and an orientation roll, pitch and yaw in millimetres and degrees respectively.

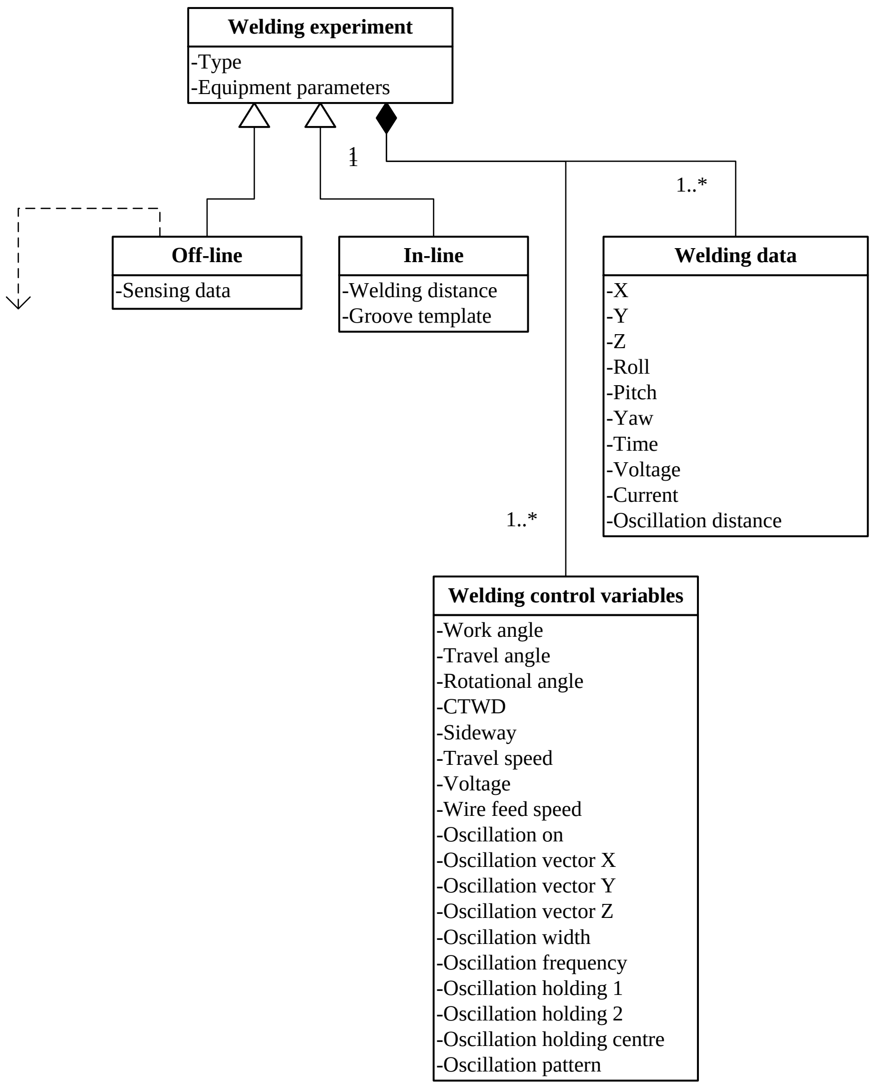


Figure 4.7: Taxonomy for experimental parameters for a welding experiment and welding data from the welding experiment. An off-line welding experiment is dependent on known sensing data, illustrated by the dashed arrow.

The output of the welding experiment is measurements of process variables made during welding, shown in figure 4.7. Welding data consists of the tool frame location by position x, y and z, and orientation roll, pitch and yaw in millimetres and degrees respectively. Furthermore, the time of measurement and the process variables are logged. Oscillation distance is included and specifies the distance from the line in the centre of the oscillation pattern to the actual TCP.

4.3 Architecture of making and analysing experiments

An architecture was made, which describes the functions of a system for making experiments and afterwards for analysing the experiments. The overall architecture of the system is shown in figure 4.8 and as it appears in this figure the system is divided into two parts.

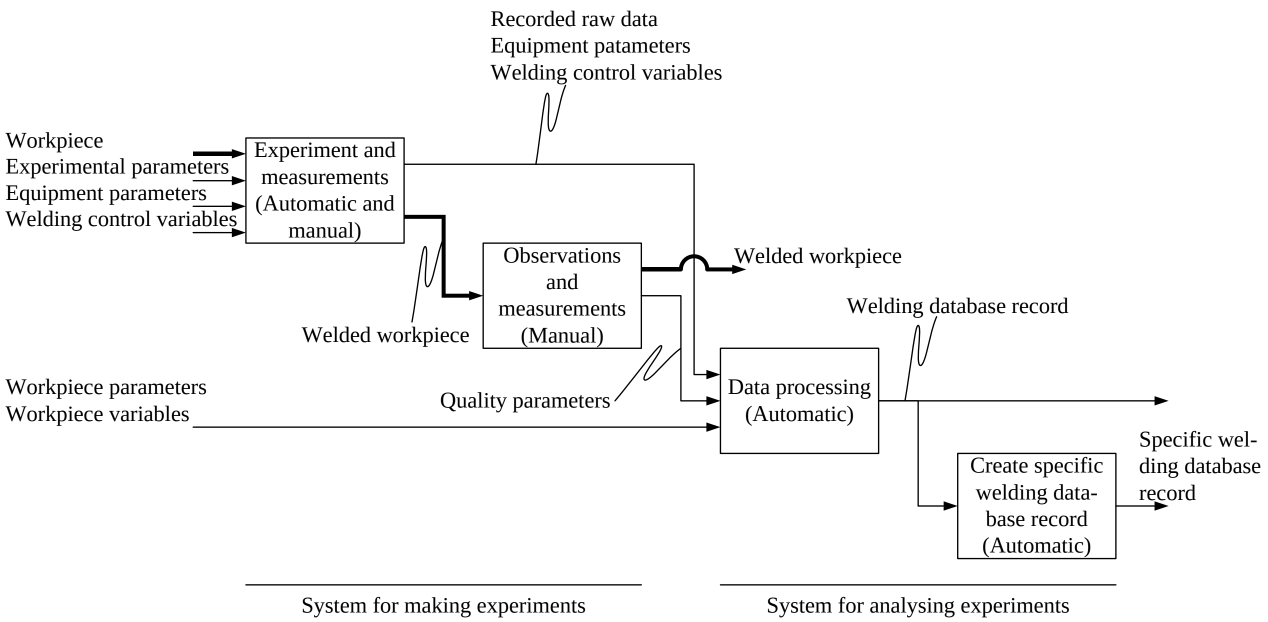


Figure 4.8: Architecture of the system for production of empirical knowledge. Thick arrows are physical parts and thin arrows are information. In the bottom it is noted that the system is split up into two parts.

The architecture is briefly described below and described in details in the next sections.

System for making experiments

The system for making experiments consists of two functions. The first function uses the experiment generator specified in section 4.2 “Architecture of an experiment generator system”. The workpiece is measured and welded from the specification in the input. The second function is to make manual observations and measurements of the welded workpiece. The output of the system for making experiments is the data collected from both automatic and manual observations and measurements. This data is specific for the welding setup and for the empirical data collection system used, and it is shown in figure 3.2 as the specific part.

System for analysing experiments

The system for analysing experiments consists of two functions. The first function receives data from each experiment and makes data processing to create a welding database record fitted to the taxonomy in figure 3.4. This function organises each welding experiment on the form of the general taxonomy. The second function creates a specific welding database record by reading data sets from the database in figure 3.4 and makes discritised or continuous output of selected parameters and variables. The output data from this function is specified for the purposes.

4.3.1 Experiment and measurements

The system for making experiments and measurements, in figure 4.8, consists of the functions illustrated in figure 4.9. Functions inside the stippled box are carried out by the “Automatic experiment production system”, which are based on the architecture described in section 4.2 “Architecture of an experiment generator system”.
The input to the system is the physical workpiece, equipment parameters, welding control variables and experimental parameters. Experimental parameters specify the operating sequences of how to carry out the experiment and make measurements. The experiment and measurements are automatically carried out by the “Automatic experiment production system”, which can perform

robotised welding experiments on the workpiece and use various sensors to measure relevant parameters before, during and after the welding experiment. Recorded raw data, which consists of sensing and welding data from the functions carried out, is output of the "Automatic experiment production system". The welded workpiece was removed manually from the fixture. The output is furthermore equipment parameters and welding control variables used, and they are identical to those in the input.

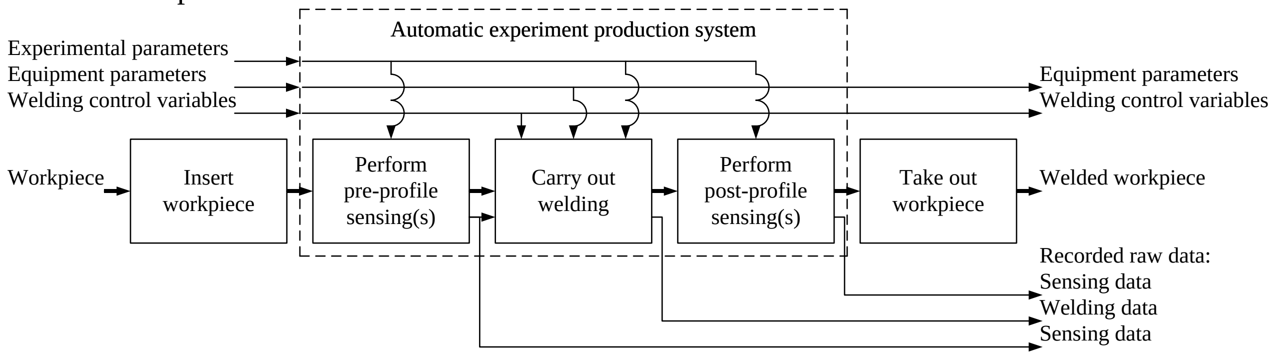


Figure 4.9: A suggested sequence to perform the function "Experiment and measurements". Functions inside the stippled box "Automatic experiment production system" are carried out automatically, while the functions outside are carried out manually.

Each single function shown in figure 4.9 is explained below:

Insert workpiece

The workpiece is placed manually in a fixture where the workpiece location is affixed to a workpiece frame shown in figure 4.3. It is important to affix the workpiece to minimise thermal distortion.

Perform pre-profile sensing(s)

Pre-welding on the weld face side is a pre-profile sensing carried out. If it is physical possible and it gives any extra information about the workpiece parameters a profile sensing is carried out on the back bead of the workpiece. The output of each profile sensing is sensing data, illustrated in figure 4.5.

Carry out welding

The welding function is carried out from equipment parameters and welding control variables specifying the settings of the manipulator mechanism and welding machine. Furthermore, the experimental parameters specify if the sensing data produced is either made off-line or in-line. Output of the welding experiment is welding data, shown in figure 4.7

Perform post-profile sensing(s)

Post-welding on the weld face side is a post-profile sensing carried out. If it is physical possible and it gives extra information about the quality parameters a profile sensing is carried out on the back bead of the workpiece. The output of each profile sensing is sensing data, illustrated in figure 4.5.

Take out workpiece

The workpiece is taken out of the fixture.

Inter task motions are not illustrated in figure 4.9 because they do not produce any recorded raw data as it is the case with profile sensing and welding experiment.

4.3.2 Observations and measurements

The system for making observations and measurements, in figure 4.8, consists of the functions illustrated in figure 4.10.

On the welded workpiece, observations and measurements of quality parameters are made, which are not possible to obtain by automatic measurements as in the previous function “Experiment and measurements”. The observations and measurements are made manually and they provide quality parameters defined in section 3.1 “Generic information model”. The function is made manually by an operator who also decides the setting of the welding control variables for the next experiment.

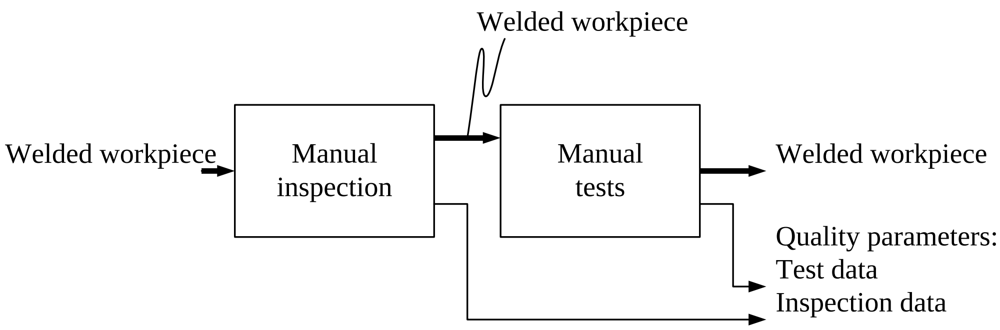


Figure 4.10: The function “Observations and measurements” is split up into two functions to gain quality parameters from the welded workpiece.

Manual inspection

Inspection of the welded workpiece is carried out manually. Quality parameters are established, which cannot be obtained from analysing sensing data, and which do not require tests to be determined. Inspections are carried out with measurements and grading according to ISO standards, described in section 3.1.6 “Quality parameters”, to produce inspection data in accordance with the quality parameters. Furthermore, the manual inspection also determines a new set of welding control variables for the next experiment. The procedure for selecting the new welding control vectors can be made as demonstrated in section 2.3.2 “Generation and use of empirical data”.

Manual tests

Manual tests are carried out to obtain quality parameters, which are not established during the profile sensing and the manual inspection. A range of tests can be made on the welded workpiece to examine the quality. Examples of methods are x-ray photo inspection, ultrasonic inspection, dye penetrant inspection, magnetic particle inspection, metallography and tensile test. The methods are in details described in [Welding Encyclopedia, 1997]. The outcome of the manual tests is measurements or grading according to ISO standards, described in section 3.1.6 “Quality parameters”.

When joining the output from all the functions in the system for making experiments you get the output as illustrated in figure 4.11.

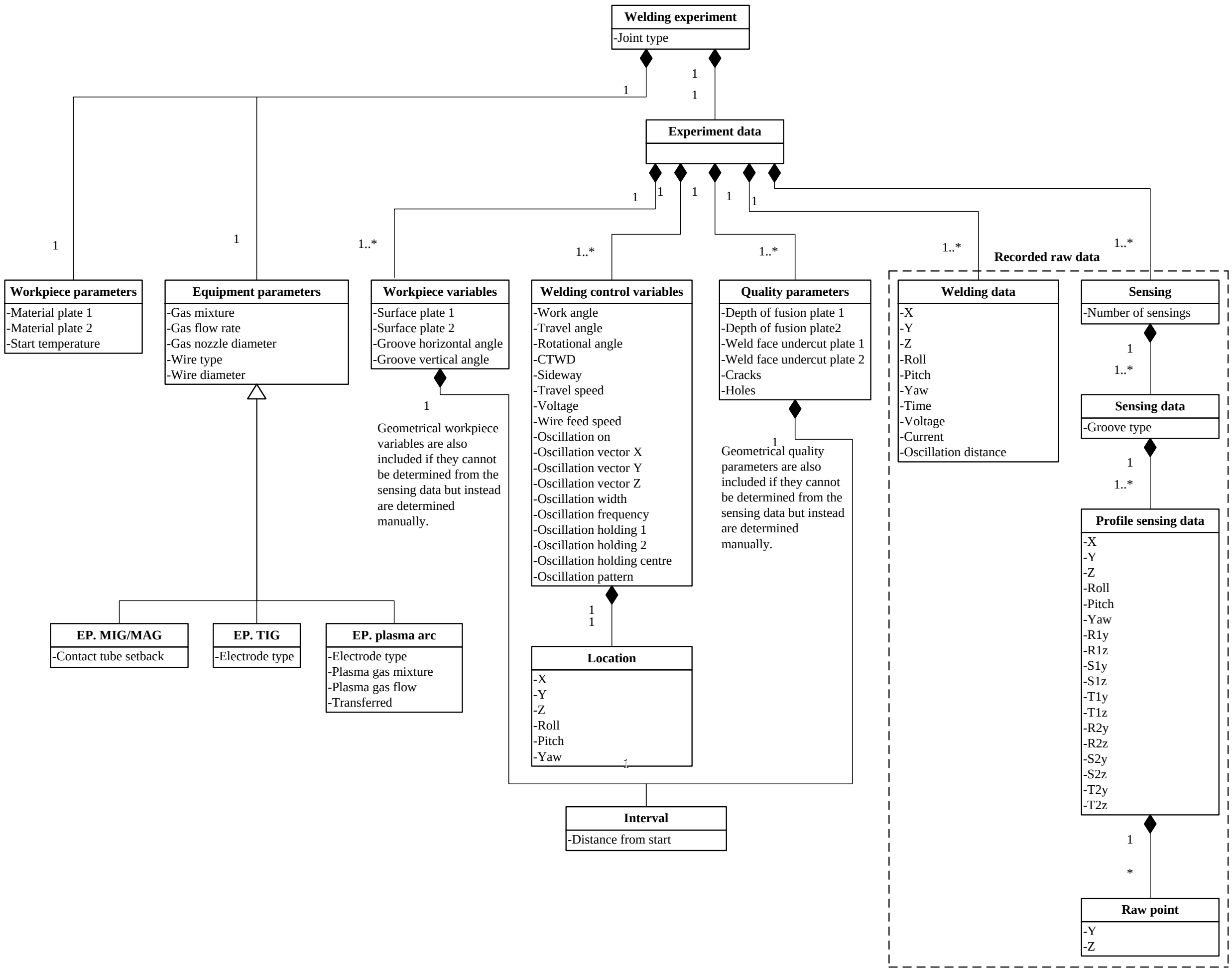


Figure 4.11: Taxonomy with the outcome of the system for making experiments. It is the specific part shown in figure 3.2.

4.3.3 Data processing

The recorded raw data shown in figure 4.11 is processed. The processing converts recorded raw data, from sensor measurements, to workpiece variables, process variables and quality parameters defined in section 3.1 “Generic information model”. These parameters and variables are joined with the remaining input consisting of welding control variables, equipment parameters and quality parameters. As a result of this joining a record is created where the workpiece parameters, workpiece variables, process variables, equipment parameters, welding control variables and quality parameters are specified along the welded seam on the workpiece. The output is a welding experiment record, with the taxonomy shown in figure 3.4, which is merged with other welding database records to a welding database record or joined with an existing welding database record.

The functions of the data processing are illustrated in figure 4.12 with a sequence of functions carrying out the analysis. The functions were built using a generic method, this means that, this means that a task with change of e.g. workpiece geometry only requires adjustment to be able to analyse the task.

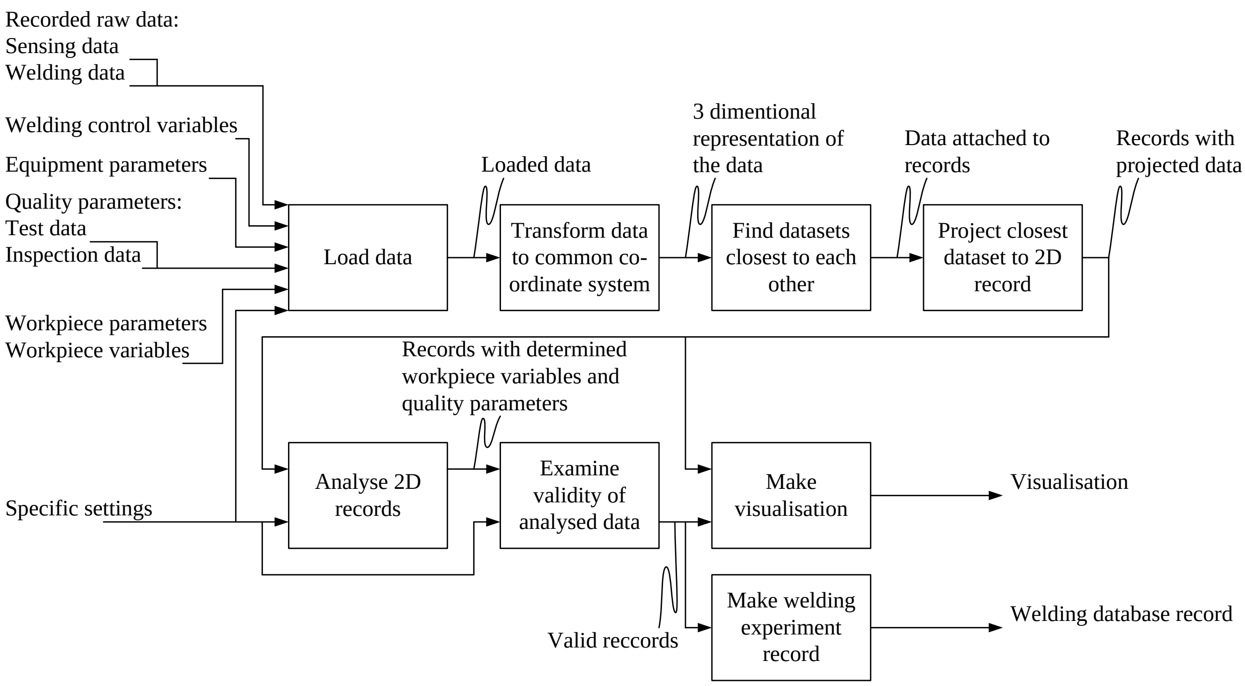


Figure 4.12: The function "Data processing" for making automatic analysis of measurement data.

Load data

Data is loaded and it is checked if the input data structure and types are legal.

Transform data to common coordinate system

The loaded data consists among other things of welding control variables, welding data and sensing data, which consist of a position and orientation and must be represented in the reference frame and merged. Figure 4.3 illustrates the transformations from the sensor and tool frame to the reference frame.

For the welding control variables and welding data, specified in figure 4.11, the locations are represented according to the reference frame.

The raw and RST points from the sensor (${}^{sensor}P$), illustrated in figure 4.11, are measured according to the sensor frame. The transformation of the points in the sensor frame to the reference frame is calculated in the following way.

$$
{}^{referance}P = {}^{referance}T_{tool} \cdot {}^{tool}T_{sensor} \cdot {}^{sensor}P
$$

After this transformation welding control variables, welding data and sensing data are represented in the reference frame and are merged together to a three dimensional representation.

Find datasets closest to each other

The experiment data, specified in figure 4.11, is not sampled at the same time. Hence, to enable the interpretation of the experiment data there has to be an integration so that values of welding data, sensing data and welding control vectors are available in certain points along the weld axis. This integration is made in this and the next function.

A start point is defined at the weld axis at the position where the signal is given, in the welding control variables, to start the welding process. The end point is correspondingly defined at the stop of the welding process. In figure 4.13, the start and end points are shown at the weld axis. For each

of the experiment data sets the distance along the weld axis between the start point and the experiment data is calculated.
In case the travel angle is different from 0° the welding data's distance from start is displaced along the weld axis. This entails that the location of the TCP was projected in the direction of X_{tool} (extension of the centre-axis of the contact nozzle or electrode) at the weld axis. The *new distance from start* is calculated to displace the welding data along the weld axis.

$$new\,distance\ \ from\,start = CTWD \cdot \sin - (travel\,angle)$$

Along the weld axis also quality parameters and workpiece variables are located and the location is specified within intervals, stated in figure 4.11.
Experiment data is attached to records in defined sample positions. The sample positions can either be made with a certain distance or at the positions for one of the experiment data sources. To attach the experimental data to records two principles are used and for each type of experiment data one principle is selected. The two principles are:

- Attach to the nearest record: The experiment data samples are attached to the record, which is within the shortest distance.
- Attach to the following record: The experiment data samples are attached to the next record in the direction from the start to the end point.

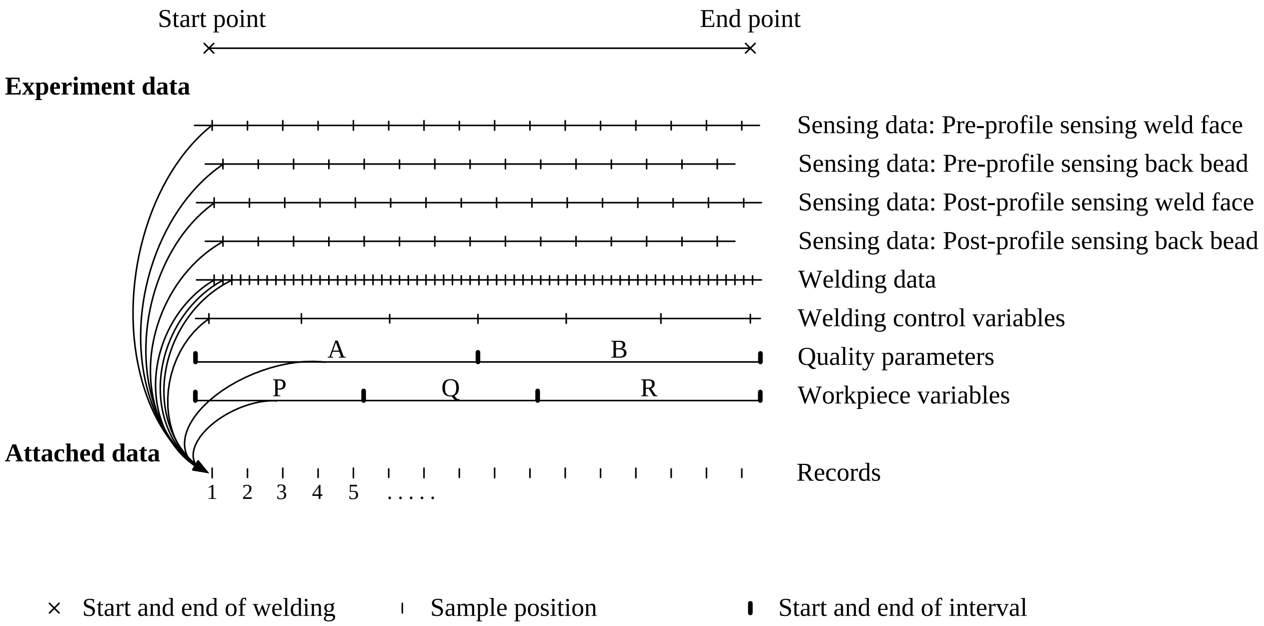


Figure 4.13: Start and end point of the experiment is marked at the weld axis. Along the weld axis sample positions and intervals of experimental data are marked with short vertical lines. The experiment data has different sampling positions and different sampling rates. For the samples of experimental data the distance from the start point along the weld axis is calculated to attach the experimental data to records.

For each record the quality and workpiece variables are attached, which stretch over the position of the record. To collect a complete set of information about the experiment at each record it is required to attach at least one of each type of experiment data to each record. Output of the function is records where experiment data are attached.

Project closest dataset to 2D record

The experiment data attached to each record is projected to a plane at the position of the record. The plane is perpendicular to the weld axis and is approximated by the welding direction vector. The welding direction vector is calculated from the position of the welding control variables. It is done by subtracting the welding control variable position after the sample position from the welding control variable position before the sample position.

$$\overrightarrow{welding\ direction} = \begin{pmatrix} X_{after\,sample\,position} - X_{before\,sample\,position} \\ Y_{after\,sample\,position} - Y_{before\,sample\,position} \\ Z_{after\,sample\,position} - Z_{before\,sample\,position} \end{pmatrix}$$

Figure 4.14 illustrates the principle of the projection of experiment data to records of projected data, which is the output of this function.

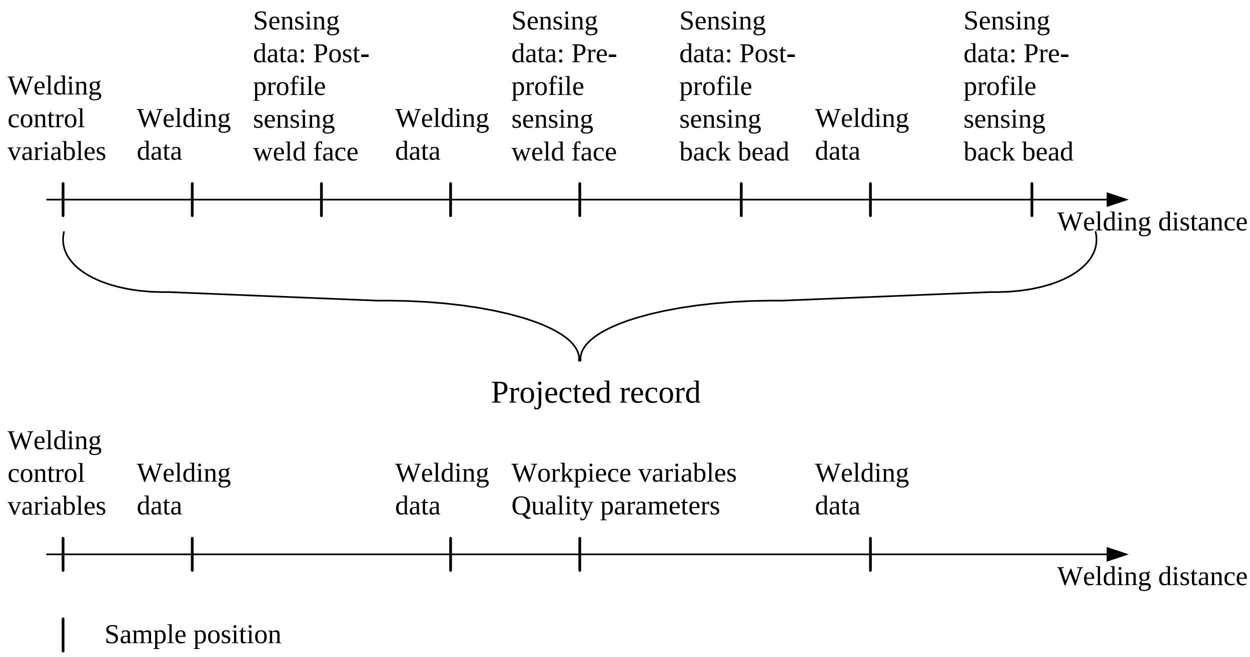


Figure 4.14: At the top of the figure is one record with attached experiment data laying at different distances from the start point on the seam. A sample position is selected to which the attached experiment data is projected. The projected experiment data is joined in a projected record, shown at the bottom of the figure.

Analyse 2D records

The objective of the analysis of the 2D records is to determine workpiece variables and quality parameters.

Research presented in the literature about analysis of records mostly deals with determination of groove location for seam tracking using breakpoints but in some cases determination of groove geometry. Examples are [Agapakis et al., 1990] and [Kim et al., 1996a], where geometric grove description for template matching is used. [Haug et al., 1998] increase robustness by applying fuzzy logic to determine the location of the groove. [Lou et al., 2005] train and save templates of features in a database and use them later for matching. [Sheu et al., 1999] describe a more general approach for segmentations to classify breakpoints for any planner curve. [Chang et al., 2005] apply post welding sensing data to construct a 3D surface using a spline, and from the spline representation it is extracted if the convexity of the welded seam is within the tolerances. The methods from the literature do not consider an analysis combining sensing data made before and after the welding process.

The analysis of 2D records consists of the following four sub functions described in appendix C:

- Determine breakpoints: Sensing data is analysed to determine breakpoints, which was defined in section 4.2.3 ”Profile sensing”. The breakpoints are used for the following three functions.
- Determine weld face and root vector: The sensing data is analysed to determine a weld face and a root vector, defined in appendix C, which are used for the following two functions.
- Determine workpiece variables: Equations to calculate the workpiece variables for the sensing data are described.
- Determine quality parameters: Equations to calculate the quality parameters for the sensing data are described.

The output of the functions is records with determined workpiece variables and quality parameters.

Examine validity of analysed data

Each record is examined if the workpiece and quality parameters are within a certain limit. The record is rejected if one of the parameters is outside the limit. The specific settings, given as input to this function, specify which parameters to examine and the lower and upper acceptance limits. This examination is made to avoid records, which are wrongly analysed in the previous function.
The output of the function is valid records.

Make visualisation

Each valid record is visualised to show the projected data with profile sensing data, raw points, determined breakpoints from the analysis and the position of the tool centre point(s) for the welding data. It was done to verify if the data processing is satisfactory.
For all the valid records visualisation is made showing the process variables, workpiece parameters, welding control variables and quality parameters along the seam and with measurement of the distance from the seam start point. It was done to verify the output of the data processing function.

Make welding experiment record

The output is a welding experiment record, which merged with other welding experiment records gives a welding database record with the taxonomy shown in figure 3.4.

4.3.4 Create specific welding database record

The input to this function is a welding database record. A welding database record has the taxonomy illustrated in figure 3.4. This function discretisizes a welding database record with intervals specified manually. The output of this function is a welding database record specific for an application and it is either in a continuous or discretisized form.

The sequence of functions in the software for creating a specific welding database record is described in figure 4.15. This function converts a welding database record, which is in the format of the generic information model, to a specific welding database record for a specific application. To do this an input is given specifying the output format, settings for discretisation and selection of variables and parameters.

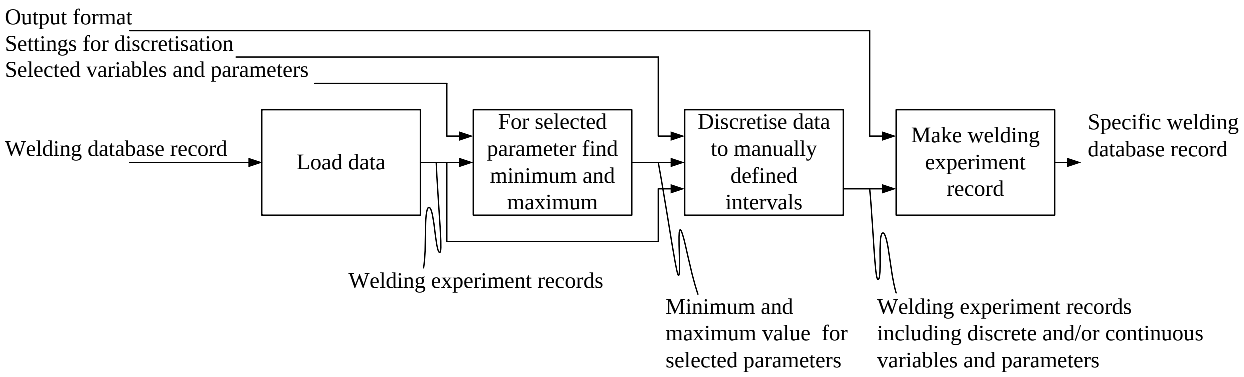


Figure 4.15: The function "Create specific welding database record" automatically creates a discrete or continuous welding database records.

Load data

A welding database record is loaded and it is checked if the input data structure and types are legal.

For selected parameter find minimum and maximum

The welding experiment records are filtered. Only the variables and parameters are passed, which are specified in the input of selected variables and parameters. For the passed welding experiment records the minimum and maximum values were found for each variable and parameter. These minimum and maximum values are passed to the next function.

Discretise data to manually defined intervals

In the input settings for discretisation are specified. They determine which variables and parameters to diskretisise and in case of diskretisation what the diskretisation intervals are. In case discretisation is selected for a parameter or variable the parameter or variable is passed through a discretisation filter. The output of this function is welding experiment records including discrete and/or continuous parameters and variables.

Make welding experiment record

The welding experiment records are delivered as a specific welding database record in the format specified in the output format, which is given as input.

4.4 Implemented system for automating production of empirical welding data

In this section a specific system is presented, which was constructed and implemented based on the architecture of a system for automating production of empirical welding data presented in section 4.3 "Architecture of making and analysing experiments". First, the software and hardware components and the setup of the system are described. Afterward, it is described how the general methods from section 4.3 "Architecture of making and analysing experiments" are applied to the specific system. The experimental parts used as cases are the T-joint and the HalfV-joint.

4.4.1 System components and setup

The components and setup of the specific system for automating the task of producing empirical data is described with hardware and software components. Figure 4.16 illustrates how the process control and data collection tool and neutral communication interface of the system were joined with the specific equipment used.

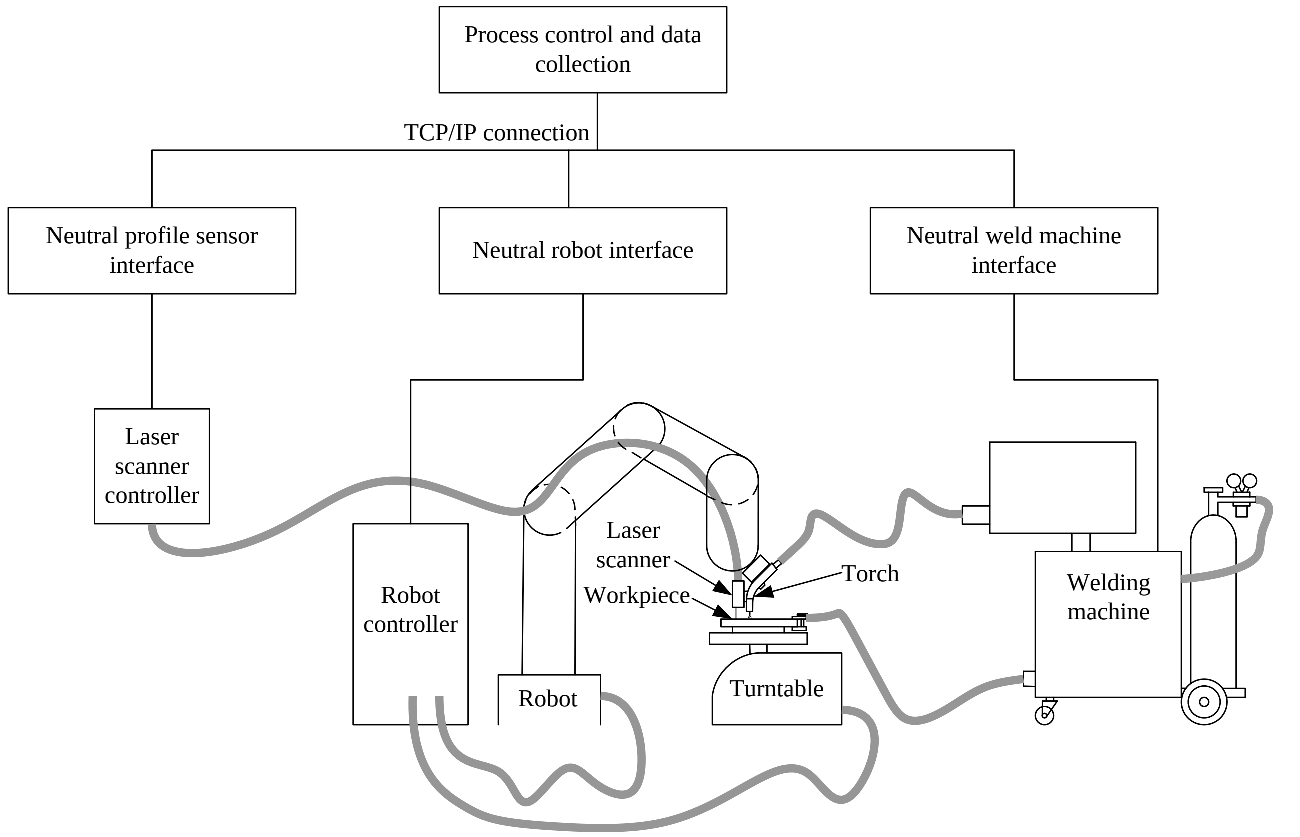


Figure 4.16: The top; the general system architecture as it is shown in figure 4.1. The bottom; the specific equipment used with a laser scanner, a robot with a turntable and a welding machine.

The system for establishing the neutral communication interfaces is based on the work described in [Nielsen, 2003], but further developed during the work of this thesis by expanding the communication protocols. The system for making process control and data collection was the commercial IPAC™ software [IWA], which is a tool for process control of the welding process but with an extension developed during the work of this thesis. The developed extension was to carry out an experimental sequence with different tasks, make data collection and expansion of the communication protocol with the neutral communication interfaces. A detailed description of the two system components, setup and calibration is made in appendix D.

The hardware and software components used as illustrated in figure 4.16 are specified in table 4.1.

Table 4.1: Hardware and software in the system are specified. A more thorough description can be found in appendix D.

Welding machine:	Migatronic BDH550 constant voltage machine.
Robot:	Reis RV15 with two degrees of freedom turntable.
Robot controller:	Reis Robotstar IV with coordinate interface.
Laser scanner:	Oldelft Seampilot.
Welding fixture:	Produced at Department of Production, AAU.
Process control tool:	Standard PC installed with IPAC™ and the developed extension.
Laser scanner interface:	Standard PC with AT/GPIB interface card to laser scanner and the neutral profile sensor interface software.

Robot interface:	Standard PC with Bit3 interface card to robot controller and the neutral robot interface software.
Weld machine interface:	Standard PC with DT302 interface card to welding machine and neutral weld machine interface software.

The experiments were constructed with one change of welding control variables during the experiment which means that two experiments with static conditions were achieved per workpiece.

4.4.2 The specific system for making experiments

For the specific system the locations of the frames are illustrated in figure 4.17.

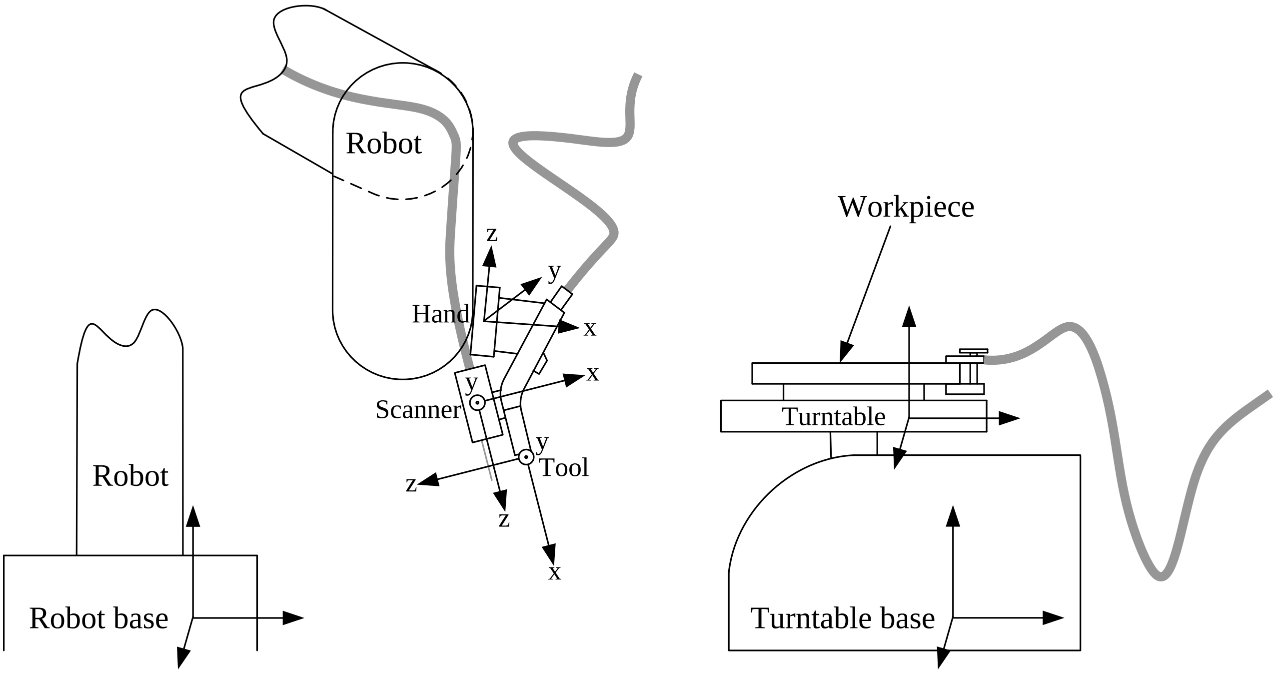


Figure 4.17: The location of the hand, scanner, tool and turntable frames for the specific system for making experiments. The robot base and turntable base frame are located at the robot base and turntable base respectively. A groove frame is determined on the workpiece.

For the specific system the transformations between the frames are shown in figure 4.18. Calibration of the robot determines ${}^{robot\ base}T_{turntable\ base}$ and the robotic and manipulating system calculates the ${}^{robot\ base}T_{hand}$, ${}^{turntable\ base}T_{turntable}$ and ${}^{turntable}T_{hand}$. Calibration of the specific system to determine ${}^{hand}T_{tool}$ and ${}^{hand}T_{scanner}$ is described in appendix D. ${}^{tool}T_{scanner}$ is calculated in the following way.

$$ {}^{tool}T_{scanner} = {}^{hand}T_{tool} \cdot {}^{hand}T_{scanner}^{-1} $$

Groove frame at the workpiece was defined as described in section 3.1.3 “Workpiece variables” and ${}^{groove}T_{tool}$ was calculated from the profile sensing profiles and welding control variables.

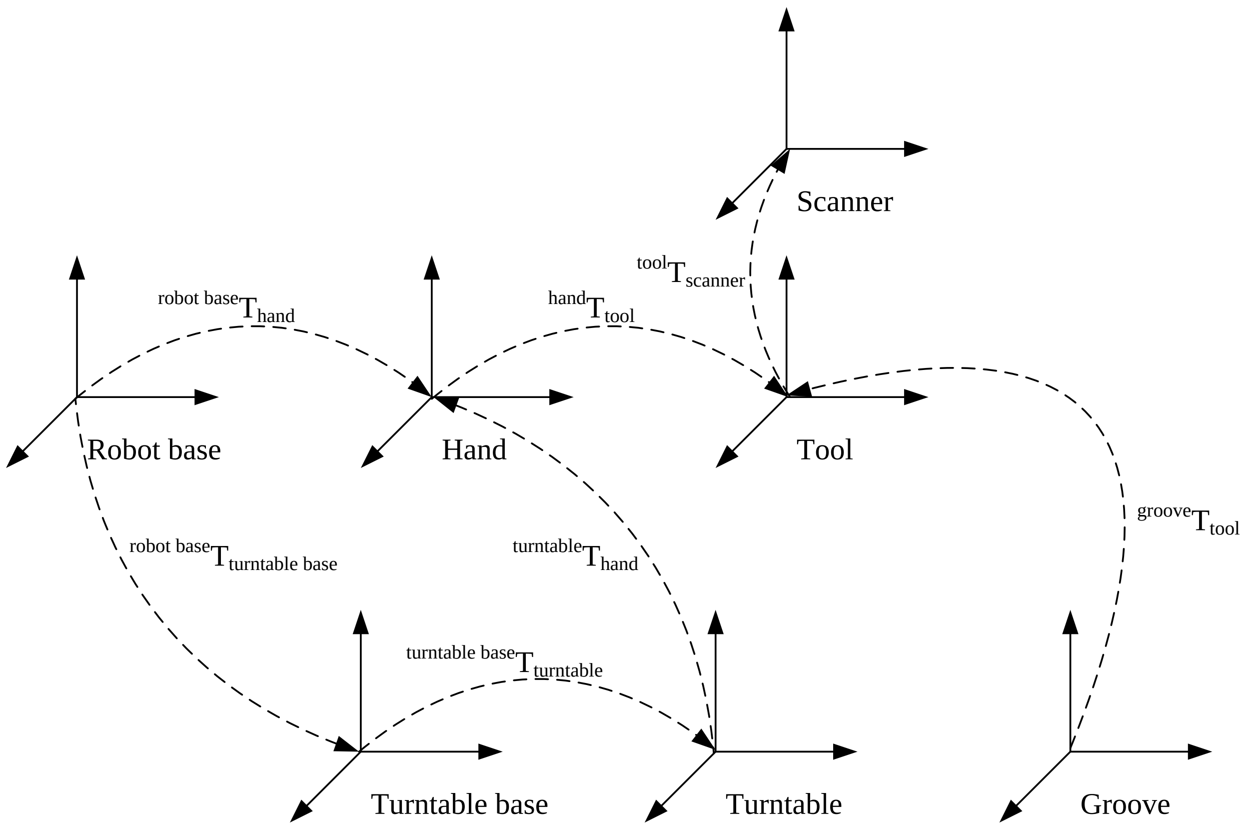


Figure 4.18: The particular frames and transformations used in the specific system.

This setup makes it possible to use robot base or turntable frame as reference frame, illustrated in figure 4.3. If the turntable is used then the workpiece is fixed according to the turntable frame or if the turntable is not used then the workpiece is fixed in the robot base frame.

The experiments presented in this thesis were carried out in the turntable frame. It was done to make the robot able to reach both the weld face and the back bead with the laser scanner by rotating the turntable 180°.

Constructing the sequence with tasks

The process control and data collection tool require an input with a sequence of tasks. The sequence is defined by an operator and can be combined for the given experimental setup. Figure 4.19 illustrates two different sequences of tasks.

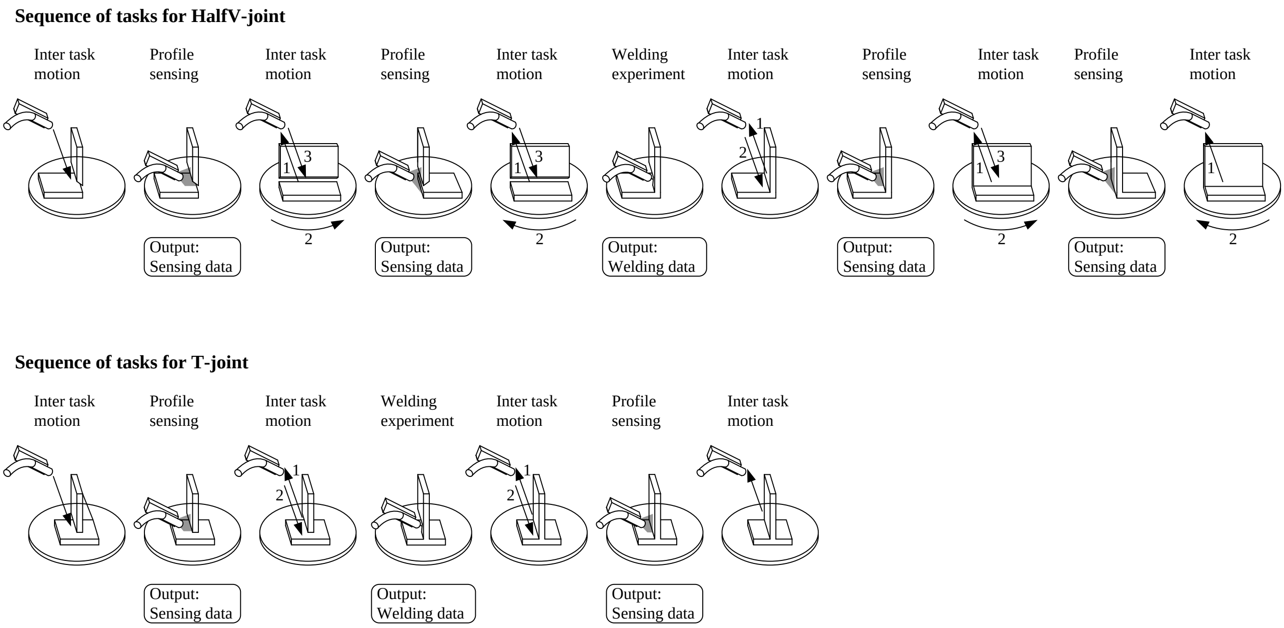


Figure 4.19: Sequence of tasks for a welding experiment for a HalfV-Joint and a T-Joint. The HalfV-Joint sequence involves more tasks because the workpiece is scanned on the back bead before and after the welding experiment. For both sequences off-line sensing is used.

Each task in the sequence needs to have the experimental parameters for inter task motion, profiles sensing and welding experiment worked out and this requires manual work. The robot locations in each task were determined by mowing the robot to the required locations to read off the robot location at the teach box. Other parameters such as travel speed were also determined by the operator. In appendix E, the particular sequences and tasks are used for the HalfV- and T-joint experiments shown.

The welding experiment task also requires equipment parameters, welding control variables and sensing data as input. The equipment parameters were set manually in the equipment by the operator and the welding control variables were input to the process control and data collection tool in files as described in appendix D. The sensing data was produced by the profile sensing task. Off-line sensing was used so motion from the welding experiment would not influence the sensor location during sensing, e.g. from changing work angle, travel angle, oscillation or CTWD.

4.4.3 Making and analysing experiments

The experiment and measurement functions are described and carried out according to the general system in figure 4.8.

Details about the actual experiment for the HalfV- and T-Joint can be found in appendix F.

4.5 Designing and carrying out experiments

Experiments were designed to produce empirical welding data and they were carried out for both the T-Joint and the HalfV-Joint to demonstrate more than one experimental setup. The experiments for the T-Joint were used to construct process-planning models in chapter 6. Both the empirical welding data for the T- and halfV-Joint experiments were stored in a welding database record and can be utilised by anyone who need empirical welding data and it can be added more empirical welding data.

4.5.1 Experimental design

The experimental setup uses the specific system described in section 4.4 “Implemented system for automating production of empirical welding data”. The experiment to carry out, to produce empirical welding data, was divided into:

- Experiments for calibrating the system: described in section 4.5.2 “Setup and calibration”.
- Experiments for producing empirical welding data: described in section 4.5.3 “Procedure for producing empirical welding data”.

4.5.2 Setup and calibration

The procedure for calibration of the equipment is described in this section. 14 experiments, two on each workpiece, were made for calibration: 8 experiments on a T-Joint and 6 experiments on a halfV-Joint.

The equipment which required calibration is described in the following.

Laser scanner

The calibration of the laser scanner was carried out as described in [Nielsen et al., 2003] and verified by scanning of known geometries and comparing the scanned result with measurements from the known geometry. After the welding experiments the calibration was verified by comparing the scanning with a polished section of the workpiece to see if they were matching, as illustrated in figure 4.20.

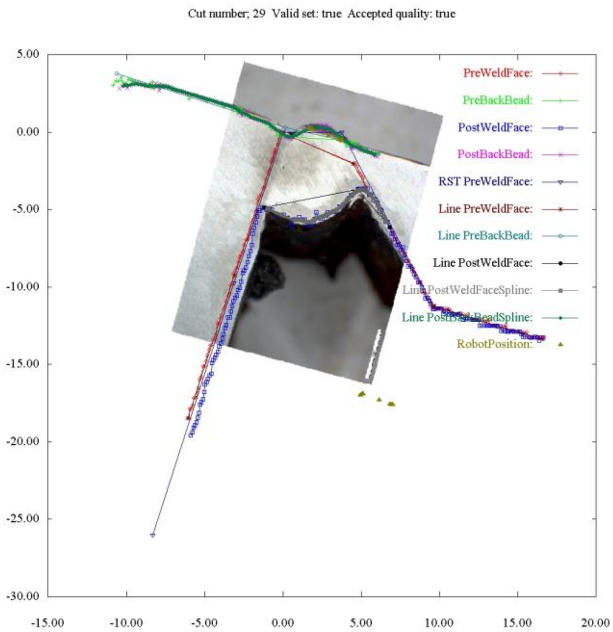


Figure 4.20: For a HalfV-Joint a picture of a polished section is merged with the result of the laser scannings and a good match is obtained. Because of distortions the pre- and post-profile sensing and the polished section in the picture are not completely aligned. Furthermore, the position of the profile sensing is affected by the robot and turntable resulting in inaccuracy because of their tolerances.

Welding machine

Calibration of the welding machine involves voltage current and wire feed speed. The displayed measurements of current and voltage at the welding machine was taken as the reference values for the current and voltage. This was done because the welding machine manufacture [Migatronic] stated that the displayed values are an accurate measure. The wire feed speed rate from the wire feed system requires calibration. Because the welding machine has both input and output, calibration was required for the welding control variables; voltage and wire feed speed to the welding machine and the process variables; voltage and current from the welding machine.

From welding control variable to welding machine

The voltage in the welding control variables was calibrated by making a series of measurements of the voltage at the welding machine when changing voltage in the welding control variables. It resulted in a graph, shown in figure 4.21, with a linear relation described by the equation which was used as calibration parameter in the neutral welding machine interface. The wire feed speed was calibrated at different speeds by measuring the welding wire length for a given period of time without starting the arc. An equation was produced and it was used as calibration parameter in the neutral welding machine interface. Additionally, the wire feed speed was verified from the experiments by measuring the actual weight of the weld seam and comparing it with the theoretical weight of the weld seam and it is shown in figure 4.21. Spatter and evaporation of the metal cause weight loss for the real experiment, which is also shown.

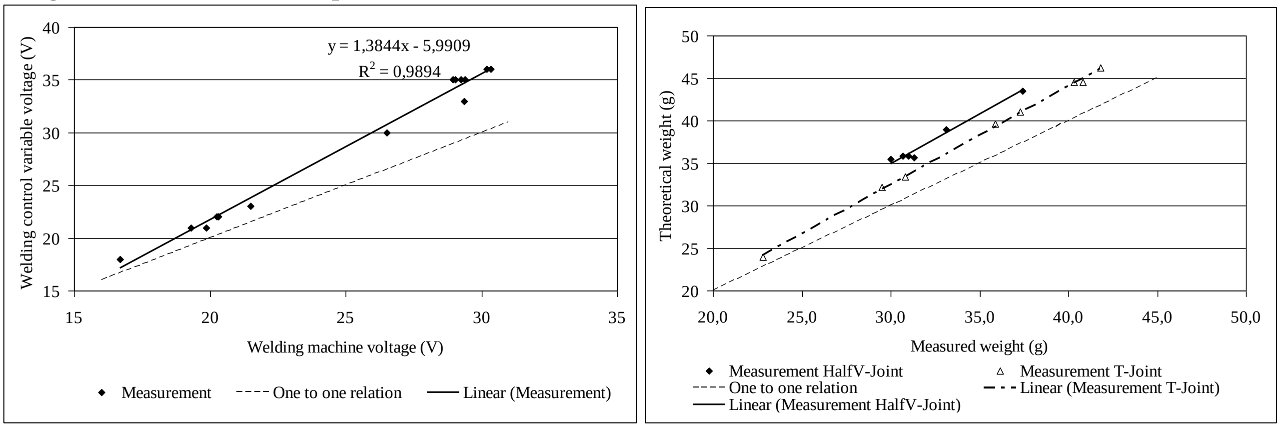


Figure 4.21: In the graph to the left is shown the settings of the voltage from the welding control variable as a function of the resulting voltage measured at the welding machine. It shows a linear relation but it deviates from the one to one relation and the calculated equation was used for calibration. In the graph to the right the theoretical weight of the weld seam is compared with measured weight for both the T-Joint and the HalfV-Joint. The theoretical weight is higher with respectively an average of 8 % and 14 %.

From welding machine to welding data

The voltage and current in the welding data were calibrated by making a series of measurements with different voltage and current values at the welding machine. For each measurement the welding machine voltage and current were compared with voltage and current in the welding data. The result of the comparison is shown in figure 4.22 where linear relations are found and described by equations. The equations were used as calibration parameters in the neutral welding machine interface.

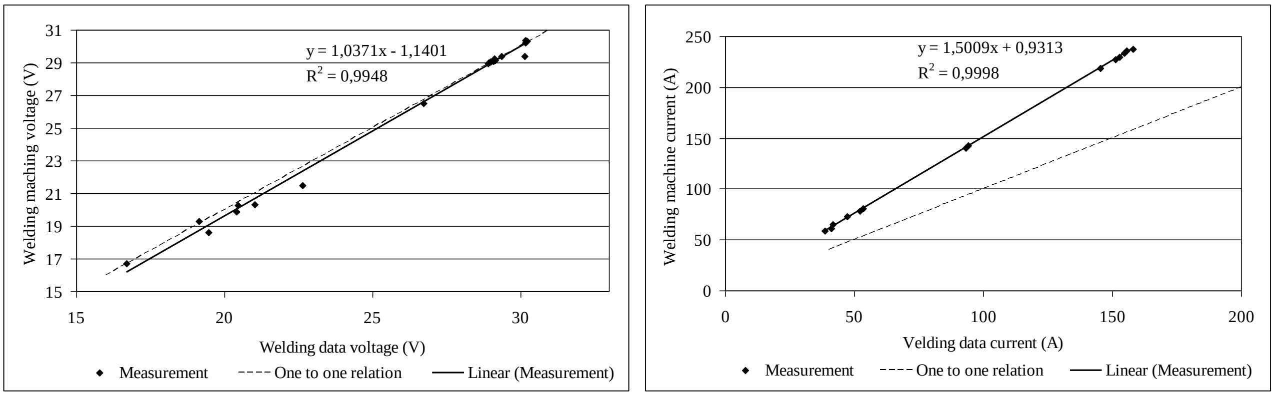


Figure 4.22: The graph to the left shows that the welding machine voltage was consistent with the voltage in the welding data and no calibration was required. The graph to the right shows that measurement of the welding machine current as a function of the current in the welding data gives a linear relation. It deviates from a one to one relation and the shown equation was used for calibration.

The gas flow rate was adjusted to a given value with a flow meter.

Robot and turntable

The robot and turntable require calibration of the internal transformations in the robot and turntable and the transformation from the robot to the turntable. The calibration procedure is specific for different robots and was not dealt with in this thesis. The location of the scanner and tool mounted at the robot required calibration which is described in appendix D.

4.5.3 Procedure for producing empirical welding data

For the T-Joint and the HalfV-Joint experiments the quality requirements to be fulfilled are shown in table 4.2 and table 4.3. The T-Joint and HalfV-Joint were tack welded in both ends to keep the plate angle and root gap fixed for the experiments.

Table 4.2: T-Joint quality parameters.

Quality parameters	
Leg length plate 1:	
Leg length plate 2:	
Depth of fusion plate 1:	≥ 1 mm
Depth of fusion plate 2:	≥ 1 mm
Weld face undercut plate 1:	B
Weld face undercut plate 2:	B
Cracks:	B
Holes:	B
QP. T-Joint	
Theoretical throat:	4-5 mm
Equal legs:	B
Convexity:	B

Table 4.3: HalfV-Joint quality parameters.

Quality parameters	
Leg length plate 1:	≥ 1 mm
Leg length plate 2:	≥ 1 mm
Depth of fusion plate 1:	> 0 mm
Depth of fusion plate 2:	> 0 mm
Weld face undercut plate 1:	
Weld face undercut plate 2:	
Cracks:	B
Holes:	B
QP. Corner-Joint	
Back bead width:	≥ root gap
Back bead height:	0-2 mm
Theoretical throat:	
Equal legs:	
Convexity:	

The task of making the experiment was divided into four tasks as described in chapter 2 section 2.3 “Empirical knowledge”. The first and second task were to define input variables and output variables of the system and define the tolerance box for the specification in table 4.2 and table 4.3. The third task was to find the settings of welding control variables which cause the required welding quality. The fourth task was to vary the welding control variables to monitor the changes of the welding quality inside the process window.
A welding operator carried out the experiments and furthermore decided the welding control variables both for the initial welding control variables and also during the series of experiments where welding control variables were changed. During the series of welding experiments the operator changed the welding control vector after observations of the welding experiment and examination of the experimental result.

T-Joint

58 experiments were carried out for the T-Joint and the welding control variables used for each experiment are shown in table 4.4.

Table 4.4: Welding control variables used for the T-Joint. Grey marking indicates change of welding control variable value according to previous experiment. The root gap were 0 millimetre for number 1 – 34, 1 millimetre for number 35 – 46 and 2 millimetres for number 47 – 58.

Experiment	Number	Work angle	Travel angle	CT-WD	Travel speed	Oscillation on	Oscillation width	Oscillation frequency	Oscillation holding 1	Oscillation holding 2	Wire feed speed	Voltage
T-Joint001A	1	-45	0	15	8	1	1	1	25	25	10	25
T-Joint001B	2	-45	0	15	6	1	1	1	25	25	10	25
T-Joint002A	3	-45	0	15	8	1	1	2	25	25	10	25
T-Joint002B	4	-45	0	15	8	1	1	2	25	25	12	25
T-Joint003A	5	-45	0	15	8	1	1	2	15	15	12	25
T-Joint003B	6	-45	0	15	8	1	1	2	15	15	12	25
T-Joint004A	7	-45	0	15	8	1	1	2	15	15	12	26
T-Joint004B	8	-45	0	15	8	1	1	2	15	15	14	26
T-Joint005A	9	-45	0	15	8	1	1	2	15	15	12	26

T-Joint005B	10	-45	0	20	8	1	1	2	15	15	12	26
T-Joint006A	11	-45	10	16	8	1	1	2	20	20	12	26
T-Joint006B	12	-45	10	16	7	1	1	2	20	20	12	26
T-Joint007A	13	-40	0	16	7	1	1	2	20	20	12	26
T-Joint007B	14	-35	0	16	7	1	1	2	20	20	12	26
T-Joint008A	15	-45	0	16	7	1	1	2	20	20	12	26
T-Joint008B	16	-50	0	16	7	1	1	2	20	20	12	26
T-Joint009A	17	-45	0	16	7	0					12	26
T-Joint009B	18	-50	0	16	7	0					12	26
T-Joint010A	19	-45	0	16	7	0					12	27
T-Joint010B	20	-45	0	18	7	0					12	27
T-Joint011A	21	-45	0	18	7	0					12	29
T-Joint011B	22	-45	0	18	7	0					13	29
T-Joint012A	23	-45	0	18	8	0					14	30
T-Joint012B	24	-45	0	18	8	0					15	30
T-Joint013A	25	-45	0	18	8	1	1	2	20	20	14	30
T-Joint013B	26	-45	0	18	8	1	1	2	20	20	15	30
T-Joint014A	27	-42	0	18	8	0					14	30
T-Joint014B	28	-48	0	18	8	0					14	30
T-Joint015A	29	-45	0	14	8	0					14	30
T-Joint015B	30	-45	0	16	8	0					14	30
T-Joint016A	31	-45	0	16	8	0					14	29
T-Joint016B	32	-45	0	16	10	0					14	29
T-Joint017A	33	-45	5	18	7	0					14	29
T-Joint017B	34	-45	5	18	6	0					14	29
T-Joint018A	35	-45	0	18	8	0					14	30
T-Joint018B	36	-45	0	18	8	0					15	30
T-Joint019A	37	-42	0	18	8	0					15	29
T-Joint019B	38	-40	0	18	8	0					15	29
T-Joint020A	39	-45	0	19	7	0					15	29
T-Joint020B	40	-45	0	19	6	0					15	29
T-Joint021A	41	-42	10	20	4	0					10	26
T-Joint021B	42	-40	10	20	4	0					10	26
T-Joint022A	43	-40	10	20	5	0					10	28
T-Joint022B	44	-40	10	20	3	0					10	28
T-Joint023A	45	-40	10	20	10	0					15	29
T-Joint023B	46	-40	10	20	13	0					15	29
T-Joint024A	47	-45	0	18	8	0					14	30
T-Joint024B	48	-45	0	18	8	0					15	30
T-Joint025A	49	-45	0	18	6	0					15	29
T-Joint025B	50	-42	0	18	6	0					15	29
T-Joint026A	51	-42	10	18	6	0					15	29
T-Joint026B	52	-42	10	20	6	0					15	29
T-Joint027A	53	-42	10	20	6	1	0.8	2	25	25	15	29
T-Joint027B	54	-42	10	20	8	1	0.8	2	25	25	15	29
T-Joint028A	55	-42	10	20	6	1	0.8	1	25	25	15	29
T-Joint028B	56	-42	10	20	8	1	0.8	1	25	25	15	29
T-Joint029A	57	-42	10	20	6	1	0.8	2	5	5	15	29
T-Joint029B	58	-42	10	20	8	1	0.8	2	5	5	15	29

Experiment number 1 – 30 were used to find the process window for the decided quality and the rest, 31 – 58 were made to explore the process window and other root gap sizes.

HalfV-Joint

For the HalfV-Joint 138 experiments were carried out and they are illustrated in appendix G. The experiments 1 - 98 were used to find the process window with the right quality and the last experiments from 99 - 138 were used to explore the process window and other root gap sizes.

4.5.4 Results of experiments

The outcome of the experiments was a welding database record specified in the taxonomy of the generic information model presented in section 3.1 "Generic information model". The welding database record consists of 58 welding experiment records for the T-Joint and 138 welding experiment records for the HalfV-Joint. It produced totally 5912 welding experimental samples with the parameters and variables inside the accepted limits specified in appendix F table F.3 and table F.4. Without deleting welding experiment samples outside the accepted limits 7056 welding experiment samples were produced. The result was that 16 per cent were deleted. The main reason was that spatter caused problems with positioning the breakpoints correctly. For none of the experiments were all the produced data deleted.
For the T-Joint, to be used in chapter 6, the outcome was 920 welding experiment samples. The requirement to these was that they should be inside 40-90 and 120-170 millimetres from the start point to be considered as static data.

The time consumption for making the two experiments and analysing the experiments by inspection, without any tests, were for the T-Joint 20 minutes and for the halfV-Joint 30 minutes. Two experiments were made on one workpiece because of the change of welding control variables after 100 millimetres. The tests made for these experiments were inspection penetrants and a polished section. The polished section was time consuming but it was required to investigate the depth of fusion.

4.6 Summery

This summery is divided into two sections. The first section is for the general part and the second section is for the specific part.

Specification and architecture for a system for automating production of empirical welding data

In sections 4.1, 4.2 and 4.3 a specification and an architecture are presented of a system for automating production of empirical welding data. The presented system is independent of the equipment to perform the experiments and it can make experiments on different workpieces and with different welding processes. The presented architecture is capable of making and analysing experiments to make an outcome which represents the empirical welding data from the experiment in the structure of the generic information model presented in chapter 3. Furthermore, the architecture also makes it possible to customise the empirical welding data in the generic information model for a specific use.

Production of empirical welding data

In section 4.4 the system for automating production of empirical welding data is applied on a specific welding equipment in the two cases T- and HalfV-Joint. It is demonstrated how the system for automating production of empirical welding data was practically implemented for two different workpieces. The time consumption for making an experiment and analysing the experiment by inspection of one workpiece, two experiments, were for the T-Joint 20 minutes and for the HalfV-Joint 30 minutes. This time does not include the tests made. A severe reduction of time consumption is achieved by using the system for automating production of experiments compared to manual robot programming and analysis of the experiments. Furthermore, a reliable documentation of the produced empirical welding data is made and it is recorded such that it can be reused and expanded.

The experiments were carried out to produce a welding database record by varying 10 welding control variables. The number of experiments necessary to achieve the required quality inside the process window was for the T-Joint 30 experiments and for the HalfV-Joint 98 experiments. For T-Joint and especially the HalfV-Joint a large number of experiments were required and this illustrates the very time consuming process of creating empirical data. Inside the process window 28 experiments were made for the T-Joint and 40 experiments for the HalfV-Joint to investigate the influence of different variables on the quality. For the T-Joint the found process window was larger than for the HalfV-Joint.

Chapter 5

Formalising operator knowledge

In chapter 2 it was argued that the welding operator has various kinds of knowledge about the welding process, which were basically not formalised. Formalising the operator knowledge is a promising and useful source to fill in the gap where analytical knowledge is not available and where empirical knowledge is an expensive resource. This chapter presents methods of formalising the operator knowledge to make it usable in various forms for creating process-planning models.

It is first explained how to categorise the silent and formalised knowledge to be able to transform the silent knowledge to formalised knowledge. The formalised knowledge is categorised into, so called, single parts of formalised knowledge and aggregated parts of formalised knowledge. Afterwards, different methods producing various types of single and aggregated parts of operator knowledge are presented.

5.1 Categorisation of operator knowledge

In chapter 2 the various kinds of operator knowledge were identified as silent knowledge in the operator's memory. Going into more details with one of the theories on how humans learn and how the memory works, a model of the flow of information to and from the environment and in the different memories is presented in figure 5.1. This model tries to illustrate and explain the processes in the brain, but does not position the processes in particular areas of the brain.

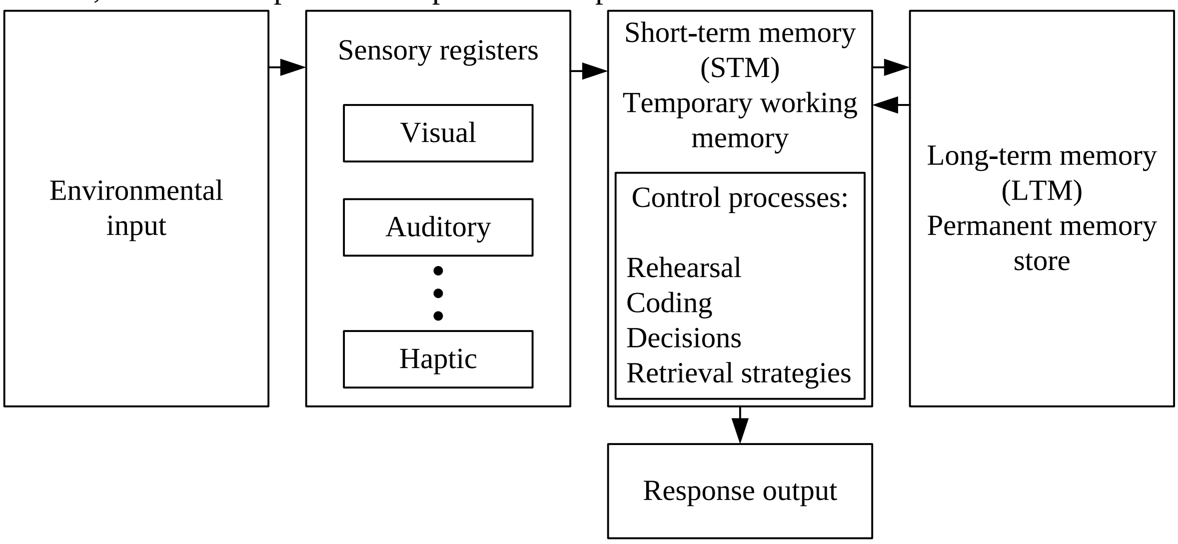


Figure 5.1: The model from [Atkinson et. al. 1971] postulates the flow of information from the environment and through three memory stores of humans. The sensory registers hold briefly the messages from the environmental input, and stimulus traces in the messages are attended to be identified and re-coded. The short-term memory has a limited capacity and duration. It can be described with the concept of "working memory" where humans consider and process information actively and consciously. The long-term memory is the permanent storage.

The long-term memory is explained further in depth by [Tulving, 1985], who arranges it systematically into three types of memories; episodic, semantic and procedural memory.

Procedural memory is unintentional. It enables learning of connections between stimuli and responses and also the complex patters of stimulus and responses. It is embedded in actions, procedures and routines.
Semantic knowledge is intentional and refers to general knowledge, concepts, rules and facts, the context of which acquisition was forgotten long time ago.
Episodic knowledge is intentional. It is the personal knowledge with specific events, which occurred at a particular time and place.

These models of how the memory works are applied to describe the operator's knowledge collection. Furthermore, it describes why and how intentional and unintentional knowledge can be collected from the operator.
The operator's main sources for learning come from theoretical courses, but also from training and practicing.
The theoretical courses contribute with analytical knowledge, which is stored in the semantic memory. The analytical knowledge is already formalised and therefore it is not an interesting new knowledge source to formalise.
Training and practicing can be related to courses or work. The knowledge is generated in the process, where the operator has stimuli input from the welding process, such as visual and auditory input. The operator responses with an output changing the welding control variables. Learning the connection between the stimuli input and the response output is stored in the procedural memory. During this process the skill of welding is increased by practising. The knowledge about welding is stored in the procedural memory and difficult to access. Reflecting on the learned skills the welding knowledge can be formalised, made intentionally and become a semantic knowledge. It can be communicated by e.g. words and drawings, but it depends on the operator to which degree it can be made intentional.

The procedural knowledge from the operator is the new kind of knowledge source, which is collected to make process-planning models for welding. This kind of knowledge is represented in the procedural knowledge and therefore cannot be collected from books or courses. It is experienced that to formalise the knowledge it can be collected either by the operator himself, through interview or a combination of those two.
The further investigation is to determine forms for representing the formalised knowledge for the collection. A systematic representation of the formalised knowledge is grouped into:

- Single parts: subcategorised formalised knowledge, where the knowledge is divided into description of only one thing about the process.
- Aggregated parts: undivided formalised knowledge, where the knowledge consists of more than one single part and describes broader relationships or the whole process.

The transformations from silent knowledge to formalised knowledge in the form of single and aggregated parts are illustrated in figure 5.2.

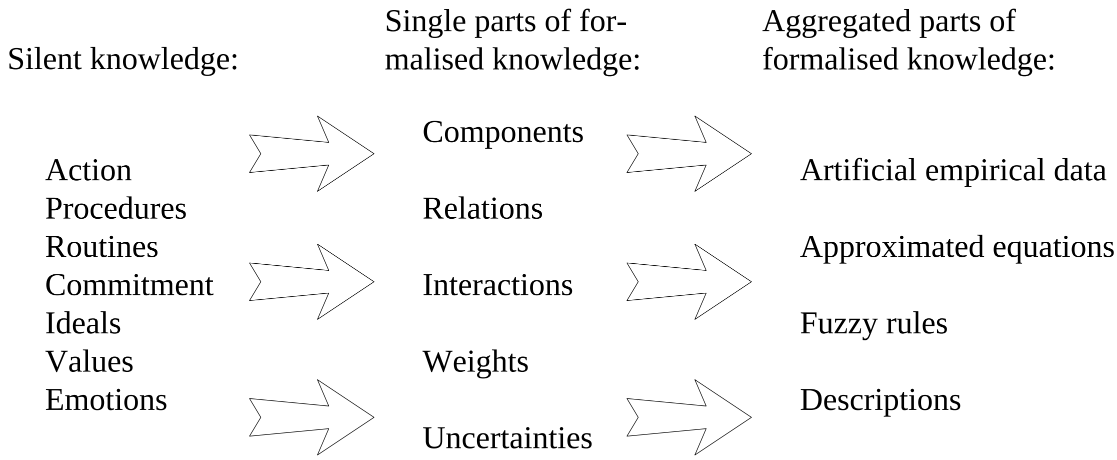


Figure 5.2: The operator knowledge is characterised by different kinds of silent knowledge. Through formalisation methods the silent knowledge can be made into a series of single parts of formalised knowledge. Through other formalisation processes more or all of the single parts of formalised knowledge can be made into a series of aggregated parts of formalised knowledge.

The following two sections 5.2 and 5.3 describe the methods, which respectively produce single parts and aggregated parts of formalised knowledge.

5.2 Production of single parts of formalised knowledge

The production of single parts of formalised knowledge is made to represent the basic parts of the operator knowledge in a systematic way. Single parts of formalised knowledge were produced in [Kristiansen et al., 2004] and used for making artificial empirical data for a small process model. In this chapter, the methods from [Kristiansen et al., 2004] are developed further, made more general and the production of each knowledge component is described. [Kristiansen et al., 2004] can be found in appendix J.
The single parts of formalised knowledge are suitable for modelling the process, and in chapter 6 they are utilised for modelling.

In this section there are five methods described to formalise and represent the silent knowledge. The formalised knowledge can in most cases be represented in a written and graphical form and the form, which best fits the operators way of expressing the knowledge, can be selected. The written or graphical representation is then transferred and applied for modelling, e.g. for producing process-planning models.

5.2.1 Components

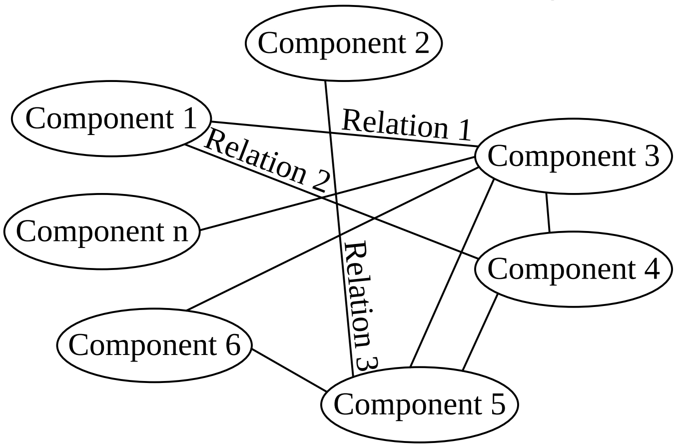
The components are all the parameters and variables of which the system consists. They influence the process or they are influenced by the process. Each component was defined with the attributes: a name, a unit of measurement, one of the categories of variables or parameters in figure 1.1, a minimum and a maximum value and a discretisation interval. These attributes were required for this work, but other attributes could also be added if they were found useful. An example of a component is the travel speed; measurement unit is millimetres per second, it is a control variable, has a minimum and a maximum value of respectively 3 and 13 millimetres per second and its discretisisation interval is set to 1 millimetre per second. The formalisation of the components was made by constructing a list, as it is illustrated in figure 5.3.

Component 1: Name, unit, category, min. value, max. value, discretisisation interval
Component 2: Name, unit, category, min. value, max. value, discretisisation interval
.
.

Figure 5.3: Representation of components in a written form. Each component is specified by a range of attributes.

5.2.2 Relations

The relations were described between components affecting each other. As an example, weld face width could be affected by wire feed speed, voltage, travel speed and oscillation width. The formalisation of the relations is shown in figure 5.4.

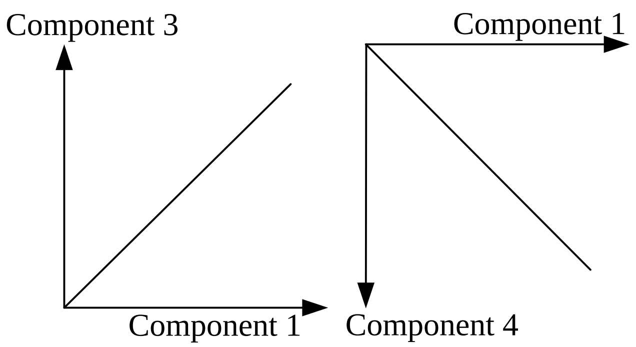


Relation 1: component 1 and component 3
Relation 2: component 1 and component 4
Relation 3: component 2 and component 5
.
.

Figure 5.4: Representation of relations. The left part of the figure corresponds to the graphical representation, and the right part corresponds to the written representation.

5.2.3 Interactions

The interactions were explained by the way one component interacts with another component. For example weld face width has two interactions: an approximately direct linear interaction with the wire feed speed and an approximately inverse linear interaction with travel speed. The formalisation of the relations is illustrated in figure 5.5. Other mathematical functions, such as a square root and second power, can also describe the interactions.

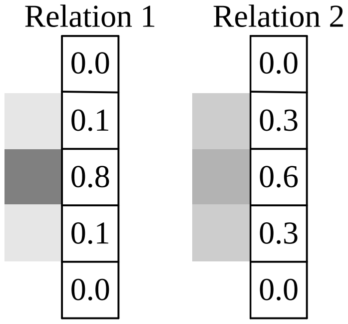


Relation 1: component 1 = component 3
Relation 2: component 1 = - component 4
.
.

Figure 5.5: Representation of interactions. The left part of the figure corresponds to the graphical representation, and the right part corresponds to the written representation.

5.2.4 Uncertainties

Uncertainties were specified to state the certainty of an interaction for a given relation. For example the way wire feed speed interacts with the current is very certain, while the way the wire feed speed interacts with the convexity is uncertain. The formalisation of the uncertainties is done by making a larger distribution for uncertain interaction than for certain interactions, as shown in figure 5.6.

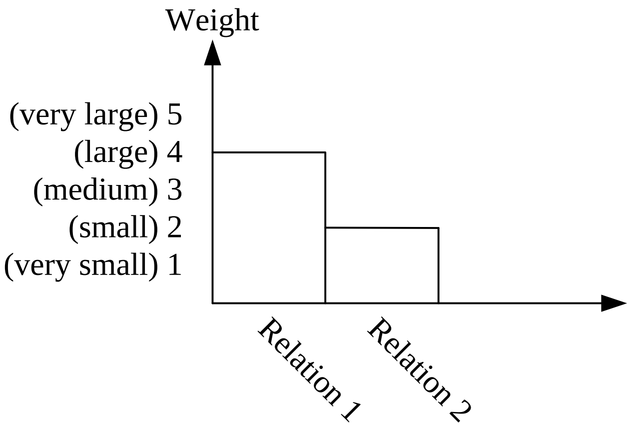


Relation 1: The interaction is certain
Relation 2: The interaction is little certain
.
.

Figure 5.6: Representation of uncertainties. The left part of the figure corresponds to the graphical representation of the weight, with an array of values summing up to one and marked by a grey scale. The closer the middle value is to one and the other values are to zero the more certain the interaction is. More equally distributed values relate to more uncertainty. The right part of the figure corresponds to the written representation.

5.2.5 Weights

The weights were given on each relation to rate the impact that, the related components have on each other. For example, the travel angle gives a small weight on the theoretical throat, while the wire feed speed gives a high weight on the theoretical throat. Formalisation of the weights is illustrated in figure 5.7.



Relation 1: The interaction has a large weight
Relation 2: The interaction has a small weight
.
.

Figure 5.7: Representation of weights. The left part of the figure is a bar chart corresponding to the graphical representation. The right part of the figure corresponds to the written representation.

5.3 Production of aggregated parts of formalised knowledge

By combining single parts of formalised knowledge it is possible to produce aggregated parts of formalised knowledge. The aggregated parts of formalised knowledge have different properties than single parts of formalised knowledge. Due to these properties it is possible to deploy them both for training and modelling. In this section four kinds of aggregated parts of formalised knowledge are introduced and the procedure to produce them is described.

5.3.1 Artificial empirical data

This method is described in [Kristiansen et al., 2004] and in this thesis it is further developed to a general method. The method makes use of the single parts of formalised knowledge as input. By joining components, relations, interactions, uncertainties and weights datasets with artificial empirical data were produced. The sequence of tasks to produce artificial empirical data is shown in figure 5.8.

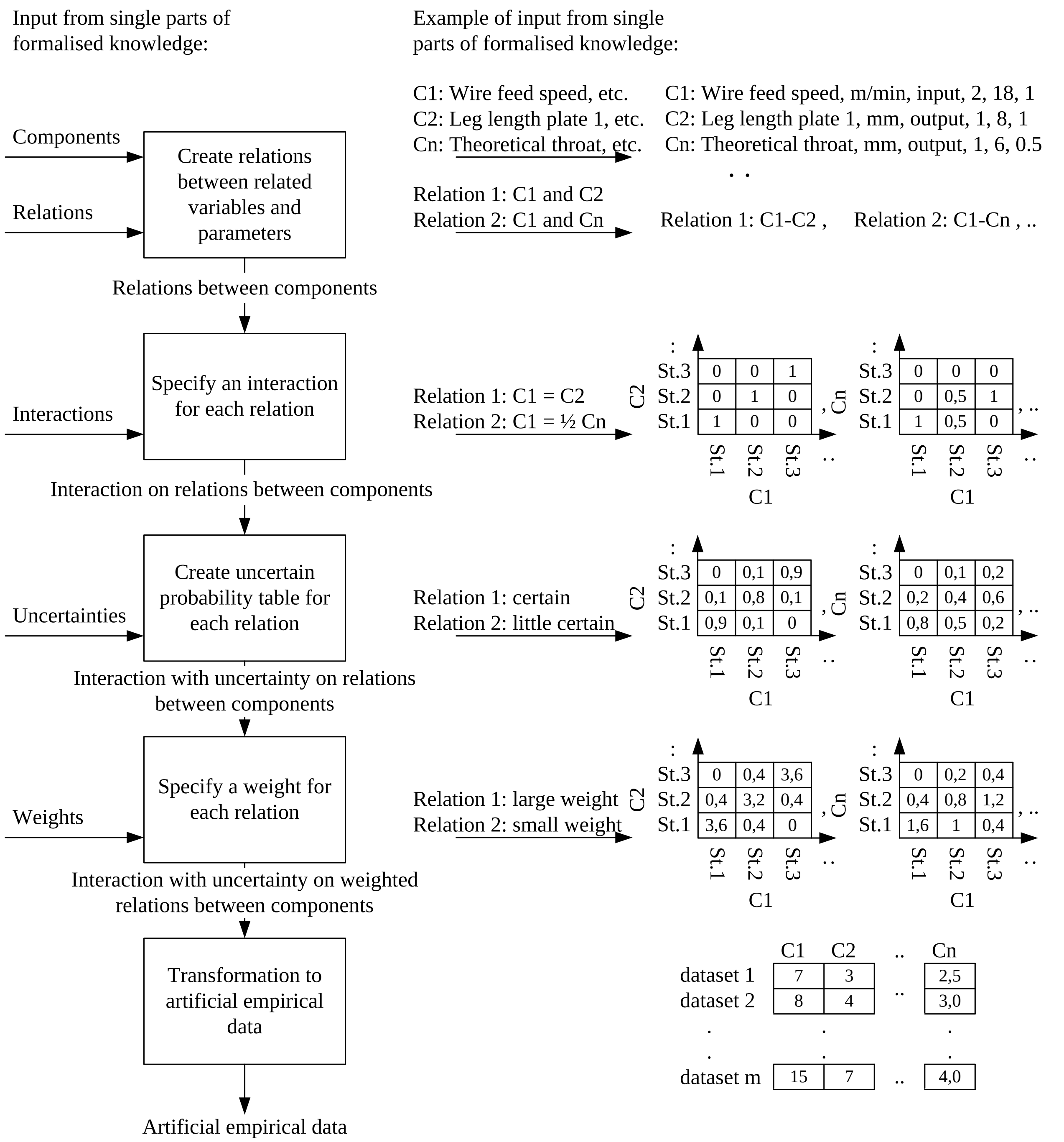


Figure 5.8: **The left part of the figure shows the general method and the right part of the figure shows its exemplification. The method transforms components, relations, interactions, uncertainties and weights to**

records, containing dataset with artificial empirical data. Components have abbreviation C and states have abbreviations St.

Each task in figure 5.8 is described below.

Create relations between related variables and parameters

This task requires components and relations, as described in sections 5.2.1 and 5.2.2. However, each component has to be specified further if it is an input or output component in the model. The relations in the model are constrained to be valid only between input and output components, which means that the relations between input and input components and between output and output components are invalid. The result of this task is a list with all the relations between the components.

Specify interaction for each relation

For each relation the interaction was specified as described in section 5.2.3. A discrete table was defined for each relation, with the input component at the horizontal axis and the output component at the vertical axis, shown in figure 5.8. Three of the component attributes; minimum and maximum value and discretisation interval, described in section 5.2.1, are used to specify the number of states at the table axis.

$$number\ of\ states = \frac{maximum\ value - minimum\ value}{discretisation\ interval} + 1$$

At each axis the states vary from the minimum to the maximum value, and the step size is defined by the discretisised interval for the respective component. The output component is described on the vertical axis and the input component on the horizontal axis. In this table the relation is written in a discrete form, and values from each column sum to one. The output of this function is a table for each relation.

Create uncertain probability table for each relation

The uncertainties are given for each of the tables describing a relation, as it is shown in section 5.2.4. Large uncertainties result in an uncertain table, which has a large variation of the values describing the relation. Small uncertainties result in a certain table, which has a little variation of the values describing the relations. The output of this function is a table for each relation, where values from each column sum to one.

Specify a weight for each relation

Each table specifying a relation is multiplied by a weight defined in section 5.2.5. The output of this function is a table, where values from each column sum to the value which was given as a weight.

Transformation to artificial empirical data

The transformation to artificial empirical data is calculated, as described in the pseudo code in figure 5.9, and it is explained in the following. For each of the output components (C_{output}) all the combinations of the input components (C_{input}) are examined. For each state in an output component a score for the given combinations of the input components is calculated. After the scores in each state in an output component is calculated the state with the highest score is selected.

For $g \leftarrow 1$ **to** *number of* C_{output}
  for $h \leftarrow 1$ **to** *number of states in* $C_{input\,1}$
  .
  .
  .
   for $j \leftarrow 1$ **to** *number of states in* $C_{input\,r}$
    for $k \leftarrow 1$ **to** *number of states in* $C_{output\,g}$
    do $C_{output\,g}$ *state* $k = C_{input1} state\ h + ... + C_{inputr} state\ j$
  select state in $C_{output\,g}$ with the highest score

Figure 5.9: Pseudo code for calculation of table with artificial empirical data. For each relation between output and input components a for-loop is made. In the for-loop a value is calculated for each state in the output component. The state for the output component with the highest score is selected along with the particular states from the input components.

The number of datasets calculated for an output component depends on the number of states in the related input components. It is calculated in the following way:

$$number\ of\ dataset = number\ of\ states\ in\ C_{input1} \cdot ... \cdot number\ of\ states\ in\ C_{inputr}$$

The artificial empirical data is represented as datasets in a table and can be used for example as training data.

An artificial empirical dataset, in [Kristiansen et al., 2004], is applied to train a direct process-planning model with relative few components. Training with artificial empirical data is compared to training with empirical data from experiments. The trained process-planning models from the two different data sources give the same classification rate in a benchmark made on unseen empirical data. Mixing two data sources also shows that the classification rate is at the same level in a benchmark, which concludes that two data sources agree with each other. Therefore it is concluded that artificial empirical data as a training source for process-planning models with relative few components can either be used instead of empirical data from experiments or as a supplement.

It is expected that for a process-planning model with more components, the accuracy of artificial empirical data will decrease because the operator's overview and comparisons are subject to more inaccuracy. It requires further investigations to determine more results about that.

5.3.2 Approximated equation

The approximated equations consist of components, relations, interactions and weights, which are single parts of formalised knowledge determined by the operator and described in sections 5.2.1, 5.2.2, 5.2.3 and 5.2.5. A method for approximating equations, which give a functional relationship, is presented in the following. To approximate an equation for a component all the relations influencing the component are used. Each relation has the components with a minimum and maximum value and the interaction to form an equation. Furthermore, the weight is used to rate the influence of the equation. The principle is illustrated in figure 5.10.

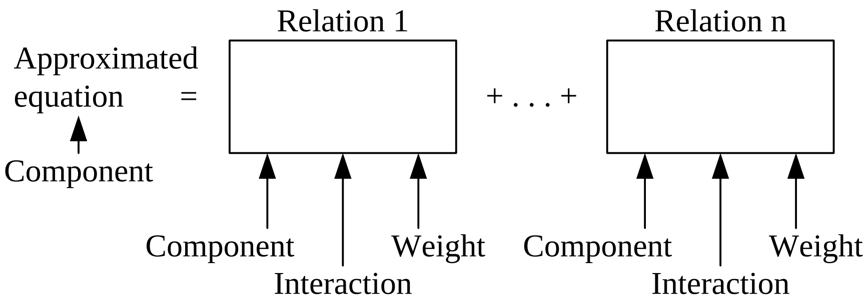


Figure 5.10: The structure for approximation of an equation. The left side of the sign of equality is the output component. The right side of the sign of equality is the required input from *n* number of relations influencing the output component.

The reason why the approximated equation should be seen only as an approximation is because the large amount of relations between the components describing the welding process and the relations for a component can have reciprocal effects. The capability and accuracy of the operator, who describes relations and reciprocal effects, limit the accuracy of this method. In order to include reciprocal effects, the relations can be multiplied, that is however not further investigated in this thesis.

An example is given in figure 5.11 which illustrates how an approximated equation is produced. The procedure for each relation is to determine the range of the output. In this case it is 4, and it is calculated from the following equation where *max* = 12 and *min* = 8:

$$range = max - min$$

For relation 1 the interaction is specified by a square root function. Relation 1 is in the interval from 0 to 15. The interval is needed in order to scale the relation to approximate within the range of the output. It requires a scale function, which is 4 divided by the square root of 15. Finally the whole equation is multiplied by the weight divided by the total weight of all the relations. This is done for all the relations contained in the approximated equation. At the end the approximated equation is added by a level, which is the min level of the component.

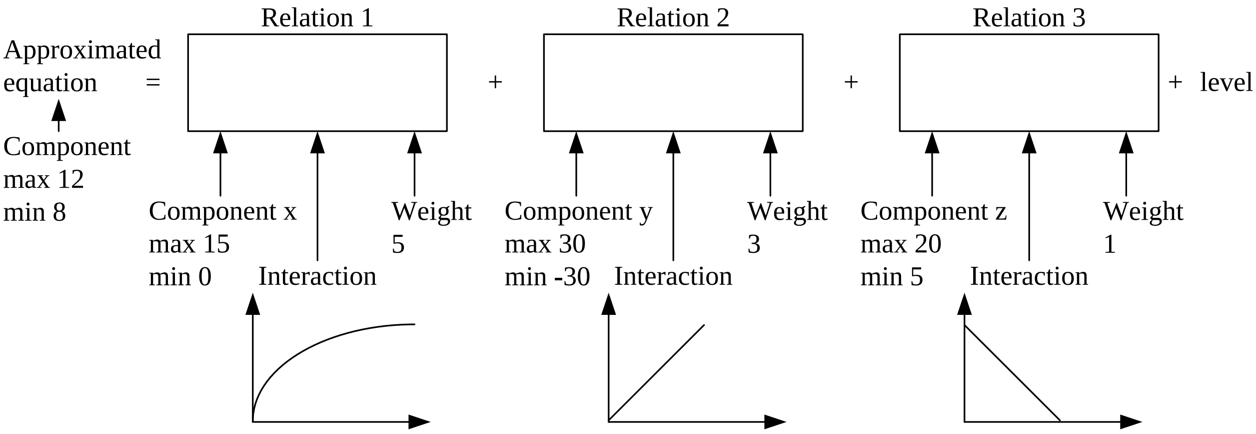


Figure 5.11: Example of approximating an equation for a component with three relations.

The approximated equation from the example in figure 5.11 is shown below.

$$Approximated\ equation = \frac{4}{\sqrt{15}} \cdot \sqrt{x} \cdot \frac{5}{9} + (y + 30) \cdot \frac{4}{60} \cdot \frac{3}{9} + 0{,}1 \cdot (-z + 20) \cdot \frac{4}{15} \cdot \frac{1}{9} + 8$$

This methodology of approximating equations is utilised in chapter 6.

5.3.3 Fuzzy rules

The concept of building fuzzy rules uses components, relations, interactions and weights, which are single parts of formalised knowledge determined by the operator. The components are converted so they have a certain degree of membership to the fuzzy sets, shown in figure 5.12.

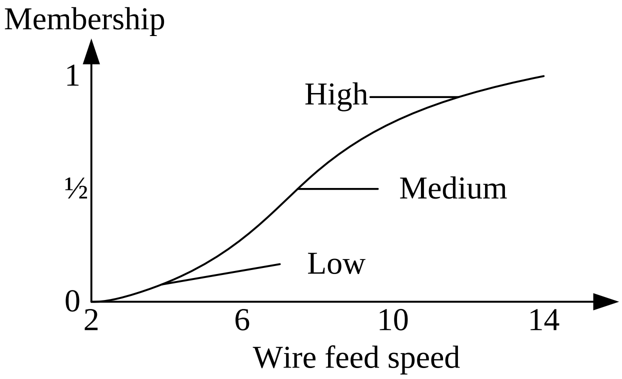


Figure 5.12: The component, wire feed speed, is scaled to the fuzzy membership.

The components and relations are used to determine which rules to construct in a rule base using rules made by IF THEN. Each rule is filled out using the interaction to decide if it is an AND or OR relation, and the weights are used to specify how strong the relations are. Further description can be found in [Jantsen, 1999a] and [Jantsen, 1999b]. Fuzzy rules are not applied in this thesis.

5.3.4 Description

A description is a method using single parts of formalised knowledge. The method uses components, relations, interactions, uncertainties and weights and they are all joined in a description. For humans a written description can be more natural to comprehend than other description methods, where a graph, table or other fixed description methods are used. A written description is used in chapter 6 section 6.4.1 "Creating the model structure", to define the task and give an overview in the first step of modelling.

5.4 Summery

In this chapter these methods are proposed where silent knowledge is converted to formalised knowledge. The formalised knowledge is divided into two categories: single parts and aggregated parts of formalised knowledge. Single parts of formalised knowledge are mainly usable for modelling, while the aggregated parts of formalised knowledge are usable for both modelling and training.

The formalised knowledge is used where no analytical knowledge is available and instead of empirical data or as supplement to empirical data. The formalised knowledge is reliable and it is demonstrated in [Kristiansen et al., 2004] for production of artificial empirical data, which gave a classification rate in a benchmark at the same level as empirical data from experiments.

Some of these presented knowledge sources are applied in this thesis for production of process-planning models in chapter 6.

Chapter 6

Building Bayesian network based process-planning models

To build a process-planning model the following tools from machine learning, Bayesian network, artificial neural network and regression model were applied. It was investigated how these three machine learning tools were used for production of process-planning model using up to three different knowledge sources, specified in chapter 2. The focus of the descriptions is on the Bayesian network, because the use of this tool for producing a process-planning model is not described in the literature. The opposite is present for the use of the other two tools which are applied several places in literature reviewed in appendix A. Only Bayesian network is presented in this chapter while the other two tools are presented in appendix H and I.

The use of each of the tools is described in three levels:

- General description
- Implementation for welding in general
- Implementation for T-Joint

When it is possible, the last two points are divided between creating the model structure and training the model.

6.1 Historical background

The Bayesian probability theory is named after Thomas Bayes, whose work is presented in [Bayes et al., 1763] and proves the Bayes' theorem. The work was extended independently by Pierre-Simon Laplace and proved a more general Bayes' theorem [Laplace, 1774]. The well known Bayes' rule with two variables determines, $P(X_2|X_1)$, the posterior probability of X_2 given X_1. $P(X_1)$ is the marginal or prior probability of X_1, $P(X_2)$ is the prior probability of X_2 and $P(X_1| X_2)$ is the conditional probability of X_1 given X_2.

$$P(X_2 \mid X_1) = \frac{P(X_1 \mid X_2)P(X_2)}{P(X_1)}$$

The theorem was later extended to include problems with more than two variables and probabilistic models, which were developed with a strong connection to graph theory. These graphic probabilistic models are a good representation of the statistical problem because directed graphs are used as visualisation. The popularity of the Bayesian networks was limited because calculation of exact inference of probability for arbitrary Bayesian networks is a NP-hard problem [Cooper, 1990]. It was not until after development of efficient inference algorithms, see [Lauritzen et al., 1988] and [Jensen et al., 1990], the use of the Bayesian network increased. Bayesian networks are applied to problems in areas such as fault diagnostics, searching, classification, pattern recognition, and they are often used as a tool for decision support.

Packages for building and manipulating Bayesian networks are available both commercially and non-commercially. In this thesis the packages Hugin [Hugin] and SamIam [SamIam] are used.

In the following, the basic theory and the definitions behind the Bayesian networks are described and a simple example from the welding domain is given to exemplify the theory. For more information about the theory see [Jensen, 2001].

6.2 General Bayesian network theory

Modelling based on a Bayesian network begins with an analysis of the system to be modelled in order to identify the variables in the systems and relations between them. From this identification, a graphical representation of the system can be made. A Bayesian network is a directed acyclic graph (DAG), which has a set of nodes. Nodes describe the identified variables in the system. The nodes which are related are connected by directed edges. The relationships between the nodes are described by a probabilistic expression, which is continuous or discrete. In the rest of this thesis only the discrete probability distribution is used, with nodes having a finite number of mutually exclusive states. The choice is motivated by the face that the continuous nodes give limitations, because they are constrained to handle only conditional Gaussian distribution, and they are not allowed to have a discrete child, described further by [Jensen, 2001]. Furthermore, a discrete node can approximate a continuous node. Each edge in the network represents a conditional probability distribution and describes the relative likelihood of each value of the child node, conditional on every possible combination of the values of the parent nodes. The definition of a Bayesian network is from [Jensen, 2001]:

Definition: A Bayesian network consists of the following:

- A set of variables and a set of directed edges between variables.
- Each variable has a finite set of mutually exclusive states.
- The variables together with the directed edges form a directed acyclic graph. (A directed graph is acyclic if there is no directed path $X_1 \rightarrow \cdots \rightarrow X_n$ so that $X_1 = X_n$.)
- To each variable X_1 with parents $X_2,\ldots,X_n$, the potential table $P(X_1|X_2,\ldots,X_n)$ is attached.

Three connection types to make node edges are shown in figure 6.1.

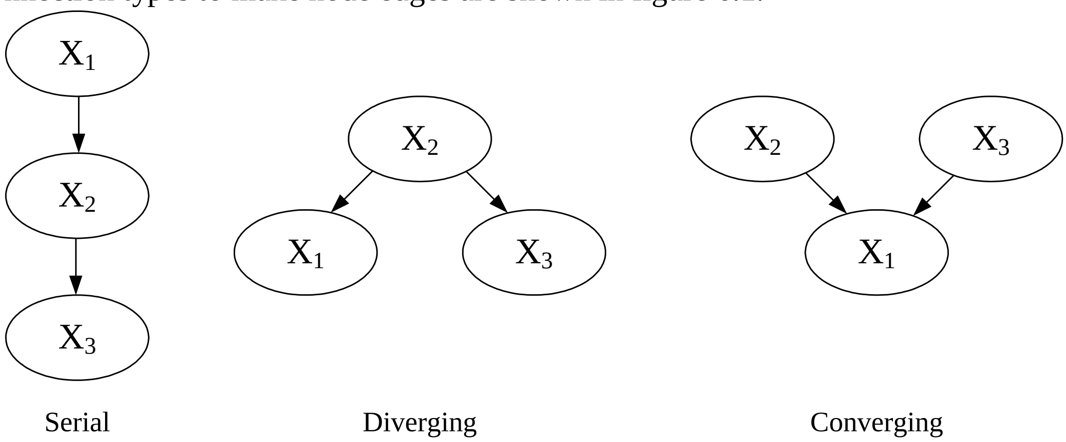


Figure 6.1: Left, is a serial connection; middle, a diverging connection; and right, a converging connection. [Jensen, 2001]

If information about a node is known, it can be entered as evidence to the node. Evidence entered to a node updates the node's probability distribution. For the serial connection in figure 6.1 evidence entered to node X_1 will influence the certainty of X_2, which again influences the certainty of X_3. Vice versa, evidence entered to node X_3 will also change the influence on X_2, which changes the influence on X_1. Nodes can be d-separated, which means that change of certainty of a node will not change the certainty of nodes from which the node is d-separated. In a Bayesian network d-separation is used to decide if evidence entered into the network is transmitted through a node. The transmission is dependent on whether a pair of nodes is d-separated and thereby independent. The definition of d-separation by [Jensen, 2001] is:

Definition: Two distinct variables X_1 and X_2 in a causal network are d-separated if, for all paths between X_1 and X_2, there is an intermediate variable X_i (distinct from X_1 and X_2) such that either:

- the connection is serial or diverging and X_i is instantiated
  or
- the connection is converging, and neither X_i nor any of X_i´s descendants have received evidence.

The definition is exemplified in the following. The serial connection in figure 6.1 with evidence entered to X_2 result in X_1 and X_3 d-separates, which means that X_1 can change certainty without the certainty of X_3 is changed, and X_3 can change certainty without the certainty of X_1 is changed. The diverging connection in figure 6.1, X_1 and X_3 are d-connected. If evidence is entered to X_2 it results in X_1 and X_3 becomes d-separated. The converging connection in figure 6.1, X_2 and X_3 are d-separated, but if evidence is entered to X_1 it results in X_2 and X_3 becomes d-connected.

The probability calculus is based on the Bayesian calculus, which is the classical probability calculus. $P(X)$ denotes the probability distribution of the variable X with the states $x_1,..x_n$, and p_i denotes probability of X being in state x_i. The sum of the probability in all states equals one.

$$P(X) = P(p_1,.., p_n); \qquad p_i \geq 0; \qquad \sum_{i=1}^{n} p_i = 1$$

Conditional probability of variable X_1 given variable X_2 is $P(X_1|X_2)$, and if X_1 has m states and X_2 has n states, a table with size n x m is generated. The sum of the probabilities in each column equals one. This is exemplified in Table 6.1.
The joint probability of variables X_1 and X_2 is $P(X_1,X_2)$. It generates a table with size n x m, but in this case the entire sum of the probability table equals one.
The outcome is the fundamental rule which gives the relation between the conditional and joint probability:

$$P(X_1, X_2) = P(X_1 \mid X_2)P(X_2)$$

Table 6.1: Example of the conditional probability table of $P(X_1|X_2)$ on the left and the joint probability table of $P(X_1,X_2)$ on the right. Both tables have size 3 x 2, $P(X_1) = (0.56, 0.44)$ and $P(X_2) = (0.32, 0.28, 0.4)$.

$P(X_1|X_2)$

	q1	q2	q3
p1	0.375	0.5	0.75
p2	0.625	0.5	0.25

$P(X_1,X_2)$

	q1	q2	q3
p1	0.12	0.14	0.3
p2	0.2	0.14	0.1

The fundamental rule conditioned on X_3 is:

$$P(X_1, X_2 \mid X_3) = P(X_1 \mid X_2, X_3)P(X_2 \mid X_3)$$

From the fundamental rule and given $P(X_1,X_2|X_3)=P(X_2|X_1,X_3)P(X_1|X_3)$ Bayes' rule is derived:

$$P(X_2 \mid X_1, X_3) = \frac{P(X_1 \mid X_2, X_3)P(X_2 \mid X_3)}{P(X_1 \mid X_3)}$$

Marginalisation is used to marginalize a variable out and in the notation is X_2 marginalized out of $P(X_1,X_2)$:

$$P(X_1) = \sum_{X_2} P(X_1, X_2)$$

The tables in a Bayesian network are called potentials and a table with real values over a domain of finite variables is the product of all the potentials of that domain. A Bayesian network represents the joint probability distribution of the entire domain of variables $U=\{X_1,X_2,..X_n\}$. The joint probability table $P(U)=P(X_1,X_2,..,X_n)$ is the product of all potentials specified in the Bayesian network, and it grows exponentially with the number of variables in U. Because of this rapid growth a more compact representation is used with all the potentials specified in the network. This more compact representation is made using the chain rule for Bayesian network:

$$\begin{aligned} P(U) &= P(X_1, X_2,.., X_n) \\ &= P(X_1 \mid X_2,.., X_n)P(X_2 \mid X_3,.., X_n)..P(X_n) \\ &= \prod_i P(X_i \mid pa(X_i)) \end{aligned}$$

$pa(X_i)$ is the parent set of X_i.

If information about the Bayesian network model is achieved, then it can be entered as evidence. Evidence can be entered if a variable is observed to be in one particular state, then this state is one and the rest are zero. Evidence can also be entered as a finding represented as a vector $\underline{e}$, which is a statement that eliminates certain impossible states of a variable and sets these probabilities to zero. Evidence can also be inserted as a likelihood vector, which differs from a finding represented as a vector, by assuming values for each state in the range of [0;1].

By multiplication of the finding vector on the joint probability table $P(U)$, $U = \{X_1, \ldots X_n\}$ is the universe of variables, the joint probability distribution $P(U,e)$ is found:

$$P(U, e) = P(U) \cdot \underline{e}$$

Applying the chain rule over the universe U of variables and with the findings $\underline{e}_1,..,\underline{e}_n$ gives:

$$P(U, e) = \prod_i P(X_i \mid pa(X_i)) \prod_j \underline{e}_j$$

For each individual variable as e.g. $X_1 \in U$:

$$P(X_1 \mid e) = \frac{\sum_{U \setminus \{X_1\}} P(U,e)}{P(e)}$$

For a number of variables the most probable instantiation can be preformed by a maximum a posteriori (MAP) analysis. The most probable instantiation of the joint probability for a number of variables, X_C, is a subset of a Bayesian network which gives the largest number, h_{MAP}, in the joint probability table. X_O is the observed variables in the Bayesian network which is not a part of X_C.

$$h_{MAP} = \arg\max_{X_c} P(X_c \mid X_o)$$

A Bayesian network can have the probabilities updated, because they allow inference based on evidence from observations. Updating the probability is for arbitrarily Bayesian networks a NP-hard problem, where the exact inference of probability is calculated. Algorithms to find both the approximated and exact inference of probability are developed. The most popular algorithms are transforming the Bayesian network into a tree structure, called junction trees. In [Jensen, 2001] one of the most efficient methods is described.

A Bayesian network model structure of a real world system can serve as decision support when taking decisions about the modelled system. The decisions can be test decisions where it is investigated for evidence to improve the decision making. The Bayesian network can also be extended by decision facilities to a decision graph with decision and utility nodes to solve decision problems. The decision node defines the action possibilities the user can choose, and the utility nodes represent the contribution for each state of the parents' node. In the decision graph the user can make active decisions which change the state of the modelled structure. [Jensen, 2001].

6.2.1 Bayesian network example

An example was constructed using a Bayesian network to show the principles of the modelling method. The example is a simplified model describing some of the causes to why the shielding gas is not sufficiently protecting the molten metal at the weld face. During the welding process the molten metal is protected by a shielding gas which is lead out from the gas cup. The shielding gas covers the molten metal to avoid oxygen from the air to react with the molten metal, what would cause oxidation of the metal giving bad welding quality. Two causes were identified to have impact on bad shielding of the molten metal. The first one is a dirty gas cup that can be due to the spatter from the welding process. This can disturb the gas flow and good protection of the melted metal is not obtained. The second one is an empty pressure tank with shielding gas. These two causes of bad shielding of the molten metal can be checked but that would require some effort. It is known that the amount of shielding gas in the pressure tank has an impact on the gas pressure meter, mounted on the pressure tank with shielding gas. The model in figure 6.2 represents the described case. More nodes could be included in the model if it is known that other parameters influence the nodes in the model. An example is the "Clean gas cup?" node, which has a parent node telling how long time ago the gas cup was cleaned last time.

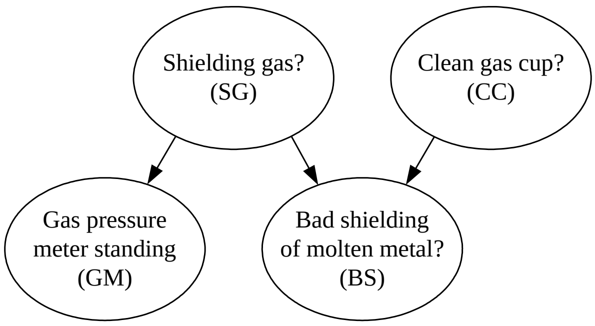


Figure 6.2: The Bayesian network represents the problem of bad shielding of molten metal. Abbreviations of the node names are written in parentheses.

Each node in figure 6.2 has a number of states. In this simplified case it is assumed that the nodes have the following states:

- "Shielding gas?" has the states yes and no because either there is shielding gas or not.
- "Clean gas cup?" has the states yes and no because either the gas cup is clean or not.
- "Gas pressure meter standing" is set to have three states: full, half full and empty and it is based on the reading of the operator.
- "Bad shielding of molten metal?" has the state yes and no because either there is a good or bad shielding of the molten metal.

For each node a probability table gives the probabilities for each state. For the nodes “Shielding gas?” and “Clean gas cup?”, which have no parents, the tables are reduced to unconditional probabilities. The probabilities are shown in table 6.2 and table 6.3. Table 6.2 shows 96 per cent probability that shielding gas is present, and 4 per cent probability that no shielding gas is present. Table 6.3 shows 90 per cent probability that the gas cup is clean, and 10 per cent probability that it is dirty.

Table 6.2: ***P(SG)*.**

SG = yes	0.96
SG = no	0.04

Table 6.3: ***P(CC)*.**

CC = yes	0.9
CC = no	0.1

For the nodes “Gas pressure meter standing” and “Bad shielding of molten metal?” the conditional probabilities depends on the state of the parent(s). The probabilities are shown in table 6.4 and table 6.5. In table 6.4 the state of the “Gas pressure meter standing” is given for the condition if the node “Shielding gas?” is yes or no. For *P(GM = empty | SG = yes)*, *P(GM = full | SG = no)* and *P(GM = ½ | SG = no)* the 1 per cent probability reflects that “Gas pressure meter standing” is malfunctioning.

Table 6.4: ***P(GM | SG)*.**

	SG = yes	SG = no
GM = full	0.34	0.01
GM = ½	0.65	0.01
GM = empty	0.01	0.98

Table 6.5: ***P(BS | SG, CC)*.**

	CC = yes		CC = no	
	SG = yes	SG = no	SG = yes	SG = no
BS = yes	0.04	1	0.8	1
BS = no	0.96	0	0.2	0

The probabilities in the tables are estimated to give an example.

An example is given to show how the probabilities in the Bayesian network are calculated manually, when knowledge is given as evidence to the network.

It is considered that a welding operator is welding a part and discovers bad shielding of the molten metal. The evidence that BS=yes is then entered to the node “Bad shielding of molten metal?” in the Bayesian network. The welding operator is interested in identifying the cause of the bad shielding of the molten metal, which originates from two sources: a dirty gas cup and a lack of shielding gas in the pressure tank. The task is to decide which of the causes should be checked first. The decision can be based on calculation of the conditional probabilities for the gas cup, *P(CC|BS=yes)*, and for the shielding gas, *P(SG|BS=yes)*. Using the fundamental rule the joint table is:

$$P(SG,GM,CC,BS) = P(SG)P(CC)P(GM \mid SG)P(BS \mid SG,CC)$$

The calculated joint probability table is in table 6.6.

Table 6.6: The joint probability table for *P(SG,GM,CC,BS)*.

	SG = yes				SG = no			
	CC = yes		CC = no		CC = yes		CC = no	
	BS = yes	BS = no	BS = yes	BS = no	BS = yes	BS = no	BS = yes	BS = no
GM = full	0.0118	0.282	0.0261	$6.53\cdot10^{-3}$	$3.6\cdot10^{-4}$	0	$4\cdot10^{-5}$	0
GM = ½	0.0225	0.539	0.0499	0.0125	$3.6\cdot10^{-4}$	0	$4\cdot10^{-5}$	0
GM = empty	$3.46\cdot10^{-4}$	$8.29\cdot10^{-3}$	$7.68\cdot10^{-4}$	$1.92\cdot10^{-4}$	0.0353	0	$3.92\cdot10^{-3}$	0

The cells in table 6.6 are summed up using marginalisation. It results in the probability for the two causes: *P(CC|BS=yes) = (yes=0.466, no=0.534)* and *P(SG|BS=yes)=(yes=0.736, no=0.264)*. Where *P(CC=yes|BS=yes)* is calculated by summing the probabilities of the columns with CC=yes and BS=yes, that is column 1 and 5, and then divided the result by the sum of the columns with BS=yes, that is column 1, 3, 5 and 7. The other conditional probabilities: *P(CC=no|BS=yes)*, *P(SG=yes|BS=yes)* and *P(SG=no|BS=yes)* are calculated in a similar manner. The marginalisation shows with a bigger probability that the gas cup is not clean than there is no more shielding gas. It would be wise to check the gas cup first. However the chance to take the right decision about what to check first can be increased by checking the state of the meter on shielding gas pressure tank. The state of the meter is read to GM=½ and it is entered as evidence to the node “Gas pressure meter standing” in the Bayesian network. The probabilities of the system are calculated using marginalization for the cells in table 6.6. The result is: *P(CC|BS=yes, GM=½) = (yes=0.314, no=0.686)* and *P(SG|BS=yes, GM=½)=(yes=0.995, no=0.005)*. This way the probability that the gas cup is clean has been reduced, and the probability that the shielding gas pressure tank is not empty is increased. Consequently it would be sensible for the welding operator to check the gas cup first.

6.2.2 Modelling tricks and strategies

Different modelling tricks and strategies for modelling a Bayesian network are usable. The ones used in this thesis are described in the following.

Divorcing

Divorcing is used to reduce the size of the tables in nodes which have many causes. The number of cells in a probability table is determined by the number of states in the node multiplied by the number of states in each parent node. Nodes with large table sizes are hard to calculate when propagating the network and the probability for each cell also needs to be determined. Introducing a mediating node between some of the parents’ nodes and the child node can reduce the probability table size, as it is illustrated in the following example. In figure 6.3, four variables X_1, X_2, X_3 and X_4 are causes to variable X_5 and specified by $P(X_5| X_1,X_2,X_3,X_4)$. If all variables have five states, the probability table has 5^5 = 3125 cells. By introducing a mediating variable X_6 with 5 states, which can describe the variables X_1 and X_2, it can be specified by $P(X_6|X_1,X_2)$. The parents to X_5 are then X_3, X_4 and X_6 and it is specified by $P(X_5| X_3,X_4,X_6)$ and will have a probability table of the size 5^4 = 625 cells.

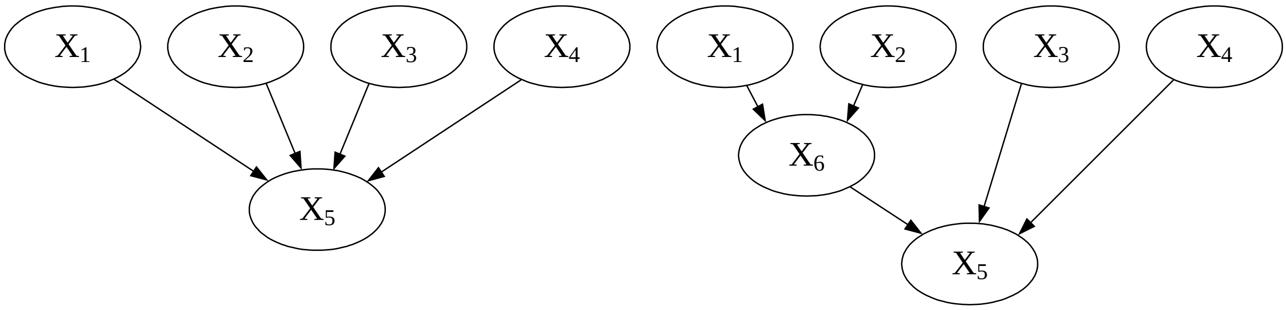


Figure 6.3: Divorcing is made by inserting node X_6, [Jensen, 2001].

Constraints

Constraint nodes are used in the Bayesian network to insert dependence relations among dependent nodes. The dependence relations appear when certain states in one node are valid only for certain states in a dependent node. Constraint nodes are inserted in the network as a child to nodes with two or more parents, where a dependency between them should be expressed. An example is given in figure 6.4, where node X_3 is a constraint node for nodes X_1 and X_2. In node X_3 a Boolean table is constructed and all true combinations of the states of X_1 and X_2 are denoted by “y” and for all false combinations by “n”. In case when the Bayesian network should deliver only allowed combinations of X_1 and X_2, “y” is entered as evidence to X_3. The dependency of the constrained nodes could be given from a rule, by an equation or by knowledge from an operator. The constraint node blocks all the solutions with impossible combinations between the parents’ nodes.

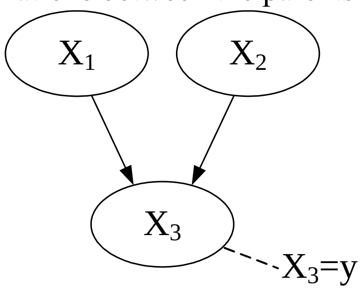


Figure 6.4: Constraints are introduced to X_1 and X_2 by the constrained node X_3, [Jensen, 2001].

Node state reduction (RE)

A child node, which is a copy of the parent node with a reduced number of states, can be inserted in the Bayesian network to decrease the table sizes in the Bayesian network. It is used on the parents to nodes with big size of the table and where the parents’ nodes have many states. It is illustrated in figure 6.5, where a node X_4 is inserted as a child node to the parent node X_1. X_4 is a copy of X_1 with a reduced number of states and expresses the same as the parent node, but with a lower resolution. Thereby it decreases the precision of the network.

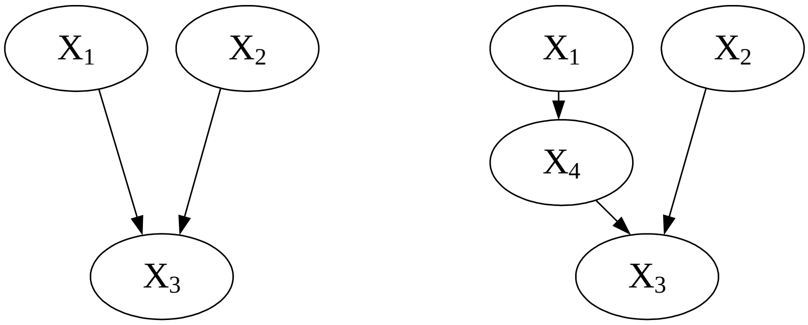


Figure 6.5: The size of the table in node X_3, on the left figure, is reduced in the right figure by inserting a node X_4 which is a copy of node X_1 just with a reduced number of states.

6.3 Implementation of welding model using Bayesian network

The description of using Bayesian network for implementing a welding model is divided into two parts; creating the model structure and training the model.

6.3.1 Creating the model structure

Modelling the structure of the Bayesian network consists of two tasks: defining the nodes and defining the edges between the nodes. Following methods are investigated to carry out the two modelling tasks:

- Automatic modelling
- Manual modelling

Automatic modelling

The overall idea of automatic modelling is to derive the structure of the model and when possible train the derived model structure. The modelling is made automatically based on knowledge, which mostly is empirical dataset. Two basic approaches exist for automatic modelling. First approach concerns conditional independence tests. Second approach is based on scoring function and a search procedure. [Acid et al., 2003].

In this thesis the conditional independence test method is investigated for automatic generation of a model but it is found to be not usable. The applied algorithms are PC (named by the developers Peter Spirtes and Clark Glymour) or NPC (Necessary Path Condition), which were implemented in Hugin, [Hugin]. By using these algorithms it is possible to enter domain knowledge to the modelling. It can be entered as structural constraints, where dependencies and non-dependencies are specified by domain experts. The automatic modelling requires datasets for training. The requirement to the size of the training dataset is dependent on the structure of the Bayesian network, the distribution of training examples and whether they are random or in some kind of an order. In [Acid et al., 2003] examples of training Bayesian networks are described with different sizes of training databases, and the number of training data increases with the number of nodes. The size of the available empirical dataset for the T-Joint and HalfV-Joint weld seam is respectively 58 and 138 experiments, described in chapter 4. It is far below the training data sizes used for similar sizes of Bayesian networks described in [Acid et al., 2003]. Bayesian network produced from the datasets are very poor networks without expected dependencies between nodes and with dependencies between nodes which does not give any sense. Training a Bayesian network to build a process-planning model for the T-Joint and HalfV-Joint weld seam requires much more empirical datasets than it is available from experiments produced for this thesis. Because of this fact automatic modelling is not used for this thesis.

Manual modelling

The manual modelling is a process where domain experts are working together with modelling experts, and through an iterative process a model structure is created. A methodology for making the iterative process is proposed and shown in figure 6.6.

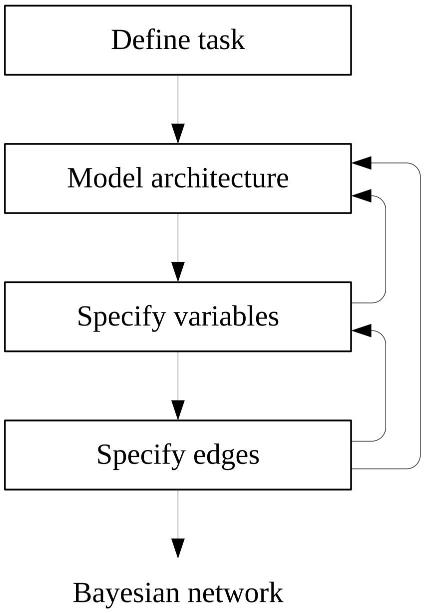


Figure 6.6: The tasks for creating the structure of the process-planning model.

Define task

For modelling the task the input and output are specified together with variables describing the process states connecting the input and output. The task is carried out as an interview, where a modelling expert interviews domain experts and makes a description of the task. The output is a description of the task.

Model architecture

Different categories of nodes are defined. It is stated whether the model structure should be static or time-stamped, whether it should be a Bayesian network or a decision graph, and how input and output should be related. Based on the defined node categories and the stated model structure are an overall structure modelled by an expert. The output of this task is a structure describing how the different categories of nodes are related.

Specify variables

All nodes in the model are defined with a name, node type and unit. The node type sets how the states in the nodes are described by e.g. numbered, labelled, interval or Boolean values. Unit describes the nodes' measurement unit. Additionally for the discrete nodes the valid interval and the number of states are defined. It is also identified what kind of knowledge sources can be used for training of the node at a later stage. The task is carried out as an interview where a modelling expert is interviewing a domain expert about all the nodes in the model. The output of this task is a definition of all the nodes.

Specify edges

This task concerns finding relationships and thereby the edges between the nodes. It is based on modelling experts' interviews of domain experts about how the nodes are related. It is related both to the task of model architecture and the task of specify variables and it is carried out as iterative loops. The output of this task is a Bayesian network where the potential tables only are specified but not filled out.

General model structure

A general model structure is developed to transform a process-planning model into a dedicated Bayesian network. The general model structure is shown in figure 6.7 where the nodes correspond to the welding variables and parameters defined in chapter 1. The principle in the general model is that all the input parameters and variables from the direct model, shown in the top layer, can have affect on the quality parameters, shown in the bottom layer. The affect can either be direct or indirect. The indirect affect goes through process state variables which affect the quality parameters. The idea of introducing process state variables is to describe internal states known from the process and to minimize the number of direct edges between the nodes in the top layer and bottom layer, since direct edges make the table size of the quality parameters grow rapidly. For inverse models the evidence is entered to the workpiece and equipment parameters. The entered evidence does not change the probability welding control variables because they are d-separated from the workpiece and equipment parameters. Afterwards evidence is entered to the quality parameters, what d-connects the workpiece and equipment parameters to the welding control variables. With this architecture it is possible to use the same model both as a direct and inverse process-planning model.

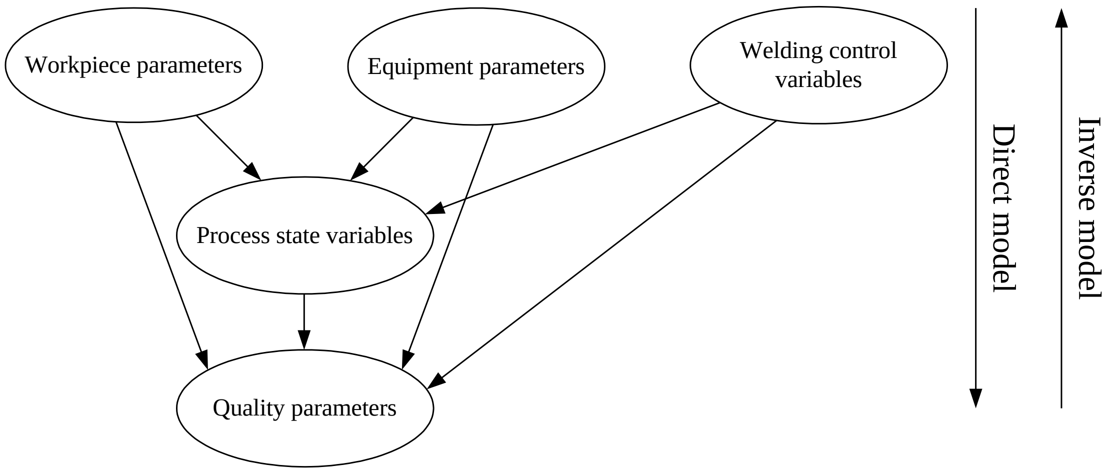


Figure 6.7: The general welding model where each node represents one or many nodes in the dedicated Bayesian network.

6.3.2 Training the model

The training was to fill the probability tables in the nodes with probabilities. Different sources of knowledge, described in chapter 2, were used together with different training methods. It turned out to be problematic to use different knowledge sources in the Bayesian network and thereby benefit from having the different knowledge sources. It was necessary to develop new and extend existing training methods of the Bayesian network. The result of this development is a contribution to use more knowledge sources for training Bayesinan networks. The training methods are listed in table 6.7:

Table 6.7: Training methods and their application.

Training method	Application
1. Least square polynomial approximation (LS)	Construct equation from empirical data to relate process parameters and variables
2. Determine constants (CE)	Construct equation from empirical data and an equation with constants to calibrate to relate process parameters and variables
3. Approximation (AP)	Construct equation or a probability table from operator knowledge to relate process parameters and variables
4. Direct probability table generation (DP)	Convert equation to a probability table using direct generation
5. Precise probability table generation (PP)	Convert equation to a probability table using precise generation
6. Uncertain probability table generation (UP)	Convert equation to a probability table using uncertain generation
7. Rules (RU)	Convert rules to a probability table
8. EM-learning (EM)	Update probability table(s) from empirical data

Method number 1, 2, 3, 5, 6 and 7 are specially developed in this thesis to make use of the different knowledge sources.

Figure 6.8 shows the principle of how the first six training methods can be combined in different ways to generate a probability table.

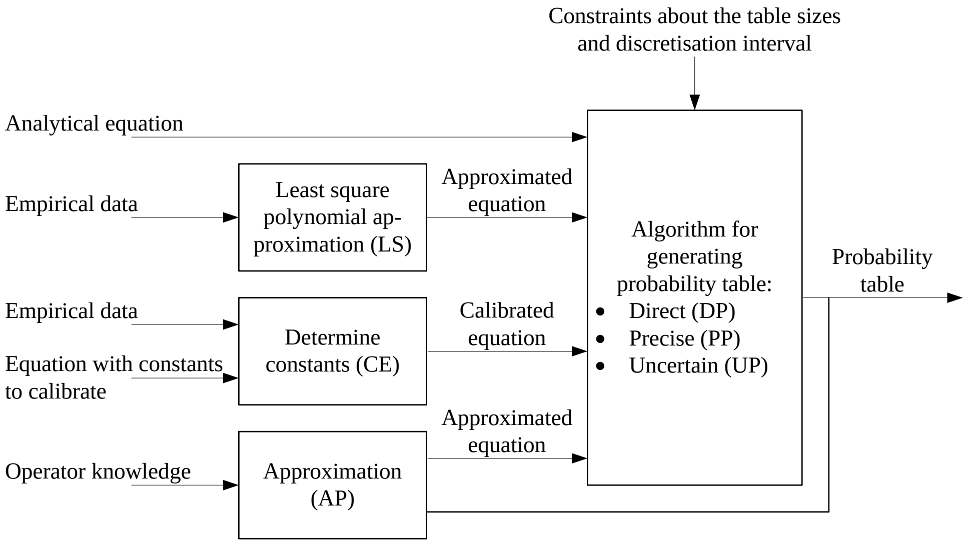


Figure 6.8: From different knowledge sources equations are made or given. The equations are converted to a probability table using three different algorithms.

The first seven listed methods are used for producing probability tables which initialize and give a background probability to the Bayesian network. The eight method, EM-learning, updates the probability tables selected, using empirical data. Probability tables which do not need updates are those that are reliable and well trained. The update can be carried out both before and during a production when more empirical datasets are available. Updating the Bayesian network during production can broaden the experience of the network to make the model more reliable and also to let the model adapt to changing conditions. Since EM-learning only is used for updating and not building up a probability table from scratch is because EM-learning requires large amounts of empirical datasets, which for welding are an expensive resource.

The eight training methods are described in details below.

Least square polynomial approximation (LS)

This method is applied on child nodes in cases where welding operator determines the relation for the edges between the parent and the child nodes and where no analytical equations are known. For the least square polynomial approximation empirical training data are used together with knowledge of a welding operator. The principle is a least square approximation on the empirical data to fit a polynomial, which gives a curve through the empirical data. An example of an approximated function is given in figure 6.9.

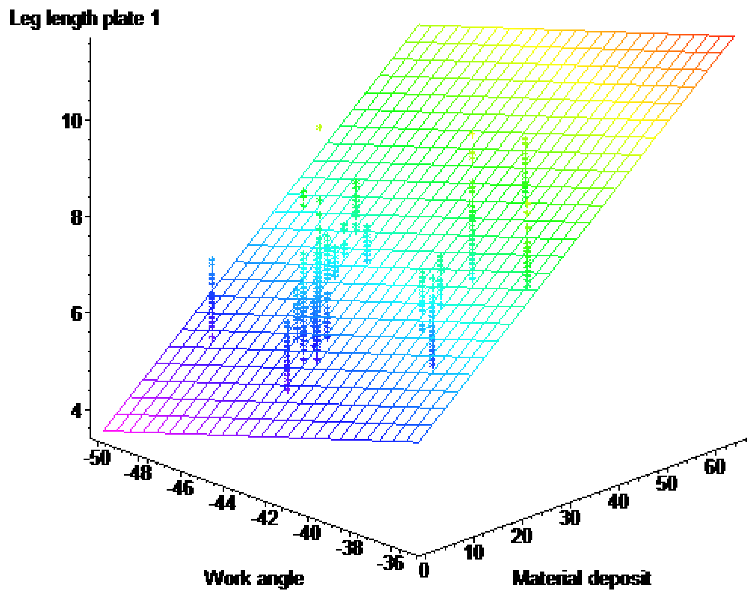


Figure 6.9: Example from a T-Joint, where leg length plate 1 is plotted as a function of the work angle and the material deposit. The material deposit is the amount of added material on a cross section of the weld seam. Crosses mark the empirical values from experiments. A linear surface is approximated to make the best fit of the empirical values from experiments.

The approximated function, in figure 6.9, is described by the following equation.

$$Leg\ length\ \ plate\,1 = 0.1401 \cdot Work\ angle + 0.0936 \cdot Material\ deposit + 10.554$$

The welding operator decides about the order of the polynomial equation by trying different orders and verifying how well each the polynomial fits to the data by summing up the residuals. A number of the polynomial orders are often evaluated to find the best fit and the lowest sum of the residuals. It is possible to automate testing different polynomials and calculation of the lowest residuals, but a welding operator is still required to evaluate the fit what prevents that a selected function is over fitting the data. The polynomial with the best approximation of the empirical dataset is used to generate a probability table for the nodes and it is described later.

Determine constants (CE)

Equations found in the literature, described in chapter 2, have some constants to be determined. Determination of these constants calibrates the equation in the area of the calibration data. The equations are used in the same way as for least square polynomial approximation, which is described above. The only difference is that the welding operator is not trying to find the best fitting polynomial because the function is given. Similarly as for the least square polynomial approximation, empirical data is used for determination of the constants.

Approximation (AP)

The probability tables or an equation to generate a probability table can be described by the welding operator, when there is no empirical or analytical knowledge available. The approximation can be made by two different methods.
The first approximation method is based on an interview with one or more welding operators, which estimate the probabilities in the probability table. If there is expert disagreement [Jensen, 2001], which is if the estimated probability differs systematically from person to person, then a common probability table can be constructed where the probability for each person has a weight according to the confidence to the person.
The second approximation method is based on constructing an equation together with the welding operator, which describes the relation for the edge(s) between the node and its parent(s). Based on this equation a probability table can be generated.

Direct probability table generation (DP)

This method is used to generate a probability table without uncertainty on the states. An equation is input to generate a probability table in a child node, which has edge(s) from the parents' node(s). The relationship of the edges can be described by the equation and a Bayesian network illustration of the relationship is shown in figure 6.10.

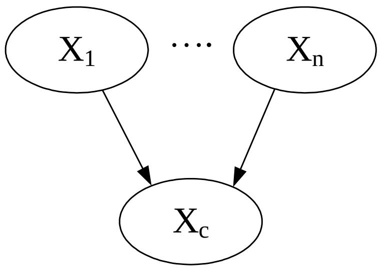
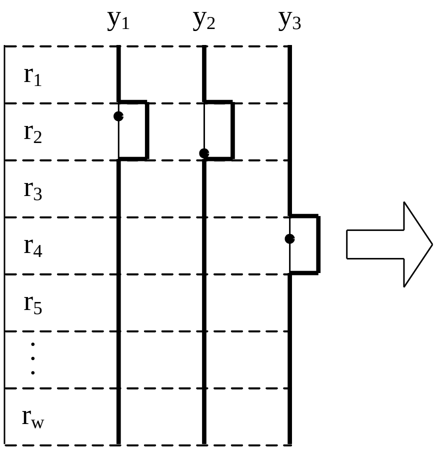


Figure 6.10: For the child node X_c, which has the parents $X_1,\ldots,X_n$, an equation is used to generate the probability table.

The parent node X_1 has the states $p_1,\ldots,p_u$ where u is the number of states and p_i is state i. Similarly for the parent node X_n with the states $q_1,\ldots,q_v$, v denotes the number of states and q_j is state j. For the parents nodes $X_1,\ldots,X_n$ all combinations of their state values are inserted in the equation:

$$y = f\left(p_i,\ldots,q_j\right); \qquad for\ i = 1\ to\ i = u,\ldots,\ for\ j = 1\ to\ j = v$$

The equation f is input, shown in figure 6.8, and it is as a function of the state of the parent nodes. For each combination of the state values the value y is calculated. For the ith,....,jth state value of the parents nodes the probability is calculated for each state in child node X_c. The child node X_c has the states $r_1,\ldots,r_w$ where w is the number of states and r_k is state k. The probability table of the child node X_c is calculated in the following way: If the y value calculated from the parents' nodes is within the interval of state r_k of the child node, the probability $P(r_k) = 100$ per cent, or if it is outside the interval of r_k $P(r_k) = 0$ per cent. It is illustrated in figure 6.11.



	y_1	y_2	y_3
r_1	0	0	0
r_2	1	1	0
r_3	0	0	0
r_4	0	0	1
r_5	0	0	0
⋮			
r_w	0	0	0

Figure 6.11: Example of how a value of y_1, y_2 and y_3, illustrated as the black dots on the figure to the left, are transformed to a probability distribution. The probability distribution is written in the probability table to the right.

This method is explained in an example where the child node X_c has two parent nodes X_1 and X_2. X_1 has two states and X_2 has three states, shown in table 6.9. The function calculating X_c from X_1 and X_2 is $y = p_i \cdot p_j$, where p_i is the ith state of X_1 and p_j is the jth state of X_2. X_c, has four states. Using the direct probability table generation method the probability table of X_c is calculated and shown in tabel 6.8.

Tabel 6.8: Example of generating a probability table for the child node X_c with the parent nodes X_1 and X_2 using direct probability table generation.

X_1	5	5	5	8	8	8
X_2	1	2	3	1	2	3
y	5	10	15	8	16	24
$X_c = 0$	0	0	0	0	0	0
$X_c = 10$	1	1	0	1	0	0
$X_c = 20$	0	0	1	0	1	1
$X_c = 30$	0	0	0	0	0	0

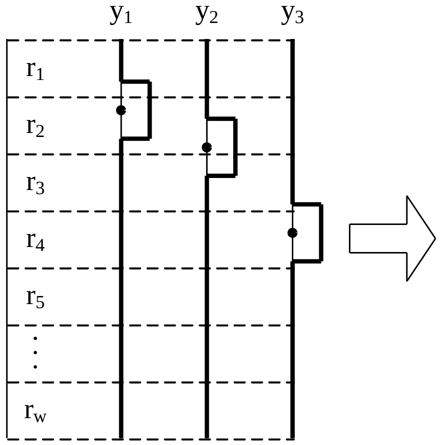
Precise probability table generation (PP)

This method is used to generate a probability table with uncertainty on the states. Identically to the DP method an equation is used as input. However the probability table is generated with fading of the probabilities what makes a more smooth relation of the edges between the parents and child node illustrated in figure 6.10. For each combination of the state values of the parents' nodes a y value is calculated. The y values are then used for calculating the probability table of the child node X_c, as it is described in the pseudo code in figure 6.12.

D is the discretization interval size of X_c having w is the number of states.
for $k \leftarrow 1$ **to** w
    do if (**abs**(y-r_k) < D)
        then $P(r_k)$ = (D – **abs**(y-r_k)) / D
    else $P(r_k)$ = 0

Figure 6.12: Pseudo code for calculation of probabilities in each column in the probability table.

The for-loop runs through all states of X_c, and for each state it is checked whether y is within the discretisized interval of that state. D is the size of the discretization interval. If y is inside the interval the probability is calculated. If y is equal to r_k the probability is 100 per cent. The probability is fading towards 0 per cent when y is approaching a state below or above. If y is outside the interval of $r_k \pm D$ then $P(rk) = 0$ per cent. This method is used to generate a probability table to insert into the child node. The procedure is illustrated in figure 6.13.



	y1	y2	y3
r1	0.25	0	0
r2	0.75	0.6	0
r3	0	0.4	0.1
r4	0	0	0.9
r5	0	0	0
⋮			
rw	0	0	0

Figure 6.13: Example of transforming the values of y_1, y_2 and y_3 to a probability distribution.

This method is explained in an example, the same example as for the direct probability table generation, where the child node X_c has two parent nodes X_1 and X_2. Using the pseudo code described in figure 6.12 the probability table of X_c is calculated and it is shown in table 6.9.

Table 6.9: Example of generating a probability table for the child node X_c with the parent nodes X_1 and X_2 using precise probability table generation.

X_1	5	5	5	8	8	8
X_2	1	2	3	1	2	3
y	5	10	15	8	16	24
X_c = 0	0.5	0	0	0.2	0	0
X_c = 10	0.5	1	0.5	0.8	0.4	0
X_c = 20	0	0	0.5	0	0.6	0.6
X_c = 30	0	0	0	0	0	0.4

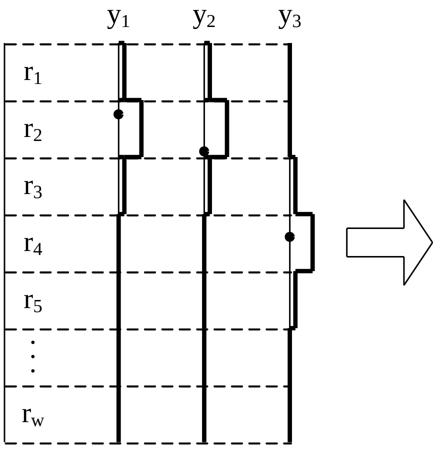
Uncertain probability table generation (UP)

This method is used to generate a probability table with a fixed uncertainty distribution on the states and a background uncertainty on all the states. Identically to the DP and PP methods an equation is used as input. However the probability table is made with a bigger uncertainty of the probability distribution, because the equation used is more uncertain and it should give the background probability for a later update using EM-learning. The given equation describes the relation for the edge between the parent nodes and child node illustrated in figure 6.10. For each combination of the state values of the parent nodes a y value is calculated. The y values are used to create the probability table of the child node X_c, which is described in the pseudo code in figure 6.14.

D is the discretization interval size of X_c having *w* is the number of states.
for $k \leftarrow 1$ **to** *w*
  do *BaseDistance* = **abs**(y-r_k)
  if *BaseDistance* $\leq D \cdot 0.5$
    then $P(r_k) = 0.75$
  else if *BaseDistance* $> D \cdot 0.5$ **and** *BaseDistance* $\leq D \cdot 1.5$
    then $P(r_k) = 0.125$
  else $P(r_k) = 0.0001$

Figure 6.14: Pseudo code for calculation of probabilities in each column in the probability table.

The for-loop runs through all states of X_c, and for each state the distance between r_k and y is calculated. It is called the BaseDistance. If the BaseDistance is within ± ½·D, $P(r_k)$ = 75 per cent. If the BaseDistance is outside ± ½·D but inside ± 1½·D, $P(r_k)$ = 12.5 per cent. Else is $P(r_k)$ = 0.0001, which is a background probability. A background probability and its use are explained later together with EM-learning. The pseudo code is exemplified in figure 6.15. It can be rewritten to give a narrower or a broader probability distribution. A narrow probability distribution can be selected if the discretization interval size is large or if the sum of the residuals is low and therefore showing a good fit.



	y_1	y_2	y_3
r_1	0.125	0.125	0.0001
r_2	0.75	0.75	0.0001
r_3	0.125	0.125	0.125
r_4	0.0001	0.0001	0.75
r_5	0.0001	0.0001	0.125
⋮			
r_w	0.0001	0.0001	0.0001

Figure 6.15: Example of transforming the values of y_1, y_2 and y_3 to a probability distribution. After learning, each column is updated to give the sum of one.

This method is explained in an example, the same example as for the direct probability table generation, where the child node X_c has two parent nodes X_1 and X_2. Using the pseudo code described in figure 6.14 the probability table of X_c is calculated and it is shown in table 6.10.

Table 6.10: Example of generating a probability table for the child node X_c with the parent nodes X_1 and X_2 using uncertain probability table generation.

X_1	5	5	5	8	8	8
X_2	1	2	3	1	2	3
y	5	10	15	8	16	24
$X_c = 0$	0.1250	0.1250	0.0001	0.1250	0.0001	0.0001
$X_c = 10$	0.7499	0.7499	0.1250	0.7499	0.1250	0.1250
$X_c = 20$	0.1250	0.1250	0.7499	0.1250	0.7499	0.7499
$X_c = 30$	0.0001	0.0001	0.1250	0.0001	0.1250	0.1250

Rule (RU)

When logical rules are available to describe relation between a child node and its parent(s) node(s) they are used to construct probability tables. The logical rules are written so they depend on the state of the parent nodes, which express a probability for each state of the child node. The rules are made from e.g. welding standards as [ISO 5817], and they can determine welding grades dependent on the geometrical shape of the weld seam.

EM-learning (EM)

EM-learning is described by [Lauritzen, 1995] and is used to update the probability tables in those nodes which have information from training sets. The training sets for the EM-learning algorithm consists of empirical training data. The algorithm reads the training data file, and for each training set the evidence is modelled into the Bayesian network. The algorithm updates the probability in the actual column in the nodes' table for the nodes with training data. In order to train a Bayesian network using EM-learning it is necessary to have a training data file that covers the range of combinations in each node to avoid that no combination is left untrained. For nodes with many parents or parents with many states, many training sets which are distributed to all combinations are necessary.

EM-learning requires a background probability distribution given to the nodes' probability tables because EM-learning trains only the columns which have empirical training datasets available. When all columns are not trained from empirical data, as it is the case with limited data source, the background probability compensates for the lack of empirical training data. The accuracy of the background probability distribution is important when the training data source is limited, but when larger training data sources are available the training overwrite the background probability distribution.

When a probability table in a node is trained with a background probability, it is necessary to leave a small probability in each cell in the probability table. It is necessary because the EM-learning is not able to update the probability in cells with the probability value zero. That is the reason why the training method "Uncertain probability table generation" leaves a probability close to zero, and not zero, in the cells.

An experience table is inserted into the probability table in each node, and every time the probability table is updated with data the experience table is also updated. The experience table counts the number of training examples used to update the probability in each column in the probability table, [Jensen, 2001]. When using a probability table with a background probability the background probability is set to have a certain experience. An example of using an experience table is shown in table 6.11. The experience table gives a good visualisation which probabilities are well trained and which are not, because the well trained columns has a high count.

A fading table can be inserted into the probability table in each node, e.g. in a production where old training data is expected to be less reliable than new training data. When using fading older trained data is given less importance than new training data. A fading factor is set to give the rate with which the previous training data is forgotten, [Jensen, 2001]. An example of using a fading table is shown in table 6.11.

Table 6.11: Example of a child node X_c with four states 0, 10, 20 and 30. X_c has one parent X_1 having three states 1, 2 and 3. Initial table: X_c is initialised with background probabilities, and the experience is set to one as the weight for these probabilities. Table 1: Using the experience table the initial table is trained with the data from table 6.12. Table 2: using the experience and fading table the initial table is trained with the data from table 6.12. The fading factor can be set to a value between zero and one, where zero is not included. One gives no fading and lowering the factor towards zero increases fading, [Hugin].

	Initial table			Table 1			Table 2		
	$X_1 = 1$	$X_1 = 2$	$X_1 = 3$	$X_1 = 1$	$X_1 = 2$	$X_1 = 3$	$X_1 = 1$	$X_1 = 2$	$X_1 = 3$
$X_c = 0$	0.49	0.01	0.01	0.123	0.005	0.005	0.085	0.004	0.004
$X_c = 10$	0.49	0.97	0.49	0.623	0.485	0.245	0.573	0.431	0.218
$X_c = 20$	0.01	0.01	0.49	0.252	0.505	0.245	0.340	0.560	0.218
$X_c = 30$	0.01	0.01	0.01	0.002	0.005	0.505	0.002	0.004	0.560
Experience table	1	1	1	4	2	2	2.952	1.8	1.8
Fading table	0	0	0	0	0	0	0.8	0.8	0.8

Table 6.12: Training data.

X_1	X_c
1	10
1	10
1	20
2	20
3	30

6.4 Bayesian network implementation for T-Joint

The description of using the Bayesian network for implementing a T-Joint model for welding is divided into two parts: creating the model structure and training the model.

The implementation for a T-Joint was first described in [Kristiansen et al., 2006] and it is to be found appendix K.

6.4.1 Creating the model structure

Manual modelling is used to create the model structure using the tasks described in figure 6.6.

Define task

The task is to model an inverse process-planning model for the T-Joint, shown in figure 6.16, when using GMAW process. The model is intended for welding of parts with variations in root gap from zero to four millimetres, where there are no sudden root gap changes. All other workpiece and equipment parameters are kept constant. Start and stop of the welding are not taken into consideration in modelling. The quality parameters specify the geometrical weld quality both externally and internally. The same equipment, as used in chapter 4 for making the empirical datasets, should be able to carry out the welding task.

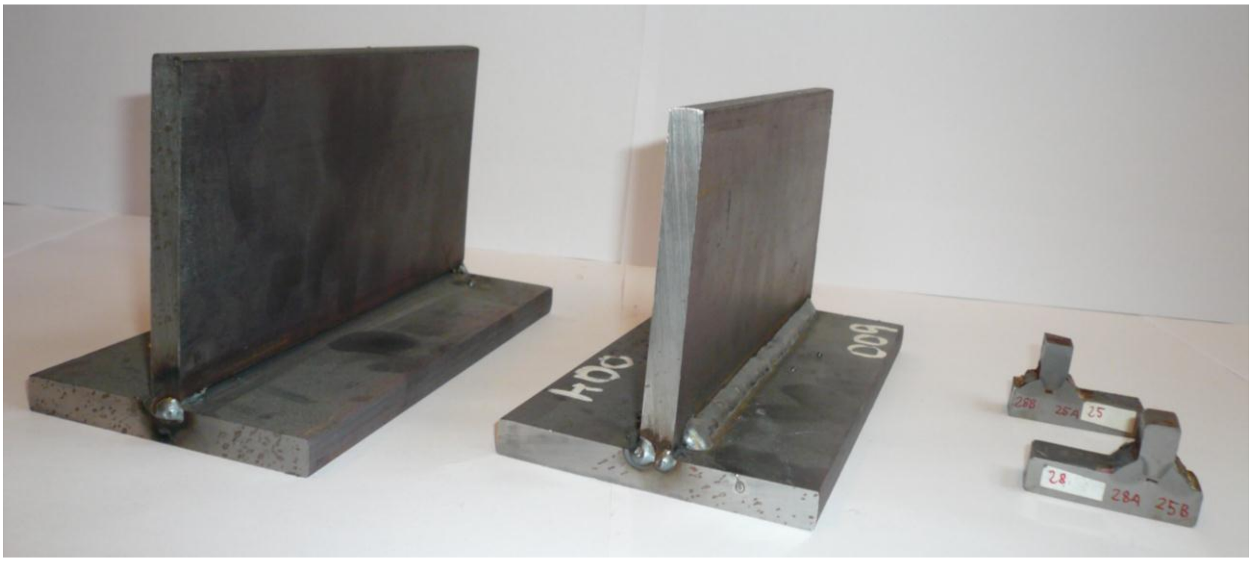


Figure 6.16: To the right is the T-Joint before welding, in the middle is the T-Joint when welded and to the right is the T-Joint after sawn apart and polished to investigate quality parameters to be measured inside.

Model architecture

The developed general welding model, shown in figure 6.7, is used to describe the node categories and relations for the edges. It is chosen to develop a static model because the welding task is characterised by:

- The only changing input is the root gap.
- The root gap varies without sudden change.
- Start and stop of the welding are not taken into consideration.

Specify variables

Through interview with welding operators and from the literature, the nodes in each of the node categories, from the general welding model in figure 6.7, is described. The nodes for the dedicated T-Joint model are described in table 6.13 with name, node type, unit, number of states and interval. Knowledge sources are investigated for all the child nodes in order to select training method to generate the probability tables. This task is related to the next task of specifying edges. Several iterations between these two tasks are carried out. The training method to generate the probability table for each node is described later in this chapter while this section is a more general description.
Only parameters and variables which have influence on the network and are varying in the experimental dataset specified in chapter 4 are included. It reduces the number of parameter and variables specified in relation to those in the generic information model in chapter 3. Significant parameters and variables which are omitted are explained in the following. Travel angle does not belong to the welding control variables in the model, even though it was measured in the experiment for the T-Joint in chapter 4. The travel angle is not in the model because none of the available knowledge sources have shown any relation between the travel angle and process state variables or quality parameters. When using the process-planning model inverse is the travel angle set to zero degrees, which was the angle in most of the training data. The oscillation pattern has the same holding at side 1 and 2 and was describe by one variable calculated the following way.

$$\mathit{Oscillation\ holding} = \mathit{Oscillation\ holding}\ 1 + \mathit{Oscillation\ holding}\ 2$$

In the model it was preferred to use numbered nodes, having the probability of the states specified by one value, because they can be used directly for calculation. Interval nodes, having the

probability of the states specified by an interval, were only deployed where node contains an expression written in the software for building the Bayesian network [Hugin].
For the quality parameters, the nodes are specifying the quality by a value or a grade, which gives the flexibility to use the preferred quality measurement. Deploying one kind of quality measurement does not exclude deploying the other kind. Conflicting settings are possible but should be avoided, e.g. setting of leg length plate 1 and leg length plate 2 excludes the use of equal legs.
The process state variable nodes are inserted to model the phenomenon's of the real welding process as precisely as possible. They are described by analytical equations together with welding operators.
To avoid some impossible state combinations of the welding control variable nodes, constraint nodes are inserted into the network. Constraints are e.g. the voltage and current are dependent and should be within an interval and oscillation variables are dependent because either there is oscillation or no oscillation.
To avoid large table sizes in the model is node state reduction used.

Specify edges

Based on the general welding model in figure 6.7 and the above specified variables, a dedicated Bayesian network was made for the T-Joint modelled in figure 6.17 and described in table 6.13. The process of constructing the dedicated model took several iterations and the knowledge from operators was used together with the analytical knowledge. The edges were identified by operator descriptions of relations together with analytical knowledge found in the literature. The welding operator knowledge was used for specifying relations where no usable descriptions of relations from analytical knowledge can be found in the literature. The relations described by the operator were approved by least square functional approximation with the empirical dataset from chapter 4. The residuals were observed to see whether there was accordance between the two knowledge sources, before the relations described by the welding operator were made into edges in the network.

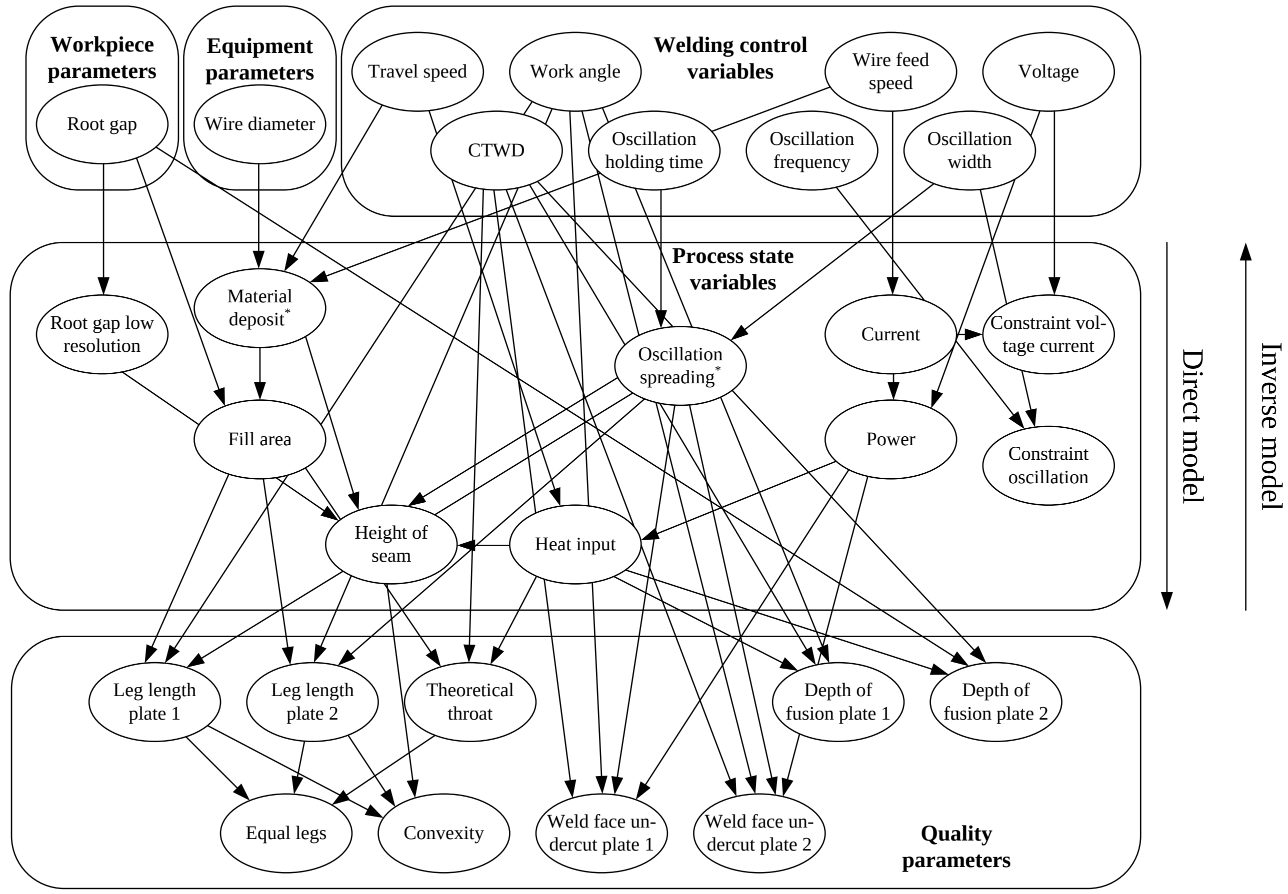


Figure 6.17: The dedicated Bayesian network used as process-planning model for T-Joint welding. The nodes marked with * has the states specified of the node type "Interval" while the rest of the nodes are of the node type "Numbered" and it also shown in table 6.13.

Table 6.13: Description of the nodes in the Bayesian network from figure 6.17.

Name	Node type	Unit	States	Interval (min-max)	Training method
Workpiece parameters:					
Root gap	Numbered	mm	21	0,..,4	
Equipment parameters:					
Wire diameter	Numbered	mm	1	1	
Control variables:					
Travel speed	Numbered	mm/min	11	3,..,13	
Work angle	Numbered	degrees	4	-5,..,10	
Wire feed speed	Numbered	m/min	6	10,..,15	
Voltage	Numbered	volt	20	17,..,36	
CTWD	Numbered	mm	8	8,..,22	
Oscillation holding time	Numbered	%	6	0,..,50	
Oscillation frequency	Numbered	Hz	8	0,0.8,..,2	
Oscillation width	Numbered	mm	6	0,..,1	
Process state variables:					
Root gap low resolution	Numbered	mm	9	0,..,4	RE

Material deposit*	Interval	mm^2	31	7-9,..,67-69	DP
Fill area	Numbered	mm^2	31	8,..,68	LS+UP+EM
Oscillation spreading*	Interval	mm^2	4	0-0.05,..,0.15-0.2	AP+PP
Current	Numbered	amp	10	150,…,240	CE+PP
Power	Numbered	J/sec	70	2050,..,8950	DP
Heat input	Numbered	J/mm	30	50,..,2950	DP
Height of seam	Numbered	mm	17	-0.6,..,2.6	LS+UP+EM
Constraint voltage current	Numbered	Boolean	2	0,1	CE+RU
Constraint oscillation	Numbered	Boolean	2	0,1	RU
Quality parameters:					
Leg length plate 1	Numbered	mm	11	2,..,12	LS+UP+EM
Leg length plate 2	Numbered	mm	11	2,..,12	LS+UP +EM
Theoretical throat	Numbered	mm	4	2,..,5	LS+UP +EM
Depth of fusion plate 1	Numbered	mm	9	0,..,4	LS+UP +EM
Depth of fusion plate 2	Numbered	mm	9	0,..,4	LS+UP +EM
Equal legs	Numbered	grade	4	1,..,4	RU
Convexity	Numbered	grade	4	1,..,4	RU
Weld face undercut plate 1	Numbered	grade	4	1,..,4	RU+LS+UP +EM
Weld face undercut plate 2	Numbered	grade	4	1,..,4	RU+LS+UP +EM

The abbreviations in table 6.13 for the training method to generate the tables are: (RE) Node state reduction, (LS) Least square polynomial approximation, (CE) Determine constants, (DP) Direct probability table generation, (PP) Precise probability table generation, (UP) Uncertain probability table generation, (RU) Rules, (AP) Approximation and (EM) EM-learning.

6.4.2 Training the model

In this section it is described how the probability tables in the model are filled with probabilities using the training methods and the empirical dataset, described in chapter 4, operator knowledge and analytical knowledge.

Root gap with low resolution

Root gap with low resolution was made to reduce the number of states for the node root gap, which has 21 states. The node state reduction method was increasing the discrete interval size from 0.2 mm to 0.5 mm.

Material deposit

Material deposit was calculated using the analytical law about mass conservation referred to in section 2.4.2 “Generation and use of analytical data”. A factor γ determines the loss due to spatter and evaporation. From experiments the loss was determined to be approximate 8 per cent giving γ = 0.92. In chapter 4 is the approximation shown figure 4.21.

$$Material\ deposit = \frac{1/4 \cdot Wire\ diameter^2 \cdot \pi \cdot Wire\ feed\ speed \cdot \gamma}{Travel\ speed}$$

The equation was used with the direct probability table generation method.

Fill area

Fill area was determined from the material deposit and the root gap. It is defined as the area of the weld seam outside the root gap and is illustrated in appendix F figure f.11. The fill area probability table was made utilizing least square function approximation on empirical data given the following equation:

$$Fill\ area = -3.155 \cdot Root\ gap + 1.096 \cdot Material\ deposit + 2.008$$

The uncertain probability table generation method generated the background probability table and it was trained with empirical data using EM-learning.

Oscillation spreading

The oscillation spreading was calculated as the area between the oscillation centreline and the actual curve made by the TCP. Oscillation spreading was made by interview with welding operators who approximated a linear dependence between the oscillation spreading and the variables oscillation holding time (O_h) and oscillation width (O_w).It was approximated by the equation:

$$\begin{aligned} Oscillation\ spreading &= O_w \cdot 1/2 \cdot \left(1 - \frac{O_h}{100}\right) + O_w \cdot \frac{O_h}{100} \\ &= O_w \cdot \left(\frac{1}{2} + \frac{1}{2} \cdot \frac{O_h}{100}\right) \end{aligned}$$

The equation was used with the precise probability table generation method.

Current

Current can be calculated from an equation by [Bolmsjö, 2001], described in chapter 2, where the constants are calculated from empirical data.

$$Wire\ feed\ speed = k_1 \cdot Current + k_2 \cdot CTWD \cdot Current^2$$

Least square polynomial approximation, using the empirical welding dataset described in chapter 4, gives the constants k_1 = 0.065 and k_2 = $-0.992 \cdot 10^{-7}$ in the above equation. The approximation shows that the second order term (k_2) has a low impact, which is also described by [Bolmsjö, 2001] who writes that a linear approximation can be made over small regions. The linear approximation is given by the following equation where the constants k_3 = 15.563 and k_4 = -0.339 were found by least square function approximation from the empirical welding dataset described in chapter 4:

$$Current = k_3 \cdot Wire\ feed\ speed + k_4$$

The linear approximation is illustrated in figure 6.18 where the experimental data are slightly curved. The equation was utilised with the precise probability table generation method.

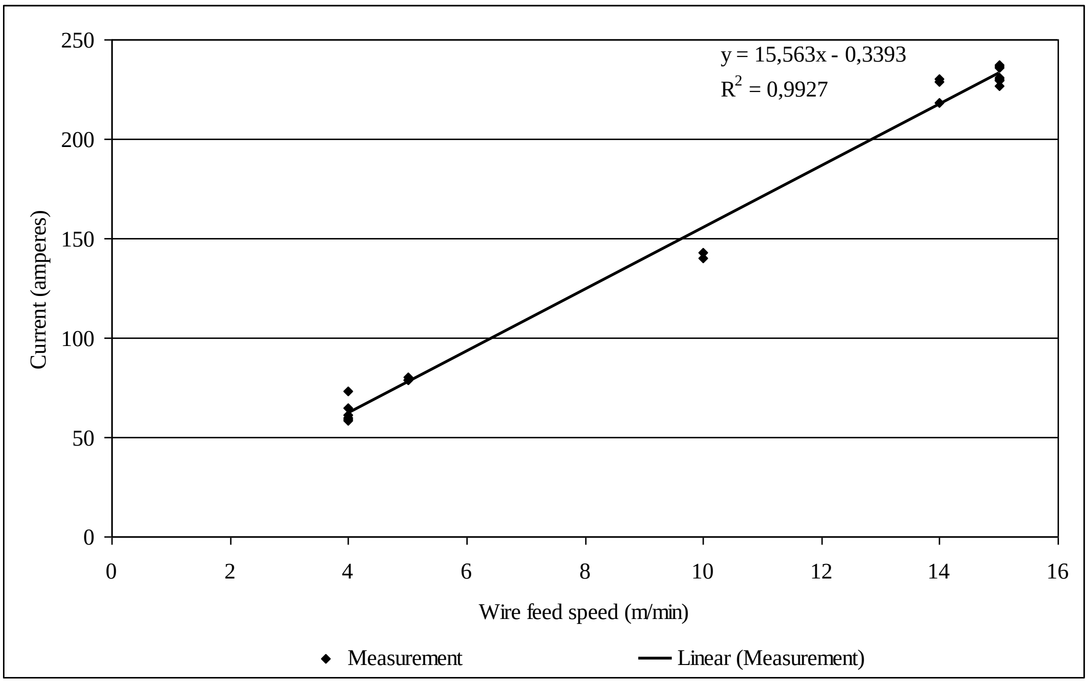


Figure 6.18: The current plotted as a function of the wire feed speed to determine the functional expression of the best linear fit.

Power

Power was calculated from the law of electric power:

$$Power = Voltage \cdot Current$$

This equation together with the direct probability table generation was then used to generate the probability table for power.

Heat input

Heat input was calculated by the following analytical equation, which describes energy conservation. Loss of energy when converting power to heat input is not included which of cause is a considerable approximation.

$$Heat\ input = \frac{Power}{Travel\ speed}$$

This equation together with the direct probability table generation method was utilised to generate the probability table for heat input.

Height of seam

The height of seam was found by least square function approximation on the empirical dataset described in chapter 4.

$$Height\ of\ seam = -0.390 \cdot Root\ gap + 0.118 \cdot Material\ deposit - 0.002 \cdot Heat\ input$$
$$+ 2.174 \cdot Oscillation\ spreading + 0.499$$

This equation is an input to the uncertain probability table generation, generating a background probability table, which was trained with empirical data utilising EM-learning.

Constraint voltage current

Constraint voltage current is a node which makes sure that only valid combinations of voltage and current are allowed. The valid combinations were calculated using the equation from [IEC 60974-1] and explained in chapter 2.

$$Voltage = k_5 \cdot Current + k_6$$

The constants were calculated by least square function approximation from empirical welding dataset described in chapter 4. The constants were k_5 = 0.063 and k_6 = 15.334. The approximated line is illustrated in figure 6.19. The constraints were set to be true if the voltage from the voltage node, shown in figure 6.19, was within ±3 volt, from voltage calculated in the above equation. Else the constraints were false because the voltage current relation is not within the limits.

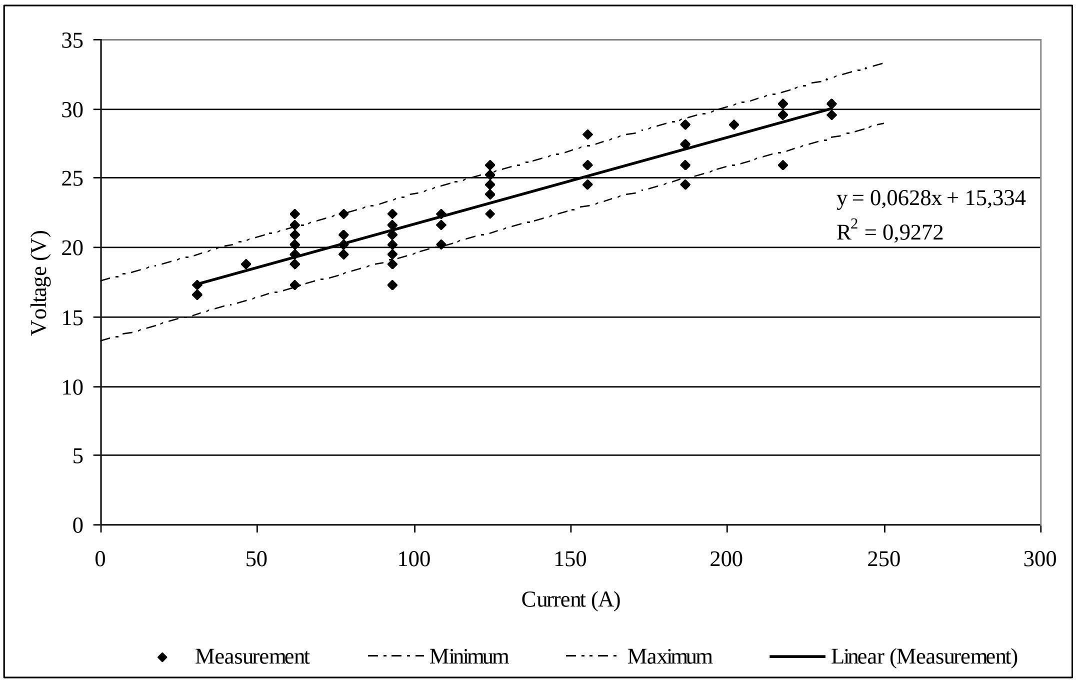


Figure 6.19: Experimental measurements of voltage related to current are fitted to a line. A minimum and a maximum limit line are drawn, respectively 3 volt below and 3 volt above the fitted line.

Constraint oscillation

Constraint oscillation was set by the following rule: Oscillation frequency and oscillation width were both either zero or they had both a value above zero. This is because there is either oscillation or there is no oscillation. From this rule the constraints in table 6.14 could be generated.

Table 6.14: Constraint for oscillation width and oscillation frequency. All valid states have the value one.

Oscillation width	0								[0.2, 0.4, 0.6, 0.8, 1.0]							
Oscillation frequency	0	0.8	1.0	1.2	1.4	1.6	1.8	2.0	0	0.8	1.0	1.2	1.4	1.6	1.8	2.0
Constraint	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1

Leg length plate 1

Leg length plate 1 was found by least square function approximation on the empirical dataset described in chapter 4.

$$Leg\ length\ \ plate\ 1 = 0.170 \cdot Work\ angle + 0.100 \cdot Fill\ \ area$$
$$-\,0.431 \cdot Oscillation\ spreading + 11.842$$

This equation was an input to the uncertain probability table generation to generate a background probability table, which was trained with empirical data using EM-learning.

Leg length plate 2

Leg length plate 2 was found in the same way as leg length plate 1 and the equation is.

$$Leg\ length\ \ plate\ 2 = -0.076 \cdot Work\ angle + 0.085 \cdot Fill\ \ area$$
$$-\,5.125 \cdot Oscillation\ spreading + 0.576$$

Theoretical throat

Theoretical throat was constructed by least square function approximation on the empirical dataset described in chapter 4.

$$Theoretical\ throat = -0.142 \cdot CTWD + 0.003 \cdot Heat\ input + 0.002 \cdot Fill\ \ area + 3.540$$

The equation was an input to the uncertain probability table generation to generate a background probability table, which was trained with empirical data utilising EM-learning.

Depth of fusion plate 1

Depth of fusion plate 1 was measured with destructive inspection by sawing up the parts across the welded seam. The probability table of these nodes was made by least square function approximation on the empirical dataset described in chapter 4.

$$Weld\ \ face\ undercut\ \ plate\ 1 = 0.003 \cdot Work\ angle + 0.048 \cdot CTWD + 0.0002 \cdot Heat\ input$$
$$\text{-}\,0.237$$

This equation was an input to the uncertain probability table generation, generating a background probability table. It was then trained with empirical data using EM-learning.

Depth of fusion plate 2

Depth of fusion plate 2 was found in the same way as depth of fusion plate 1 and the equation is.

$$Weld\ \ face\ undercut\ \ plate\ 2 = 0.989 \cdot Root\ gap\ \text{-}\ 0.053 \cdot CTWD + 0.0007 \cdot Heat\ input$$
$$\text{-}\,0.488$$

Equal legs

Equal legs were found from a rule to give a grade from B (highest quality) to E (lowest quality), according to standard [ISO 5817] number 1.16. The ISO standard only has the categories B, C and D, but if it goes outside the limits grade E is given. Equal legs set a maximum leg length difference, which is the length difference between leg length plate 1 and plate 2 illustrated in figure 6.20. The grade was calculated from the standard and it can be rewritten to the following expression and implemented as the probability table in the node:

$$\begin{aligned}
&\textit{if}\ (1.5 + 0.15 \cdot \textit{Theoretical throat} \geq \textit{abs}(\textit{Leg length plate}\ 1 - \textit{Leg length plate}\ 2))\ \textit{then B}\\
&\textit{else if}\ (2 + 0.15 \cdot \textit{Theoretical throat} \geq \textit{abs}(\textit{Leg length plate}\ 1 - \textit{Leg length plate}\ 2))\ \textit{then C}\\
&\textit{else if}\ (2 + 0.2 \cdot \textit{Theoretical throat} \geq \textit{abs}(\textit{Leg length plate}\ 1 - \textit{Leg length plate}\ 2))\ \textit{then D}\\
&\textit{else E}
\end{aligned}$$

Convexity

Convexity was calculated from a rule to give a grade from B to E according to standard [ISO 5817] number 1.10. The grade was calculated from the standard and it can be rewritten to the expression below and implemented as the probability table in the node.
The convexity was measured as the height of seam and it had a maximum according to the width of reinforcement illustrated in figure 6.20. Width of reinforcement was calculated from leg length plate 1 and 2 using Pythagoras' equation in a simplified way where the plate angle is set to 90 degrees so Pythagoras' equation can be applied. A restriction exists on the maximum height of convexity. However it is not included because the node height of seam cannot have so high values.

$$\begin{aligned}
&\textit{if}\ (1 + 0.1 \cdot \textit{sqrt}(\textit{Leg length plate}\ 1^2 + \textit{Leg length plate}\ 2^2) \geq \textit{Height of seam})\ \textit{then B}\\
&\textit{else if}\ (1 + 0.15 \cdot \textit{sqrt}(\textit{Leg length plate}\ 1^2 + \textit{Leg length plate}\ 2^2) \geq \textit{Height of seam})\ \textit{then C}\\
&\textit{else if}\ (1 + 0.25 \cdot \textit{sqrt}(\textit{Leg length plate}\ 1^2 + \textit{Leg length plate}\ 2^2) \geq \textit{Height of seam})\ \textit{then D}\\
&\textit{else E}
\end{aligned}$$

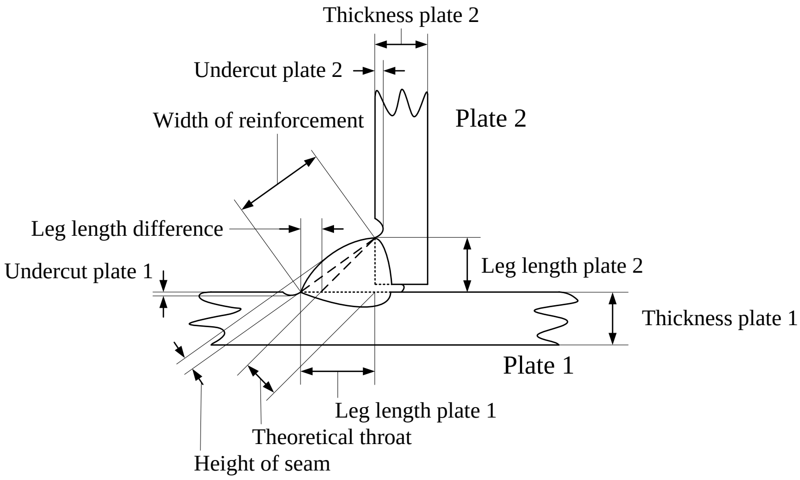


Figure 6.20: Measurements of weld seam according to [ISO 5817] standard.

Weld face undercut plate 1

Weld face undercut plate 1 was made according a rule to give a grade from B to E specified in standard [ISO 5817] number 1.7. The grade was given by a welding operator, who manually inspects the parts following the rule:

$$\begin{aligned}
&\textit{if}\ (0.05 \cdot \textit{Thickness plate i} \geq \textit{Undercut plate i}\ \text{and}\ 0.5 \geq \textit{Undercut plate i})\ \textit{then B}\\
&\textit{else if}\ (0.1 \cdot \textit{Thickness plate i} \geq \textit{Undercut plate i}\ \text{and}\ 0.5 \geq \textit{Undercut plate i})\ \textit{then C}\\
&\textit{else if}\ (0.2 \cdot \textit{Thickness plate i} \geq \textit{Undercut plate i}\ \text{and}\ 1 \geq \textit{Undercut plate i})\ \textit{then D}\\
&\textit{else E}
\end{aligned}$$

The probability table of these nodes were made by least square function approximation on the empirical dataset described in chapter 4 and on the grades given by the rule. It created an equation. This equation was an input to the uncertain probability table generation, generating a background probability table. It was then trained with empirical data using EM-learning.

Weld face undercut plate 2

Weld face undercut plate 2 was found in the same way as weld face undercut plate 1.

6.5 Summary

A methodology for producing a process-planning model based on a Bayesian network is introduced. The methodology includes an architecture for a general welding model, shown in figure 6.7, to transform a process-planning model into a Bayesian network model structure. The production of the Bayesian network based process-planning model required development of the training methods to make use of the analytical and empirical knowledge together with operator knowledge for training the probability tables.

The Bayesian network based process-planning model can for the same model be used both as a direct and an inverse process-planning model. In appendix H and I is developed direct and inverse process-planning model based on respectively an artificial neural network and a regression. For these modes the direct and inverse process- planning model are not include in the same model.

The modelling and training of the three models, based on Bayesian network, artificial neural network and regression, are constructed from the same knowledge sources. It makes them suitable for benchmarking, which is done in the following chapter.

Chapter 7

Test results

In this chapter process-planning models, based on different tools, were tested to judge their enhancements and deficits for being suited for producing reliable process-planning models. It is done to recommend the modelling tool which shows advantages for developing reliable process-planning models. The process-planning model based on the Bayesian network has the main focus and is benchmarked with other process-planning models.

The results in this chapter are presented in two sections.

The first section contains the results of a preliminary investigation. It was carried out to examine the possibility and feasibility of using operator knowledge for building small process-planning models and to examine the use of Bayesian network compared with other machine learning tools. Small direct process-planning models were tested on a butt-joint using the following tools from machine learning:

- Bayesian network
- Decision tree
- Artificial neural network

The second section contains the test results for the process-planning models developed in chapter 6 and appendix H and I. The process-planning model based on Bayesian network was benchmarked with the other process-planning models and it was made for both direct and inverse process-planning models. Process-planning models were tested on the T-joint (described in chapter 4) are made using the following investigations:

- The prediction of direct process-planning models based on the following tools are tested:
    - Bayesian network
    - Artificial neural network
    - Regression model
- The sensitivity and consistency of inverse process-planning models based on the following tools is tested:
    - Bayesian network
    - Artificial neural network
    - Regression model
- An experimental verification of the inverse process-planning model based on the following tool is made:
    - Bayesian network

The benchmark used for both the direct and inverse process-planning models is the accuracy of the models' predictions compared with data from experiments. The inverse models can give more solutions to the same input, as illustrated in figure 1.1, for this reason where the inverse results explained and commented in a discussion.

7.1 Results of preliminary investigation of butt-joint

The purpose of the preliminary investigation was to investigate the possibility and feasibility in making use of knowledge from welding operator interviews as input source for creating process-planning models. Furthermore, process-planning models created with Bayesian networks were compared with process-planning models created by means of the machine learning tools: artificial neural network and decision tree. I.e. the objective of the preliminary investigation was to examine:

- To what extend it is possible to use operator knowledge to create small process-planning models.
- The performance of Bayesian network compared to other machine learning tools to create process-planning models.

The work is presented in [Kristiansen et al., 2004] and printed in appendix J. In this section it is developed further and concluded.

The target of the preliminary investigation was to develop a direct process-planning model as shown in figure 7.2. The model has to serve as a classifier predicting the quality parameters for welding. The model is a direct process-planning model and it has four inputs and four outputs. The input and output were discretised into three levels. In the investigation the following knowledge sources were used:

- Empirical knowledge
- Operator knowledge
- Combined empirical and operator knowledge.

The process-planning model created was intended for welding a butt-joint with a square groove of thin plates without backing, shown in figure 7.1.

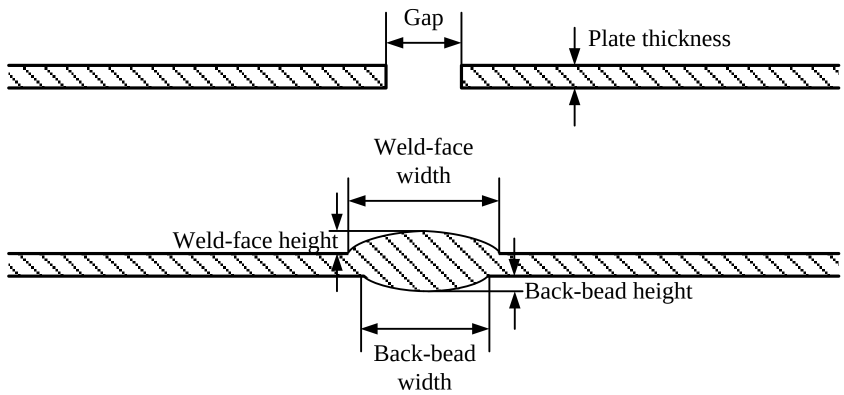


Figure 7.1: Butt-joint with measurements of workpiece and quality parameters.

The parameters and variables from the experiment are shown in figure 7.2 and thoroughly described in appendix J.

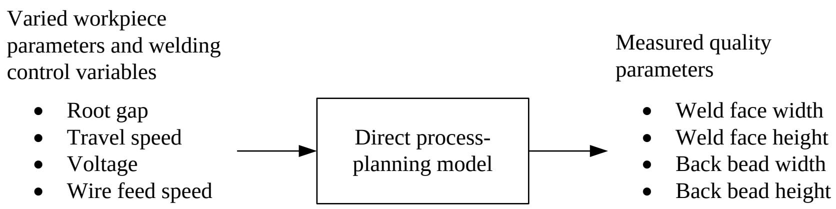


Figure 7.2: Four workpiece parameters and welding control variables used as input to the process-planning model for predicting four quality parameters.

Additionally to [Kristiansen et al., 2004], a process-planning model based on a decision tree was constructed. Decision trees are described in [Mitchell, 1997] and [Clemmentine algorithms, 2004]. Three process-planning models based on Bayesian network, artificial neural network and decision trees were created and benchmarked. Details are described in [Kristiansen et al., 2004]. The result of the benchmark of the small process-planning model illustrated in figure 7.2 is shown in table 7.1.

Table 7.1: Average percentage for correct prediction in benchmark between three process-planning models based on different learning methods and with training data from empirical data, operator data or a combination of the two data sources.

	Empirical knowledge	Operator knowledge	Combined empirical and operator knowledge
Bayesian network	46%	60%	58%
Decision tree	62%	60%	63%
Artificial neural network	58%	65%	60%

This investigation demonstrated that operator knowledge and combined empirical and operator knowledge gives at least as good prediction as empirical knowledge used alone. The time consumption for collecting operator knowledge is less than 10 per cent of producing empirical knowledge and no equipment for experiments is required. From this investigation it is strongly believed that operator knowledge is useful for making process-planning models and it is even more important for larger models with a higher complexity with more parameters and variables in the models.
The benchmark between the process-planning models based on different learning methods showed a slightly better prediction for the decision tree and the artificial neural network than the Bayesian network.

7.2 Results of main investigation of T-Joint

Modelling of the T-Joint has the objective to investigate the following points:

- To what extend it is possible and feasible to use operator knowledge in large models.
- The performance of Bayesian network compared to other tools often used to create process-planning models.

The three tools, described in chapter 6 and appendix H and I, for creating a direct process-planning model and an inverse process-planning model were benchmarked. The approach were to benchmark the two models based on machine learning tools and additionally make a benchmark of them to regression. Furthermore, the inverse process-planning model based on a Bayesian network was verified experimentally.

The knowledge sources for the modelling were:

- Operator knowledge
- Empirical knowledge
- Analytical knowledge.

58 experiments were available from the empirical knowledge source and none of the experiments were made with identical settings of parameters and variables. Of these experiments 44 experiments were selected for training and 14 experiments were selected for testing. The experiments were randomly selected for either training or testing. The experiments used for training consists of 802 datasets and from the experiments used for tests consists of 118 datasets. The experiments to produce the empirical datasets are described in chapter 4. One experiment produces many datasets with the result that many of the datasets are equal or else showing the variation of the equality parameters for fixed workpiece parameters, equipment parameters and welding control variables.

The direct and inverse process-planning model is the same model when it is based on Bayesian network. But, when the direct and inverse process-planning model is based on artificial neural network and regression it is two different models, which still are trained from the same dataset.

7.2.1 Prediction utilising direct process-planning models

In order to verify the direct process-planning models based on the three tools from chapter 6 and appendix H and I, the following investigation was designed:

- Exam the models' predictions compared with empirical data

Verification of the direct process-planning models was carried out using the 14 empirical test experiments. The settings of workpiece parameters, equipment parameters and process control variables from the empirical experiments were input to the process-planning models. The quality parameters, predicted by each process-planning model, were then compared to the experimental quality parameters. The setup is illustrated in figure 7.3.

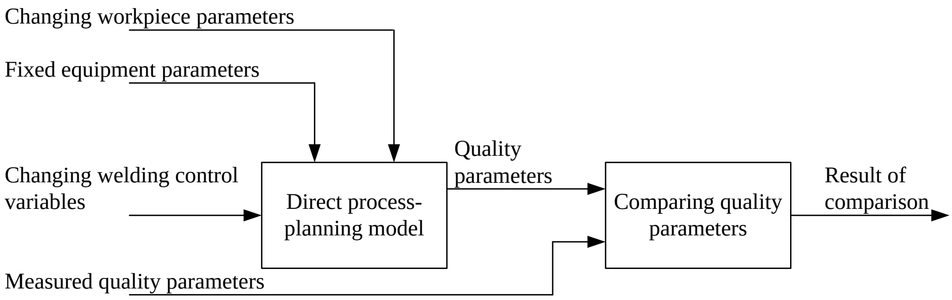


Figure 7.3: The setup in order to carry out an analysis to compare quality parameters from experimental datasets with quality parameters from a direct process-planning model given the same settings as in the experiment.

A histogram is showing the prediction result, shown in figure 7.4, figure 7.5 and figure 7.6. The horizontal axis rates the accuracy by the number of discrete states the model prediction is away from the experimental result. In table 7.2 the discretisized interval is shown. The vertical axis rates the prediction in the given state represented in per cent. For each quality parameter the accuracy from all discrete states is summed 100 per cent. An example of the histogram is given for the parameter “Theoretical throat”. A column with 90 per cent at the -1 column can be explained by the fact that the model in 90 per cent of the testing experiments estimated the theoretical throat to be 0.5-1.5 mm too short.

Table 7.2: From table 6.13 the discretisized intervals of the quality parameters are further specified. Exemplified for "Leg length plate 1" the first state is 1.5-2.5 mm, the second state is 2.5-3.5 mm and this way it goes to the final (eleventh) state and it is 11.5-12-5 mm. The quality parameters specified by a grade does not have a discretisized interval, but they always jumps with one grade.

Quality parameter	Interval (min-max)	Discretisized interval	Unit
Leg length plate 1	2,..,12	±0.5	mm
Leg length plate 2	2,..,12	±0.5	mm
Theoretical throat	2,..,5	±0.5	mm
Depth of fusion plate 1	0,..,4	±0.25	mm
Depth of fusion plate 2	0,..,4	±0.25	mm
Equal legs	1,..,4		grade
Convexity	1,..,4		grade
Weld face undercut plate 1	1,..,4		grade
Weld face undercut plate 2	1,..,4		grade

Bayesian network

The process-planning model based on Bayesian network predicted the quality as explained in the following. For each test experiment the corresponding welding control parameters and variables were entered into the Bayesian network as evidence. The quality parameters were then found in each node as the state with the highest probability.
Exemplified, the evidence entered can have the form of:

$$e = \left\{ \begin{array}{l} \text{Root gap} = 1.2 \\ \text{Wire diameter} = 1 \\ \text{Work angle} = 0 \\ \text{Travel angle} = 0 \\ \text{CTWD} = 14 \\ \text{Travel speed} = 8 \\ \text{Oscillation width} = 1 \\ \text{Oscillation frequency} = 2 \\ \text{Oscillation holding time} = 30 \\ \text{Wire feed speed} = 12 \\ \text{Voltage} = 30 \end{array} \right\}$$

The predicted probability distribution for "Leg length plate 1" would after propagating the Bayesian network look like:

$$P(\text{Leg length plate1}|e) = \begin{pmatrix} 0.01\% \text{ for } 2 \text{ mm} \\ 0.01\% \text{ for } 3 \text{ mm} \\ 0.01\% \text{ for } 4 \text{ mm} \\ 12.48\% \text{ for } 5 \text{ mm} \\ 74.76\% \text{ for } 6 \text{ mm} \\ 12.50\% \text{ for } 7 \text{ mm} \\ 0.06\% \text{ for } 8 \text{ mm} \\ 0.06\% \text{ for } 9 \text{ mm} \\ 0.06\% \text{ for } 10 \text{ mm} \\ 0.04\% \text{ for } 11 \text{ mm} \\ 0.01\% \text{ for } 12 \text{ mm} \end{pmatrix}$$

It can be explained as, for the "Leg length plate 1" the 6 mm leg length gives the highest probability with 74.76 per cent and this leg length is selected. The leg lengths are discretised so each of them is actually ±0.5 mm

The result of the process-planning model based on the Bayesian network prediction is shown in figure 7.4.

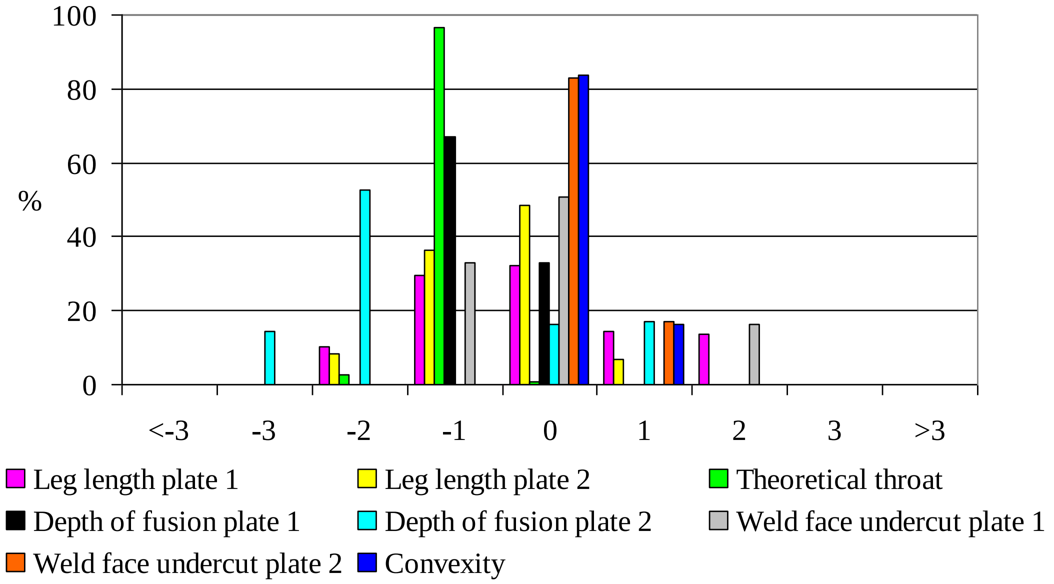


Figure 7.4: Correct prediction gives an average at 44 per cent and prediction within +/-1 state gives an average at 85 per cent.

Artificial neural network

Five different types of artificial neural network models, quick, dynamic, multiple, prune and exhaustive prune, described in appendix H were trained to find the model, which gives the best prediction. The best result was achieved with the artificial neural network in Clementine with a dynamic training method [Clemmentine algorithms, 2004]. The testing data was used to verify the model and the result is illustrated in figure 7.5.

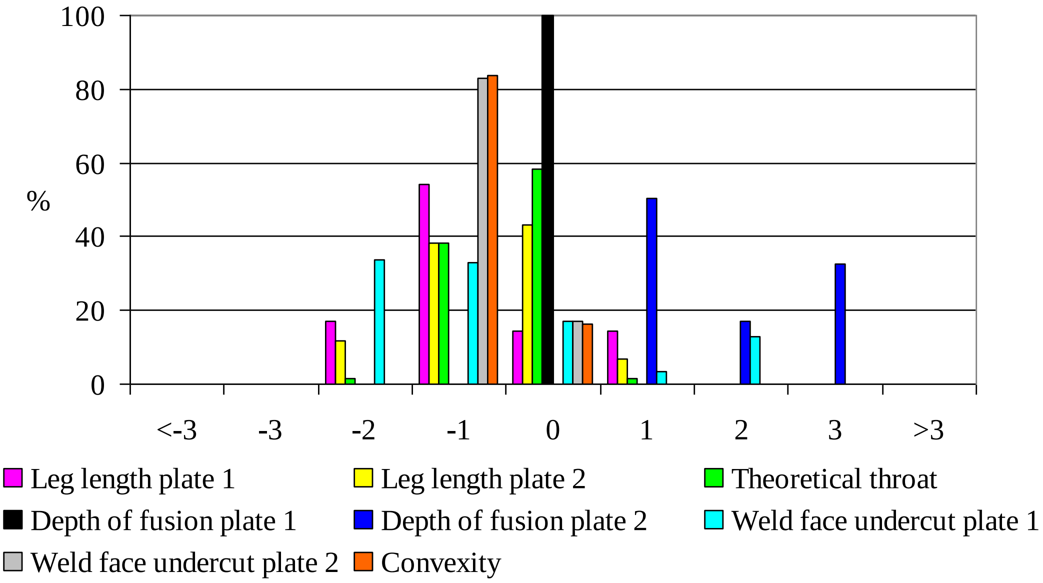


Figure 7.5: Correct prediction gives an average at 33 per cent and prediction within +/-1 state gives an average at 84 per cent.

Regression model

A linear regression model was verified with the testing data, and the result is shown in figure 7.6.

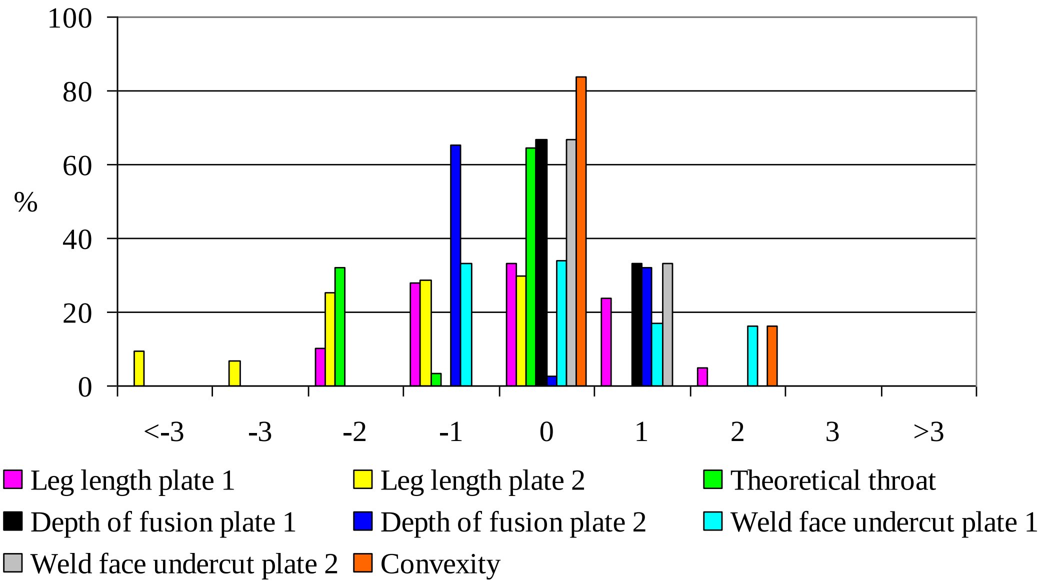


Figure 7.6: Correct prediction gives an average at 48 per cent and prediction within +/-1 state gives an average at 85 per cent.

Summary

For the direct process-planning model, the model based on linear regression showed a slightly better result than the model based on Bayesian network, because the correct prediction was respectively 48 per cent compared to 44 per cent and the prediction +/- 1 state was for both 85 per cent. The model based on artificial neural network showed the worst prediction even though the best trained model out of five models based on different training methods was selected.

The probability distribution for Bayesian network and artificial neural network based process-planning models are mainly in the states -1 and 0, while regression based process-planning model has a more uniform distribution in the states -1, 0 and 1. It is illustrated in table 7.3 and indicates that the Bayesian network and artificial neural network based process-planning models mainly under estimates while the regression based process-planning model both over and under estimates.

Table 7.3: The predictions in figure 7.4, figure 7.5 and figure 7.6 for the different process-planning models are summed up for each model and shown in per cent to benchmark how many states there predictions are from correct prediction.

States away from correct prediction / Process-planning model based on:	<-3	-3	-2	-1	0	1	2	3	>3
Bayesian network	0	2	9	33	44	9	4	0	0
Artificial neural network	0	0	8	41	33	10	4	4	0
Regression	1	1	8	20	48	17	5	0	0

Overall, all the models showed the ability to predict the quality parameters, but the models based on Bayesian network and regression gave the significantly best results. The use of more knowledge sources for modelling the Bayesian network was not indicated in the results, when compared to regression.

7.2.2 Sensitivity and consistency utilising inverse process-planning models

In order to verify the inverse process-planning models based on the three modelling tools from chapter 6 and appendix H and I, the following two investigations were designed:

- Exam the sensitivity.
- Exam the consistency.

The two ways of investigating are first described and afterwards the results for the three modelling principles are presented.

Exam the sensitivity

A sensitivity analysis was carried out for one workpiece parameter by changing the value of the parameter and observing the welding control variables. A similar analysis can be carried out for all workpiece, equipment and quality parameters. To the setup of the sensitivity analysis datasets were produced with fixed equipment parameters and quality parameters and changing of workpiece parameters. The datasets were entered to the inverse process-planning models to test the resulting welding control variables, as illustrated in figure 7.7. The resulting welding control variables were logged and plotted as a function of the changing workpiece parameters. The plot was analysed for the process-planning models' sensitivity for changing workpiece parameters.

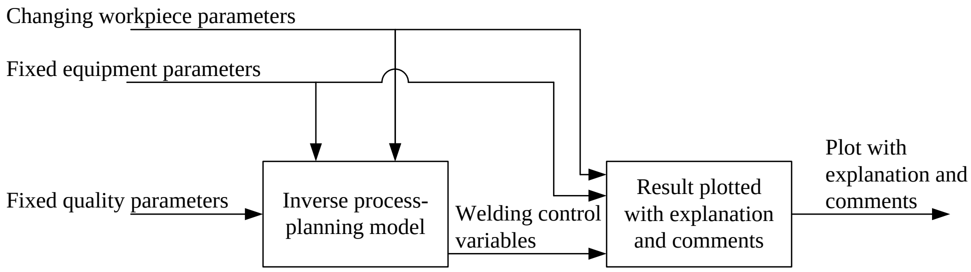


Figure 7.7: The setup in order to carry out a sensitivity analysis, and in this case it is illustrated for changing workpiece parameters.

The verification was made with a changing root gap from zero to four millimetres calculated in discrete steps of 0.2 millimetres, where the inverse process-planning model predicts the following welding control variables: wire feed speed, voltage, travel speed, work angle, oscillation width, and oscillation holding time. A limitation was made for the analysis by fixing the states of the following welding control variables:

$$CTWD = 18\,mm$$
$$Travel\,angle = 0\,degrees$$
$$Oscillation\ frequency = 1.2\,Hz$$

It was done to avoid some possible failures and because of lack of training data. CTWD was fixed because a too small CTWD could result in a collision, especially when oscillation were used, which causes weaving of the tool centre point. For the travel angle enough empirical data with different angles was not produced for use of this variable. Oscillation frequency was fixed because a change could result in an invalid oscillation pattern for the test system implemented. The quality to achieve was fixed to:

$$Leg\ length\ \ plate\,1 = 6\,mm$$
$$Leg\ length\ \ plate\ 2 = 6\,mm$$
$$Depth\,of\ \ fusion\ plate\ 1 = 1\,mm$$
$$Depth\,of\ \ fusion\ plate\ 2 = 1\,mm$$
$$Convexity = 4\ in\ grade$$
$$Weld\ \ face\,undercut\ \ plate\ 1 = 4\ in\ grade$$
$$Weld\ \ face\,undercut\ \ plate\ 2 = 4\ in\ grade$$

Exam the consistency

To verify if the model is consistent with itself, the welding control variables from the inverse model were inserted into the direct model. If the quality parameters given to the inverse model are equal to the quality parameters from the direct model, the model is consistent with itself. Figure 7.8 illustrates how the consistency was verified. The higher consistency a model has the more reliable the model is.

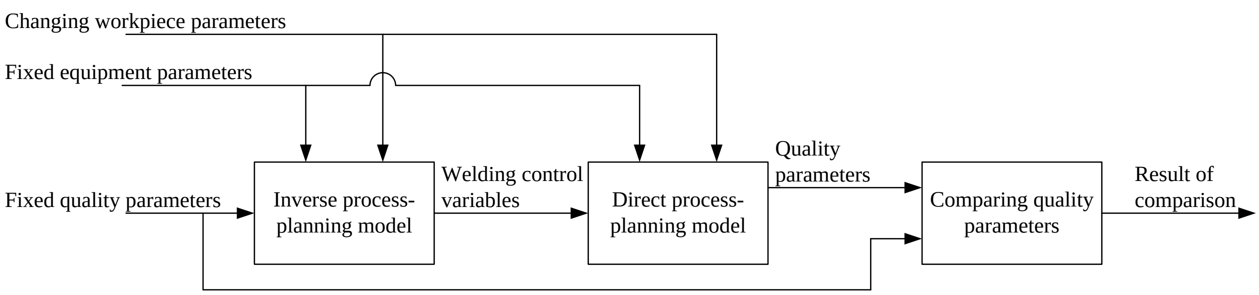


Figure 7.8: In order to verify if the process-planning model is consistent with itself, the illustrated setup was used to calculate a result for comparison of different process-planning models. In this case it is illustrated for changing workpiece parameters.

With the strategy illustrated in figure 7.8 changing of equipment and quality parameters can also be verified but that is not carried out in this thesis.

Bayesian network

The sensitivity of the inverse process-planning model based on Bayesian network was examined. To examine the inverse process-planning model, the welding control variables were created as illustrated in figure 7.9. Evidence was entered for the workpiece, equipment and quality parameters. Furthermore, evidence was also entered for three fixed welding control variables CTWD, travel angle and oscillation frequency. The evidence had the form of:

$$e = \left\{ \begin{array}{l} Root\ gap = 1.0 \\ Wire\ diameter = 1.0 \\ Constraint\ voltage\ current = 1 \\ Constraint\ oscillation = 1 \\ Leg\ length\ plate\ 1 = 6 \\ Leg\ length\ plate\ 2 = 6 \\ Depth\ of\ fusion\ plate\ 1 = 1 \\ Depth\ of\ fusion\ plate\ 2 = 1 \\ Convexity = 4 \\ Weld\ face\ undercut\ plate\ 1 = 4 \\ Weld\ face\ undercut\ plate\ 2 = 4 \\ CTWD = 18 \\ Travel\ angle = 0 \\ Oscillation\ frequency = 1.2 \end{array} \right\}$$

A vector with the decision order of the welding control variables was selected and the order was:
1: wire feed speed, 2: voltage, 3: travel speed, 4: work angle, 5: oscillation width and 6: oscillation holding time.
The decision order is important because after the evidence from each welding control variable is given the network is propagated, which can change the network's prediction. The decision order is determined so the variables that have the most effect on the welding process are selected first. Dependent variables are put next to each other to maintain this dependency. As illustrated in figure 7.9 the most probable state of the welding control variable in the decision order is selected, evidence for the state is entered and the network is propagated. It is then repeated in the decision order until all welding control vectors are decided.
The prediction of the first welding control variable, wire feed speed, with probabilities for the states between 10 and 15 m/min has the form of:

$$P(Wire\ feed\ speed \mid e) = \begin{pmatrix} 16.9\%\ for\ 10\ m/min. \\ 20.6\%\ for\ 11\ m/min. \\ 19.8\%\ for\ 12\ m/min. \\ 19.1\%\ for\ 13\ m/min. \\ 15.5\%\ for\ 14\ m/min. \\ 8.1\%\ for\ 15\ m/min. \end{pmatrix}$$

For the wire feed speed example the state with 11 m/min was selected and entered as evidence. The small difference between the highest probabilities for the wire feed speed 11, 12 and 13 m/min show that the model is uncertain and small changes of the evidence can change the state which has the highest probability. This problem is discussed later in the section 7.2.3 “Experimental verification utilising inverse process-planning model”.

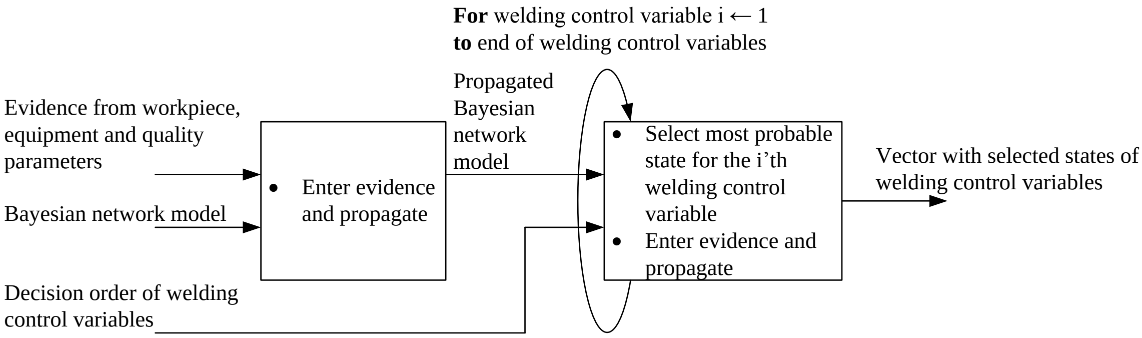


Figure 7.9: To the left side of the figure: Entering of evidence from workpiece, equipment and quality parameters to a model based on a Bayesian network. To the right side of the figure: The decision order is used to set the propagation order to produce welding control variables.

The chosen order of the welding control variables for selecting and entering evidence influences the result. This is caused by the fact that that every time evidence is entered into a node and the network is updated, another probability distribution is achieved in the rest of the network nodes.

The welding control variables produced are illustrated in figure 7.10. For an increasing root gap from zero to four millimetres the main changes are a decrease in travel speed, voltage and wire feed speed. At 3 and 3.8 mm, in figure 7.10, some of the welding control variables in the model jump and it can be caused by the model switch to another solution. The cause of the switch can be that when the root gap is increased other states are slightly more probable and will be selected. In the following loops, see figure 7.9, the more probable states are selected, the model is propagated and the model goes towards another solution space. These other solutions can be valid and can result in the same welding quality. Methods to avoid this problem are suggested in section 7.2.3 “Experimental verification utilising inverse process-planning model”.

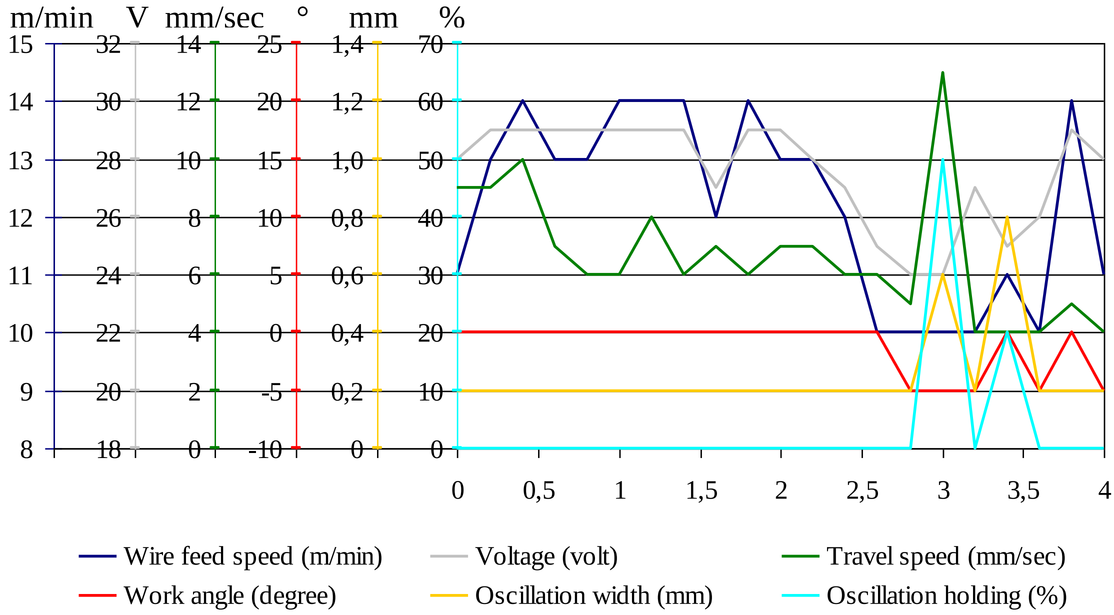


Figure 7.10: Welding control variables from a process-planning model based on a Bayesian network when changing the root gap from 0 to 4 mm.

Explanation and comments

Decreasing the wire feed speed and voltage are the two main variables for keeping the depth of fusion constant because an increasing root gap requires less heat input to keep the same depth of fusion. To compensate for the decreased wire feed speed and the increased consumption of material caused by a larger root gap, the travel speed is reduced. The work angle is changed to point the welding torch more towards plate 2 when the root gap increases to keep melting plate 2. When the root gap increases it is a good strategy to increase the holding time in order to keep transferring heat and melt both plates 1 and 2. At 3 mm the model is rapidly changing the variables travel speed, oscillation width and oscillation holding. The change of travel speed affects the quality because it is too rapid to keep a stable weld pool and there is no compensation from an increased wire feed speed. Furthermore the quality is also affected because when the travel speed is increased and the wire feed speed is constant the input of masse is lower. Because of masse conservation is the geometric quality parameters affected. The fluctuation around 3-4 mm root gap indicates that the model is more unreliable in that range.

Consistency

The consistency of the model is high with 71 per cent correct prediction and 96 per cent prediction within ± 1 state.

Discussion

The model gives a moderate change of the welding control variable values up to the interval between 3-4 millimetres where the variable values fluctuates. The explanation for this fluctuation is that training datasets are only made for root gaps of 0, 1 and 2 millimetres and outside this area there might be noisy or faulty training data which can influence the result in a higher degree.

By using another decision order of the welding control vector it is possible to achieve a more fluctuating result of the welding control vector. It is the case when a decision is taken on a node with an equal probability distribution, which is very sensitive to select another most probable state. The selection of another state affects the rest of the decisions taken in the welding control vector

and can cause fluctuations. Small variations which can cause a node with an equal probability distribution to select another most probable state could be e.g. small changes in root gap.
To avoid selecting a decision order and to moderate the fluctuation of the model a MAP function, described in section 6.2 “General Bayesian network theory”, can probably advantageously be used, because the probability is maximised for a group of variables. The MAP calculation is not implemented in Hugin [Hugin], used for this thesis. Applying the MAP function can be done by using SamIam [SamIam], but due to time consumption for remodelling it is beyond the scope of this thesis.
Another possibility to avoid this fluctuation is to implement at constraint node, described in section 6.2.2 “Modelling tricks and strategies”, which make sure there is mass conservation in the process-planning model.

Artificial neural network

Exam of the sensitivity, as described before in this section, was made on the inverse process-planning model based on artificial neural network. Five different artificial neural networks, listed in appendix H, were trained. The prediction of six welding control variables were analysed for an increasing root gap and the fixed welding control variables and quality parameters listed before in this section. The five artificial neural networks of different types were examined. The response on the welding control variables when changing the root gap from zero to four millimetres was as follows:

- Quick network predicted no change.
- Dynamic network predicted no change.
- Multiple network reduced the travel speed with 2 mm/sec.
- Prune network reduced travel speed with 1 mm/sec and increased the wire feed speed with 1 m/min.
- Exhaustitive prune network increased the wire feed speed with 1 m/min.

Generally the effect of changing the root gap on the welding control vector was little or none. The results indicate that the trained artificial neural networks are not consistent about finding one solution, which indicates that they either select different solutions or they are not well trained. The lack of training is the result of the limited amount of training data for this size of neural network model.
The network giving the most response is selected and it is the prune network predicting the result illustrated in figure 7.11.

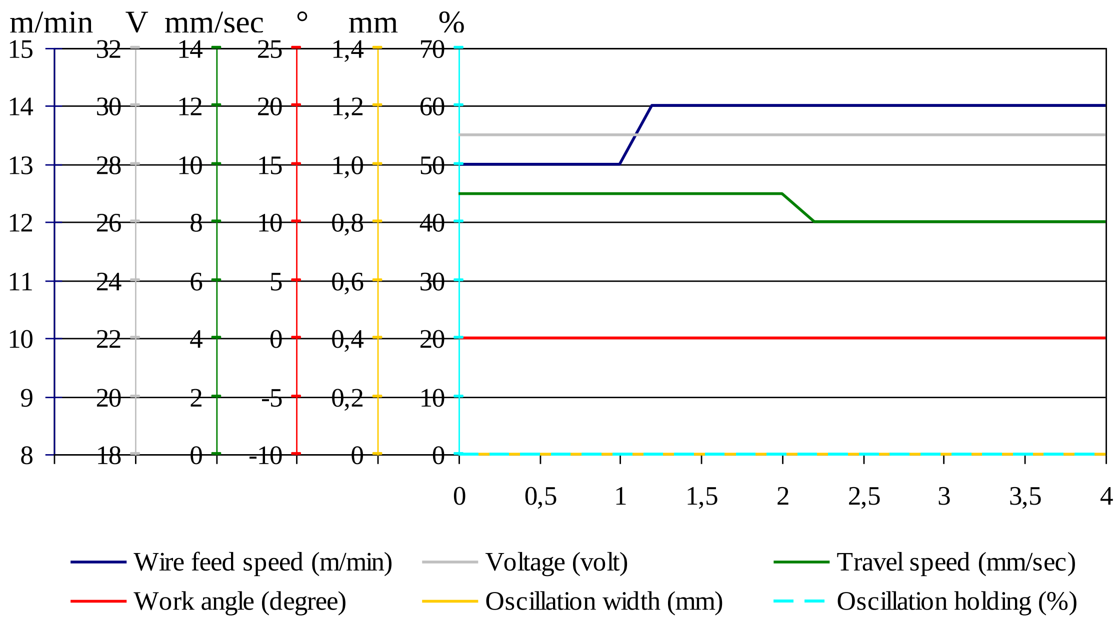


Figure 7.11: Welding control variables from a process-planning model based on artificial neural network, trained using prune when changing the root gap from 0 to 4 millimetres. Both oscillation width and oscillation holding are 0 for all root gaps.

Explanation and comments

A slightly increased wire feed speed and a reduced travel speed gives more weld material to fill the increasing root gap. A constant depth of fusion is not achieved with these welding control variables because an increasing root gap requires less heat input. The two main variables controlling heat input, wire feed speed and voltage are almost kept constant. Work angle or oscillation pattern are not changed to compensate for the varying root gap. It is required to avoid changes of the geometry shape and thereby quality along the weld seam.

Consistency

The consistency of the model is evidently the lowest of the three investigated methods with 44 per cent correct prediction and 88 per cent prediction within ± 1 state.

Discussion

The welding control variables are not changing sufficiently to compensate for the changing root gap. Furthermore, the trained networks are giving different results and, therefore, it is difficult to select the network that gives the most reliable model.

Regression model

Exam of the sensitivity, as described before in this section, was made on the inverse process-planning model based on regression. The prediction of six welding control variables were analysed for an increasing root gap from zero to four millimetres and with the fixed welding control variables and quality parameters listed before in this section. The regression model is examined by using the inverse process-planning models, which were constructed for each of the six welding control variables to test. The construction of the regression models are in appendix I. The resulting welding control variables for making the sensitivity exam is shown in figure 7.12.

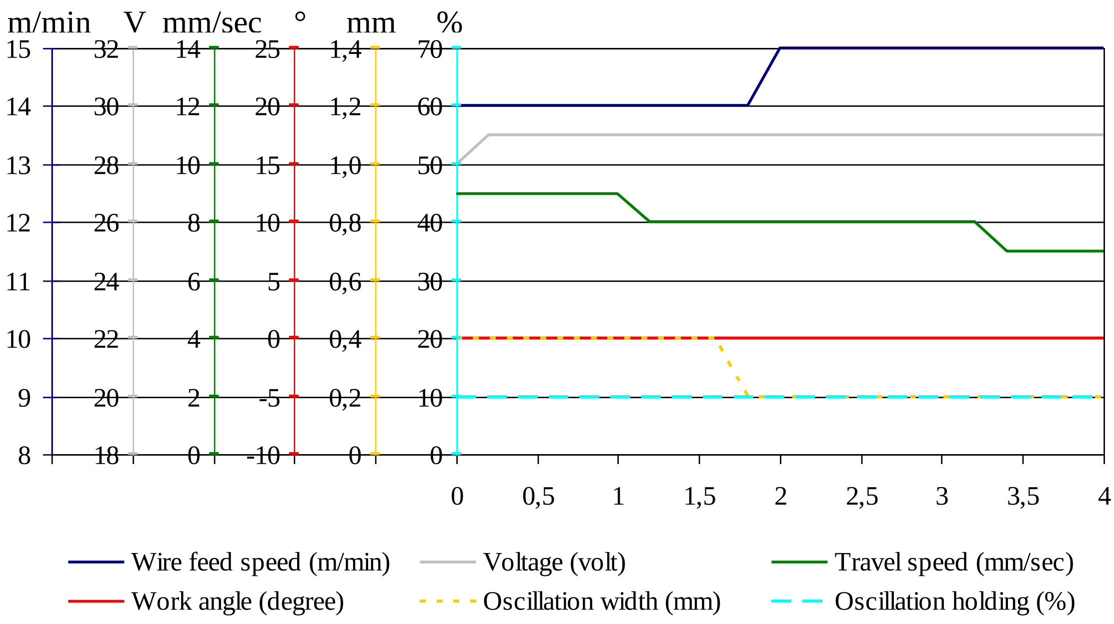


Figure 7.12: Welding control variables from a process-planning model based on linear regression when changing the root gap from 0 to 4 mm.

Explanation and comments

A slightly increased wire feed speed and a reduced travel speed gives more weld material to fill the increasing root gap. A constant depth of fusion is not achieved with these welding control variables because an increasing root gap requires less heat input. The two main variables controlling heat input, wire feed speed and voltage are almost kept constant. Decreasing the oscillation width from 0.4 to 0.2 mm for an increasing root gap causes that the arc has difficulties in reaching plate 2 and to make the required interfusion and geometrical shape. Increasing oscillation width is instead preferable because the arc more easily would reach plate 2 for an increasing root gap.

Consistency

The consistency of the model is high with 73 per cent correct prediction and 91 per cent prediction within ± 1 state.

Discussion

Producing the regression model was fast and there was no doubt which model to select. The drawback is that a linear regression model does not handle nonlinearities. A non linear regression model can be selected but it has more parameters in the model which requires more empirical data.

Summary

The inverse process-planning model based on Bayesian network shows reliable welding control vectors except between 3-4 mm root gap. In this interval the variable values fluctuate and a possible cause was lack of training data in this interval. Conversely, in case of the model based on regression and especially artificial neural network, there is an indication that the welding control vectors are not compensating enough for the changing root gap. The consistency of both the model based on Bayesian network and regression is high, unlike the model based on artificial neural network. An indication from this simulation result is that the artificial neural network model has difficulties in cooping with the limited amount of empirical training data. Whereas the models created with regression and Bayesian network capture some of the characteristics in the process and show more consistency. The advantages of the regression can be that the modelling and training is simple compared to the other methods. Bayesian network can benefit from more data sources for modelling and training.

7.2.3 Experimental verification utilising inverse process-planning model

The inverse process-planning model based on a Bayesian network was verified by welding experiments. For the verification a workpiece was produced with a changing root gap between 0 and 4 mm.

To carry out the welding experiments a sequence consisting of three tasks is required as illustrated in figure 7.13.
The first task is to produce a series of vectors with welding control variables covering the possible input window. The possible input window is all combinations of the workpiece, equipment and quality parameters for the given task.
The second task is to convert the series of welding control vectors to the format which fits the process control tool. This format is for the specific setup described in appendix D.
The third task is to carry out the experiment and analyse it using the experimental system described in chapter 4.

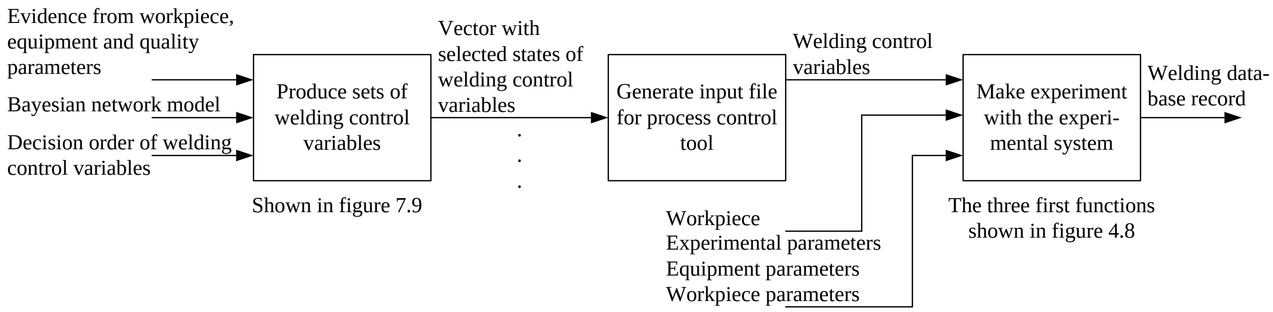


Figure 7.13: The sequence of tasks to experimentally verify the process-planning model based on a Bayesian network.

A welding experiment was carried out with the welding control variables shown in figure 7.10. Because of the jump of the travel speed at 3 millimetres root gap a satisfactory quality was not achieved at the weld seam around 3 millimetres root gap because of too little welding metal. The rest of the welded seam achieved an acceptable quality for the external dimensions except at the start and end. To avoid the lack of quality the travel speed at 3 millimetres root gap was smoothened to the same level as the travel speed for the neighbouring root gaps. It is illustrated in figure 7.14.

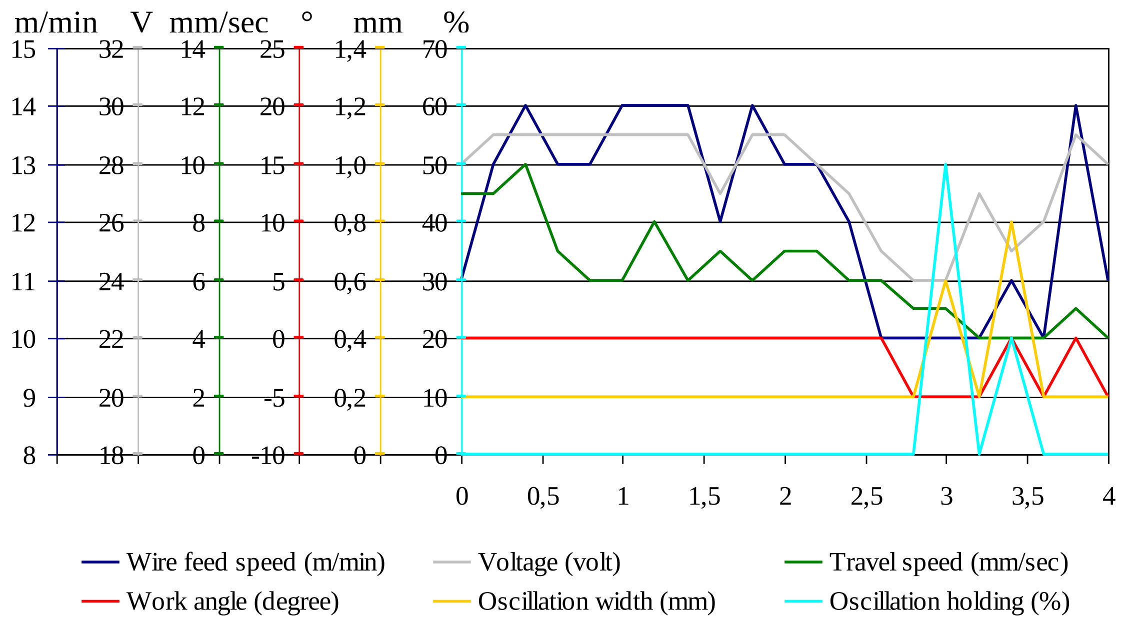


Figure 7.14: Welding control vectors with correction at the 3 mm root gap, where travel speed is changed from 13 mm/sec to 5 mm/sec.

The welding control vectors, illustrated in figure 7.14 were used for an experiment with a variation of root gap. The experiment resulted in the weld seam depicted in figure 7.15.

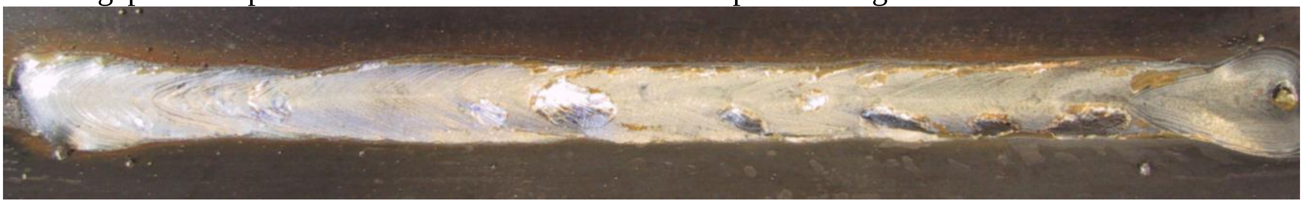


Figure 7.15: Picture of a weld seam on a part with a root gap changing from 4 millimetres at the left of the picture to 1 millimetre at the right side of the picture.

The weld seam, depicted in figure 7.15, was analysed by the experimental system and inspected by a metallography test to measure the depth of fusion. Results of the tests are shown in figure 7.16.

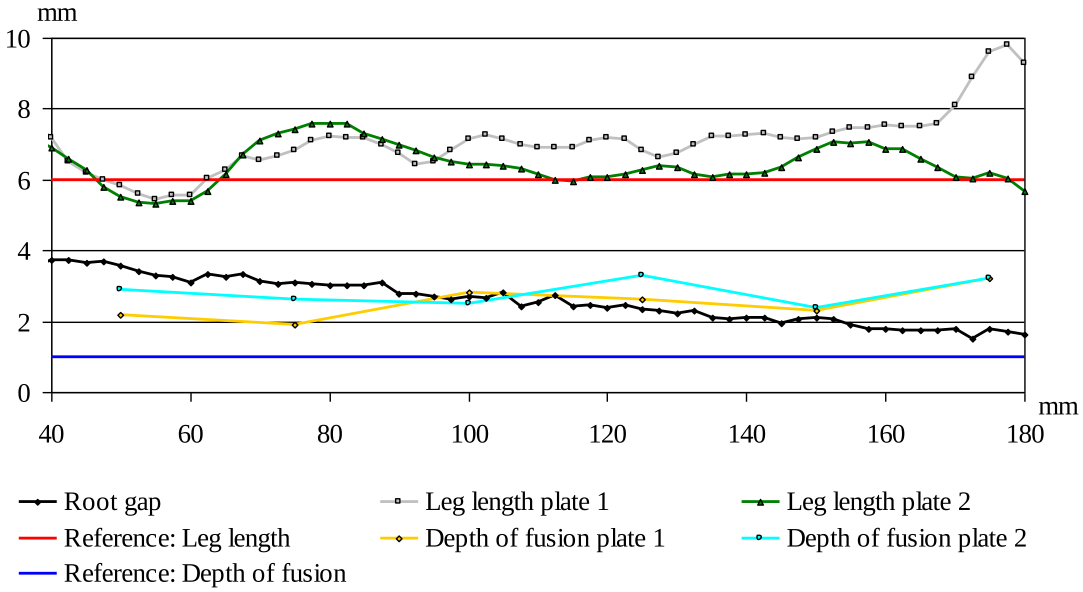


Figure 7.16: Quality measurements from the welded part illustrated for the measured root gap changing along the weld seam. Lines are plotted for the quality requirement reference.

The root gap is not reaching 4 and 0 millimetres because these values are at the entire end of the workpiece. At the start and at the end of the welding experiment the results were not reliable because no dedicated welding procedures to handle start and end of welding were produced. Therefore the quality for these sections is not commented.

For the rest of the weld seam the quality is as follows. The reference contact length was set to 6 millimetres and the resulting contact length for plates 1 and 2 is lying between 6 and 7.5 millimetres. The reference depth of fusion was set to 1 millimetre and the resulting depth of fusion is lying around 2-3 millimetres, which tells that the heat input is too large. Grade 4 was given for the convexity and weld face undercut plates 1 and 2 along the whole weld seam. The resulting grades, contact length and depth of fusion for plates 1 and 2 is constant along the whole weld seam and indicates that the compensation for the changing root gap is achieved. The depth of fusion plates 1 and 2 is around 1-2 mm too deep, which is not the expected result, but acceptable for welding of this part. The deeper interfusion point to a larger heat input than desired, which for other parts can cause problem as the weld pool drops through the root gap.

Discussion

The experimental verification of this work is limited to two experiments with a varying root gap. But these experiments verify the produced Bayesian network model because:

- It can work as an inverse process-planning model and can produce welding control variables to control the welding process so the resulting quality is close to the reference quality.
- It can extrapolate from the empirical training data, which was made for 0, 1 and 2 millimetre root gap, to an unseen root gap. But if the extrapolation is too significant the model has shown instability, as with the travel speed for 3 millimetres root gap.
- It can handle small changes in root gap even though each experiment was made for a fixed root gap. It is expected that it also applies for other variations of workpiece parameters.

The instability problem is expected to be minimised by using a MAP function. At the start and stop of the welded seam the external dimensions are very different compared to the middle part of the welded seam. It is also expected because the produced Bayesian network model is not considering this problem, but the model needs to be extended to handle it. This limited experimental verification shows promising results and further work using Bayesian network is recommended.

7.3 Benchmark

For the three process-planning models created in chapter 6 and appendix H and I a comparison is made in table 7.4. The comparison is divided into a part concerning modelling, training and verification.

Table 7.4: Comparison result.

	Bayesian network	Artificial neural network	Regression
Modelling			
Time consumption:	High	Medium for network size selected manually Low for network size selected automatic	Low
Usable knowledge sources:	Empirical Analytical Operator	Empirical (Operator knowledge is usable if it is converted to artificial empirical data as described in chapter 5, but it is not used in this thesis)	Empirical (Operator knowledge is usable for constructing equations as described in chapter 5, but it is not used in this thesis)
Required experience level:	High	Low	Low (Medium when operator is used for construction equation)
Reusability:	Model can be reused by inserting and deleting nodes	No	No, for new input Yes, for new output
Training			
Time consumption:	Medium	Low	Low
Usable knowledge sources:	Empirical Analytical Operator	Empirical	Empirical
Updating without re-building:	Yes	Yes, but with risk of overtraining	The model parameters can be updated but not the equation
Verification			
Verification methods:	Empirical tests Visualisation of edges, nodes, probability tables and experience tables	Empirical tests	Empirical tests

Ensure model reliability:	Estimated by looking in the probability and experience tables to check the number of training data and the distribution	Cannot be ensured by looking into the model	Cannot be ensured by looking into the model
Meaningful model for operators:	Yes, but it requires experience	No	Yes, but it requires a little experience

The main conclusions that can be drawn from table 7.4 are:

- Modelling and training the regression and artificial neural network models are much faster compared to the Bayesian network model, which requires a higher experience level.
- The Bayesian network is flexible and has the benefit of using many different sources of knowledge and has a high visibility to ensure the reliability of the model.
- The Bayesian network is flexible in extending and reusing process-planning models for other welding tasks.

7.4 Summery

The preliminary investigation showed that operator knowledge is a beneficial knowledge source that can be used for making small process-planning models and it can be combined with empirical data. Operator knowledge alone or combined with empirical knowledge is shown as efficient knowledge sources for training of three different process-planning models using learning.

The result of the investigation of the large process-planning models from chapter 6 and appendix H and I is shown in table 7.5.

Table 7.5: Benchmark result.

	Bayesian network	Artificial neural network	Regression
Direct process-planning models			
Prediction result	44% and 85% for +/-1	33% and 84% for +/-1	48% and 85% for +/-1
Inverse process-planning models			
Comments from discussions	The quality requirements are achieved for the increasing root gap except for when the model switch at 3 millimetres root gap	The quality requirements for the increasing root gap is not achieved	The quality requirements for the increasing root gap is not achieved
Consistency	71% and 96% for +/-1	44% and 88% for +/-1	73% and 91% for +/-1

The direct and inverse process-planning models based on Bayesian network and regression show much better results than the model based on artificial neural network. The model based on regression is fast and simple to construct, but not reusable whereas the model based on Bayesian network takes a lot of time to construct, but it is then flexible to be extended and reused.

The model based on Bayesian network has this benefit compared to the two other models that it can use other knowledge sources and therefore does not only rely on the expensive empirical knowledge.
The experimental verification of the process-planning model based on Bayesian network, showed that the model could achieve the quality requirements for an unseen workpiece with a varying root gap, except for the depth of fusion which was around 1-2 milliners too deep but for this weld it is acceptable.
The process-planning model based on Bayesian network shows the best results together with process-planning model based on regression. Because of the results and suggestions presented to improve the Bayesian network based process-planning model it is recommend to continue with further development and use of this tool.

Chapter 8

Conclusion

In this chapter the thesis is summarised with the results and development presented in three achieved contributions. Furthermore, the perspectives of the achievements are laid-out together with the possibilities of future development.

8.1 Summery of results

As stated in the introduction the welding process is a multivariable process which is dynamic and non-linear. Its physics are not completely understood. This is the result of the fact that the planning and control to automate the welding process is made mainly on relatively simple cases and with strict boundary conditions, as seen from state of the art in chapter 1.
It is identified that the present process-planning models for welding are inadequate concerning automation of productions with small-batch sizes. The process-planning models are resource demanding to make because of the modelling task for analytical models and the collection of empirical data for empirical models. Furthermore, in the literature no combination of knowledge sources exists which benefits from advantages of using several knowledge sources. To improve these difficulties three main contributions are achieved during this Ph.D. work. These contributions are:

1. A generic information model is developed to store dynamic empirical welding data, and a system is made to produce welding data from experiments.

2. Techniques are developed to formalise operator knowledge, which is applied as a knowledge source to produce process-planning models.

3. A process-planning model based on Bayesian network is produced combining three different knowledge sources and it is shows promising results for future work.

Below, each contribution is described more thoroughly. For each contribution it is elaborated and stated which of the research objectives from chapter 1 it answers.

8.1.1 Contribution one

Contribution one refers to research objective number one and three.

1. How can empirical knowledge be formalised so it can be saved, reused and communicated?
3. How can the creation of empirically knowledge be automated and used as input for training a process-planning model based on learning?

Background

Formalising empirical knowledge for the welding process is troublesome because the process includes a lot of parameters and variables, which require a general and unique description. It is also the experience achieved from investigating the empirical dataset in the literature, appendix A section A.4 “Modelling process knowledge”, that empirical datasets are problematic to reuse because the description of parameters and variables are missing and they are not described in a standardised way. Furthermore, welding is a dynamic process depending on the process history and the descriptions of the empirical data are mainly made from steady state conditions. Moreover, welding experiments are time consuming to produce because no automation of the experiments and no data analysis are carried out.

Achievement

A taxonomy of a generic information model is suggested, figure 3.4, with a corresponding description of all parameters and variables. The main achievements of the taxonomy compared to existing work, which is the work of [Rippey, 2004], are:

- The model can represent dynamic welding data. It makes the model beneficial for capturing start and stop conditions of the welding process and for changing welding control and workpiece variables.
- Process variables collected during welding execution are stored in the database.
- Groove orientation is described according to the tool, using [Lauridsen, 1991] to give the exact angles of the tool orientation.
- The geometry includes bonds representation so only feasible configurations of joints and grooves are represented.

Using the same taxonomy for future experiments makes communication of the empirical welding data possible and therefore they are made reusable. This is an improvement, which can save resources for future development of process-planning models.

Related to the taxonomy of a generic information model an architecture of a system for automating production of empirical welding data is suggested. In the architecture a system is proposed, which can make welding experiments and can analyse the experiments so that the empirical data fits the form of the taxonomy. The architecture is independent of the brand of the manipulator, welding machine and profile sensor but requires that they are interfaced by a computer.
An implementation of the system for automating production of empirical welding data showed that when using weld face scanning two welding experiments and their analysis without destructive tests took 20 minutes and when using both weld face and back bead scanning two welding experiments and their analysis took 30 minutes to carry out.
Because of the use of a generic information model the extraction of the required empirical welding data is possible, given a certain purpose such as modelling and training of a process-planning model.

When applying the generic information model and sharing empirical welding data between different partners, e.g. industrial and research partners, it is possible to achieve considerable savings when producing empirical welding data. Furthermore, it is possible to extend the collection of welding data by collecting data during production.

8.1.2 Contribution two

Contribution two refers to research objective number two.

2. How can operator knowledge be formalised so it can be saved, reused and communicated?

Background

Operator knowledge is a rarely used source for making process-planning models. The cases where it is used are e.g. fuzzy logic and expert systems. It is because the operator knowledge is a silent knowledge source, holding e.g. the skills, procedures and routines, which need to be transformed to a formalised knowledge representation. The acquisition and formalisation of operator knowledge has been a big hurdle to overcome before using this source, and the reasons are:

- Operator knowledge is not precise; it is given as rough values and numbers.
- The knowledge can be misleading because operators can misunderstand the physical relations of the process.
- Different operators can have different opinions when describing the welding process.

Achievement

Methods for collecting silent knowledge from operators and produce formalised knowledge have been developed.
Five methods exist for producing subcategorised formalised knowledge. The knowledge is divided and describes only one thing about the process. These methods describe the process by components, relations, interactions, uncertainties and weights.
Four methods exist for producing undivided formalised knowledge. The knowledge consists of more than one single part and describes broader relationships or the whole process. These methods describe the process by artificial empirical data, approximated equation, fuzzy rules and description. Fuzzy rules are in this category not a new development because it is described in the literature, as it can be seen in appendix A section A.4 “Modelling process knowledge”.

The contribution and perspectives from the development of these methods are that the operator knowledge can be formalised and therefore knowledge can be saved, reused and communicated. The operator knowledge is then not attached to one person and dependent on this person. The use of operator knowledge is demonstrated in this thesis for most of the methods, which are used to model and train a Bayesian network.

8.1.3 Contribution three

Contribution three refers to research objective number four, five and six.

4. How and to what extend can different types of knowledge be combined and used for training a process-planning model based on automatic learning?
5. How can a reliable process-planning model be created by using a Bayesian network?
6. How good is the performance of a process-planning model based on a Bayesian network compared with a process-planning model based on regression analysis and artificial neural networks?

Background

Different kinds of knowledge sources for production of process-planning models are available and with contribution number two, operator knowledge is also made an available source. Combining different knowledge sources for making process-planning models is rarely applied, as shown in appendix A section A.4 “Modelling process knowledge”. For this reason the appendix states that the possible benefits of combining different knowledge sources are not investigated. Furthermore, most methods for making process-planning models are not able to cope with more than a single kind of knowledge source. The Bayesian network is an almost unproven method in the sense of being the base for making process-planning models for welding. It has the ability to use and combine multiple knowledge sources. Benchmarking the performance of process-planning models based on Bayesian networks with other traditional methods and determining an eventual performance improvement is a research objective.

Achievement

The pre-investigation, described in chapter 6, shows that empirical data can be combined with artificial empirical data produced from operator knowledge and it gives the best result when using only one of the sources. In the main investigation, also described in chapter 6, it is shown how operator knowledge, analytical knowledge and empirical knowledge are combined to make a process-planning model based on a Bayesian network. The combination of three knowledge sources is shown useful for making process-planning models. It is demonstrated that it is a promising approach in future to utilise the knowledge sources more efficiently and benefit from each of them.

An approach for both modelling and training using different knowledge sources to make reliable process-planning models based on a Bayesian network is developed and demonstrated. A general static welding process-planning model for applying Bayesian network is presented, illustrated in figure 6.7. The advantage of using the model is to make use of the specified structure and to have the direct and inverse process-planning model combined in the same model.
A benchmark, comparing the developed process-planning model based on a Bayesian network with a process-planning model based on an artificial neural network and regression, showed the following:

- The Bayesian network and regression based process-planning models show a significantly better reliability than the process-planning model based on artificial neural network for both direct use and inverse use.
- The process-planning model based on regression is fast and simple to construct but not reusable, whereas the process-planning model based on a Bayesian network is time consuming to construct, but it is expected to be flexible for extension and reuse.
- The Bayesian network based process-planning model can use different knowledge sources, whereas the regression and artificial neural network based models rely only on the expensive empirical knowledge or artificial empirical data.
- By using a Bayesian network based model the process-planning model is compared with the artificial neural network and changed from being a black box model to a grey box model.

The process-planning model based on a Bayesian network is experimentally verified and it showed a result, which recommends further development and use of this tool.

Applying process-planning models based on a Bayesian network can contribute to the welding industry, where process-planning models are used to reduce the cost of production when using more kinds and cheaper knowledge sources. A Bayesian network with its graphical model and the probabilities can make the process-planning model more visible and make use of interaction with operator, compared to the black box models. Compared to the analytical based models, e.g. FEM models, the modelling and computational tasks are reduced and the possibilities of including parameters and variables are higher because operator and empirical data can describe relations, which are not described sufficiently analytically.

8.1.4 Minor contributions

Minor contributions are achieved additionally during this Ph.D. work and these are the following:

1. Modification of the architecture of a production system proposed by [Holm et al., 1994] by describing the function “Prepare production”. It is shown in appendix A section A.1 “Architecture of a production system”. With this modification it is possible to see how a process-planning model, not only for welding but general for industrial processes, is incorporated in a production system.

2. List of methods are proposed, explained in chapter 6, to develop software tools for Bayesian network for including and combining the three kinds of knowledge sources: empirical knowledge, analytical knowledge and operator knowledge and for training process-planning models. These methods can decrease the time consumption for training the Bayesian network significantly.

8.1.5 Recommendation

With further development and maturing of the methodologies described in the contributions of this thesis, it is anticipated that they can be brought to industrial use. This is ascribable to the fact that the methodologies cover some identified gaps in the area of making cheap and reliable process-planning models, and the results presented in this thesis strengthen the recommendation for future development.

8.2 Perspectives for future development

The perspectives and possibilities for further development of the work described in this thesis are presented.

8.2.1 Apply methodology to other processes

This Ph.D. scholarship is entitled "Application of automatic learning methods for modelling and control of industrial processes", but it is only focused on the welding process. By extending this research it can be applied to other industrial processes, which have the same class of problems: as a lack of reliable process-planning models and difficulties in measuring the process states or quality during execution. Examples of such processes are e.g. milling, painting and gluing.

8.2.2 Extend the modelling area

The presented process-planning model based on the Bayesian network can be extended to cover larger areas of modelling. These areas can be the following as for example:

- More difficult welding tasks.
- Dynamic model.
- A welding process with more parameters and variables.
- Include data from more sensors.

More difficult welding tasks

The model can be extended to cover more complex welding tasks, e.g. the presented HalfV-Joint. It is challenging because the root opening needs to be filled and achieve a certain quality of the back bead when the sides of the groove has a dissimilar plate thickness. The challenge is to investigate whether the behaviour of the welding process can be modelled when more quality parameters and workpiece parameters and variables are involved and the process window is smaller.
Furthermore, it is interesting to determine to what extend the existing process-planning model for the T-Joint can be reused when modelling other types of groves and weld joints. It is also interesting to determine whether all the workpiece geometries in the taxonomy in figure 3.4 can be modelled in the same process-planning model.

Time-stamped model

As mentioned earlier, the taxonomy in figure 3.4 is able to store dynamic welding data. It could be an interesting investigation to extend the Bayesian network based process-planning model from a static to a time-stamped process-planning model. The time-stamped model is required for modelling starting and ending of the welding process and the change of workpiece geometry during the welding process.

A welding process with more parameters and variables

The taxonomy in figure 3.4 includes neither the MIG/MAG process nor the TIG and the plasma arc process. Future research can be done including these processes and other welding processes in the Bayesian network based process-planning model. Furthermore, the process-planning model for the MIG/MAG welding process and the taxonomy in figure 3.4 can be extended to include pulsed welding.

Include data from more sensors

A range of sensors are available for measuring the welding process. One example is the arc sensor used in the work of this thesis to measure the voltage and current during the welding process. Other examples are e.g. thermal cameras, which can make measurements online as shown in [Orye, 2005]. Information gained from the sensors can be utilised as an online input to the Bayesian network based process-planning model in a closed loop control. In this case it is important to consider the computational time of the Bayesian network when propagating the network.

8.2.3 Automate data collection and modelling

In this thesis a taxonomy for empirical data is presented, data collection for empirical data is automated and the use of empirical data for modelling Bayesian network is automated. In a similar manner it is another research topic to investigate whether it is possible to develop a similar taxonomy and a similar automation when using operator knowledge. Furthermore, it can also be useful to join the combined knowledge sources when modelling. It is of interest because making the data collection, modelling operator knowledge and combining knowledge sources are considerably time consuming and require practice with the methods utilised in this thesis.

References

Books, thesis and articles

[Acid et al., 2003] S. Acid and L. M. Campos, “Searching for Bayesian network structures in the space of restricted acyclic partially directed graphs”, Journal of artificial intelligence research, Vol. 18, Page 445-490, 2003

[Agapakis et al., 1990] John E. Agapakis, Joel M. Katz, Joshua M. Friedman, Geoffrey N. Epstein, “Vision-aided robotic welding. An approach and a flexible implementation”, International Journal of Robotics Research, Vol. 9 Issue. 5, pages 17-34, 1990, ISSN 02783649

[Andersen et al., 1997] K. Andersen, G. E. Cook, R. J. Barnett, A. M. Strauss, “Synchronous weld pool oscillation for monitoring and control”, IEEE Transaction on industry applications, Vol. 33, Number 2, March/April 1997, ISSN 00939994

[Atkinson et. al. 1971] Richard C. Atkinson, Richard M. Shiffrin, “The control of short-term memory”, Scientific American, Vol. 225, pages 82-90, 1971, ISSN 00368733

[Bayes et al., 1763] Mr. Bayes, Mr. Price, “An Essay towards Solving a Problem in the Doctrine of Chances. By the Late Rev. Mr. Bayes, F. R. S. Communicated by Mr. Price, in a Letter to John Canton, A. M. F. R. S.”, Philosophical Transactions (1683-1775), Vol. 53, pages 370-418, 1763, ISSN 02607085

[Bingsen et al., 1994] Chen Bingsen, Peng Jinning, “Expert systems and their development”, Welding in the World, Le Soudage Dans Le Monde, Proceedings of the International Conference on Advanced Techniques and Low Cost Automation, Vol. 34, Pergamon Press Ltd, pages 247-253, 1994, ISSN 00432288

[Bingül et al., 2000] Zafer Bingül, George E. Cook, Alvin M. Strauss, “Application of fuzzy logic to spatial thermal control in fusion welding”, IEEE Transactions on industry applications, Vol. 35, no. 6, November/December 2000, pages 1523 -1530, ISSN 00939994

[Boelskifte et al., 1994] Jacob Boelskifte, Ingvar Hafsteinsson, “Kinematic control for off-line programmed robotic root-pass welding of pipebranches”, Student project from Department of Production Aalborg University, 1994

[Bolmsjö, 2001] Gunnar Bolmsjö, “Process and Quality Monitoring and Control”, Robotica, Vol. 42, number 1, pages 67-83, 2001

[Chan et al., 1999] Billy Chan, Jack Pacey, Malcolm Bibby, “Modelling gas metal arc weld geometry using artificial neural network technology”, Canadian Metallurgical Quarterly, Vol. 38 Issue 1, pages 43-51, 1999, ISSN 00084433

[Chang et al., 2005] Chia-Lung Chang, Yen-Hung Chen, “Measurements of fillet weld by 3D laser scanning system”, The International Journal of Advanced Manufacturing Technology, Vol. 25 Issue 5-6, pages 466-470, 2005, ISSN 02683768

[Christensen et al., 2003] Kim H. Christensen & Torben Sørensen, “A Neural Network Approach for GMA Butt Joint Welding”, International Journal for the Joining of Materials, Vol. 15 Issue. 4, pages 1-7, 2003, ISSN 09056866

[Christensen, 2003] Kim Hardam Christensen, “Arc welding automation : Process modelling & control based on neural networks”, PhD thesis, Department of Mechanical Engineering Technical University of Denmark, July 2003, ISBN 87-90130-03-0.

[Clausen et al., 2001] H. B. Clausen, M. Lützen, A. Friis-Hansen, N. Bjørneboe, “Bayesian and neural network for preliminary ship design”, Marine Technology, Vol. 38 Issue. 4, pages 268-277, October 2001

[Clemmentine algorithms, 2004] “Clementine® 9.0 algorithms guide”, documentation on the Clemmentine software, 2004

[Cook et al., 1995] George E. Cook, “Weld modeling and control using artificial neural network”, IEEE Transactions on industry applications, Vol. 31, No. 6, November/December 1995. ISSN 0093-9994/95

[Cooper, 1990] Gregory F. Cooper, “Computational complexity of probabilistic inference using Bayesian belief networks“, Artificial Intelligence, Vol. 42 Issue 2, pages 393-405, 1990, ISSN 00043702

[De et al., 2004] A. De; T. DebRoy, “Probing unknown welding parameters from convective heat transfer calculation and multivariable optimization”, Journal of Physics D: Applied Physics, Vol. 37 Issue 1, pages 140-150, 2004, ISSN 00223727

[Di et al., 2001] Li Di, T. Srikanthan, R. S. Chandel, Inoue Katsunori, “Neural-network-based self-organized fuzzy logic control for arc welding”, Engineering Applications of Artificial Intelligence, Vol. 14, Issue 2, 2001, pages 115-124, ISSN 09521976

[Dilthey et al., 1999] Ulrich Dilthey, Jens Heidrich, “Using Al-methods for parameter scheduling, quality control and weld geometry determination in GMA-welding”, ISIJ International, Vol. 39 Issue 10, pages 1067-1074, 1999, ISSN 09151559

[Dilthey et al., 2003] Ulrich Dilthey and Haitem Hichri, “Structure of a monitoring and control system for the on-line checking of GMA welding processes on the basis of a neuro-fuzzy architecture”, Welding and Cutting, no. 6, pages 316-321, 2003

[Drews et al., 2000] P. Drews, St. Pieper, K. Willms, “Optisches sensorsystem für die 3D-nahtverfolgung beim laserstrahlschweißen”, Forschung im Ingenieurwesen, Vol. 66 Issue 3, pages 101-106, 2000, ISSN 00157899

[Gauss, 1809] Carl Fridrich Gauss, “Theoria Motus Corporum Coelestium in Sectionibus Conicis Solem Ambientum”, 1809

[Gauss, 1821] Carl Fridrich Gauss, “Theoria combinationis observationum erroribus minimis obnoxiae”, 1821

[Goldak et al., 2006] J. Goldak, J. Zhou, S. Tchernov, D. Downey, S. Wang, B. He, “Predicting distortion and residual stress in complex welded structures by designers”, Proceedings of the 7th International Conference on Trends in Welding Research, pages 531-540, 2006, ISBN 978-0-87170-842-7

[Harwig, 1997] Dennis D. Harwig, “Weld parameter development for robot welding”, Robotics Today, Vol. 10 Issue 1, 1997, pages 1-7, ISSN 01936913

[Harwig, 2000] Dennis D. Harwig, “A wise method for assessing arc welding performance and quality”, Welding Journal, Vol. 79 Issue 12, 2000, pages 35-39

[Haug et al., 1998] K. Haug, G. Pritschow, “Robust laser-stripe sensor for automated weld-seam-tracking in the shipbuilding industry”, IECON '98. Proceedings of the 24th Annual Conference of the IEEE Industrial Electronics Society, Vol. 2, pages 1236 -1241, 1998, ISBN 0-7803-4503-7

[Hebb, 1949] Donald Olding Hebb, “The organization of behavior : a neuropsychological theory”, New York : Wiley, 1949, ISBN 0471367273

[Holm et al., 1994] Hans Holm, Ulla Rasmussen, Jørgen A. Nielsen, Per Liljenberg, “An Outline for a State Space Based Manufacturing Theory: Control Part of Automatic One-of-a-Kind Production”, Issues of Integration in Manufacturing, Proceedings of the ninth IPS Research Seminar April 18-20, pages 253-304, 1994, ISBN 87-89867-01-7

[Holm et al., 2002] H. Holm, P. V. Jeberg and C. Bro, “Applications of numerical model for off-line programming of posture robot welding”, WTIA Technology Week, 26-30’ August 2002, Paper no. 81, 2002, ISBN 0 909539 98 7

[Holm et al., 2003a] Hans Holm, Heine Bach, Martin V. Hansen, Dieter Franke “Planning of finite element modelled welding control variable trajectories by PI-controllers and by iterative learning”, ASM Proceedings of the International Conference: Trends in Welding Research, pages 967-972, 2003, ISBN 0-87170-780-2

[Holm et al., 2003b] Hans Holm, Hans Christian E. Kjeldsen, Jens K. Kristensen, “A reference architecture for the design of an industrial temperature feedback welding control system”, Journal of Materials Processing Technology, Vol. 139 Issue 1-3, pages 499-504, 2003, ISSN 09240136

[Jantsen, 1999a] Jan Jantzen, “Design of fuzzy controllers”, Tech. report no 98-E 864, Technical University of Denmark, 1999

[Jantsen, 1999b] Jan Jantzen, “Tutorial on fuzzy logic”, Tech. report no 98-E 868, Technical University of Denmark, 1999

[Jeberg et al., 2006] Peter V. Jeberg, Hans Holm, Steffen Lambaek, “Planning of dynamic trajectories for weld process control variables by finite element simulation and iterative learning”, Proceedings of the 7th International Conference on Trends in Welding Research, pages 641-646, 2006, ISBN 978-0-87170-842-7

[Jeberg, 2005] Peter V. Jeberg, “Automatic process optimised weld planning of full penetration I-joint GMA welding”, PhD thesis, Department of Production Aalborg University Denmark, January 2005, ISBN 87-91200-49-0.

[Jensen et al., 1990] F. V. Jensen, K. G. Olesen and S. K. Andersen, “An algebra of Bayesian belief universes for knowledge based systems”, Institute of Electronic Systems, Aalborg University, 1988

[Jensen, 2001] Finn V. Jensen, “Bayesian Networks and Decision Graphs”, Springer-Verlag 2001, ISBN 0-387-95259-4.

[Jiang et al., 2004] Ping Jiang, Zi-yu Li; Yang-quan Chen, "Iterative learning neural network control for robot learning from demonstration", Control Theory & Applications, Vol. 21 Issue 3, pages 447-452, 2004, ISSN 10008152

[Juang et al., 2002] S. C. Juang, Y. S. Tarng, "Process parameter selection for optimizing the weld pool geometry in the tungsten inert gas welding of stainless steel", Journal of Materials Processing Technology, Vol. 122 Issue 1, pages 33-37, 2002, ISSN 09240136

[Kim et al., 1996a] Jae Seon Kim, Young Tak Son, Hyung Suck Cho, Kwang Il Koh, "A robust visual seam tracking system for robotic arc welding", Mechatronics, Vol. 6 Issue 2, pages 141-163, 1996, ISSN 09574158

[Kim et al., 1996b] I. S. Kim, W. H. Kwon & E. Siores, "An investigation of a mathematical model for predicting weld bead geometry", Canadian Metallurgical Quarterly, Vol. 35 Issue 4, pages 385-392, 1996, ISSN 00084433

[Kim et al., 2005] I. S. Kim, J. S. Son, C. E. Park, I. J. Kim, H. H. Kim, "An investigation into an intelligent system for predicting bead geometry in GMA welding process", Journal of Materials Processing Technology, Vol. 159 Issue 1, pages 113-118, 2005, ISSN 09240136

[Kjeldsen et al., 2003] Hans Christian Kjeldsen, Hans Holm, Jens K. Kristensen, "New low-cost camera temperature measurements compared to analogous temperature state simulations", ASM Proceedings of the International Conference: Trends in Welding Research, pages 924-929, 2003, ISBN 0-87170-780-2

[Kojima, 2002] T. Kojima, S. Ohtani, T. Ohashi, "igitalization of manufacturing skill – A case study of welding operation planning", Proceedings of the 1st CIRP(UK) seminar on digital enterprise technology, pages 49-52, 2002

[Kristiansen et al., 2004] Morten Kristiansen, Ole Madsen, "Experimental data and operator knowledge used for classifying welding quality", Proceedings of IASTED International Conference on Artificial Intelligence and Applications - AIA 2004, Vol. 2, pages 712-717, 2004, ISBN 0889864047

[Kristiansen et al., 2006] Morten Kristiansen, Ole Madsen, "Process-planning models for welding using Bayesian network", Proceedings of the 7th International Conference on Trends in Welding Research, pages 635-640, 2006, ISBN 978-0-87170-842-7

[Kumar et al., 2004] A. Kumar, T. DebRoy, "Guaranteed fillet weld geometry from heat transfer model and multivariable optimization", International Journal of Heat and Mass Transfer, Vol. 47 Issue 26, pages 5793-5806, 2004, ISSN 00179310

[Lancaster, 1984] J. F. Lancaster, "The physics of welding", International Institute of Welding, Pergamon press, 1984, ISBN 0-08-030554-7

[Laplace, 1774] Pierre Simon Laplace, "Memoir on the Probability of the Causes of Events", translated from original French where it originally was presented in Mémoires de mathématique et de physique, pages 621-656, 1774

[Lauridsen, 1991] Jan Kirkegaard Lauridsen, "Computer aided off-line programming of multipass TIG-welding", PhD thesis, Department of Production Aalborg University Denmark, December 1991

[Lauridsen, 1999] Jan Kirkegaard Lauridsen, "Dokumentation for BDH-styring", Internal publication at Department of Production Aalborg University Denmark, 1999

[Laurinen, 2004] Perttu Laurinen, Heli Junno, Lauri Tuovinen, Juha Röning, "Studying the quality of resistance spot welding joints using Bayesian networks", Proceedings of IASTED International Conference on Artificial Intelligence and Applications - AIA 2004, Vol. 2, pages 705-711, 2004, ISBN 0889864047

[Lauritzen et al., 1988] S. L. Lauritzen, D. J. Spiegelhalter, "Local Computations with Probabilities on Graphical Structures and Their Application to Expert Systems", Journal of the Royal Statistical Society. Series B (Methodological), Vol. 50 Issue 2, pages 157-224, 1988, ISSN 00359246

[Lauritzen, 1995] Steffen L. Lauritzen, "The EM algorithm for graphical association models with missing data", Computational Statistics & Data Analysis, Vol. 19 Issue 2, pages 191-201, 1995

[Lee et al., 1998] C. Lee, Xu Yangsheng, "Reduced-dimension representation of human performance data for human-to-robot skill transfer", Proceedings of the 1998 IEEE/RSJ international conference on intelligent robots and systems, Vol. 3, pages 1956-1961, 1998, ISBN 0-7803-4465-0

[Legendre, 1805] A. M. Legendre, "Nouvelles méthodes pour la détermination des orbites des comètes", Sur la Méthode des moindres quarrés, appears as an appendix, 1805

[Lindgren, 2001a] Lars-Erik Lindgren, "Finite element modeling and simulation of welding part 1: Increased complexity", Journal of Thermal Stresses, Vol. 24 Issue 2, pages 141-192, 2001, ISSN 01495739

[Lindgren, 2001b] Lars-Erik Lindgren, "Finite element modeling and simulation of welding part 2: Improved material modeling", Journal of Thermal Stresses, Vol. 24 Issue 3, pages 195-232, 2001, ISSN 01495739

[Lindgren, 2001c] Lars-Erik Lindgren, "Finite element modeling and simulation of welding part 3: Efficiency and integration", Journal of Thermal Stresses, Vol. 24 Issue 4, pages 305-334, 2001, ISSN 01495739

[Lindgren, 2001d] Lars-Erik Lindgren, "Current state of welding simulations", Simulation of material processing: Theory, methods and applications, 2001, ISBN 90 2651 822 6

[Lippmann, 1987] Richard P. Lippmann, "An introduction to computing with neural nets", IEEE acoustics, speech and signal processing society, pages 4-20, 1987, ISSN 0740-7467

[Longman, 1995] "Dictionary of comtemporary English", 1995, ISBN 0-582-23750-5

[Luo et al., 2005] Hong Luo, Xiaoqi Chen, "Laser visual sensing for seam tracking in robotic arc welding of titanium alloys", The International Journal of Advanced Manufacturing Technology, Vol. 26 Issue 9-10, pages 1012-1017, 2005, ISSN 02683768

[Madsen et al., 2002] O. Madsen and C. Bro, "An intelligent planning and control system for laser welding", WTIA Technology Week, 26-30' August 2002, Paper no. 85, 2002, ISBN 0 909539 98 7

[Madsen, 1992] Ole Madsen, "Sensor based robotic multi-pass welding", PhD-thesis, Department of Production Aalborg University Denmark, 1992, ISBN 87-89867-02-5.

[Madsen, 1998] Ole Madsen, "Sensor server sensrv (AAU): An GPIB-interface to the OLDELFT SeamPilot sensor, Internal document from Department of Production, Aalborg University, 1998

[Mahrle et al., 2000] A. Mahrle, J. Schmidt, D. Weiss, "Simulation of temperature fields in arc and beam welding", Heat and Mass Transfer, Vol. 36 Issue 2, pages 117-126, 2000, ISSN 09477411

[Maul et al., 1996] Gary P. Maul, Richard Richardson, Brett Jones, "Statistical process control applied to gas metal arc welding", Computers & Industrial Engineering, Vol. 31 Issue 1-2, pages 253-256, 1996, ISSN 03608352

[McCulloch et al., 1943] W. S. McCulloch and W. Pitts, "A local calculus of the ideas immanent in nervous activity", Bulletin of mathematical biophysics, Vol. 5, 1943

[Minsky et al., 1969] Marvin Minsky, Seymour Papert, "Perceptrons: An introduction to computational geometry", The MIT Press, 1969

[Mitchell, 1997] Tom M. Mitchell, "Machine Learning", McGraw-Hill International 1997, ISBN 0-07-115467-1.

[Mitchell, 1999] Tom M. Mitchell, "Machine Learning and Data Mining", Communications of the ACM, Vol. 42, No. 11, pages 31-36, 1999, ISSN 00010782

[Montgomery, 2001] D. C. Montgomery, "Design and analysis of experiments", 5. ed., Wiley, 2001, ISBN 0-471-31649-0

[Moon et al., 1996] Hyeong-Soon Moon, Suck-Joo Na, "A Neuro-Fuzzy Approach to Select Welding Conditions for Welding Quality Improvement in Horizontal Fillet Welding", Journal of Manufacturing Systems, Vol. 15 Issue 6, pages 392-403, 1996, ISSN 02786125

[Moon et al., 1997] Hyeong-Soon Moon, Suck-Joo Na, "Optimum design based on mathematical model and neural network to predict weld parameters for fillet joints", Journal of Manufacturing Systems, Vol. 16 Issue 1, pages 13-23, 1997, ISSN 02786125

[Murray, 2002] P. E. Murray, "Selecting parameters for GMAW using dimensional analysis", Welding Journal, Vol. 81 Issue 7, pages 125-131, 2002, ISSN 00432296

[Nielsen et al., 2003] Anders H. Nielsen, Arne B. Hansen, Jørgen Toft, Søren F. Ørts, "Calibration (AAU) Version 2.0", Student project from Department of Production, Aalborg University, 2003

[Nielsen, 2003] Anders H. Nielsen, "Udvikling af generelle interfaces i et sensorbaseret styresystem til robotiseret lysbuesvejsning", Student project from Department of Production Aalborg University, 2003

[Nonaka, 2001] Ikujiro Nonaka, David Teece, "Managing industrial knowledge : creation, transfer and utilization", Sage publications, 2001, ISBN 0-7619-5498-8

[Orye, 2005] Hans Christian Kjeldsen Orye, "Sensor based welding automation modelling: Including a special developed low-cost temperature imaging system", PhD-thesis, Department of Production Aalborg University Denmark, December 2005.

[Peng et al., 2000] Pai Peng, Jinsong Tian, Lin Wu, Ming Da, "An intelligent hybrid system of welding parameters for robotic arc welding task-level off-line programming", Intelligent Systems in Design and Manufacturing III, Proceedings of SPIE, Vol. 4192, 2000, ISSN 0277-786.

[Rippey, 1997] W. G. Rippey, J. A. Falco, "The NIST Automated Arc Welding Testbed", Proceedings of the 7th International Conference on Computer Technology in Welding, San Francisco, CA, July 8-11, 1997

[Rippey, 2004] William G. Rippey, "A Welding Data Dictionary", NISTIR 7107, National Institute of Standards and Technology, March 2004

[Ropohl, 1975] Günter Ropohl, "Systemtechnik – Grundlagen und Anwendung", Carl Hanser Verlag München Wien, 1975, ISBN 3-446-11829-2

[Rosenblatt, 1958] F. Rosenblatt, "The perceptron: A probabilistic model for information storage and organization in the brain". Psychological Review 65, pages 386–408, 1958

[Rumelhart et al., 1986] D. E. Rumelhart, G. E. Hinton, R. J. Williams, "Learning internal representations by error propagation", Parallel distributed processing: Explorations in the microstructure of cognition, Vol. 1, MIT Press, pages 318-362, 1986, ISBN 0-262-18120-7

[Serway, 1996] Raymond A. Serway, "Physics : For scientists & engineers with modern physics", Saunders college publishing, ISBN 0-03-015654-8

[Sheu et al., 1999] Hsin-Teng Sheu, Wu-Chih Hu, "Multiprimitive segmentation of planar curves-a two-level breakpoint classification and tuning approach", Pattern Analysis and Machine Intelligence, Vol. 21 Issue 8, pages 791 -797, 1999, ISSN 01628828

[Smartt et. al. 2003] Herschel B. Smartt, Kevin L. Kenney, Charles R. Tolle, "Intelligent Control of Modular Robotic Welding Cell", ASM Proceedings of the International Conference: Trends in Welding Research, 2003, pages 985-990, ISBN 0-87170-780-2

[Smartt et al., 2006] H. B. Smart, E. D. Larsen, D. P. Pace, R. J. Bitsoi and C. R. Tolle, "Design of a robotic welding system", Proceedings of the 7th International Conference on Trends in Welding Research, pages 623-628, 2006, ISBN 978-0-87170-842-7

[Suga et al., 1994] Y. Suga, M. Naruse, T. Tokiwa, "Application of neural network to visual sensing of weld line and automatic tracking in robot welding", Welding in the World, Le Soudage Dans Le Monde, Vol. 34, pages 275-282, 1994, ISSN 00432288

[Tarng et al., 2002] Y. S. Tarng, S.C. Juang, C.H. Chang, "The use of grey-based Taguchi methods to determine submerged arc welding process parameters in hardfacing", Journal of Materials Processing Technology, Vol. 128 Issue 1-3, pages 1-6, 2002, ISSN 09240136

[Tay et al., 1997] K. M. Tay, C. Butler, "Modelling and optimizing of a MIG welding process - a case study using experimental designs and neural networks", Quality and Reliability Engineering International, Vol. 13 Issue 2, pages 61-70, 1997, ISSN 07488017

[Tulving, 1985] Endel Tulving, "How many memory systems are there?", American psychologist, Vol. 40, no. 4, pages 385-398, 1985

[Walpole et al., 2002] R. E. Walpole, R. H. Myers, S. L. Myers, K. Ye, "Probability & statistics for engineers & scientists", 7. ed., Prentice Hall, 2002, ISBN 0-13-098469-8

[Welding Encyclopedia, 1997] "Jefferson's Welding Encyclopedia", American welding society, 18th. Edition, 1997, ISBN 0-87171-506-6

[Yanhong et al., 1994] Wei Yanhong, Zhang Xiuzhi and Tian Xitang, "An expert system for generating welding procedures of boilers and pressure vessels", Welding in the World, Vol. 34, pages 381-388, 1994, ISSN 0034-2288.

[Yeasin et al., 2000] Mohammed Yeasin and Subhasis Chaudhuri, "Towards automatic robot programming: learning human skill form visual data", IEEE Transactions on systems, man and cybernetics – part B: cybernetics, Vol. 30, no. 1, pages 180-185, 2000

Standards

[DS/EN 1011-1] DS/EN 1011-1, "Welding – Recommendations for welding of metallic materials - Part 1: General guidance for arc welding", 1. ed., 1998

[DS/EN 1011-2] DS/EN 1011-2, "Welding – Recommendations for welding of metallic materials - Part 2: Arc welding of ferritic steels", 1. ed., 2001

[DS/EN 1011-3] DS/EN 1011-3, "Welding – Recommendations for welding of metallic materials - Part 3: Arc welding of stainless steels", 1. ed., 2001

[DS/EN 1011-4] DS/EN 1011-4, "Welding – Recommendations for welding of metallic materials - Part 4: Arc welding of aluminium and aluminium alloys", 1. ed., 2001

[IEC 60974-1] International Electrotechnical Commission, “IEC 60974: Arc welding equipment - Part 1: Welding power sources”, 3. ed., 2005

[ISO 5817] DS/EN ISO 5817 “Welding – Fusion-welded joints in steel, nickel, titanium and their alloys (beam welding excluded) – Quality levels for imperfections (ISO 5817:2003)”, 2. ed., 2005

Software and products

[Clemmentine] Clementine® 7.0 User’s Guide, User’s Guide available when installing software (www.spss.com/clementine), 2002.

[Hugin] Hugin Expert, Hugin Help available when downloading and installing software (www.hugin.com), Hugin Researcher version 6.2, 2003.

[IWA] IWA A/S, Intelligent Welding Automation, Datasheet on IPAC: Intelligent planning and control, Datasheet available from download (www.iwa.dk).

[Migatronic] Svejsemaskinefabrikken Migatronic A/S, Datasheet on the BDH 550 STB PULS SYNC, document 79536008.

[Rocol] ROCOL, Flawfinder dye penetrant: NDT crack detection spray, Technical data, Rocol Lubricants, 2004.

[SamIam] SamIam, Sensitivity Analysis, Modeling, Inference and More, Developed by the Automated Reasoning Group at UCLA, version 2.2, Datasheet available from download (http://reasoning.cs.ucla.edu/samiam/).

[VirtualArc] Dick Skarin, Brith Claesson and Göran Bergling, “VirtualArc: Transform welding from ‘black art’ to practical science”, documentation on the commercial software from ABB, 2005.

Abbreviations

BB	Back Bead.
CAD	Computer-Aided Design
CTWD	Contact To Workpiece Distance (Illustrated in appendix B figure b.3).
DAG	Directed Acyclic Graph.
FEM	Finite Element Model.
GMAW	Gas Metal Arc Welding.
IDEF	Integrated DEFinition methods. $IDEF_0$ is a functional modelling method.
MAG	Metal Active Gas.
MAP	Maximum A Posteriori: MAP estimation is the Bayesian inference operation; it corresponds to finding the posterior's maximum.
MIG	Metal Inert Gas.
NP	Non-deterministic Polynomial-time.
NP-hard	Non-deterministic Polynomial-time hard.
PI control	Proportional Integral control.
QP	Quality Parameters.
TCP	Tool Centre Point.
WBB	Welded Back Bead.
WF	Weld Face.
WV	Workpiece Variables
WWF	Welded Weld Face.

Appendix A

Process knowledge in a production system

An analysis is made to find possible applications for automatic learning methods for modelling and control of industrial processes. To make modelling and control of industrial processes, process knowledge is required and it is a key issue, in this analysis, to determine how different kinds of process knowledge can be applied.
This appendix contains a description of an architecture for a small-batch-size and one-of-a-kind production system. The architecture is analysed to determine where process knowledge can be applied and where automatic learning methods can be applied to model process knowledge. Furthermore, a review of the field of machine learning is given to evaluate and classify the methods. Finally, state of the art is identified for applying different knowledge sources for making modelling and control of industrial processes. The industrial process in focus is welding.
The appendix is structured in the following way:

Section A.1
An architecture of a complete productions system is described to disclose functions in a system for small-batch-size and one-of-a-kind production.

Section A.2
The architecture is used to identify where process knowledge is applied in a production system.

Section A.3
Evaluation of different machine learning methods is made to classify their utilisation and to find places in a production system where they can be applied for modelling process knowledge.

Section A.4
Modelling process knowledge to make process-planning models is selected for further in depth analysis. The analysis is carried out according to the following points:

- Different ways of applying a process-planning model to control a production process.
- State of the art of how empirical and analytical knowledge sources are used for process-planning and control.

A.1 Architecture of a production system

The architecture of a system with small-batch-sizes and one-of-a-kind production is described. The characteristics of small-batch-sizes and one-of-a-kind production systems compared to many other production systems is that the product changes from order to order and the number of identical products in an order is small or one. This means that some functions are performed by a higher frequency. These functions are e.g. “Design product”, “Plan production” and “Prepare production”.

The architecture for modelling the production system is described using a functional system architecture because it is well suited for a system with functions transforming materials and information to products as output. The modelling technique used for this purpose is $IDEF_0$.

The described architecture of a productions system is made as generic as possible to make it applicable for a wide range of manufacturing companies. Later identification of possible improvements should then be suitable for general manufacturing companies with small-batch-sizes and one-of-a-kind productions. The attention of the modelling is focused on the "Prepare production" and "Control production" functions in a production system and these functions are described more thoroughly when decomposing the architecture. Therefore a further decomposition of the "Contracts negotiation" and "Product design" tasks with product specification and modelling is omitted.

This architecture is made as consistent as possible with the architecture proposed by [Holm et al., 1994]. It focuses on the fine planning and control of the production and the production processes.

This architecture is the base for identifying where process knowledge is applied in a production system to develop solutions which reduce the manual tasks to produce process knowledge in the small-batch-sizes and one-of-a-kind production systems.

A.1.1 A-0 Small-batch-sizes and one-of-a-kind manufacture

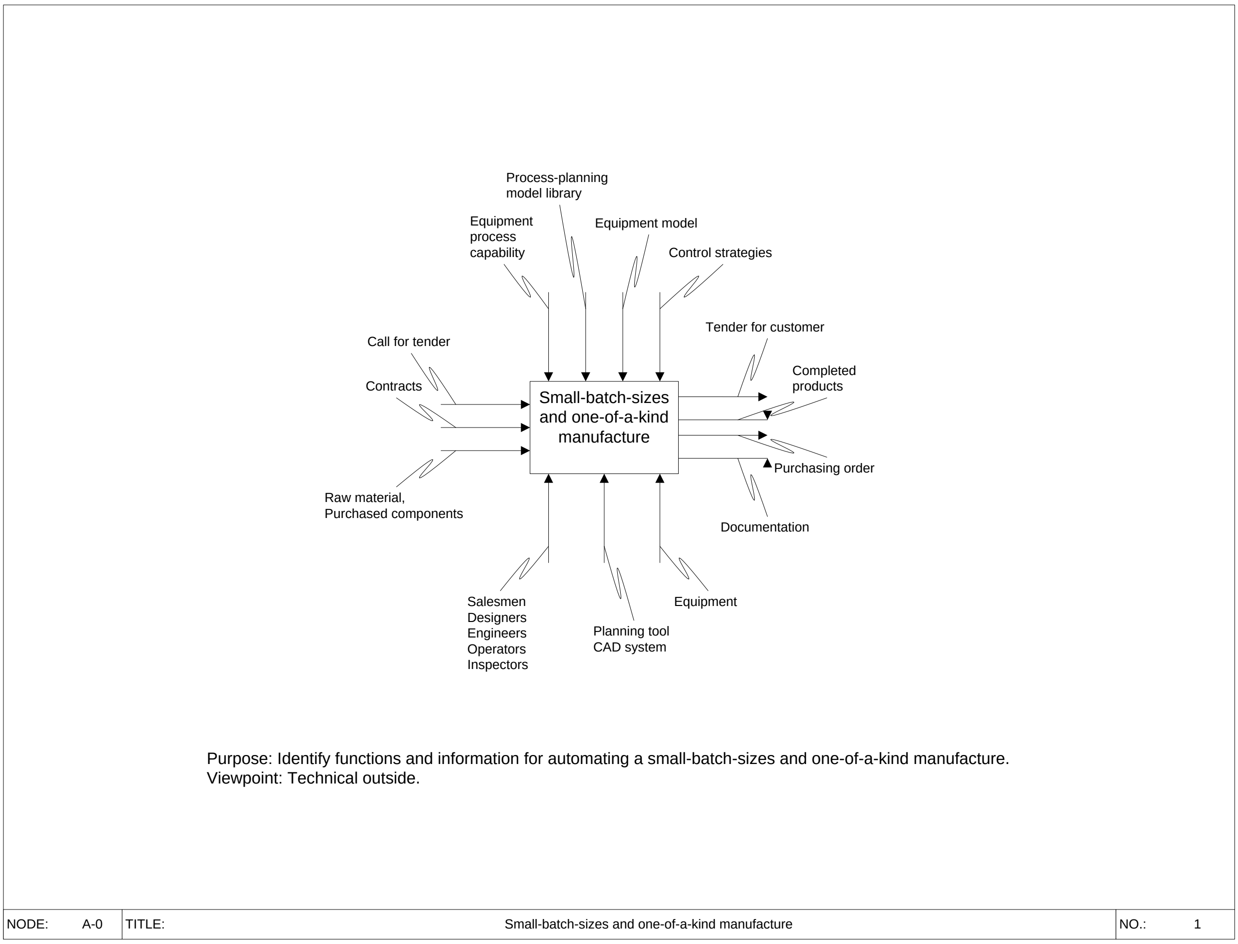


Figure A.1: Node A-0.

Figure A.1 shows the function "Small-batch-sizes and one-of-a-kind manufacture" which represents the production system.

The inputs to the system are:

- A customer request for a tender for a given product/delivery is included in “Call for tender”.
- Product specifications, delivery time and price are included in “Contracts”.
- Raw materials and purchased components for use in the production.

The outputs from the system are:

- Completed products.
- Prize, due date, product specification and delivery specifications are all described in “Tender for customer”.
- “Purchasing order” includes contract negotiation with sub contractor and purchasing of raw materials.
- Documentation of the quality and requirements on completed products.

The constraints of the system are:

- The general capability of the production equipment including available processes, dimensional limits, which are described in the “Manufacturing capabilities”.
- The capability and limits of single or groups of equipment and production parts taking into account time, quality, cost, which are included in the “Equipment process capability”.
- Models of the processes, which are described in the “Process-planning model library”, are described more thoroughly later in this appendix.
- CAD-models and kinematics for the equipment are described in the “Equipment model”.
- Different strategies for scheduling and prioritizing tasks in the production are described in the “Control strategies”.

The mechanisms in the system are:

- Salesmen, designers and engineers carry out manual tasks in many functions in the production system.
- Planning tool and CAD system help salesmen, designers and engineers to carry out their tasks.
- Equipment and operators carry out tasks in the production.

A.1.2 A0 Small-batch-sizes and one-of-a-kind manufacture

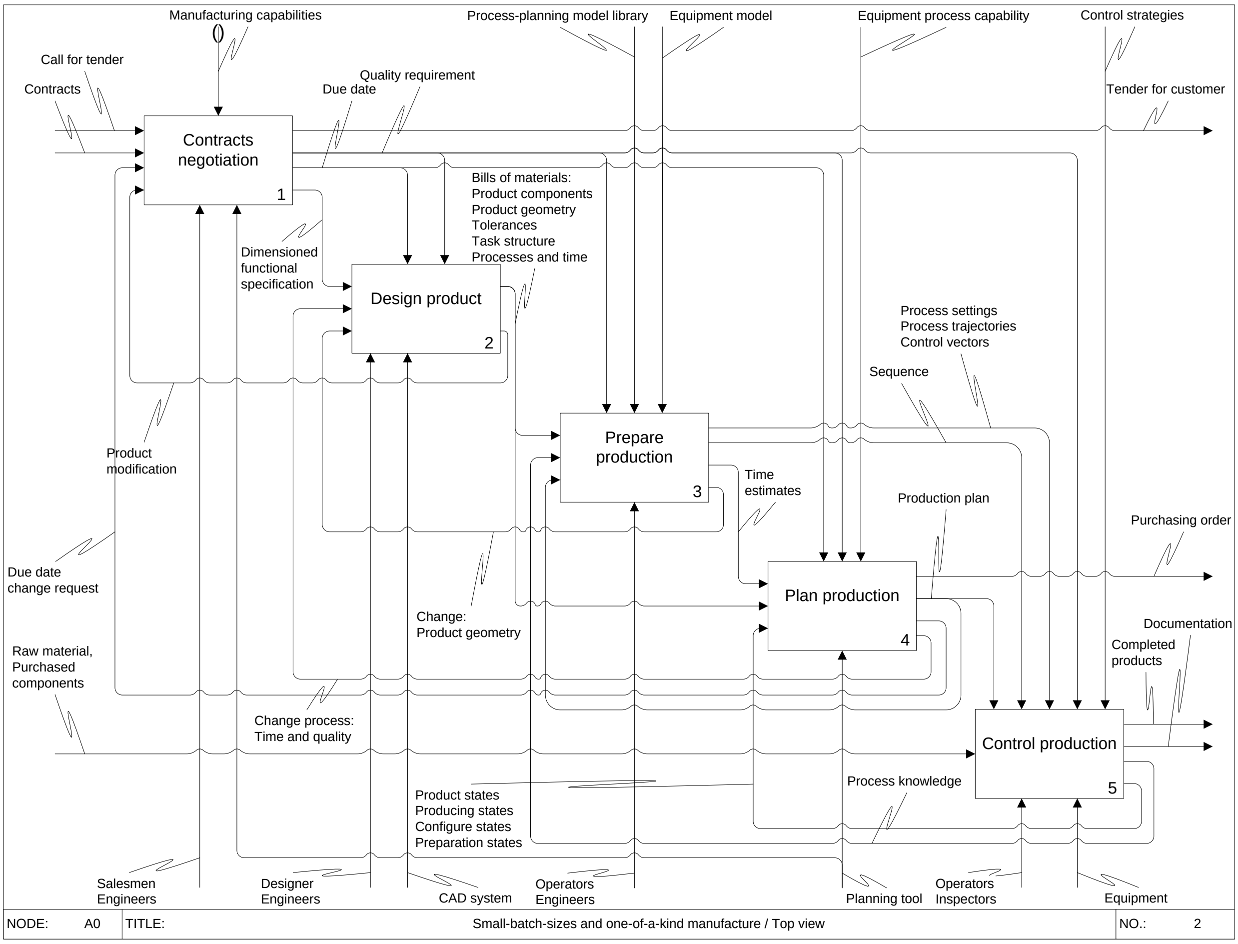


Figure A.2: Decomposing of A0.

The functions shown in figure A.2 are to some extent carried out in parallel and they are described beneath.

In the function “Contracts negotiation” the contact to the customer is handled. When a customer makes a “Call for tender” then the “Contracts negotiation” function transforms the request to a “Tender for customer” with price, due date and specifications. The “Tender for customer” is made under the constraints of the manufacturing capabilities and the actual state of the manufacturing capabilities. A contract can be negotiated with the customer and the “Contracts negotiation” function produces due dates, quality requirements and a dimensioned functional specification. The “Contracts negotiation” function can modify contracts with a customer if a request for product modification or for due date change is given.

The function “Design product” is where the product is designed in details with calculations of strength and performance of product and CAD models of the geometry. A bill of materials is made containing product components, drawings of the product geometry, tolerances, task structures and a list of processes with time and cost. Request of changes in the product geometry in order to carry out or optimize the production processes and update the time, quality and costs of the production processes is input to the “Design product” function. This input can lead to product modification and change in the bill of materials.

In the “Prepare production” function the process settings, trajectories or control vectors are generated for the production equipment together with a trajectory sequence and an operation schedule. When these plans are generated an estimate of the production time can be calculated for the “Plan production” function. To make the “Prepare production” function the bill of materials, quality requirements, process-planning models, models of the equipment are necessary. When automating the process it is very process specific how many of these models and information are required.

In the function “Plan production” a production plan is generated and updated based on the basis of bills of materials, time estimates of process time from the “Prepare production” function, known equipment process capability, due date and the product, producing, configuration and preparation states of the “Control production” function. Furthermore, orders are purchased from sub contractors. The production plan is made in different detail levels depending on if the production task is carried out manually or automated and on how the production tasks are organized. The “Plan production” function is often highly automated by software planning tool solutions.

In the “Control production” function the raw materials and purchased components are transformed into finished products. Constraints control how the “Control production” function is carried out and feedback of the states are sent to the “Plan production” function. Operators and software tools make fine planning of the production in this function.

Further decomposing of the system is carried out by the functions “Prepare production” and “Control production”. These are selected because “Prepare production” is where further investigations of the project are made and “Control production” is very dependent on “Prepare production”.

A.1.3 A3 Prepare production

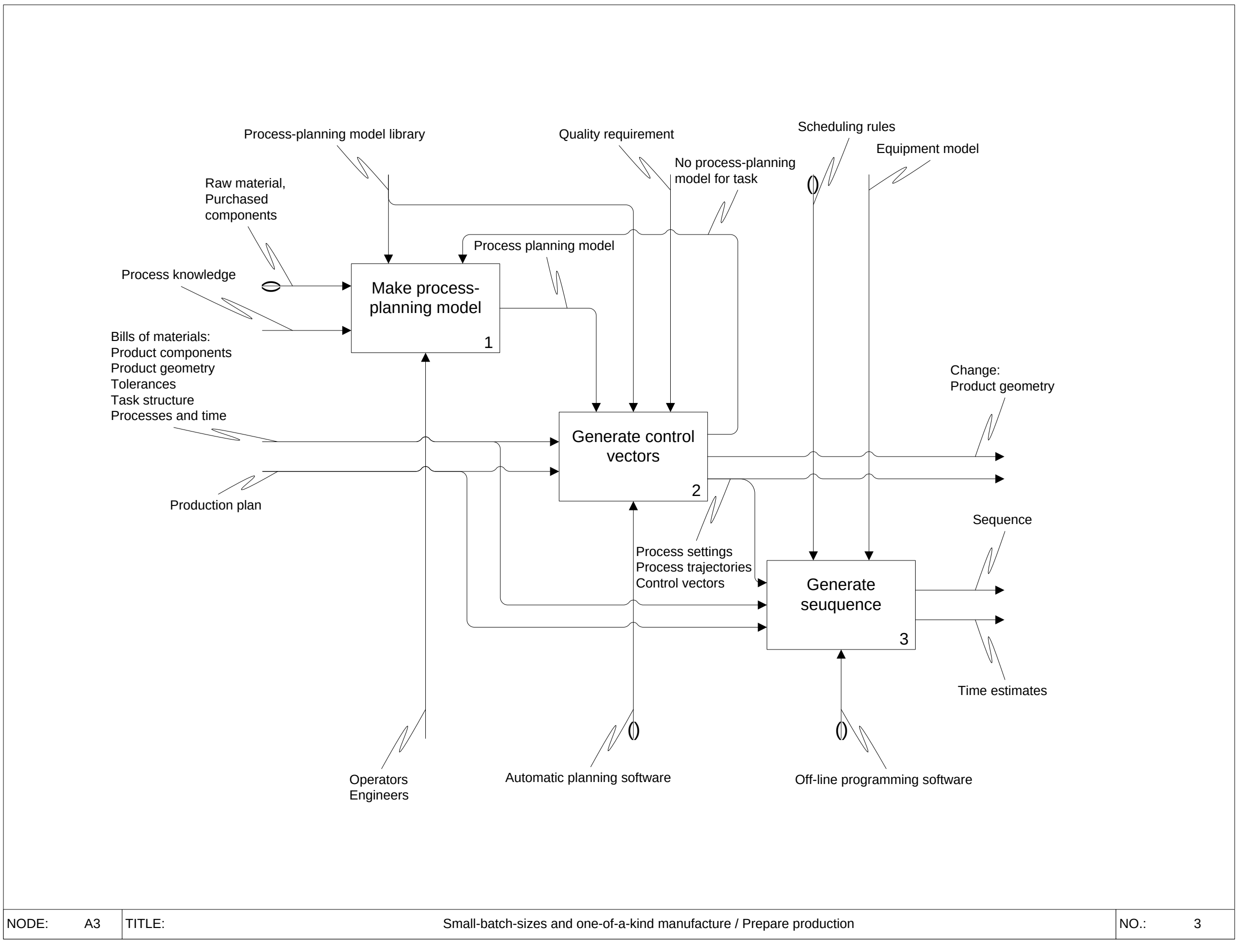


Figure A.3: Decomposing of A3.

The decomposing of the “Prepare production” function shown in figure A.3 consists of three functions, which are described below.

The “Make process-planning model” function makes a new process-planning model when it is requested. How the process-planning model is made depends on what type of process-planning model is requested. Producing process-planning models basically demands empirical knowledge from experiments, knowledge from experienced operators or analytical knowledge from experts. The knowledge sources describe the process or determine relations of the process so process settings, process trajectories and control vectors can be produced. How process-planning models are made is described later in this appendix.

The “Generate control vectors” function finds the production tasks in the production plan, which requires process settings, process trajectories or control vectors to be executed. For each of these production tasks the required information from the bill of materials is used together with the quality requirements and process-planning models from the process-planning model library to generate process settings, process trajectories and control vectors. How the generation of the process setting, trajectories and control vectors are made depends on the production task, how well the process is understood and how reliable the process-planning models are. It is more thoroughly described later in this appendix. Automatic or semiautomatic software can carry out the “Generate control vector” function. If a suitable process-planning model is not found in the process-planning model library for the “Generate control vector” function then a request is made to make a process-planning model.

In the “Generate sequence” function a sequence of the process trajectories and operations is made for the production tasks in the production plan. Equipment models are used to check the movements, check for collisions and time estimation is made.

A.1.4 A5 Control production

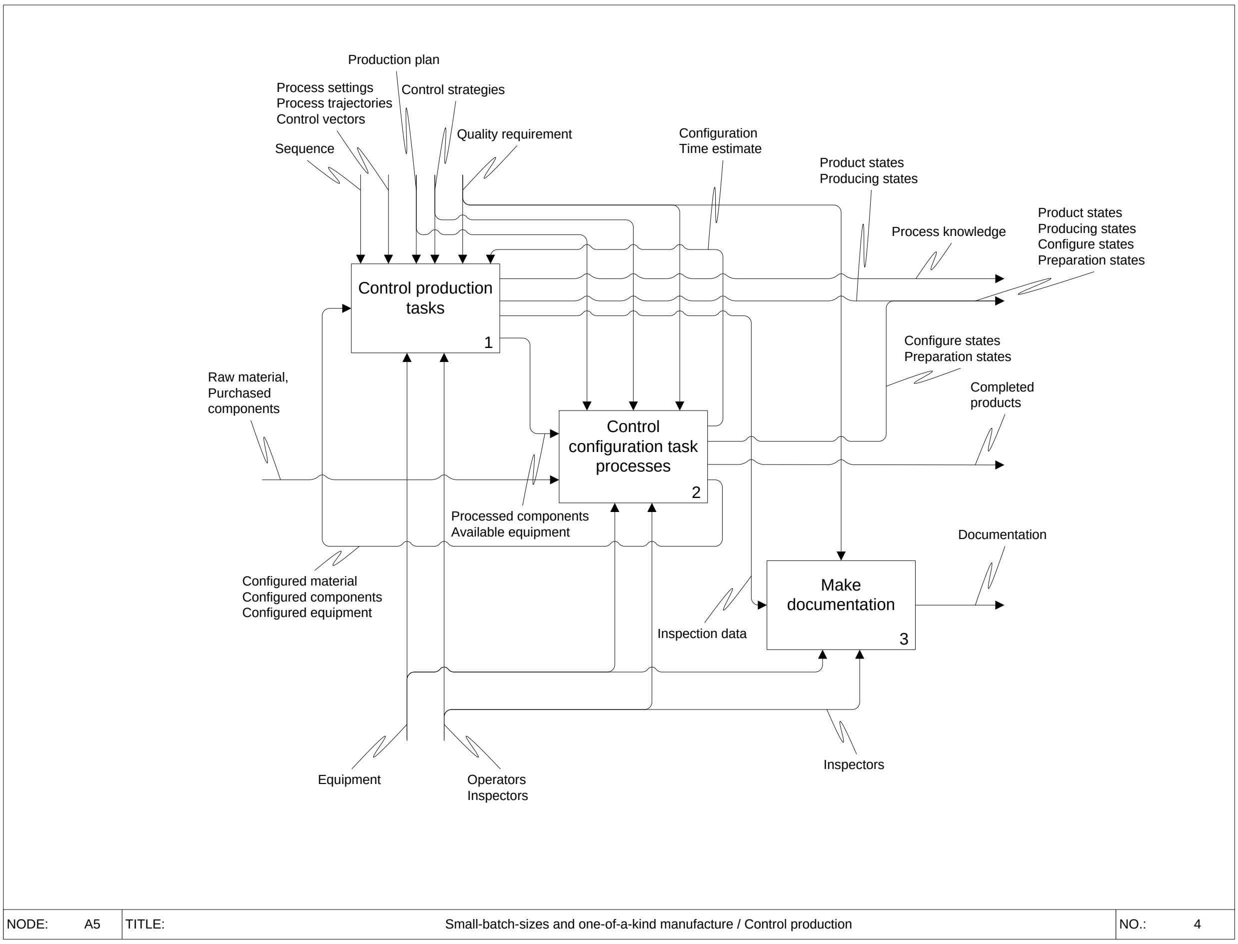


Figure A.4: Decomposing of A5.

Decomposing of the “Control production” function is shown in figure A.4 and it consists of three functions, which are described below.

The “Control production tasks” function controls the production tasks in the production plan and schedules the trajectory sequence and operation schedule after given control strategies. The process settings, process trajectories and control vectors are executed from the trajectory sequence and operation schedule. Materials are input to the function, and output is processed materials, information about available equipment and inspection data. The production tasks in “Control production task” can be made manually, automatic or combined.

The “Control configuration task processes” function is controlled by the production plan and the control strategies. Raw materials and purchased components are input to the function and the function makes all the preparatory work for the “Control production task” function so raw material is transformed into completed products.

In the “Make documentation” function inspectors verify if the inspection data fulfils the quality requirements. The output is documentation of the quality of the completed products.

A.2 Identification of places to model process knowledge using machine learning

Places are identified in the production system where it is possible or could be possible to use methods from machine learning to model process knowledge. Examples are given in literature of where machine learning and other methods for modelling process knowledge are applied. The descriptions are categorized into five tasks in the architecture of a production system.

A.2.1 Contracts negotiation A1

For the “Contracts negotiation” function process knowledge is not normally required because this knowledge is too specific for carrying out the function. But in some cases process knowledge could be useful to help estimate e.g. quality and price for a production task required by a customer.

A.2.2 Design product A2

The “Design product” function decides which production processes to use. The designer needs to have some process knowledge to make a design which can be produced and which reduces factors as e.g. costs. The functions “Prepare production” and “Plan production” could be asked but that requires a detailed design. A possible use of machine learning to help carry out this function is described below.

Designer support with design guidelines using process knowledge

When designing a new product the designer has to choose different parameters e.g. shapes, dimensions and materials. Choosing different values of the parameters influences which production processes are to be used and the performance of the processes. The performance of the processes is e.g. quality and strength of the products, and it requires process knowledge to predict. An example of a system using machine learning is described in [Clausen et al., 2001]. The system helps to design a ship from the parameters: breadth, length, speed, depth, draught, displacement and loading capacity. The system uses simple regression, Bayesian- and artificial neural networks to learn the function of ship design where 87,000 ships are used as empirical data. When a new ship is designed the required design parameters are entered in the design system and the rest of the design parameters are estimated.

A.2.3 Prepare production A3

In this function the process knowledge is available from the process-planning model library, operators, engineers and scheduling rules. In the function A31 “Make process-planning models” operators and engineers produce process-planning models using their knowledge or by carrying out experiment to produce new process-planning models. In the function A32 “Generate control vectors” the process-planning models are used to make process settings, process trajectories and control vectors for the tasks in the production plan. In function A33 “Generate sequence” the single tasks are put into a sequence of tasks. To do this scheduling rules are used, which can contain process knowledge to e.g. secure the quality of a task sequence. Possible use of machine learning methods is described below.

Use process-planning models to control production equipment

In function A31 “Making process-planning models” the process-planning models are made. They can be made from different knowledge sources where empiric and analytic knowledge is used. In this task the construction of process-planning models have to:

- Reduce the number of experiments for making process-planning models.
- Represent process-planning models so they can be reused and expanded to cover a larger span of processes and settings.

Machine learning methods are in many places used as process-planning models. Many examples of making process-planning models are described in the literature with use of different methods from machine learning. [Cook et al., 1995] use artificial neural network for making direct and inverse process-planning models for welding. Experiments are made where 2 quality weld parameters and 4 control welding parameters are measured, and artificial neural network with a direct and inverse process-planning model is trained. [Yanhong et al., 1994] describe a system where welding knowledge is represented in databases so it can be used in an expert system. First, the data is treated so it is systematic represented for use in a knowledge base. To make the knowledge base two methods are used. The first is a decision tree (ID3 algorithm) and the second is a method for learning sets of rules (AQ algorithm). The two methods summarize the knowledge from the treated data and the methods can then be used as expert systems for welding. [Moon et al., 1996] describe a system to decide welding parameters. The system uses a trained artificial neural network as an inverse process-planning model to make welding parameters from geometrical requirements. A fuzzy rule base is built to check the welding parameters for weld defects and it is built using process windows where feasible welding conditions are found. If welding defects occur then a second fuzzy rule base is built that suggests adjustments of the welding conditions to avoid welding defects. In [Moon et al., 1997] the same neural network, as used in [Moon et al., 1996], is trained as an inverse process-planning model. Training data experiments are made using a 2^{n-1} fractional factorial design. [Peng et al., 2000] describe a system for welding. See figure A.5. From decided workpiece parameters as e.g. material, thickness, joint and groove the system uses a hybrid reasoning system to select e.g. welding method and welding wire. The reasoning system combines rule-based reasoning and case-based reasoning, and first it searches for matching cases and if none are found it goes on reasoning. From the selected parameters a trained artificial neural network is used to select control variables.

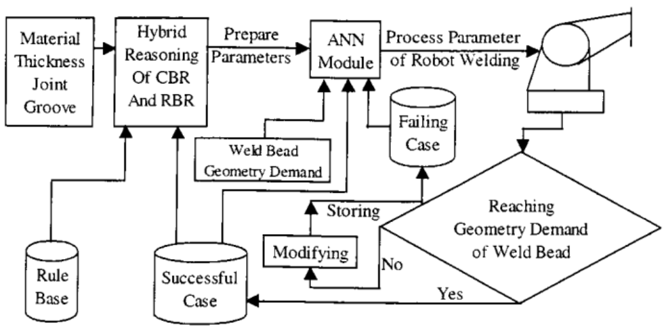


Figure A.5: System architecture. [Peng et al., 2000]

[Smartt et al., 2003] and [Smartt et al., 2006] present an architecture of an intelligent machine for a gas metal arc welding cell. Biological models of social insects inspire the architecture design. The idea is that the intelligent machine consists of a number of machine functions that are carried out in a distributed system. Various agents handle the machine functions and they have an incorporated knowledge expressed as fuzzy logic rules and behaviour of how to perform their local task. The use of fuzzy logic allows the use of back propagation to learn the system. The process-planning model is split up into each agent which by rules and learning can carry out its task.

Find optimal control variable from process-planning models

In function A32 “Generate control vectors” process settings, process trajectories and control variables for a task are generated. From the requirements to the process a process-planning model is used to determine the settings of the parameters. It is possible that more parameter settings fulfil the quality requirements. A solution has to be found that optimizes the parameter setting so the consumption of e.g. cost and time is reduced. [Harwig, 1997] and [Harwig, 2000] describe a systematic experimental strategy to make a welding productivity window where welding parameters can be selected to achieve a high productivity. Equations for the heat input and the productivity are constructed and weld tests are made to observe the quality of the weld. From the equations and the weld tests a welding productivity window is made showing the optimum welding parameters.

Schedule task using process knowledge

In function A33 “Generate sequence” a trajectory or a schedule is made for a set of tasks. A number of constraints could influence the schedule, e.g. process capabilities, process bindings, equipment bindings and limits. When generating the trajectory or schedule it also has to be optimized in order to minimise e.g. costs and time. Methods from machine learning can be used to make the scheduled task by first making a schedule and then optimize it according to the required parameters.

A.2.4 Plan production A4

In the “Plan production” function a production schedule is made and continuously updated. Using knowledge about the processes can increase the accuracy of the time estimates. A production plan can first be made when bills of materials are made and process times are known. For use in making the production plan, the support of using machine learning is described in the following.

Estimating production- and changeover time using process knowledge

Making the production plan requires e.g. estimates of production- and changeover time and selection of the machinery to use if there are more choices. If there is no fixed information available then a method from machine learning with knowledge of the production processes could be used to give estimates of the requested production and changeover time.

A.2.5 Control production A5

In function A51 “Control production tasks” the production processes are carried out using the process knowledge in the process settings, process trajectories and control variables. From this function inspection data is delivered to the function A53, which together with process knowledge and quality requirements can generate documentation of the quality.

Train and adapt process-planning models during production

During production, carried out in function A51 “Control production tasks”, information about the process is generated. Data is saved and can be used for continuing development and adjustment of the process-planning models which is possible if also the output for a set of input parameters is given e.g. the quality parameters from the process. The benefits are that the space of process-planning models is enlarged and the process-planning models can be adapted to slowly changes of parameters not included in the process-planning model. The slowly changing parameters could for example be wearing and weather conditions e.g. temperature and humidity changes. [Peng et al., 2000] describe a system where the welding results are classified as successful or failing and stored in two separate databases. See figure A.5. The databases are used for training of an artificial neural network and then the artificial neural network is continuously updated.

Interpret sensor output using process knowledge

Sensors can be used in function A51 "Control production tasks" to measure some parameters during or after the process execution. To interpret the sensor output some knowledge about the process is often required. Machine learning methods have been used for this interpretation and some examples are given in the literature. [Cook et al., 1995] describe a system with laser scanning for seam tracking and quality control. The laser scanner is placed in front of the welding torch. The scanned profiles are interpreted by an artificial neural network that determines the position of the weld seam which is transferred to a position controller. After the execution of the welding the laser scanner scans the welded seam. From this scanning the weld profile height, given by a number of points, is input to an artificial neural network that determines the location of the edges, undercuts and the crown of the weld. The principle is illustrated in figure A.6. This can be used for quality control.

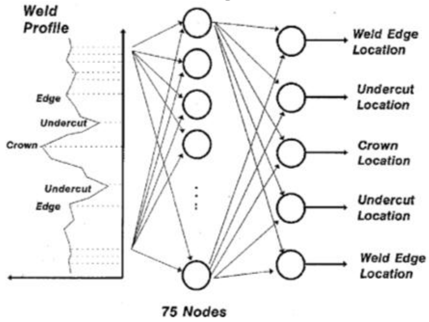


Figure A.6: The principles of using an artificial neural network for detecting the edges, undercuts and crown from a weld profile. [Cook et al., 1995].

Design a control system using process-planning models

When a control system for process control has to be designed then a model of the process is required to design the control. A process-planning model using machine learning could be built and used to design the control system.

Use process knowledge to detect errors, to measure and to record the quality

In function A53 "Make documentation" documentation of the quality is produced, where the quality requirements are depending on the quality level of the construction. The quality level is given in standards as e.g. ISO. An inspector makes the documentation based on inspection data produced during and after the production using different methods which for welding can e.g. be x-ray and ultrasound scanning. The inspector can receive help and advises from a system which uses process knowledge, quality requirements and inspection data to point out critical points to inspect or to make reports documenting the quality. This can reduce the costs of inspections. An example is given in the literature. [Maul et al., 1996] describe a method using statistics to detect if the quality is achieved. The parameters that affect the quality of gas metal arc welding are current, voltage, travel speed, wire feed speed and gas flow. If any of these parameters operate outside some predetermined range of values then the welding quality is theoretically affected. By tracking the parameters and ensuring that they are inside their predetermined range then a high welding quality can be guaranteed. By using control charts limits can statistically be set for the parameters. [Dilthey et al., 2003] present a system using artificial neural network, fuzzy logic and genetic algorithms to monitor the welding process and predict quality parameters described geometric. Voltage and current are monitored and together with a description of the welding task. It is described that the system can be applied online both for checking and control of the welding control variables.

A.3 Machine learning

Further investigations in the field of machine learning and data mining was carried out because these methods seem to be a successful approach for further development of process-planning models for industrial processes. The background for the field of machine learning and data mining is that is has rapidly grown since the computational power, storage of large amounts of data has dropped in cost, and collection of data over computer networks is increased in ease. For machine learning and data mining a lot of algorithms have been developed and they are shown useful in many kinds of problems and they have been commercially implemented in many applications. The algorithms are limited to work best for data described by numeric or symbolic features and where data is collected to a single database. These are algorithms for the first generation of machine learning and data mining. It is expected that a second generation of algorithms will be developed where the algorithms are able to handle more data sources and more types of data. For example data containing numeric and symbolic features together with text and image features and even with human hypotheses. [Mitchell, 1999].

A broad range of machine learning methods exist together with algorithms for implementing them. The advantages, which are not available in the empirical and analytical methods, are investigated. Advantages of some of the machine learning algorithms are:

- Possibilities to formalise some of the knowledge sources which are hard to formalise, e.g. knowledge from operators.
- It is possible to mix different knowledge sources and use them for modelling and training.

A basic model of how a learning method works is shown in figure A.7. A program has a certain performance in doing a task, but applying various kinds of experience is training the program and the knowledge from the experience is stored in the program. The program is dependent on the quality of the experience applied for training if it has a better performance in doing the task after training.

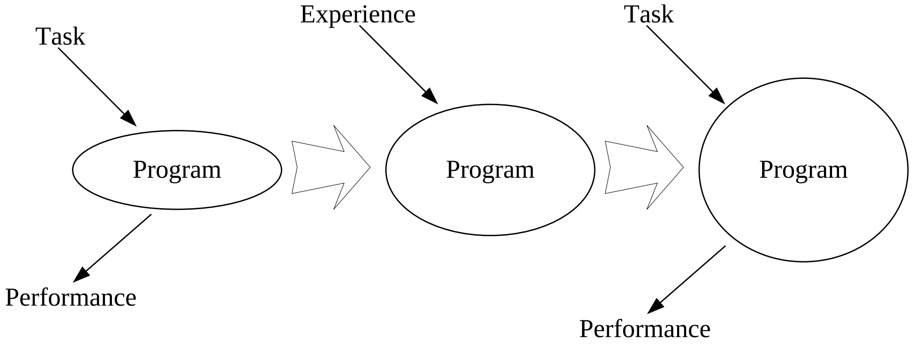


Figure A.7: A program has a performance measure P for solving a given class of tasks T. By learning from experience the program improves its performance P for solving the tasks T.

The learning obtained using machine learning results in a persistent change in the memory of the machine learning program. This is a difference compared to closed loop control, which is described in task “A.4.1 Control of production process”, where no learning takes place but instead adaptation. For some machine learning methods it is possible to build in adaptation to cope with e.g. changing conditions in the environment.

Machine learning methods have different applications from which they can be classified. The machine learning methods can be split into the following categories:

- Classification (Pattern recognition): The process of forming a distribution of objects into classes where the forming process is made based on the objects attributes.
- Decision-making: The process of reaching a decision based on incomplete information.
- Optimizing: The search to find a minimized or maximized solution to the problem in the problem space.

A.3.1 Evaluating methods from machine learning

In the field of machine learning a number of methods are developed, and a number of these methods are selected for investigation of their usability in the described functions in a production system. These methods are selected because they cover a range of the methods from the field of machine learning, they are prospective usable and they are commonly used and documented. The following methods from machine learning are investigated:

- Decision trees
- Bayesian network
- Decision graphs
- Artificial neural network
- Instance-Based learning
- Genetic algorithms

For the listed methods it is described what types of problem they can solve.

Decision trees

Decision trees make classification and they classify a discrete value function defined over discrete valued instances. A tree structure is built based on all the learning instances and the tree structure is used to classify incoming instances. The method is robust to noisy training data [Mitchell, 1997].

Bayesian network

Bayesian network makes classification and decision support. From modelling and training a probabilistic and directed network is built. It classifies discrete and real-valued functions. The method is robust to noisy training data. Probabilities for decision recommendations can be calculated. The method can incorporate knowledge from operators and experts, who provide probabilities depending on their belief. It is possible to make updates of the beliefs in the network during execution when more knowledge is generated [Mitchell, 1997] [Jensen, 2001].

Decision graphs

Decision graphs are for decision support and optimisation. From modelling and training a probabilistic and directed network is built which includes utilities. The method can handle that a decision changes the state of the described system. Utilities can be entered in the model and be the base for taking decisions and for optimising [Jensen, 2001].

Artificial neural network

Artificial neural network is for classification and the method is inspired by the biological learning system. It classifies real and vector-valued functions over discrete and continuous instance [Mitchell, 1997].

Instance-Based learning

Instance-Based learning is for classification. The method stores instances among other instances so no training is necessary to produce an explicit description. The stored instances are used for classification of incoming instances [Mitchell, 1997].

Genetic algorithms

Genetic programming is handled under genetic algorithms. Genetic algorithms are for optimising and classification. It tries to learn a task by a fitness function and to optimise the fitness function so it is not just in a local minimum. The principle of the algorithms is to imitate biological evolution [Mitchell, 1997].

The described machine learning methods are able to solve different problems. Identification is made of which problem each machine learning method can be applied to. The identification can be seen in table A.1.

Argument for the choices:
Decision trees only classify discrete valued data and are for this reason not useful for some of the classification tasks. Decision trees are not well suited for adaptation to changing conditions and are therefore not used for “Train and adapt process-planning models during production”.
Bayesian networks can handle classification and decision making and fit for tasks with these requirements.
Decision graphs can be used for decision making and finding optimal solutions taking cost into account. It can also take action into account.
Artificial neural networks handle continuous and discrete values and are flexible for classification tasks.
Instance based learning handles continuous and discrete values and is flexible for classification tasks.
Genetic algorithms can classify and optimise and can handle continuous and discrete values.

Table A.1: Classification of which application of process modelling from a production system the method from machine learning is able to handle. C = Classification, D = Decision-making and O = Optimizing.

Method / Application		Decision trees	Bayesian network	Decision graphs	Artificial neural network	Instance based learning	Genetic algorithms
		C	C,D	D,O	C	C	C,O
Designer support with design guidelines using process knowledge	C	X	X		X	X	X
Use process-planning models to control production equipment	C,D	X	X	X	X	X	X
Find optimal control variable from process-planning models	O			X			X
Schedule task using process knowledge	O			X			X
Estimating production- and changeover time using process knowledge	C		X		X	X	X
Train and adapt process-planning models during production	C		X		X	X	X
Interpret sensor output using process knowledge	C	X	X		X	X	X
Design a control system using process-planning models	C		X		X	X	X
Use process knowledge to detect errors, to measure and to record the quality	C	X	X		X	X	X

A.3.2 The development of welding systems using machine learning

The development of systems for welding using machine learning methods has been going on for years and a number of systems have been proposed in the literature. [Bingsen et al., 1994] describe the development of expert systems in the field of welding. In the world nearly 100 expert systems are developed for welding and this number does not include development in developing countries. In China 20 expert systems have been built. The Chinese systems can be divided in the following categories:

- Procedure selector and generator (9 systems).
- Diagnostics of welding defects and prediction of weld cracking (7 systems).
- CAD of welding apparatus (2 systems).
- Assessment of structures containing defects (2 systems).

A.4 Modelling process knowledge

In an analysis of different methods to model process knowledge state of the art is investigated. Process knowledge is required many places in the production system. A very essential place, which is more thoroughly investigated, is to apply process knowledge to the task of: use making process-planning models to control production equipment. Modelling process knowledge by making process-planning models is described in the following section and it will only include industrial processes. Different strategies can be used to automate a process. It is characteristic for the strategies that the knowledge of the process is modelled in a process-planning model, so the process can be controlled. Process-planning models can be divided into the two main categories: direct process-planning model and inverse process-planning model. They are illustrated in figure A.8.

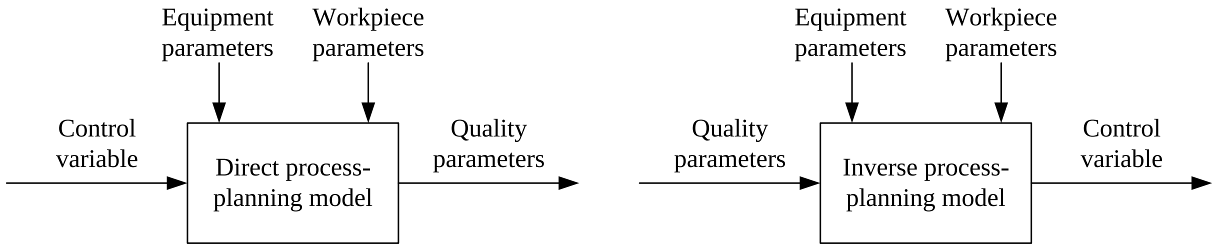


Figure A.8: Left: a direct process-planning model. Right: an inverse process-planning model.

The process-planning model has two constrains. The first constraint is workpiece parameters, which are parameters set from the geometry and materials, and they are mainly decided during the "Contracts negotiation" and "Product design". The workpiece parameters are influenced by disturbances, which e.g. are introduced in the production. The second constraint is equipment parameters, which are parameters set by the choice of production process and equipment, and they are mainly decided during the "Contracts negotiation", "Product design" and "Production planning". The equipment parameters are also influenced by disturbances.

Direct process-planning model

For the direct process-planning model the control variables are input and they are adjustable during the process execution. The output from the direct process-planning model is the quality parameters, which are the result of the process to the given input and constraints.

Inverse process-planning model

For the inverse process-planning model the input is the desired quality parameters, and the output is the control variables to achieve the desired quality parameters.

To design an inverse process-planning model for control, the direct process-planning model can be used for simulation to produce training cases. Examples of direct process-planning models are [Laurinen, 2004] who uses a model based on Bayesian network to predict the quality for spot welding and [Kim et al., 2005] who use both models based on artificial neural network and regression to predict bead geometry for welding. To control a process it is the inverse process-planning model that has to be used. The development of inverse process-planning models will be further investigated.
Both open and closed loop control can be used off-line to make a program and a reference respectively. Taken out from the architecture in figure A.2 it will look like figure A.9.

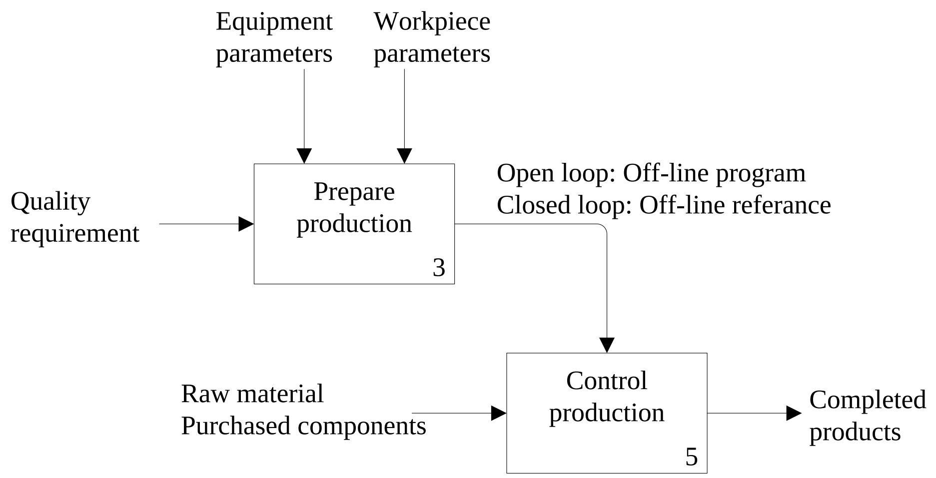


Figure A.9: Implementation of open and closed loop control.

A.4.1 Control of production processes

Control of the process can be categorized into the two main classes: open loop control and closed loop control. It is shown in figure A.10. For the open loop control and the closed loop control empirical and analytical process-planning models or combinations of these two models can be made.

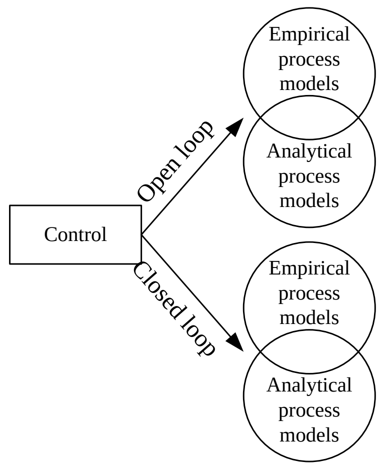


Figure A.10: Methods to control a process and the knowledge sources to built the model.

Open loop control

Open loop control, shown in figure A.11, requires that it is possible in the controller, by use of the inverse process-planning model, to describe the physical system, called the process. Furthermore, it is required to describe the equipment and also keep the disturbances from the surroundings low. From the input to the controller desired control variables are produced, which together with the disturbances from the equipment are the actual control variables to the process. The process input is the actual control variable, which should control the process to give a desired quality as output. The physical system and the process need to be controllable, which means that the desired control variables take strong enough effect on the system performance to control the quality parameters.

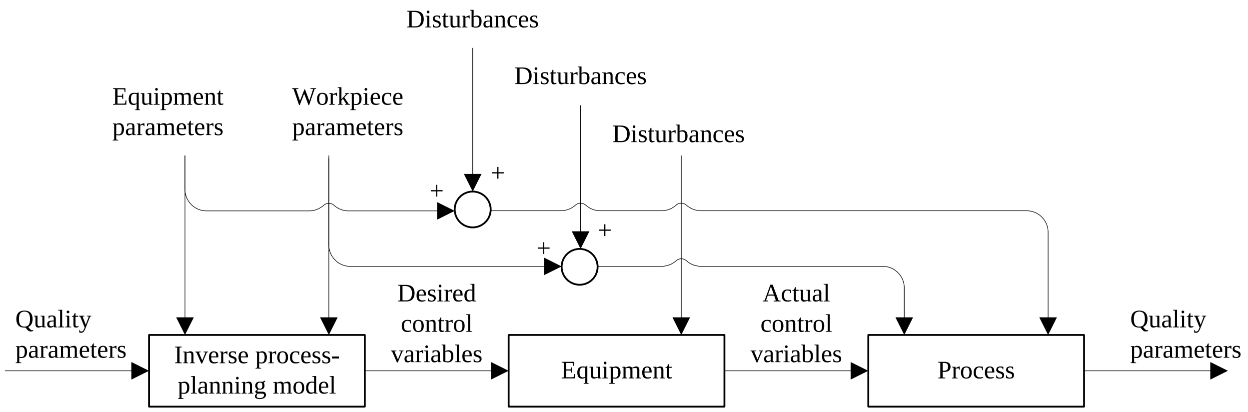


Figure A.11: General representation of an open loop control.

The process knowledge is modelled in the controller. The controller in an open loop control can be based on empirical or analytical knowledge to produce an inverse process-planning model, and it is discussed in section A.4.2 “Empirical process-planning models” and A.4.3 “Analytical based process-planning models”. The equipment changes the desired control variables to actual control variables because the equipment introduces e.g. delay and deviations.

Examples of research where an open loop control is used were given in section A.2.3 “Prepare production A3” in [Cook et al., 1995], [Moon et al., 1996] and [Peng et al., 2000].

Closed loop control

Closed loop control, shown in figure A.12, has a feed back loop from the physical system, called the process, which is input to the controller. In the controller an inverse process-planning model is included. The error is calculated in the controller and it is the difference between the input; that is the desired reference and the measured reference. The error is input to the controller and the rest of the closed loop controller works as the open loop controller.

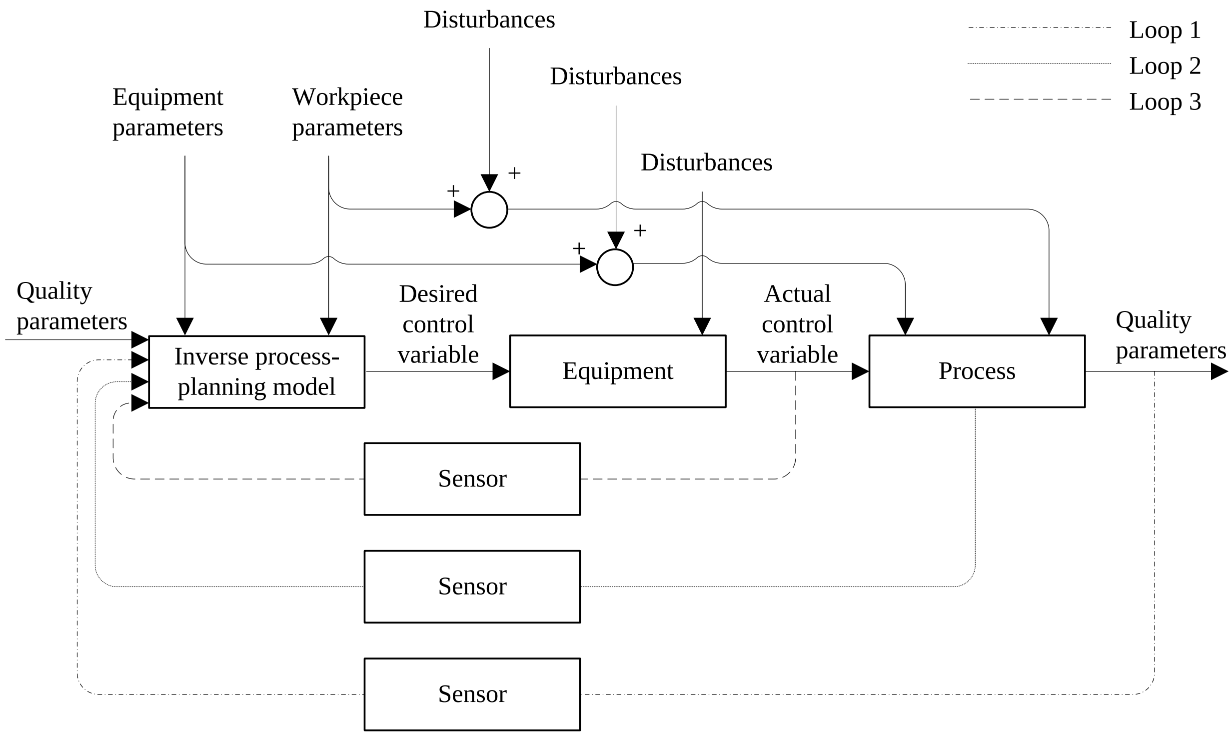


Figure A.12: General representation of a closed loop control with three possibilities of making feedback.

The closed loop controller has to run real-time during execution, and it is necessary to measure some output variables. For some processes, e.g. welding and painting, it is often inconvenient or impossible to measure the quality variables during execution. When the sensors are not able to measure the quality parameters real-time then maybe other parameters from internal in the process or the actual control variables to the process can be measured instead. By doing this it is possible to construct a closed loop control as illustrated in figure A.12.

Examples of research where a closed loop control is used are presented. [Orye, 2005], [Holm et al., 2003b] and [Kjeldsen et al., 2003] describe a system for welding where a planner with a finite element model off-line calculates the heat distribution in the workpiece geometry based on the trajectories generated by the controller in the planner. The desided reference is a surface temperature distribution at the workpiece. On-line during the process a camera measures the heat distribution on the surface of the workpiece in the area where the arc touches the workpiece. The measured heat distribution is feed back and compared with the off-line calculated heat distribution and the controller adjusts the control variables to minimise the error between the off-line calculated and the actual heat distribution. [Di et al., 2001] describe a system where neural network based self organized fuzzy logic control is used for welding. A case is described where the width of the weld pool is controlled. The difference between the desired weld pool width and the feedback with the real weld pool width is entered into the controller which generates control variables. The real weld pool width is not measured but calculated from some measurable parameters from the welding execution, but this is not described. [Andersen et al., 1997] describe research for GTAW where oscillations with arc current pulses are induced to the molten weld pool. A model of the expected pool shapes from drop oscillations is build. Using a light sensor the oscillations of the weld pool is monitored and used for monitoring and control of the weld pool because the oscillations are related to the weld pool dimensions and state of penetration. The principle of the described systems is illustrated in figure A.13.

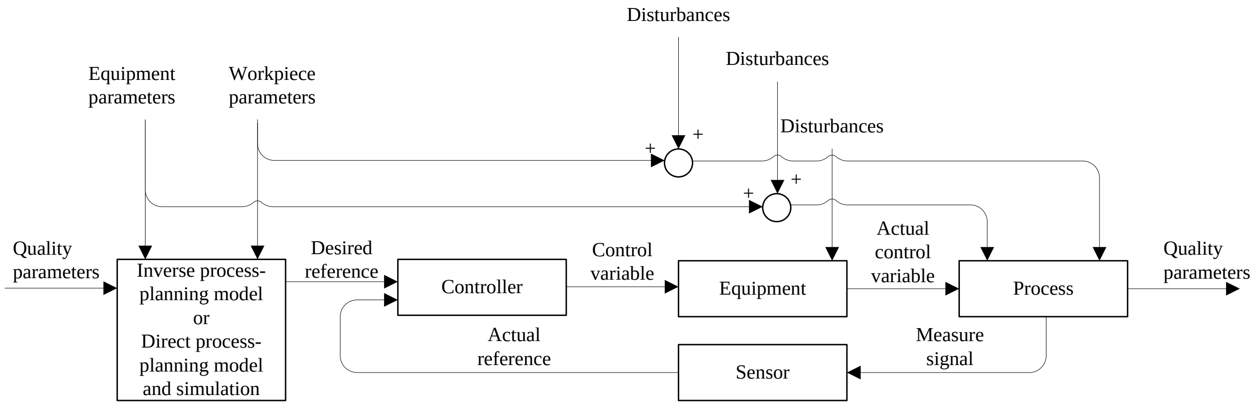


Figure A.13: Control where a planner off-line makes a desired reference. From the desired reference and the actual reference the controller produces control variable on-line.

Minimising disturbances for both open and closed loop control

For both open and closed loop systems research is made to minimize the disturbances from the equipment and workpiece parameters by using different sensor systems. The principle for doing this is illustrated in figure A.14.

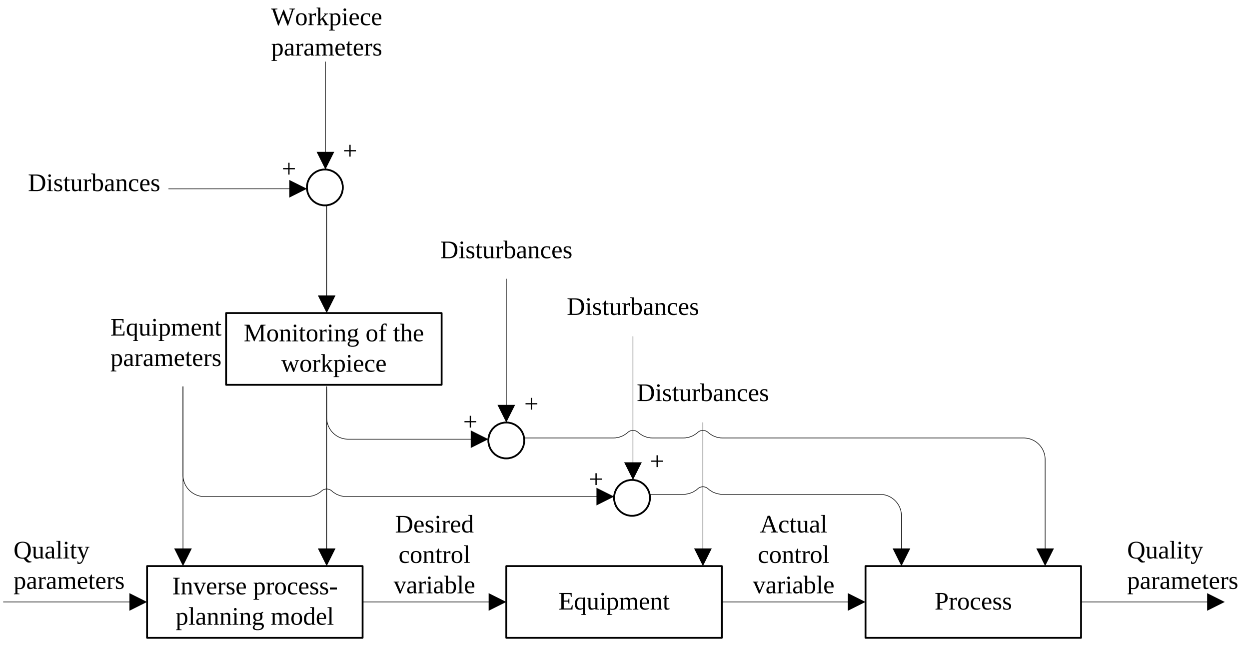


Figure A.14: Representation of a system to monitor the workpiece for minimising the disturbances on workpiece parameters between the "Inverse process-planning model" and the "Process".

[Madsen et al., 2002] describe a system for laser welding. A geometry model of the workpiece is used to plan the welding task. Before welding a laser scanner scans the weld joint on-line and the scanned profiles are used as input for the controller. The geometry model of the workpiece is updated by the scanned profile so if the scanning gets unstable then the updated geometry model is used in the controller. [Suga et al., 1994] describe a system to detect the weld line direction. A CCD camera takes pictures of the weld joint in front of the welding process with influence of light from the arc. The pictures are filtered and are then input to a neural network which is trained to give the direction of the weld seam. [Drews et al., 2000] describe a sensor system to follow a weld seam. The sensor system sends out three laser lines over the weld joint at the workpiece and a CCD camera watches the lines and a 3D- model is made from them. [Bingül et al., 2000] describe a research system for pulsed GMAW. The system uses through-the-arc sensing of the voltage for controlling the torch position for weld joint tracking. The welding torch is oscillating across the V-grove joint and the measured voltage is input to a Fuzzy logic and a PID controller which both are used to track the welding joint.

A.4.2 Empirical process-planning models

Empirical process-planning models are defined as models based on empirical data. Empirical process-planning models with untreated empirical data are rarely used because often the empirical data is treated with some mathematics. This treatment with mathematics brings the empirical models in the direction of analytical models.

The empirical process-planning models are made from experiments with different settings of the input parameter and variables. For each experiment the input parameters and variables with the corresponding output, described by the quality parameters of the process, are stored in a database. All the experimental data in the database represent knowledge of the process because the relation between input parameters and variables and the quality parameters is kept. The database can be used inversely to control the process because to certain required quality there can be found control variables.

Making empirical process-planning models require a lot of data because the working area of the process has to be covered with a certain density of data sets to make reliable process-planning models. Each time one parameter is added to the input parameters or variables then the amount of necessary experiments is minimum doubled. Statistically methods can be used to reduce this rapid increasing of the number of experiments.

In section A.2.3 “Prepare production A3” examples were given of empirical process-planning models using machine learning. The examples were [Cook et al., 1995], [Yanhong et al., 1994], [Moon et al., 1996], [Peng et al., 2000], [Smartt et al., 2003] and [Smartt et al., 2006]. Other examples of empirical process-planning models are the following:

[Madsen et al., 2002] describe a system for welding where welding experience and results from welding experiment covering a comprehensive range of welding conditions can be entered in a database. This database is used for controlling the process. [Moon et al., 1997] describe two approaches to make process-planning models. For both methods experiments are made using factorial design where sets of 5 quality variables are found for 6 welding process parameters. The empirical knowledge from the experiments is used to train an artificial neural network and make a non-linear mathematical model. [Murray, 2002] describe a method where regression and dimensional analysis is used on experimental data to find the relationship and range of stable welding parameters. From this relationship it is possible to select welding parameters that lead to desire operating conditions. [Maul et al., 1996] use control charts made from experimental welding data. By using control charts limits can statistically be set on the range of the welding parameters where a high welding quality can be guaranteed. If any welding parameter operates outside the predetermined range of values then theoretically the welding quality is affected. Some rules for setting these limits are made from welding experiments. [Chan et al., 1999] describe research where empirical data is used for training of artificial neural network for a direct and inverse process-planning model. The network is trained to predict the weld geometry from welding parameters. [Kim. et al., 1996b] analyse experimental data and describe a method where experimental data is treated with regression and afterwards described using a mathematical equation. The equation relates welding parameters to geometrical parameters. The equation is inverted to give the inverse relationship. [Juang et al., 2002] and [Tarng et al., 2002] are using Taguchi to design empirical experiments and produce a direct process-planning model. Optimisation is applied to the model and in this way it is used as an inverse process-planning model. [Dilthey et al., 1999] use artificial neural network and genetic algorithms together with optimization to produce an inverse-process-planning model based on empirical training data. In [Christensen, 2003] and [Christensen et al., 2003] artificial neural network is used as an inverse process-planning model trained from empirical data. Furthermore, a closed loop control is built where the front bead height is measured during the process execution and feed back in a control loop. [Tay et al., 1997] is another example where an artificial neural network is built and trained with empirical data based on Taguchi design. A direct process-planning model is constructed and it is used for simulation to manually find inverse solutions.

A.4.3 Analytical based process-planning models

The analytical process-planning models are mathematical models made from physical laws describing the physics of the process. The physical laws have their base in empirical experiments, which have been formalised on mathematical form. The knowledge of the analytical process-planning models lies in this description of the physics and it is usable to control the process if it is a sufficiently precise description. The models can be used because when a mathematical model of the physics is made then it is possible to model the process set-up and use the analytical model to calculate relations between input and output parameters and variables. Analytical process-planning models are based on experiments with different parameters. These experiments are analysed and generalised by scientists and from them mathematical and physical models are made. A review of the area of making models of the welding process and doing simulations are in [Lindgren, 2001a], [Lindgren, 2001b], [Lindgren, 2001c] and [Goldak et al., 2006].
Making analytical process-planning models requires a lot of modelling work and there are some limits in what can be modelled because it is difficult to model certain processes mathematically because the physics of the processes are not completely understood. Making the models as flexible and general as possible will make them useful in a broader range of situations.

[Holm et al., 2002] and [Holm et al., 2003a] describe research where a heat conduction finite element model is extended with a weld pool surface model which includes gravitational forces and weld pool surface tension. This model is used in an off-line programming system where a CAD based model of the workpiece geometry is converted to a finite element model. A finite element simulation of the welding task is performed and afterwards the quality parameters of the welding are controlled by analyzing the thermal history of the welding. Depending on the result of the welding simulation the control variables can be changed and another simulation can be made. The work is further developed and verified in [Jeberg et al., 2006] and [Jeberg, 2005]. Simulations using iterative learning control are used to improve the iterative process of finding the process parameters. [De et al., 2004] and [Kumar et al., 2004] make a heat transfer model and together with optimization it is used to find uncertain parameters about the process state. The work does not go all the way back to decide welding variables. [Mahrle et al., 2000] make a heat transfer model and simulations using the model. It is explained how it can be applied to make an inverse process-planning model.

A.4.4 Commercial systems

In the search for commercial products with process-planning models to decide the welding control variables is the following. [VirtualArc] is a program from ABB based on Bayesian neural network, which off-line can be used for optimising the welding parameters and it can predict weld shape, penetration, weld quality and welding defects.

A.4.5 Discussion

The mentioned work for making process-planning models is summarised in table A.2.

Table A.2: Classification of the work in the area of making process-planning models.

Model / Control	Empirical process-planning models	Analytical process-planning models
Open loop control	**Raw data** [Madsen et al., 2002]: Experimental results or operator experience entered in database. **Mathematical models** [Juang et al., 2002]: Taguchi and optimization. [Tarng et al., 2002]: Taguchi and optimization. [Moon et al., 1997]: Regression model and optimization. [Murray, 2002]: Regression model and dimensional analysis. [Maul et al., 1996]: Control charts avoiding defective welds by making settings and rules. [Kim et al., 1996b]: Regression model inverted. **Machine learning** [Dilthey et al., 1999]: Artificial neural network, genetic algorithms for modelling and optimization. [Tay et al., 1997]: Artificial neural network and simulations used to manual find inverse solutions. [Moon et al., 1997]: Artificial neural network. [Chan et al., 1999]: Artificial neural network. [Cook et al., 1995]: Artificial neural network. [Moon et al., 1996]: Artificial neural network and fuzzy logic. [Yanhong et al., 1994]: Decision	[De et al., 2004] and [Kumar et al., 2004]: Heat transfer model and optimization. Uses process state variables instead of welding control variables for optimization. [Jeberg et al., 2006] and [Jeberg, 2005]: Finite element model and simulation with control loop. Iterative learning control used to improve the iterative process. [Mahrle et al., 2000]: Heat transfer model and simulations. Talks about how to use it for an inverse model. [Holm et al., 2002]: Finite element model and simulation with control loop. [Holm et al., 2003a]: Finite element model and simulation with control loop using PI control and iterative learning control.

	tree and learning sets of rules. [Peng et al., 2000]: Rule based reasoning, case based reasoning and artificial neural network. [Smartt et al., 2003] and [Smartt et al., 2006]: Agent and fuzzy logic to make control with welding knowledge.	
Closed loop control	**Machine learning** [Di et al., 2001]: Artificial neural network, fuzzy logic and control with measurements of parameters used to estimate the welded seam. [Christensen, 2003] and [Christensen et al., 2003]: Artificial neural network and control with measurement of the welded seam shape.	[Orye, 2005], [Kjeldsen et al., 2003] and [Holm et al., 2003b]: Finite element model with simulation and offline control. Online thermal vision measurements are used for control. [Andersen et al., 1997]: Model of the weld pool. Measurements of the pool size is made from oscillations and used to control the pool size.

Generally the empirical and analytical methods for making process-planning models and the use of open loop control or with sensors for closed loop control are usable in many cases to make automation of processes. In the case of welding the problems of the applicability of these methods are identified. The identified problems are:

- Open loop control: Requires a process-planning model where the process is thoroughly modelled and disturbances are not affecting the equipment and the process. For welding the modelling of the process is an obstacle because the physics of the process are not fully understood.
- Closed loop control: Requires modelling of the process and furthermore real time execution where output parameters are measured and feed back to the control. For the welding process these measurements are troublesome, because of the environment in and around the process.
- Empirical process-planning models: Require a lot of experimental work, which is an expensive source.
- Analytical process-planning models: Require modelling of the physical process, which is not completely understood.

The use of operator knowledge to produce process-planning models for welding is an area, which is unexplored as it is showed in the literature survey. Further investigation in utilising this knowledge source could be beneficial and give alternatives to empirical and analytical knowledge.

In the literature many process-planning models are found which are specific for a given workpiece or setup. When the production is small-batch-sizes and one-of-a-kind it is especially important to have process-planning models which are reliable to changing conditions of both workpiece and setup. To proceed the investigation to make flexible and reliable process-planning models efficient the following strategy is used:
Empirical- and analytical process-planning models are combined with methods from machine learning and operator knowledge. It is illustrated in figure A.15. The idea by doing this is:

- Analytical process knowledge is formalized but does not cover the entire area of the welding processes.
- Empirical process knowledge can be created in the areas where there is lack of analytical knowledge.
- Operator knowledge is a relatively unexplored knowledge source, which possibly can has some advantages at some point compared to analytical and empirical process knowledge.
- By using machine-learning methods it is possible to combine different knowledge sources.

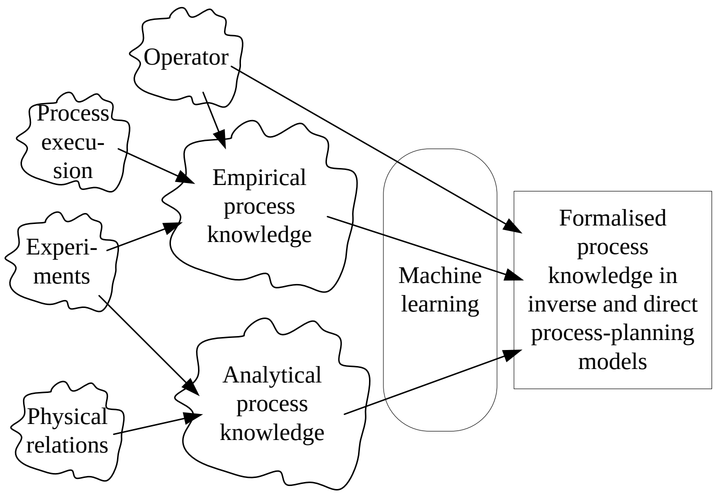


Figure A.15: Illustration of how machine learning can be implemented to produce process-planning models from empirical, analytical and operator knowledge.

A.5 Summary

A functional system architecture is described for small-batch-sizes and one-of-a-kind production systems. In the architecture of a production system 8 tasks are identified where process knowledge is used or can be used to carry out the task. The 8 tasks are places where process knowledge definitely is present or useful to carry out a task. For the tasks examples were given of work found in the literature of how to carry out the tasks with a focus on examples using machine learning methods. A range of methods is used but it is found that artificial neural networks are very used in many applications.
A range of machine learning methods were reviewed to see how they are used to model process knowledge in a variety of different ways. They can store process knowledge from experiments, operators and analytical rules and equations. This knowledge can be used later as expert knowledge in systems by raising efficiency or by minimising cost by doing human tasks and by securing quality. The selected machine learning methods and their possible use is found and shown in table A.1.

The architecture was more thoroughly described for the “Preparation production” and “Control production” tasks; because it is in these functions the main preparation for the processes and the process execution is carried out. When making process-planning models is it mostly the inverse solution which is required. A state of the art analysis was made to investigate methods where process knowledge to control the process for open and closed loop control are made using empirical and analytical process-planning models. The analysis shows that many different ways are used to solve the task of making inverse process-planning models. Only a few examples of methods for closed loop control were found in the literature and it is expected that the difficulties in sensing of the welding process is the cause. Both the empirical and analytical process-planning models are models which are expensive and time consuming to produce. The causes are mainly that the empirical models require a severe amount of experimental data, and the analytical models is time consuming to model and there is a lack of knowledge of the physics in the welding process.

Appendix B

The MIG/MAG welding process

In the following the MIG/MAG welding process and the equipment for MIG/MAG welding are presented together with the welding quality. The appendix is based on [Lancaster, 1984], where a more thorough description of the welding process is found.

B.1 The equipment

The setup for automatic MIG/MAG welding is illustrated in figure B.1. In the setup a welding machine, a manipulation mechanism and a guidance system are included.
The welding machine consists of a power supply, a wire feed system, a gas supply, a welding torch and perhaps a water cooling supply. The power supply delivers a strong current (DC) and a low voltage to the cathode wire, which is connected to the workpiece, and to the anode wire, which is connected to the welding torch. The wire feed system feeds the welding wire at a controllable rate. The welding wire is also referred to as the electrode. The current flows in the anode wire and is transferred to the welding wire in the welding torch very close to the arc to minimize resistance. The gas supply delivers a certain gas flow rate of shielding gas from the welding torch.
The manipulation mechanism moves the welding torch at a controlled travel speed and travel pattern. In figure B.1 the manipulation mechanism is a robot, but it could also be e.g. a human operator.

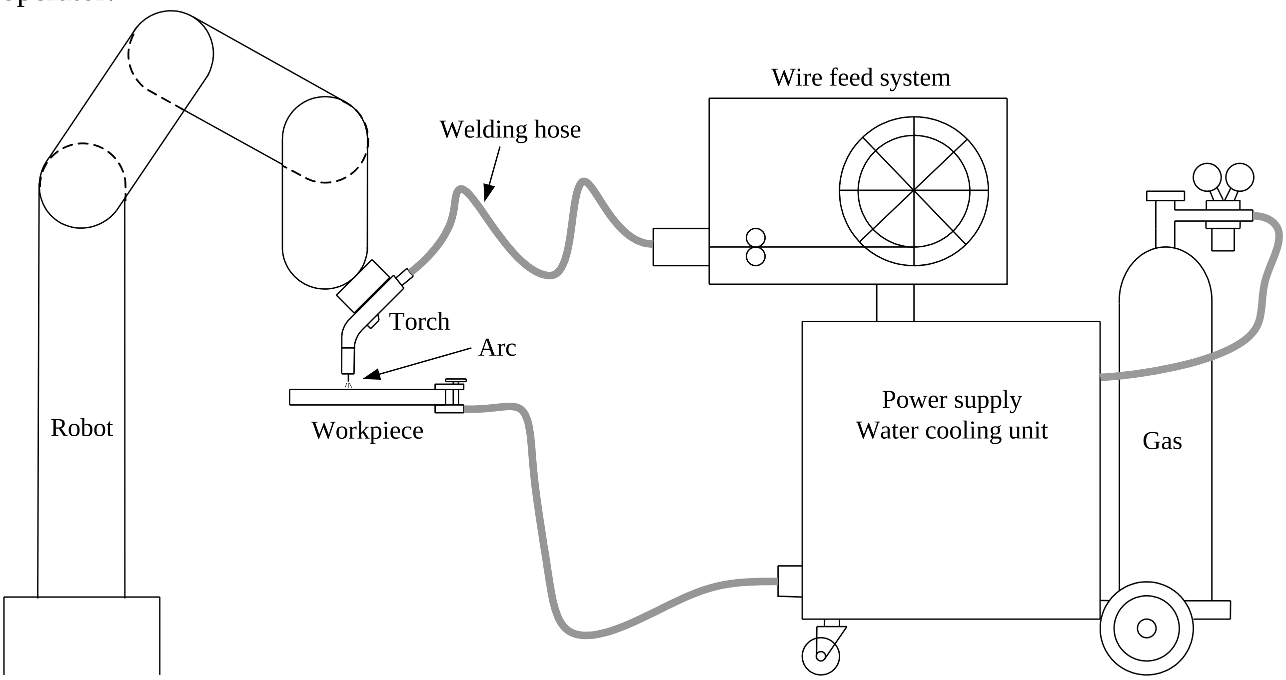


Figure B.1: Illustration of the overall process setup for automatic MIG/MAG welding.

B.2 The process

In the MIG/MAG welding process a consumable electrode is used which is fed by the wire feed system. The electrode is always the anode and the workpiece is the cathode for the MIG/MAG process. Across the gap between the electrode and the workpiece an arc is created. From the established arc heat energy is produced, where some of the heat melts the electrode and causes growth of drops of melted metal, which detach from the electrode tip. The consumed electrode is replaced by new electrode material, which is fed by the wire feed system. The details of the welding process are illustrated in figure B.2 with the arc and the drops of molten metal from the electrode, where the arc and drops of molten metal melt the base metal to a weld pool. The weld pool is moved across the workpiece and leaves behind solidified weld material that is fused with the base material.

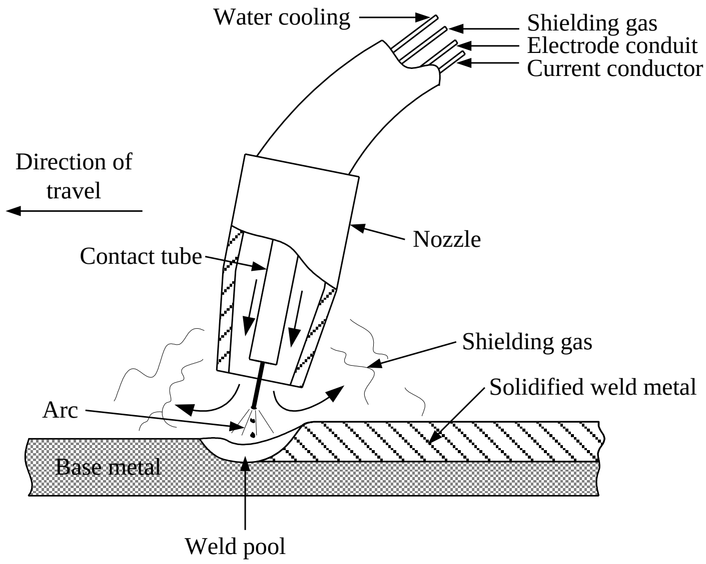


Figure B.2: The principle of the MIG/MAG process. The nozzle and the workpiece are made in a cutaway view to illustrate the process.

Shielding gas protects the melted electrode and the molten metal from oxygen and nitrogen in the atmosphere, which can make a reaction causing porosity in the solidified weld metal. The type of protection gas used can be inert, e.g. helium or argon, for metal inert gas (MIG) welding or active, containing e.g. CO_2 or O_2, for metal active gas (MAG) welding. For MIG welding an inert gas is used, which does not react with other materials. For MAG welding the active protection gas splits up in the arc and to some degree reacts with the molten metal. Alternatively, or as a supplement to the shielding gas, a flux can be used. It is either fed to the weld groove before welding or comes from a flux core within the welding wire.

The heat produced from the welding process is partly transferred to the weld pool and the rest is mainly conducted away by the workpiece, the torch, the protection gas and as radiation to the surroundings. The melted electrode metal is mainly transferred to the weld pool, but it is also evaporated or has formed small droplets on the surface of the workpiece (spatter).

During welding an electric circuit is established. The terminal voltage U_t from the power supply is described as follows:

$$U_t = U_w + U_e + U_a$$

U_w denotes the voltage drop over the electrical wire, U_e denotes the voltage drop over the electrode from the contact tube to the electrode tip with length l_s illustrated in figure B.3 and U_a denotes the voltage drop over the arc with length l_a. The voltage drop over the arc gives the most significant voltage drop, especially for weak welding currents because of the resistivity of the electrical wire.

For fluctuating current the equation is not only determined by the resistance over the voltage drops but also the inductance over the electrical cables.

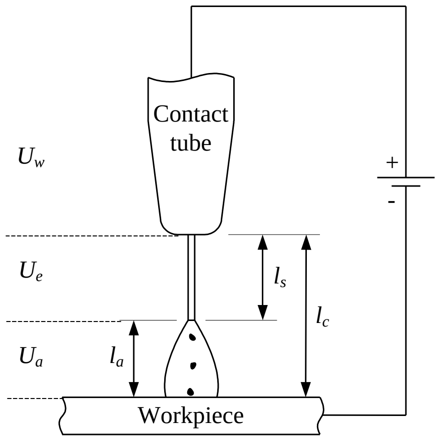


Figure B.3: The contact tube to workpiece distance, (CTWD) l_c, sticks out distance l_s and arc length l_a. The electrical contact between the contact tube and the electrode is not at the tip of the contact tube but over a distance inside the contact tube.

The metal transfer of the electrode to the workpiece can basically be in tree modes, which are illustrated in figure B.4. Factors affecting the metal transfer mode are mainly the welding current, electrode diameter, shielding gas type and electrode composition.

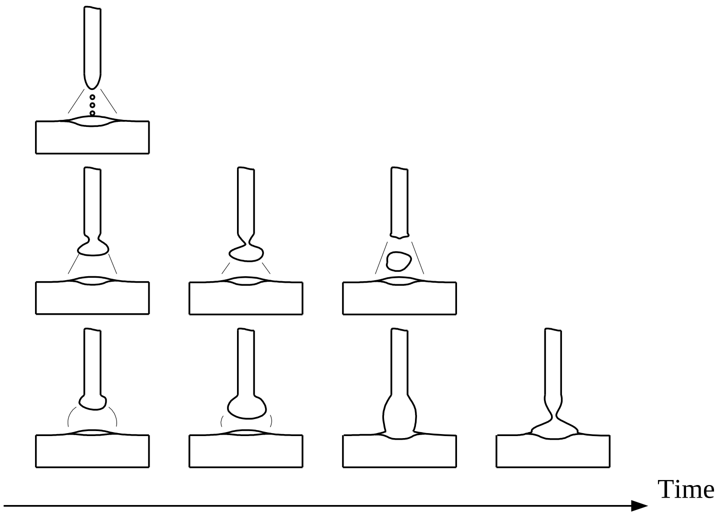


Figure B.4: Top shows spray transfer. Middle shows globular transfer. Bottom shows short circuit transfer.

The three types of metal transfer modes are described below.

Spray transfer

Spray transfer is characterised by a current level above a transition current where the electrode melts to very small drops which detach the electrode. The transition current is dependent on a number of factors, such as electrode diameter, electrode composition and shielding gas mixture. Arc forces on the drops are stronger than gravity which enables welding in all directions. The number of drops is in the order of a few hundred per minute.

Globular transfer

Globular transfer is characterised by a current level between spray transfer and short circuit transfer where the drop size is larger than the electrode diameter. The electrode melts to big drops which detach and fall down in the weld pool. The gravity forces on the drop are bigger than the arc force. The number of drops is in the order of few drops per second.

Short circuit transfer

Short circuit transfer is characterised by a low current that forms a drop at the electrode tip and before the drop detaches it touches the workpiece and short circuit, which causes the welding current to increase. The increased current melts down the drop and causes the electrode to disconnect with the workpiece, the current drops and a new drop starts forming. The number of short circuits is in the order from one to a few hundred per second.

The MIG/MAG welding process can be carried out with a constant or pulsed power supply.
The pulsed power supply makes current pulses that try to detach the molten metal droplets at certain times. Pulsed welding has a number of variables to describe the shape of the pulses e.g. pulse time, pulse pause time, pulse current and pause current.
For the constant voltage power supply a voltage and a wire feed speed are selected on the power supply and wire feed system, and then the power supply delivers a flat characteristic output which is exemplified in figure B.5. The current is determined as a function of the wire feed speed. Thus, if the wire feed speed is increased the current is automatically increased in order to melt the extra amount of wire and vice versa. An important property of the constant voltage characteristic is the self-adjusting arc. It keeps the arc in a steady state working point with a constant arc length for a given wire feed speed. The arc length can be changed momentary by e.g. shape change of the workpiece geometry or for manual welding when the operator changes the contact to workpiece distance. If the change gives a shorter arc length the arc voltage drops and the current will increase, which causes an increased burn off rate of the electrode and the arc length increases to the steady state working point illustrated in figure B.5. In a similar fashion a long arc length will give higher arc voltage and a lower current, which causes a lower burn off rate, and the arc length will go towards the steady state working point.

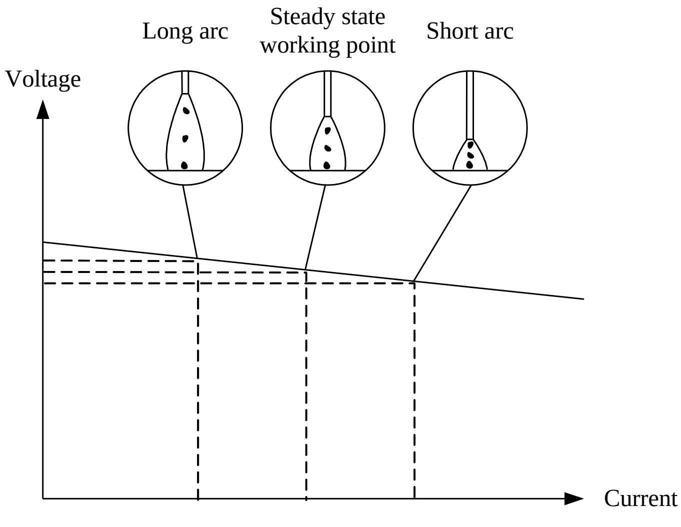


Figure B.5: Example of static output for constant voltage characteristic.

Motion of the welding torch relative to the workpiece is described by the motion variables. The motion variables are the CTWD, the welding speed, which is the welding torch speed along the weld groove, the travel angle, illustrated in figure B.6, the work angle, illustrated in figure B.6, and the travel motion type which can be straight or oscillating. Furthermore, motion variables can also specify the sideways and upwards displacement of the welding torch pointing at the weld groove, illustrated in figure B.6.

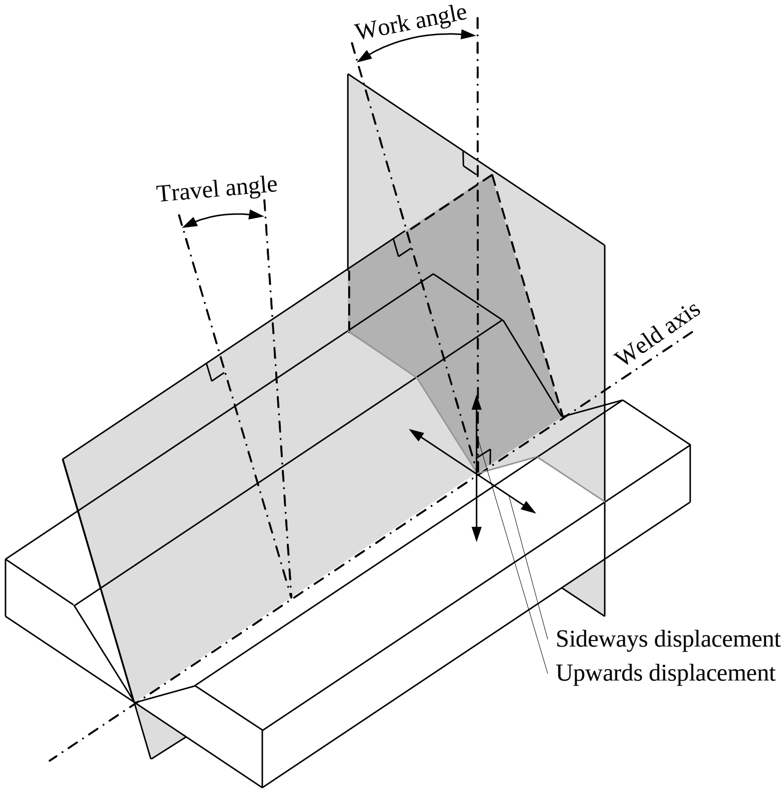


Figure B.6: Travel angle is the angle of the welding torch compared to the direction of the weld axis. Work angle is the angle of the welding torch in the perpendicular plane to the weld axis.

The oscillating motion of the welding torch, also called weaving, can have different patterns as illustrated in figure B.7.

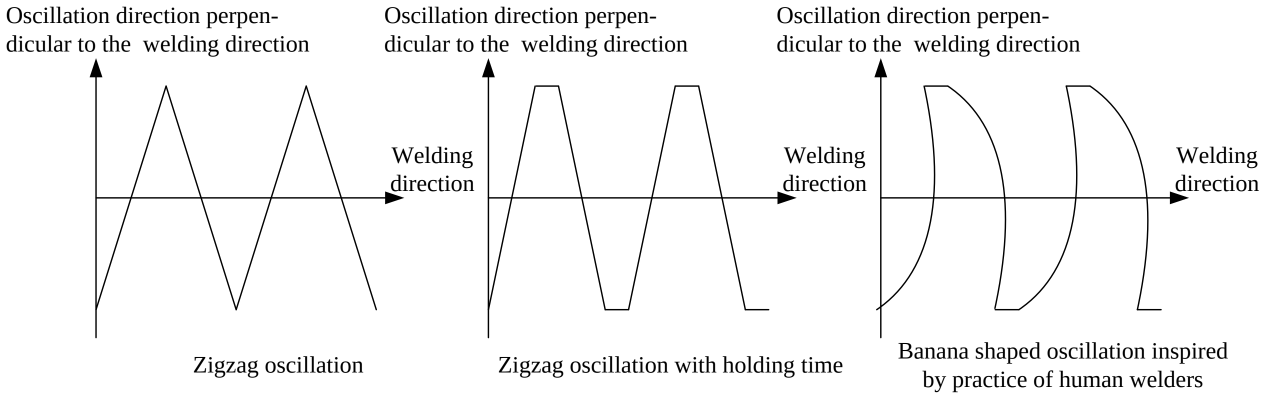


Figure B.7: Three different oscillation patterns.

The oscillation motion is together with the other motion variables for the welding torch specified thoroughly in chapter 3.

B.3 The quality

The weld quality is the result of the welding process. It can be described by the following three categories; geometrical weld quality, metallurgical weld quality and manufacturing properties, which are most commonly employed for industrial welding.

B.3.1 Geometrical weld quality

The geometrical weld quality is both external and internal for the weld bead and the parameters to measure can vary depending on the workpiece geometry. External parameters are visible from the outside and these are e.g. leg-lengths, width and height of weld face and back bead, convexity, theoretical throat, undercut and overfill. Internal parameters are not visible from the outside and these are e.g. depth of fusion and penetration. Both the external and internal parameters are illustrated in figure B.8. Both for the external and internal geometrical weld quality disturbances can occur, which are described by welding defect parameters, such as cracks, inclusions and porosity.

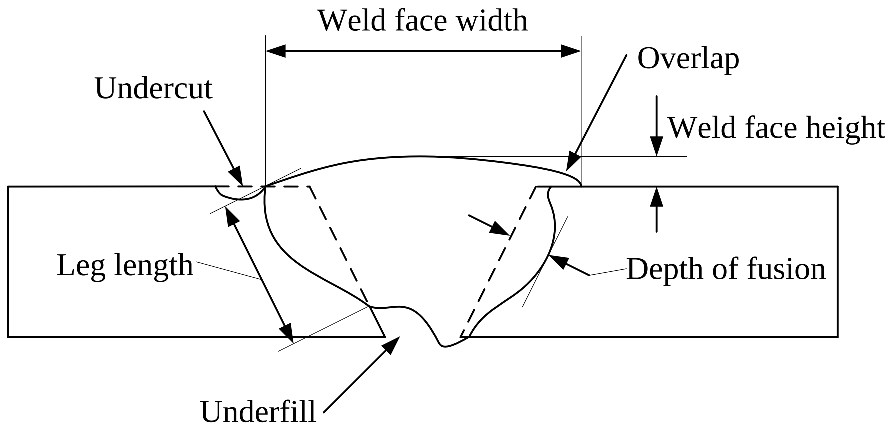


Figure B.8: Illustration of some geometric weld quality parameters for a groove weld. The welding is made from upside and welding direction is perpendicular to the illustration.

B.3.2 Metallurgical weld quality

The metallurgical weld quality includes the microstructure, mechanical properties and chemical properties. It is affected in both the fusion zone and the heat-affected zone of the base material and it is dependent on the materials joined, the filler material and the settings used of the wending control variables and equipment parameters. In the fusion zone base material is mixed with the filler material and it cools down, solidifies and reaches the surrounding temperature. In the heat affected zone the base material is heated over a point where the microstructure is affected. The history of the thermal influence, the material composition and the initial grain structure in the heat affected zone affects the grain growth and the resulting microstructure. Parameters as distortions and residual stresses also belong to this group.

B.3.3 Manufacturing properties

The manufacturing properties are not described from the final welding result of the physical workpiece as in the two previous categories. The parameters are set by the manufacture to e.g. minimize fabrication time and expenses such as material deposit rate and heat input. These parameters are related to the welding process, but also the whole chain of manufacturing processes. For welding the chain of manufacturing processes for instance include weld bead preparation, which is important before welding to make a good foundation for the welding. Another parameter is the heat input, which is important during welding to minimize distortion.

The weld quality parameters are described in standards where ISO 5817 is an example of geometrical weld quality and DS/EN 1011 is an example of metallurgical weld quality. For the manufacturing properties the criteria and requirements are defined by the individual production demands.

Appendix C

Analyse 2D records

A method for carrying out analysis of the 2D records is presented in this appendix. The purpose of the analysis is to determine workpiece and quality parameters.

For determination of workpiece and quality parameters, profile sensing data with breakpoints of the workpiece is required before welding. This data is for the weld face and, if physically possible, for the back bead. Similarly for determination of quality parameters, profile sensing data with breakpoints of the workpiece is required after welding. This data is also for the weld face and, if physically possible, for the back bead.

The tasks to analyse 2D records are shown in figure C.1. The first task is to determine the breakpoints if they are not delivered in the records with projected data. Two methods are proposed to carry out this task. The second task uses the welding direction and the breakpoints to determine the orientation of the workpiece joint and specifies it by two vectors: a weld face vector and a root vector. The third and the fourth task determine respectively the workpiece and quality parameters. Each of these four tasks is described separately in the following section.

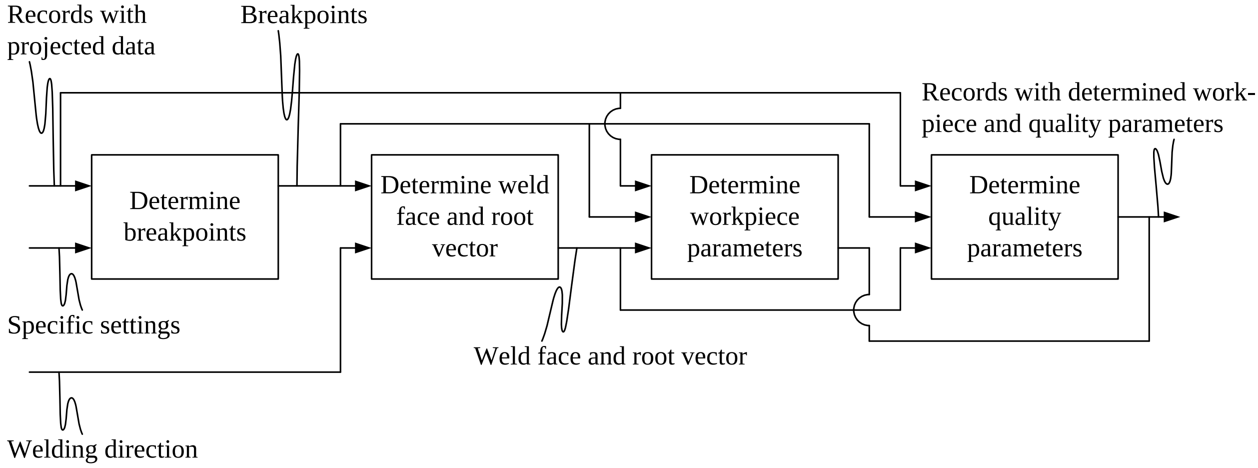


Figure C.1: The task “Analyse 2D records” is split up into subtasks to determine workpiece and quality parameters from records with projected data from profile sensing.

The following delimitation is made for the task of analysing 2D records: The workpieces have a square groove at the back bead.

C.1 Determine breakpoints

Two methods for profile segmentation are presented. They require a template for analysis of the different joints and grooves. Settings of variables to interpret the profile sensing data are in the templates.

In case the breakpoints are not delivered from the profile sensor, but only the raw points, it is required to determine the breakpoints. In most cases filtering and smoothing of the raw points are required before determining the break points.

Filtering detects and deletes points which are outliers.

Smoothing was made by taking the list of raw points in a profile and by calculating a new list with smoothened raw points. For each raw point *(X_n, Y_n)* a smoothened raw point *(X'_n, Y'_n)* is calculated:

$$X_n^{'} = \frac{X_{n-p} + .. + X_n + .. + X_{n+p}}{1+2p} \quad \text{and} \quad Y_n^{'} = \frac{Y_{n-p} + .. + Y_n + .. + Y_{n+p}}{1+2p}$$

Where $1+2p$ determines the number of raw points to use for smoothing by the user specified variable p.

RST-points were given in the profile sensing data, which depends on the particular profile sensor. Two methods for calculating the RST-points are presented. Both of them are applied to detect sharp corners and this makes some groove types difficult to analyse. The methods are:

- Detect second order derivatives of sensing profile.
- Detect distance and direction from point to point of sensing profile.

C.1.1 Detect second order derivatives of sensing profile

This method is explained in [Madsen, 1992] and the principle is illustrated in figure C.2.

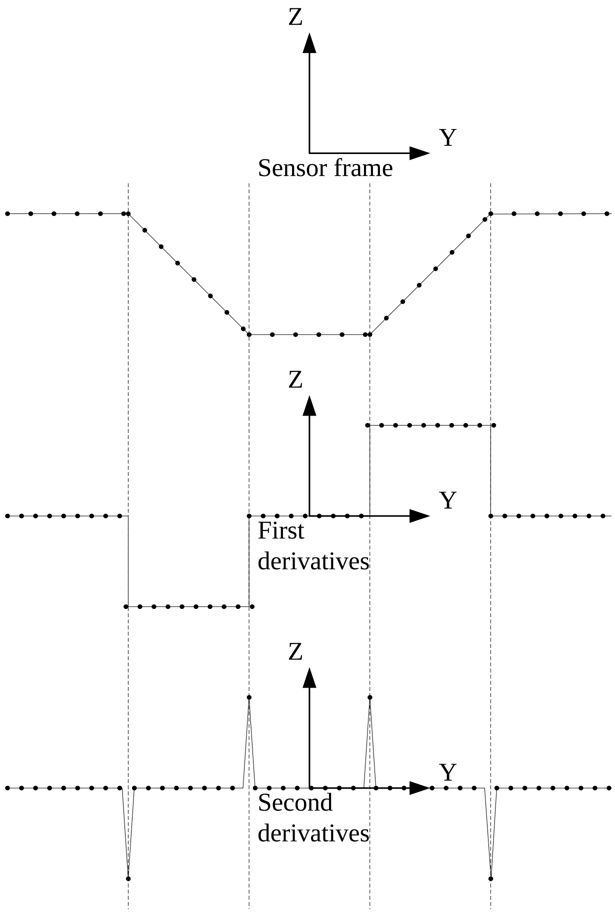


Figure C.2: Raw points from profile sensing data, shown at the top, are derived to first order derivatives, shown at the middle. The first order derivatives are derived to second order derivatives, shown at the bottom. For the second order derivatives the peeks indicate the break at the initial curve with raw points [Madsen, 1992].

C.1.2 Detect distance and direction from point to point of sensing profile

This method processes the number of raw points from the profile sensing data. It tries to build the longest possible straight line of segments using a least square method for fitting straight lines. The principle requires settings of how far the next raw point can be away from the fitted line segment to be accepted for the line segment. The settings are: max linear distance away from and along the fitted line segment, and max perpendicular distance perpendicular away from the line segment. The pseudo code for the method is shown in figure C.3 and the principle is illustrated in figure C.4.

RawPointList is a data structure containing a list of ordered raw points from profile sensing data.
MaxLinearDistance is a real number set from the customised settings.
MaxPerpendicularDistance is a real number set from the customised settings.
LineSegment is a data structure containing a *StartPoint* (X_s, Y_s) and an *EndPoint* (X_e, Y_e). The *StartPoint* and *EndPoint* are at the most outer projection of the inserted raw points. From the *LineSegment* a vector along and perpendicular to the *LineSegment* can be calculated.
if size of *RawPointList* ≥ three
  then *LineEnd* ← FALSE
    LineSegment ← least square fit of the two first points from *RawPointList*
  else *LineEnd* ← TRUE
while *LineEnd* == FALSE **or** more points in *RawPointList*
  do *Point* ← get next point from *RawPointList*
  LinearDistance ← distance from *EndPoint* of *LineSegment* to *Point* in direction along the *LineSegment*
  PerpendicularDistance ← distance from *EndPoint* of *LineSegment* to the *Point* in direction perpendicular to the *LineSegment*
  if *LinearDistance* < *MaxLinearDistance* **and** *PerpendicularDistance* < *MaxPerpendicularDistance*
    then *LineSegment* ← least square fit of *Point* to the *LineSegment*
  else *LineEnd* ← TRUE

Figure C.3: Pseudo code for making one line segment from raw point, with constraints on how far the point can be apart and deviate in perpendicular direction to the line.

The algorithm for making line segments, shown by pseudo code in figure C.3, is executed until the profile with all the raw points is processed. The output is a number of line segments.

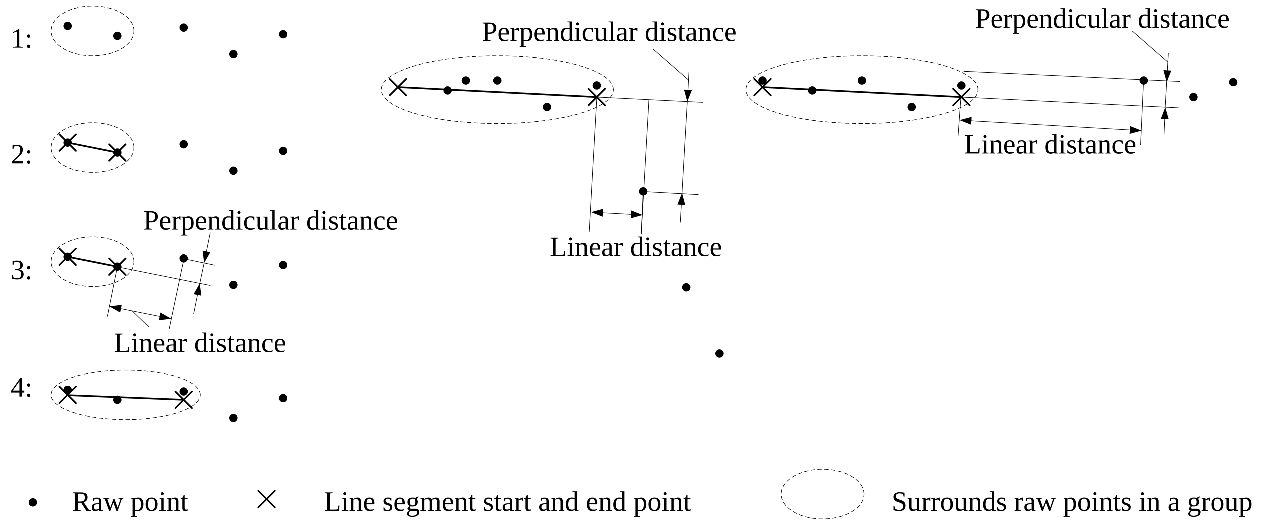


Figure C.4: Left: 1, the two first raw points are grouped; 2, a line segment is fitted; 3, the linear and perpendicular distance to the following raw point are checked; 4, if the point is within the limits a new line segment is fitted and step 3 is repeated. Middle: example of a long perpendicular distance. Right: example of a long linear distance.

Depending on the analysed joint and groove type, a number of line segments describing the shape were generated. Start and end point from the line segments were converted to breakpoints.

C.2 Determine weld face and root vector

To make the 2D analysis of the records it was required to determine a weld face and root vector.

The welding direction was found from analysis of two records in the 3D space and the welding direction is an input to this task. Knowing the welding direction, plate 1 and plate 2 can be determined by utilising the following definition taken from chapter 3:

Plate 1 is for symmetrical joints, as butt- and edge- joints, in the direction of the Y_{groove} vector. Plate 1 is for unsymmetrical joints: a plate where the leg length, on a drawing, is unaffected by an increasing root gap. Plate 2 is the opposite plate of plate 1.

The plate number is added to the breakpoint, shown in figure C.5. Breakpoint on the weld face side has the abbreviation wf and breakpoint on the back bead side has the abbreviation bb.

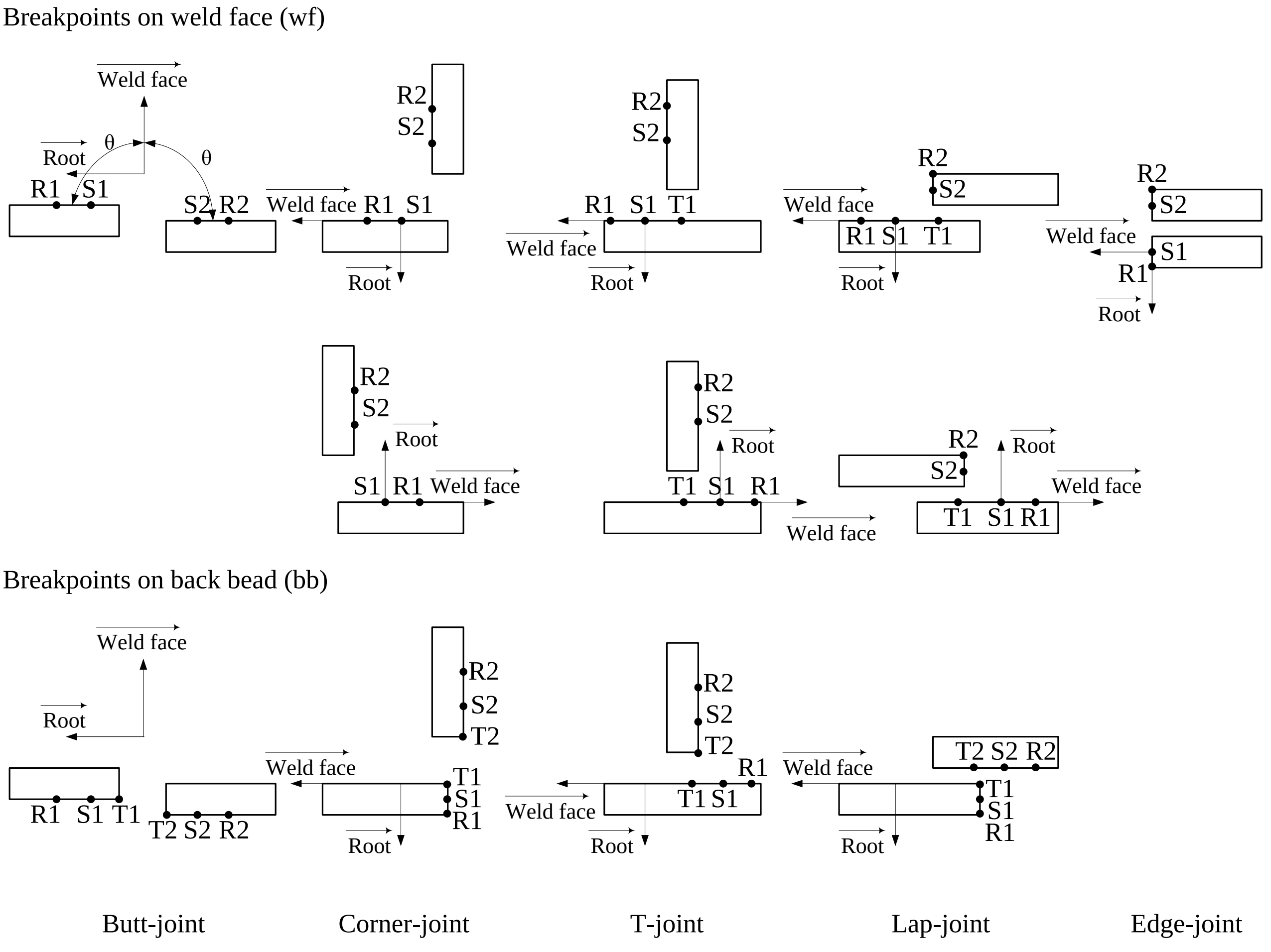


Figure C.5: Breakpoint position before welding on the weld face and back bead for workpiece geometries with different joints and the welding direction into the paper. At the weld face side, T1 and T2 are not placed at joints where the groove type influences the position. Profile sensing is not made at the back bead of the edge-joint because no extra information is achieved.

Definition of weld face and root vector

To determine the workpiece variables it is necessary to define a weld face vector and a root vector, shown in figure C.5.

Weld face vector

Butt-joint:

Determination of the profile sensor vector pointing in the direction of the profile sensor

$$\overrightarrow{profile\ sensor} = -\overrightarrow{S1_{wf}\hat{}R1_{wf}}$$

Determination of the plate angle between plate 1 and 2

$$plate\ angle = angle\left(\overrightarrow{S1_{wf}R1_{wf}}, \overrightarrow{profile\ sensor}\right) + angle\left(\overrightarrow{S2_{wf}R2_{wf}}, \overrightarrow{profile\ sensor}\right)$$

Determination of the weld face vector by rotating $\begin{pmatrix} a \\ b \end{pmatrix} = \overrightarrow{S1_{wf}R1_{wf}}$ with $\theta = \frac{plate\ angel}{2}$ degrees

$$\overrightarrow{weld\ \ face} = \begin{pmatrix} a \cdot \cos\theta + b \cdot \sin\theta \\ -a \cdot \sin\theta + b \cdot \cos\theta \end{pmatrix}$$

Corner-, T- and lap-joint:

$$\overrightarrow{weld\ \ face} = \overrightarrow{S1_{wf}R1_{wf}}$$

Edge-joint:

$$\overrightarrow{weld\ \ face} = \overrightarrow{S1_{wf}R1_{wf}}$$

Root vector

$$\overrightarrow{root} = \overrightarrow{weld\hat{}\ face}$$

C.3 Determine workpiece variables

The determination of workpiece variables are as follows. The equations were set up to achieve robustness of the workpiece parameter determination e.g. for the end of plates which are not cut straight and unaligned plates.

C.3.1 Plate angle

Butt-joint:

Solved as shown above for the definition of the weld face vector for the butt-joint.

$$plate\ angle = angle\left(\overrightarrow{S1_{wf}R1_{wf}}, \overrightarrow{profile\ sensor}\right) + angle\left(\overrightarrow{S2_{wf}R2_{wf}}, \overrightarrow{profile\ sensor}\right)$$

Corner- and T-joint:

The angle between the $S1_{wf}R1_{wf}$ vector and the $S2_{wf}R2_{wf}$ vector.

$$plate\ angle = angle\left(\overrightarrow{S1_{wf}R1_{wf}}, \overrightarrow{S2_{wf}R2_{wf}}\right)$$

C.3.2 Root gap

All the joints:
The length of projecting the $T1_{wf}T2_{wf}$ vector at the root vector.

$$root\ gap = \left| \frac{\overrightarrow{T1_{wf}T2_{wf}} \cdot \overrightarrow{root}}{\left|\overrightarrow{root}\right|^2} \overrightarrow{root} \right|$$

C.3.3 Offset

Butt- and corner-joint:
The length of projecting the $T1_{bb}T2_{bb}$ vector at the weld face vector.

$$offset = \left| \frac{\overrightarrow{T1_{bb}T2_{bb}} \cdot \overrightarrow{weld\ \ face}}{\left|\overrightarrow{weld\ \ face}\right|^2} \overrightarrow{weld\ \ face} \right|$$

C.3.4 Overlap

Lap-joint:
The length of projecting the $T2_{wf}T1_{bb}$ vector at the weld face vector.

$$overlap = \left| \frac{\overrightarrow{T2_{wf}T1_{bb}} \cdot \overrightarrow{weld\ \ face}}{\left|\overrightarrow{weld\ \ face}\right|^2} \cdot \overrightarrow{weld\ \ face} \right|$$

C.3.5 Thickness plate 1 and plate 2

Butt-joint:
For plate 1 the thickness is the distance between point $S1_{wf}$ and the line spanned by $R1_{bb}$ and $S1_{bb}$.
For plate 2 it is the distance between point $S2_{wf}$ and the line spanned by $R2_{bb}$ and $S1_{bb}$.

$$thickness\ \ plate\ 1 = dist\left(S1_{wf}, line\left(R1_{bb}, S1_{bb}\right)\right)$$
$$thickness\ \ plate\ 2 = dist\left(S2_{wf}, line\left(R2_{bb}, S2_{bb}\right)\right)$$

Corner-joint:
For plate 1 the thickness can only be determined if the profile sensing is made so wide that $R1_{bb}$ reaches the edge of plate 1. Thickness of plate 1 is the length of projecting the $T1_{bb}R1_{bb}$ vector at the hat of $R1_{wf}S1_{wf}$ vector.
For plate 2 the thickness is determined as for a butt-joint.

$$thickness\ \ plate\ 1 = \left| \frac{\overrightarrow{T1_{bb}R1_{bb}} \cdot \overrightarrow{\widehat{R1_{wf}S1_{wf}}}}{\left|\overrightarrow{\widehat{R1_{wf}S1_{wf}}}\right|^2} \overrightarrow{\widehat{R1_{wf}S1_{wf}}} \right|$$

T-joint:
For plate 1 the thickness cannot be determined by the specified profile sensing.
For plate 2 the thickness is determined as for butt-joint.

Lap-joint:
Can only be determined if the profile sensing is made so wide that $R2_{wf}$ and $R1_{bb}$ reach the edge of the plates.
For plate 1 the thickness is determined as for a corner joint.
The plate thickness of plate 2 is the length of projecting the $R2_{wf}T2_{wf}$ vector at the hat of the $R2_{bb}T2_{bb}$ vector.

$$thickness\ plate\ 2 = \left| \frac{\overrightarrow{R2_{wf}T2_{wf}} \cdot \overrightarrow{\hat{R2_{bb}T2_{bb}}}}{\left|\overrightarrow{\hat{R2_{bb}T2_{bb}}}\right|^2} \overrightarrow{\hat{R2_{bb}T2_{bb}}} \right|$$

Edge-joint:
Can only be determined if the profile sensing is made so wide that $R1_{wf}$ and $R2_{wf}$ reach the edge of the plates.
For plate 1 the plate thickness is the length of the projecting $R1_{wf}T1_{wf}$ vector at the root vector.
For plate 2 the plate thickness is the length of the projecting $R2_{wf}T2_{wf}$ vector at the root vector.

$$thickness\ plate\ 1 = \left| \frac{\overrightarrow{R1_{wf}T1_{wf}} \cdot \overrightarrow{root}}{\left|\overrightarrow{root}\right|^2} \overrightarrow{root} \right|$$

$$thickness\ plate\ 2 = \left| \frac{\overrightarrow{R2_{wf}T2_{wf}} \cdot \overrightarrow{root}}{\left|\overrightarrow{root}\right|^2} \overrightarrow{root} \right|$$

C.3.6 Scarf angle

Scarf-groove:
Angle between the $T1_{bb}T1_{wf}$ vector and $T1_{wf}R1_{wf}$ vector.

$$scarf\ angle = angle\left(\overrightarrow{T1_{bb}T1_{wf}}, \overrightarrow{T1_{wf}R1_{wf}}\right)$$

C.3.7 Depth of bevel plate 1 and 2

V-, bevel-, U- and J-groove:
For plate 1 the depth of bevel is the distance between point $T1_{wf}$ and the line spanned by $S1_{wf}$ and $R1_{wf}$.
For plate 2 the depth of bevel is the distance between point $T2_{wf}$ and the line spanned by $S2_{wf}$ and $R2_{wf}$.

$$depth\ of\ bevel\ plate\ 1 = dist\left(T1_{wf}, line\left(S1_{wf}, R1_{wf}\right)\right)$$

$$depth\ of\ bevel\ plate\ 2 = dist\left(T2_{wf}, line\left(S2_{wf}, R2_{wf}\right)\right)$$

C.3.8 Depth of flare plate 1 and 2

Flare-V- and flare-bevel-groove:
For plate 1 the depth of flare is the distance between point $T1_{wf}$ and the line spanned by $S1_{wf}$ and $R1_{wf}$.
For plate 2 the depth of flare is the distance between point $T2_{wf}$ and the line spanned by $S2_{wf}$ and $R2_{wf}$.

$$depth\ of\ bevel\ plate\ 1 = dist\left(T1_{wf}, line\left(S1_{wf}, R1_{wf}\right)\right)$$
$$depth\ of\ bevel\ plate\ 2 = dist\left(T2_{wf}, line\left(S2_{wf}\ R2_{wf}\right)\right)$$

C.3.9 Bevel angle plate 1 and 2

V- and bevel-groove:
For plate 1 the bevel angle is the angle between $S1_{wf}R1_{wf}$ vector and the $T1_{wf}S1_{wf}$ vector hat.
For plate 2 the bevel angle is the angle between $S2_{wf}R2_{wf}$ vector minus the $T2_{wf}S2_{wf}$ vector hat.

$$bevel\ angle\ plate\ 1 = angle\left(\overrightarrow{S1_{wf}\,R1_{wf}}, \hat{\overrightarrow{T1_{wf}\,S1_{wf}}}\right)$$

$$bevel\ angle\ plate\ 2 = angle\left(\overrightarrow{S2_{wf}\,R2_{wf}}, -\hat{\overrightarrow{T2_{wf}\,S2_{wf}}}\right)$$

U- and J-groove:
Two breakpoints are identified at the raw point going from $S1_{wf}$ to $T1_{wf}$ and from $S2_{wf}$ to $T2_{wf}$ by applying the method presented in figure C.3. The identified breakpoints are called $U1_{wf}$ and $U2_{wf}$ respectively. Bevel angles are calculated in the same way as the V- and bevel-groove, but instead of using $T1_{wf}$ and $T2_{wf}$ to span the vector from the groove $U1_{wf}$ and $U2_{wf}$ are used.

$$bevel\ angle\ plate\ 1 = angle\left(\overrightarrow{S1_{wf}\,R1_{wf}}, \hat{\overrightarrow{U1_{wf}\,S1_{wf}}}\right)$$

$$bevel\ angle\ plate\ 2 = angle\left(\overrightarrow{S2_{wf}\,R2_{wf}}, -\hat{\overrightarrow{U2_{wf}\,S2_{wf}}}\right)$$

C.3.10 Groove radius plate 1 and 2

U- and J-groove:
The groove radius is determined by making least-square fitting of a circle to the raw points at the curved section of the groove.
For plate 1 the raw points are between $T1_{wf}$ and $U1_{wf}$ and they are given as data points (x_i,y_i), where i is the raw point number. The parameters of a circle (a_1, a_2, a_3, a_4) are determined by making the best fit of the data points to the equation of a circle.

$$a_1 x_i^2 + a_1 y_i^2 + a_2 x_i + a_3 y_i + a_4 = 0$$

After determination of the parameters for the circle, the radius of the circle, which is the groove radius, can be found:

$$\left(x_0, y_0\right) = \left(-a_2/2a_1, -a_3/2a_1\right)$$
$$groove\,radius = \sqrt{a_4/a_1 - x_0^2 - y_0^2}$$

For plate 2 a similar fit between $T2_{wf}$ and $U2_{wf}$ is made.

C.3.11 Flare radius plate 1 and 2

Flare-V- and flare-bevel-groove:
A fit is made similar to the fit for the U- and J-groove, but the difference is that the fit for plate 1 is between $T1_{wf}$ and $S1_{wf}$ and the fit for plate 2 is between $T2_{wf}$ and $S2_{wf}$.

C.4 Determine quality parameters

Determination of the quality parameters is made in the following way. The breakpoints are detected for the workpiece after welding, illustrated in figure C.6. T-points are placed at the edge between the base material and the welded seam. When the welded seam forms a smooth surface with the base material detection of the T-points, the suggested methods has difficulties. Weld face and root vectors are those determined from the profile sensing before welding, but in case of distortion new ones are recalculated. Breakpoint after welding on the weld face side has the abbreviation wwf and breakpoint after welding on the back bead side has the abbreviation wbb.

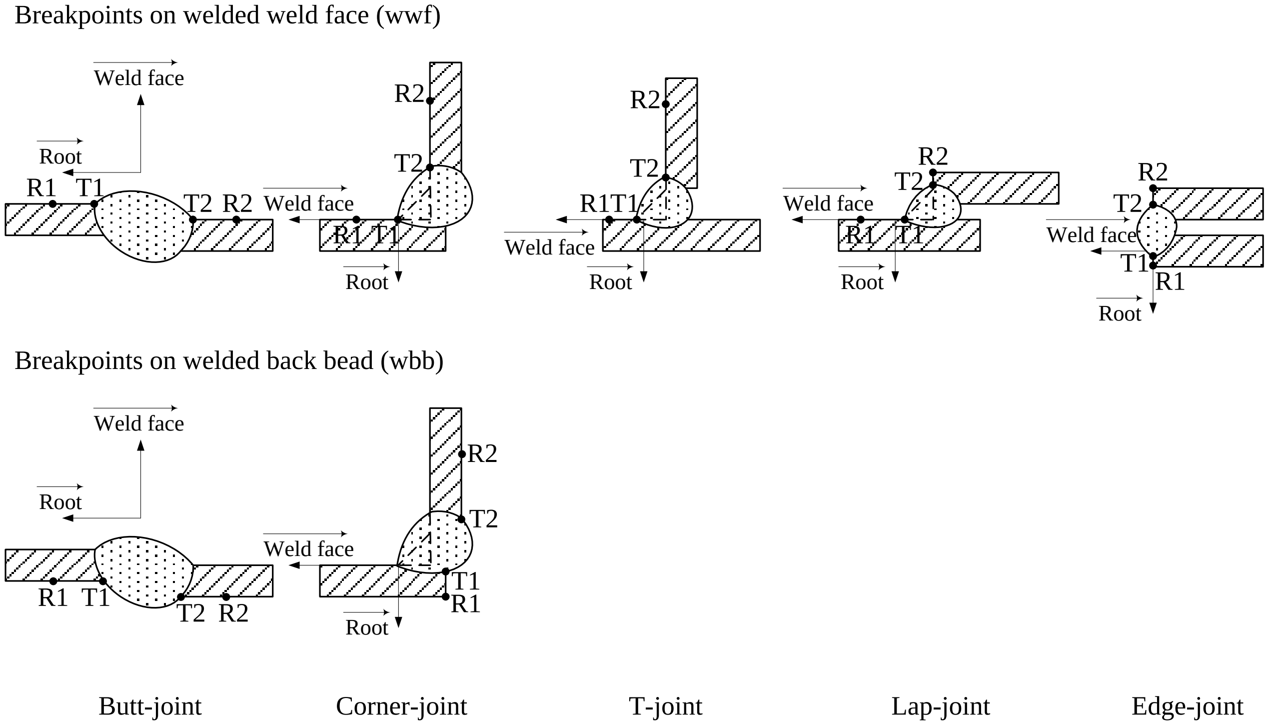


Figure C.6: Breakpoint position after welding on the weld face and back bead, for workpiece geometries with different joints and the welding direction into the paper. S breakpoints are lying on a straight line between an R and T breakpoint and for this reason they are not shown. Profile sensing is also not necessary for determination of the quality parameter for the T-, lap- and edge-joint and therefore it is not shown.

C.4.1 Leg length plate 1 and 2

Corner-, T- and lap-joint:
An intersection point is found as the intersection between the following two lines. The first line is spanned between $R1_{wwf}$ and $T1_{wwf}$ and the second line is spanned between $R2_{wwf}$ and $T2_{wwf}$.

$$intersection\ point = intersect\left(line\left(R1_{wwf}, T1_{wwf}\right), line\left(R2_{wwf}, T2_{wwf}\right)\right)$$

Leg length plate 1 is the distance between point $T1_{wwf}$ and the intersection point.
Leg length plate 2 is the distance between point $T2_{wwf}$ and the intersection point.

$$leg\ length\ \ plate\ 1 = dist\left(T1_{wwf}, intersection\ point\right)$$
$$leg\ length\ \ plate\ 2 = dist\left(T2_{wwf}, intersection\ point\right)$$

C.4.2 Weld face width

Butt- and edge-joint:
The length of projecting the $T1_{wwf}T2_{wwf}$ vector at the root vector.

$$weld\ \ face\ width = \left| \frac{\overrightarrow{T1_{wwf}T2_{wwf}} \cdot \overrightarrow{root}}{\left|\overrightarrow{root}\right|^2} \overrightarrow{root} \right|$$

C.4.3 Weld face height

Butt- and edge-joint:
Raw points between $T1_{wwf}$ and $T2_{wwf}$ are given as data points $(x_i,y_i) = p_i$, where i is the raw point number. The minimum and maximum heights are found between the data points, together with the two lines spanned by $T1_{wwf}$ and the root vector, and by $T2_{wwf}$ and the root vector. This check takes into consideration that the weld face height can be either positive or negative and that the plates can be unaligned. In figure C.7 some of these considerations are illustrated.

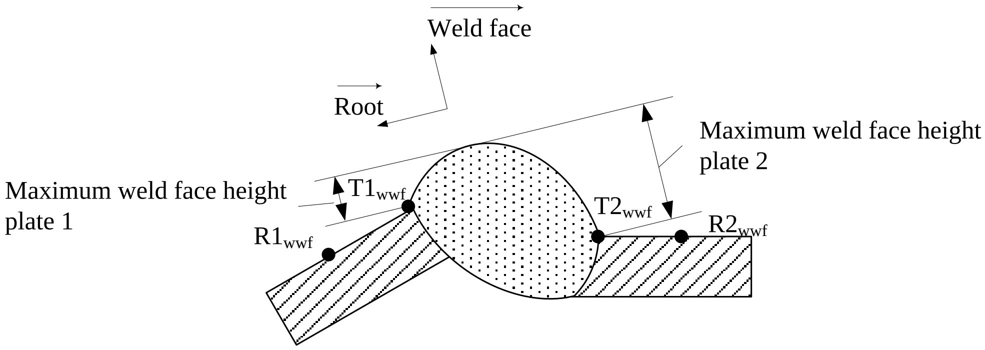


Figure C.7: The weld face height can be calculated as the distance from $T1_{wwf}$ or $T2_{wwf}$, in the direction of the weld face vector, to the outermost data point. The shortest distance is defined as the weld face height. The same definitions apply for the negative weld face height.

In figure C.8 the pseudo code is to determine the weld face height.

PosDistLine1, NegDistLine1, PosDistLine2, NegDistLine2 are real values set to zero.
while size of $data\ points \geq i$

$$\overrightarrow{projection1} = \frac{\overrightarrow{T1_{wwf}\, p_i} \cdot \overrightarrow{weld\ \ face}}{\left|\overrightarrow{weld\ \ face}\right|}\overrightarrow{weld\ \ face}$$

$$\overrightarrow{projection2} = \frac{\overrightarrow{T2_{wwf}\, p_i} \cdot \overrightarrow{weld\ \ face}}{\left|\overrightarrow{weld\ \ face}\right|}\overrightarrow{weld\ \ face}$$

if $\overrightarrow{projection1}$ is in direction of $\overrightarrow{weld\ \ face}$
then if $\left|\overrightarrow{projection1}\right|$ > *PosDistLine1*
then *PosDistLine1* = $\left|\overrightarrow{projection1}\right|$
else
then if $-\left|\overrightarrow{projection1}\right|$ < *NegDistLine1*
then *NegDistLine1* = $-\left|\overrightarrow{projection1}\right|$
if $\overrightarrow{projection2}$ is in direction of $\overrightarrow{weld\ \ face}$
then if $\left|\overrightarrow{projection2}\right|$ > *PosDistLine2*
then *PosDistLine2* = $\left|\overrightarrow{projection2}\right|$
else
then if $-\left|\overrightarrow{projection2}\right|$ < *NegDistLine2*
then *NegDistLine2* = $-\left|\overrightarrow{projection2}\right|$
if *PosDistLine1 > PosDistLine2*
then *WeldFaceHeightPosetive = PosDistLine2*
else *WeldFaceHeightPosetive = PosDistLine1*
if *NegDistLine1 > NegDistLine2*
then *WeldFaceHeightNegative = NegDistLine1*
else *WeldFaceHeightNegative = NegDistLine2*
if *WeldFaceHeightPosetive > -WeldFaceHeightNegative*
then *WeldFaceHeight = WeldFaceHeightPosetive*
else *WeldFaceHeight = WeldFaceHeightNegative*

Figure C.8: Pseudo code for determining the weld face height.

C.4.4 Back bead width

Butt- and corner-joint:
The length of projecting the $T1_{wbb}T2_{wbb}$ vector on the root vector.

$$weld\ \ face\ width = \left| \frac{\overrightarrow{T1_{wbb}T2_{wbb}} \cdot \overrightarrow{root}}{\left|\overrightarrow{root}\right|^2} \cdot \overrightarrow{root} \right|$$

C.4.5 Back bead height

Butt- and corner-joint:

Is determined in the same way as the weld face height. The only two differences are:

- Raw points between $T1_{wbb}$ and $T2_{wbb}$ are given as data points.
- The weld face vector is changed to opposite direction.

C.4.6 Theoretical throat

Corner-, T- and lap-joint:

The plate angle is known and for the lap-joint it is set to 90°. The shortest leg length of the leg length plate 1 and leg length plate 2 is found. It is used afterwards for calculation of the theoretical throat.

$$theoretical\ throat = shortest\ leg\ length \cdot \cos\left(\frac{plate\ angle}{2}\right)$$

C.4.7 Equal legs

Corner-, T- and lap-joint:

The grade is calculated according to standard [ISO 5817] number 1.16. The standard for equal legs sets a maximum leg length difference between leg length plate 1 and plate 2, as illustrated in figure C.9. It can be rewritten to the following expression, which calculates the grade for equal legs.

$$\begin{aligned}
&if\ (1.5 + 0.15 \cdot Theoretical\ throat \geq abs(Leg\ length\ \ plate\ 1 - Leg\ length\ \ plate\ 2))\ then\ B \\
&else\ if\ (2 + 0.15 \cdot Theoretical\ throat \geq abs(Leg\ length\ \ plate\ 1 - Leg\ length\ \ plate\ 2))\ then\ C \\
&else\ if\ (2 + 0.2 \cdot Theoretical\ throat \geq abs(Leg\ length\ \ plate\ 1 - Leg\ length\ \ plate\ 2))\ then\ D \\
&else\ E
\end{aligned}$$

C.4.8 Convexity

Corner-, T- and lap-joint:

The grade is calculated according to standard [ISO 5817] number 1.10. The convexity was determined from the height of the seam illustrated in figure C.9. The standard sets a maximum height of seam according to the width of reinforcement. Width of reinforcement was calculated from plate angle and leg length plate 1 (llp1) and plate 2 (llp2), using the cosines relation.

$$width\ of\ \ reinforcement = \sqrt{llp1^2 + llp2^2 - 2 \cdot llp1 \cdot llp2 \cdot \cos\ plate\ angle}$$

Height of seam was calculated using a simplified method of the one used for calculating weld face height, shown in figure C.8. The simplification is that only a positive height is found and there is only one line to determine the distance to the data points. Raw points between $T1_{wwf}$ and $T2_{wwf}$ are given as data points. The maximum height is found between the data points and the lines are spanned by the $T1_{wwf}T2_{wwf}$ vector and point $T1_{wwf}$. Calculation of the grade for the convexity can be written as the following expression:

$$\begin{aligned}
&\mathit{if}\ ((1+0.1\cdot \mathit{width\ of\ reinforcement} \geq \mathit{height\ of\ seam})\mathit{and}\ (3 \geq \mathit{height\ of\ seam}))\,\mathit{then}\ B\\
&\mathit{else\ if}\ ((1+0.15\cdot \mathit{width\ of\ reinforcement} \geq \mathit{height\ of\ seam})\mathit{and}\ (4 \geq \mathit{height\ of\ seam}))\,\mathit{then}\ C\\
&\mathit{else\ if}\ ((1+0.25\cdot \mathit{width\ of\ reinforcement} \geq \mathit{height\ of\ seam})\mathit{and}\ (5 \geq \mathit{height\ of\ seam}))\,\mathit{then}\ D\\
&\mathit{else}\ E
\end{aligned}$$

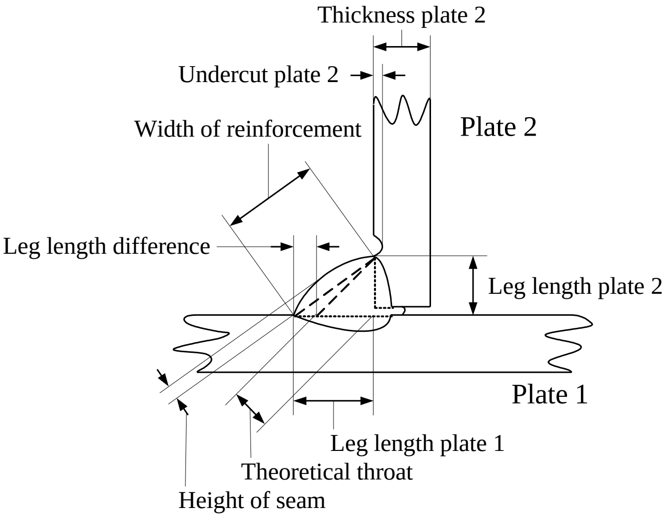


Figure C.9: Measurements of weld seam according to [ISO 5817] standard.

Appendix D

Setup of specific system to produce welding experiments

The specific system for production of experiments to generate empirical welding data is described. This appendix consists of two parts. Part D.1 describes the system components and system setup which was done in a number of files. In part D.2 the frames in the system are defined. Furthermore, in part D.2 it is described how the calibration of the transformation between the frames was made.
The existing software in the system was developed at Department of Production at Aalborg University and at IWA [IWA] and it was only very little documented. For this thesis further development was made on the existing software to generate automatic experiments and this appendix is the documentation of the system and its setup.

D.1 Setup files

To make the experiments a system with a process control and data collection tool was developed. The process control and data collection tool controls all the equipment, which was the laser scanner, robot and welding machine. It was done by sending messages described in a communication protocol through a neutral interface with questions and instructions about measuring the part, carry out the experiment and send the experimental results. At the same time the process control and data collection tool also received messages through the neutral interface from the equipment with e.g. measurements. For the setup with a laser scanner, robot and welding machine was the communication and setup files shown in figure D.1. The communication through the neutral interface between the process control and data collection tool and the neutral equipment interfaces was based on the TCP/IP protocol with a specified language for communication described by [Nielsen, 2003]. Between the neutral interfaces and the physical equipment an equipment specific communication was used. The flexibility of the setup, by using neutral interfaces and a TCP/IP connection, made it possible to add and remove equipment for a specific task.

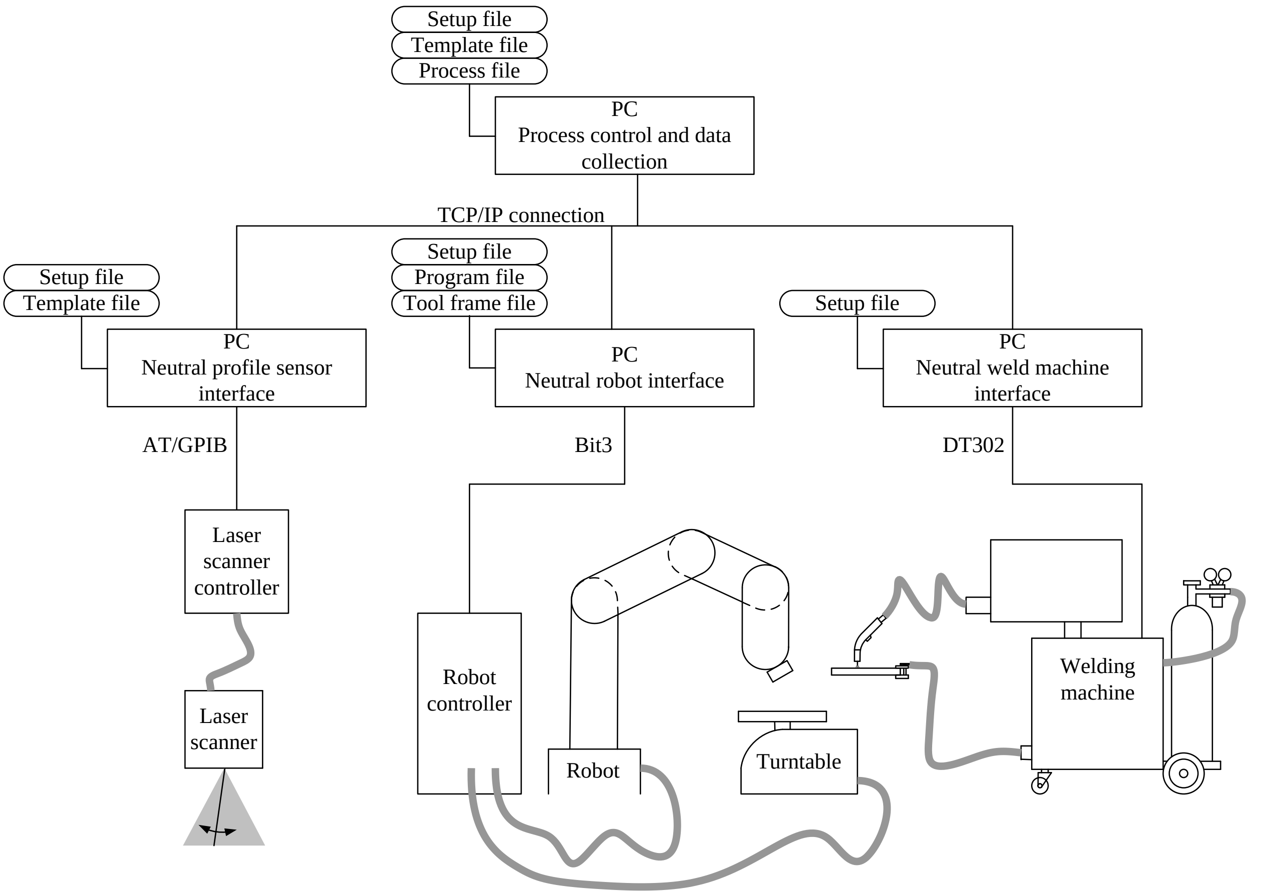


Figure D.1: The setup of the communication between the process control and data collection tool and the equipment: laser scanner, robot controller and welding machine.

Four programs were implemented on PCs and each required one or more setup files. The programs on the four PCs were:

- Neutral profile sensor interface
- Neutral weld machine interface
- Neutral robot interface
- Process control and data collection tool

The setup of the four programs is described in the following.

D.1.1 Neutral profile sensor interface

The neutral profile sensor interface is developed at Department of Production and described in [Madsen, 1998] and [Nielsen, 2003]. In the thesis is the communication protocol extended to send raw points from laser scanning. The neutral profile sensor interface connects via TCP/IP to the process control and data collection tool and with an equipment specific connection to the laser scanner, which is a SeamPilot optical profile sensor from Odelft, Holland. The equipment specific connection is made via an AT/GPIB interface card from National Instruments installed on the PC.

The neutral profile sensor interface program is running as a state machine that sends and receives messages from the process control and data collection tool. Depending on these messages the neutral profile sensor interface program is in different states where it can send and receive signals from the laser scanner. In the neutral profile sensor interface different templates are to analyse raw points from the laser scanner for producing analysed data points described by breakpoints.

In figure D.2 is the file to setup the neutral profile sensor interface shown.

```
[GENERAL]
ScannerType=OLDELFT_SENSOR
templatelocation=d:\\testcell\\data\\
defaulttemplate=normal
samplingFrequency=5
sensortype=oldelft

[FILES]
SensorSimulatorDataFileName=d:\\testcell\\data\\filtereddatascan.txt

[SCANNERPORT]
port=1500

[LOGDATA]
logfile=d:\\scannerLogFile.txt
logging=true
```

Figure D.2: The setup file "scanner.ini".

[GENERAL]
ScannerType: Specify by name the laser scanner to use.
templatelocation: Specify the path of the template to use.
defaulttemplate: The filename of the template to use. In the template is specified the parameters of how the laser scanner measurements are interpreted and the template setup is shown in figure D.3.
samplingFrequency: Specifies the number of the scanner measurements per second. By setting a jumper inside the SeamPilot laser scanner controller it can be changed if it should measure the profiles when the laser goes forward and backwards or only forward. For these experiments were only used forward.
sensortype: Specify if the selected scanner should run in reality or as a simulator. (oldelft/simulator)
[FILES]
SensorSimulatorDataFileName: Specify the path and filename of the file with laser scanner profile data used for simulating laser scanner measurements.
[SCANNERPORT]
port: Specify at which port the scanner interface is listening for messages from the process control and data collection tool.
[LOGDATA]
logfile: Specify the path and the filename of the log file the neutral profile sensor interface creates for logging data from the communication with the process control and data collection tool.
logging: Specify if the log file should be created. (true/false)

In figure D.3 is the file to setup the laser scanner template described.

```
#Template_Data_File_Start

TemplateName:        normal
location:            d:\\testcell\\data\\

type:                TjointRoot
ScanAngle:           10
MaxNoNotOK           1
MaxNoNoMatch         1
n1                   3
n2                   4
Nleft                1
Nright               1
T                    1

#Template_Data_File_End
```

Figure D.3: The template file with setup parameters. The file "normal" is used for the T-joint with root gap.

TemplateName: Specify the filename of the template, which is the filename of itself.
Location: Specify the path to the TemplateName.
type: Specify the methodology to interpret the raw laser scanner data. The interpreted raw laser scanner data is described by breakpoints described in section D.2.3 Process control and data collection tool. A interpretation is implemented for the three types rootPass, Tjoint and TjointRoot, which respectively are a HalfV-Joint, a T-Joint without root gap and a T-joint with root gap. In section D.2.3 Process control and data collection tool the geometry types are explained.
ScanAngle: Specify the width of the laser scanner angle and it is possible to choose between W10, W14, W20, W30 and W40, which refers to the scanning angle in degrees.
MaxNoNotOK: Not used.
MaxNoNoMatch: Specify the number of profiles which are not recognisable before the sensor responds that is cannot recognise the profile.
n1: The raw data is a list of points and an example is illustrated in figure D.4. When interpreting the raw points is a section of raw points selected one by one. The section of raw points selected is mowed from each end of the list of raw points towards the middle and a list of first order derivative points is calculated. An iteration more is made where a section of the first order derivative points is selected from the list of the first order derivative points and a list of second order derivative points are calculated. The parameter n1 specify the number of points in the selection of points moved from the left, shown in figure D.4.
n2: This parameter works the same way as n1 except of n2 is the size of the moving selection of points starting from the right, shown in figure D.4.
Nleft: Specify how many bends there should be found on the section of data when mowing from the left on the point in the second order derivative list. The bend and breaks are found from the largest values of the second derivative. See example on figure D.4.
Nright: Specify the same way as Nleft the number of bends but this is for the section from mowing from the right on the second order derivative data.
T: Specify the threshold of the second order derivative. When the second order derivative is smaller or bigger than the threshold then a bend or a break of the raw points is detected. The two horizontal lines in figure D.4 show the thresholds upper and lover value.

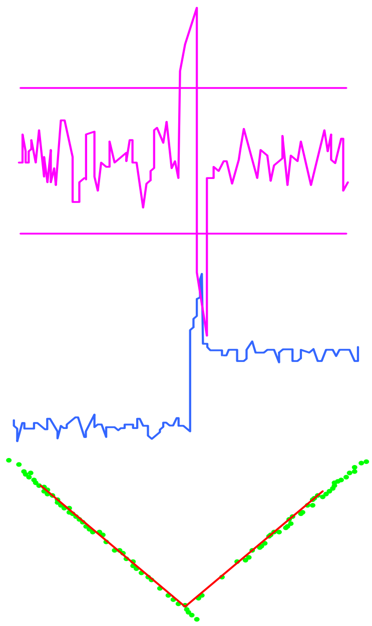


Figure D.4: For the T-joint without root gap is illustrated the creation of breakpoint coordinates. The green dots are the raw points from the laser scanner. The blue line is the first order derivative. The pink line is the second order derivative and the two horizontal pink lines are the upper and lower threshold. When the second order derivative is outside the threshold is a bend or break detected on the raw data and these bends and breaks are the places for breakpoints. The red line is calculated from the calculated breakpoint coordinates.

D.1.2 Neutral weld machine interface

The neutral weld machine interface is developed at Department of Production and described in [Lauridsen, 1999] and [Nielsen, 2003]. In the thesis is the communication protocol extended to send welding data at a certain rate. The neutral weld machine interface connects via TCP/IP with the process control and data collection tool, via TCP/IP with the neutral robot interface and with an equipment specific connection to the BDH 550 welding machine from MIGATRONIC, Denmark which is equipped with an interface card. The equipment specific connection is on the PC with a DT302 interface card and is described by [Lauridsen, 1999].

The neutral weld machine interface program is running as a state machine that sends and receives messages from the process control and data collection tool. Depending on these messages the neutral weld machine interface program is in different states where it can send and receive signals from the welding machine.

In figure D.5 is the file to setup the neutral weld machine interface shown.

```
[SOCKETLOG]
logfileLocation=D:\\messagetrafficWM.log
logging=true

[WELDMACHINEPORT]
port=1700

[MODE]
simulationWelding=BDH550AAU
```

Figure D.5: The setup file “weldmachine.ini”.

[SOCKETLOG]
logfileLocation: Specify the path and the filename of the log file which the neutral weld machine interface can create to log data from the communication with the process control and data collection tool and the neutral robot interface.
logging: Specify if the log file should be created. (true/false)
[WELDMACHINEPORT]
port: Specify at which port the neutral weld machine interface is listening for messages from the process control and data collection tool and the neutral robot interface.
[MODE]
simulationWelding: Specify if the welding machine used is the real welding machine or a simulated welding machine. The simulated welding machine produces simulated welding data. (BDH550AAU/simulator)

D.1.3 Neutral robot interface

The neutral robot interface is developed at Department of Production and described in [Nielsen, 2003]. In the thesis is the communication protocol extended to with functionality to log data from robot and turntable. The neutral robot interface connect via TCP/IP with the process control and data collection tool, via TCP/IP with the neutral weld machine interface and with an equipment specific connection to REIS RSIV robot controller controlling the REIS RV15 robot and the RDK500 workpiece positioner from REIS, Germany. The equipment specific connection is on the PC with a Bit3 model 406 adapter card from Bit3 Computer Corporation.
The neutral robot interface program is running as a state machine that sends and receives messages from the process control and data collection tool. Depending on these messages the neutral robot interface program is in different states where it sends and receives signals from the laser scanner.
In figure D.6 is the file to setup the neutral robot interface illustrated.

```
[SOCKETLOG]
logfileLocation=D:\\messagetraffic.log
on=true

[SERVERPC]
ipAddress=130.225.59.142
port=1400

[FILELOCATION]
robotprogram=D:\\robotprogramMorten.dat

[MODE]
simulationRobot=REISAAU

[WELDING]
on=true
ipAddress=130.225.59.122
port=1700

[CRATERTIMES]
startCrater=1000
endCrater=1000
```

Figure D.6: The setup file “configdata.ini”.

[SOCKETLOG]
logfileLocation: Specify the path and the filename of the log file which the neutral robot interface can create to log data from the communication with the process control and data collection tool and neutral weld machine interface.
on: Specify if the log file should be created. (true/false)
[SERVERPC]
ipAddress: Specify the IP address of the PC with the process control and data collection tool. The neutral robot interface is server and needs to know which PC with the process control and data collection tool to connect to.
port: Specify the port at which the process control and data collection tool have to listen.
[FILELOCATION]
robotprogram: Specify the path and file name of the start file with setup information which is required by the neutral robot interface and the file is shown in figure D.7.
[MODE]
simulationRobot: Specify which robot is used and it could be a real robot or a simulation of a robot. It is changed by writing “AAUsim” and “REIS”.
[WELDING]
on: Specify if the neutral robot interface is controlling the neutral weld machine interface. (true/false)
ipAddress: Specify the IP address of the PC with the neutral weld machine interface, to which the neutral robot interface has to connect to, because the neutral robot interface is server.
port: Specify the port where the neutral weld machine interface should listen.
[CRATERTIMES]
startCrater: Specify the time in milliseconds the robot motion should sleep when starting welding.
endCrater: Specify the time in milliseconds the robot motion should sleep when ending welding.

In figure D.7 is the file defining the frames used in the neutral robot interface shown.

```
#start_of_weldingControlVector_file

#start_of_task_description

specificationFrame        TABLE
hTtFrame                  d:\\setup.dat

#end_of_task_description

#end_of_weldingControlVector_file
```

Figure D.7: The program file “robotprogramMorten.dat”

specificationFrame: Specify what frame the robot should refer to. The choice is between table frame or Cartesian frame and is described in section D.2 System frames.
hTtFrame: Specify the path and filename of the file with the ${}^{h}T_{t}$ transformation and it is shown in figure D.8.

In figure D.8 is the file illustrated for setting up the reference frame to tool frame transformation in the neutral robot interface.

```
BeginFrame “t_hand_torch”
 Position (-3.95179,246.193,345.909)
        I       (-0.00321961,0.721644,0.692257)
        J       (-0.0036089,-0.692264,0.721635)
        K       (0.999988,-0.000174903,0.00483316)
  Attributes
                ReferenceFrame “Hand”

EndFrame
```

Figure D.8: The tool frame file for the neutral robot interface.

Position: Specify the position from reference frame to tool and it is described in D.2 System frames.
I, J and K: Specify the orientation from reference frame to tool and it is described in D.2 System frames.
ReferenceFrame: Specify the reference frame and for the transformation described by the position and orientation I, J and K. It is described in section D.2 System frames.

D.1.4 Process control and data collection tool

The process control and data collection tool connects via TCP/IP with the neutral profile sensor interface, neutral robot interface and neutral weld machine interface. The process control and data collection tool used was a modification of the IPAC™ software, which is commercial software from IWA [IWA]. The IPAC software for process control was in this work modified by the following points:

- A welding experiment was specified in a number of files, in a format developed to make experiments at different workpiece geometries. The files describing a welding experiment are in appendix E. In the process control and data collection tool was made an interface to read the files and it was implemented so the process control and data collection tool carried out the experiment after the description in the files.
- For carrying out the experiment was the process control tool modified to save the laser scanned profiles to a file and then later read the file and use the saved laser scanning to execute a welding experiment.
- The process control tool was also modified to measure data from laser scanner, robot and welding machine during the experimental sequence and store data in files. For this task was the communication protocol the with laser scanner, robot and welding machine expanded.

The process control and data collection tool uses three setup files: ipacmodels.xml, ipacfacilities.xml and ipacrelations.xml. [IWA]

Figure D.9 show the file “ipacfacilities.xml”, which is used by the process control and data collection tool to describe the calibration and communication setup. In the facility with type “AAUHead” is describes the transformation from the wrist of the robot to respectively the tool and the laser scanner. These values are described in section D.2 System frames. In the facility with type “AAUReisRobot”, “laserScannerOdelft” and “weldingMachineBDH550” the used equipment is specified together with the TCP/IP communication to the neutral robot interface, neutral profile sensor interface and neutral weld machine interface, respectively. [IWA] describes the details of the file.

```
<facilities>
  <facility TYPE="AAUHead">
    <att NAME="id" VALUE="AAUhead" />
    <att NAME="facilityType" VALUE="head" />
    <att NAME="Xtorch" VALUE="0" />
    <att NAME="Ytorch" VALUE="0" />
    <att NAME="Ztorch" VALUE="0" />
    <att NAME="Atorch" VALUE="0" />
    <att NAME="Btorch" VALUE="0" />
    <att NAME="Ctorch" VALUE="0" />
    <att NAME="Xsensor" VALUE="-184.664" />
    <att NAME="Ysensor" VALUE="-16.6947" />
    <att NAME="Zsensor" VALUE="56.4174" />
    <att NAME="Asensor" VALUE="2.41838" />
    <att NAME="Bsensor" VALUE="-1.57075" />
    <att NAME="Csensor" VALUE="0.733686" />
  </facility>
  <facility TYPE="AAUReisRobot">
    <att NAME="id" VALUE="AAUReisRobot"/>
    <att NAME="facilityType" VALUE="robot"/>
    <att NAME="IPaddress" VALUE="130.225.59.122"/>
  </facility>
  <facility TYPE="laserScannerOldelft">
    <att NAME="id" VALUE="OLDELFT"/>
    <att NAME="facilityType" VALUE="laserScanner"/>
    <att NAME="IPaddress" VALUE="130.225.59.122"/>
    <att NAME="PortNo" VALUE="1500"/>
    <att NAME="ScannerFileName" VALUE="d:\iwa\data\oldelftScanner.dat"/>
  </facility>
  <facility TYPE="weldingMachineBDH550">
    <att NAME="id" VALUE="BDH550"/>
    <att NAME="facilityType" VALUE="weldingMachine"/>
    <att NAME="IPaddress" VALUE="130.225.59.122"/>
    <att NAME="PortNo" VALUE="1700"/>
  </facility>
  ...
</facilities>
```

Figure D.9: A part of the setup file “ipacfacilities.xml” used to set up the process control and data collection tool for making experiments.

The parameters for analysing of the laser scanner data analysing is set up in “ipacmodel.xml”, which is shown in figure D.10. The welding control variables are set up in the file “ipacmodel.xml” in figure D.10 and in the file “ipacrelations.xml” in figure D.11.

In the file “ipacmodels.xml” is the “relationFileName” specified with the path and filename of the file “ipacrelations.xml”. In “profilesourcereferencemodel” is for the HalfV-Joint and the T-Joint specified how the interpretation of the laser scanning is made and [IWA] gives a detailed description. In “inverseprocessmodel” is for the HalfV-Joint and the T-Joint specified the values of the welding control variables. The constant values are written in the file and the variable values referrers to values in the file “ipacrelations.xml” in figure D.11. [IWA] describes the details of the file.

```
<models relationFileName="d:\iwa\data\applications\AAU\ipacrelations.xml">
  <profilesourcereferencemodel id="HalfV" name="ss" nomNewWCV="2"
    curveLengthBetweenWCV="0.005">
    <profilesourceFileBased
      type="BranchPipeFullBevelPipe"
      sensorTemplateStaticProfile="outerFlange"
      sensorTemplateDynamicProfile="outerFlange"
      maxDistT1T2="5.5"
      minDistT1T2="1.0"
      maxAngleT1R1_T2R2="50"
      minAngleT1R1_T2R2="40"
      NmaxStaticError="100"
      NmaxStaticRST="1"
      NmaxTackCount="102"
      NmaxNormalCount="1"
      NmaxError="50"
      NseamQueue="2"
      NnewSeam="1"
      minDistance="1.0"/>
  </profilesourcereferencemodel>

  <profilesourcereferencemodel id="TJoint" name="ss" nomNewWCV="2"
    curveLengthBetweenWCV="0.005">
    <profilesourceFileBased
      type="TJoint"
      sensorTemplateStaticProfile="outerFlange"
      sensorTemplateDynamicProfile="outerFlange"
      maxDistT1T2="3.5"
      minDistT1T2="-1.0"
      maxAngleT1R1_T2R2="100"
      minAngleT1R1_T2R2="80"
      NmaxStaticError="100"
      NmaxStaticRST="1"
      NmaxTackCount="102"
      NmaxNormalCount="1"
      NmaxError="50"
      NseamQueue="2"
      NnewSeam="1"
      minDistance="1.0"/>
  </profilesourcereferencemodel>

  <inverseprocessmodel
    Id="AAUTJoint"
    WeavingModelReference="test1">
    <identification Name="IPAC B14 laser" Type="default ipm"/>
    <constant Name="arcCorrection" Value="10"/>
```

```
    <constant Name="jobMode" Value="12233"/>
    <constant Name="weldingOn" Value="1.0"/>
    <constant Name="sideWayX" Value="0.0"/>
    <constant Name="OVx" Value="-1.0"/>
    <constant Name="OVy" Value="1.0"/>
    <constant Name="OVz" Value="0.0"/>
    <constant Name="oscillationOn" Value="1"/>
    <relationreference Reference="travelAngle_TJoint_IPAC"/>
    <relationreference Reference="workAngle_TJoint_IPAC"/>
    <relationreference Reference="rotationAngle_TJoint_IPAC"/>
    <relationreference Reference="sideWayY_TJoint_IPAC"/>
    <relationreference Reference="Defocus_TJoint_IPAC"/>
    <relationreference Reference="laserPower_TJoint_IPAC"/>
    <relationreference Reference="weldingSpeed_TJoint_IPAC"/>
    <relationreference Reference="wireFeedSpeed_TJoint_IPAC"/>
    <relationreference Reference="voltage_TJoint_IPAC"/>
    <relationreference Reference="stickOut_TJoint_IPAC"/>
    <relationreference Reference="OW_TJoint_IPAC"/>
    <relationreference Reference="OF_TJoint_IPAC"/>
    <relationreference Reference="OT_TJoint_IPAC"/>
  </inverseprocessmodel>
  <inverseprocessmodel
    Id="AAUHalfV"
    WeavingModelReference="test1">
    <identification Name="IPAC B14 laser" Type="default ipm"/>
    <constant Name="arcCorrection" Value="10"/>
    <constant Name="jobMode" Value="12233"/>
     <constant Name="stickOut" Value="5000.0"/>
     <constant Name="weldingOn" Value="1.0"/>
     <constant Name="sideWayX" Value="0.0"/>
     <constant Name="OW" Value="2.6"/>
     <constant Name="OF" Value="1.0"/>
     <constant Name="OT" Value="35"/>
     <constant Name="OVx" Value="1.0"/>
     <constant Name="OVy" Value="0.0"/>
     <constant Name="OVz" Value="0.0"/>
     <constant Name="oscillationOn" Value="1"/>
     <relationreference Reference="travelAngle_HalfV_IPAC"/>
     <relationreference Reference="workAngle_HalfV_IPAC"/>
     <relationreference Reference="rotationAngle_HalfV_IPAC"/>
     <relationreference Reference="sideWayY_HalfV_IPAC"/>
     <relationreference Reference="Defocus_HalfV_IPAC"/>
     <relationreference Reference="laserPower_HalfV_IPAC"/>
     <relationreference Reference="weldingSpeed_HalfV_IPAC"/>
     <relationreference Reference="wireFeedSpeed_HalfV_IPAC"/>
     <relationreference Reference="voltage_HalfV_IPAC"/>
 </inverseprocessmodel>
  ...
```

```
</models>
```

Figure D.10: A part of the template file “ipacmodels.xml” used for the experimental setup.

Figure D.11 shows an example of how a relation is set up for a welding control variable in the file “ipacrelations.xml”. In the figure is shown how the welding control variable wire feed speed is set up for an experiment. The same principle is used for all the welding control variables.

```
<relations>
  <relation ID="wireFeedSpeed_TJoint_IPAC" NAME="wireFeedSpeed for TJoint IPAC">
    <discrete>
      <inputvariable NAME="curveLength" />
      <outputvariable NAME="wireFeedSpeed" />
      <expressionsequence>
        <expression EXP="12.0;"  DOMAINSTART="0.0" DOMAINEND="0.10"/>
        <expression EXP="15.0;"  DOMAINSTART="0.10" DOMAINEND="0.25"/>
      </expressionsequence>
    </discrete>
  </relation>
...
</relations>
```

Figure D.11: The process file with an example of wire feed speed variable setup in the file “ipacrelations.xml”.

For each relation are the id and the name described. There are used discrete descriptions for all the used variables. An input variable, in this case the “curveLength”, defines which state the output variable, in this case the “wireFeedSpeed”, should be in. In “expressionsequence” is the relation between the input variable and the output variable described. In this example is the description:
When the “curveLength” is between 0.0 and 0.10 is the “wireFeedSpeed” set to 12.
When the “curveLength” is between 0.10 and 0.25 is the “wireFeedSpeed” set to 15.
For this experiment were the “curveLength” defined in metre and the “wireFeedSpeed” defined in meter per minute.

D.2 System frames

The frames used in the system and their relations are described in this section and shown in figure D.12. Furthermore is the calibration of the system described.

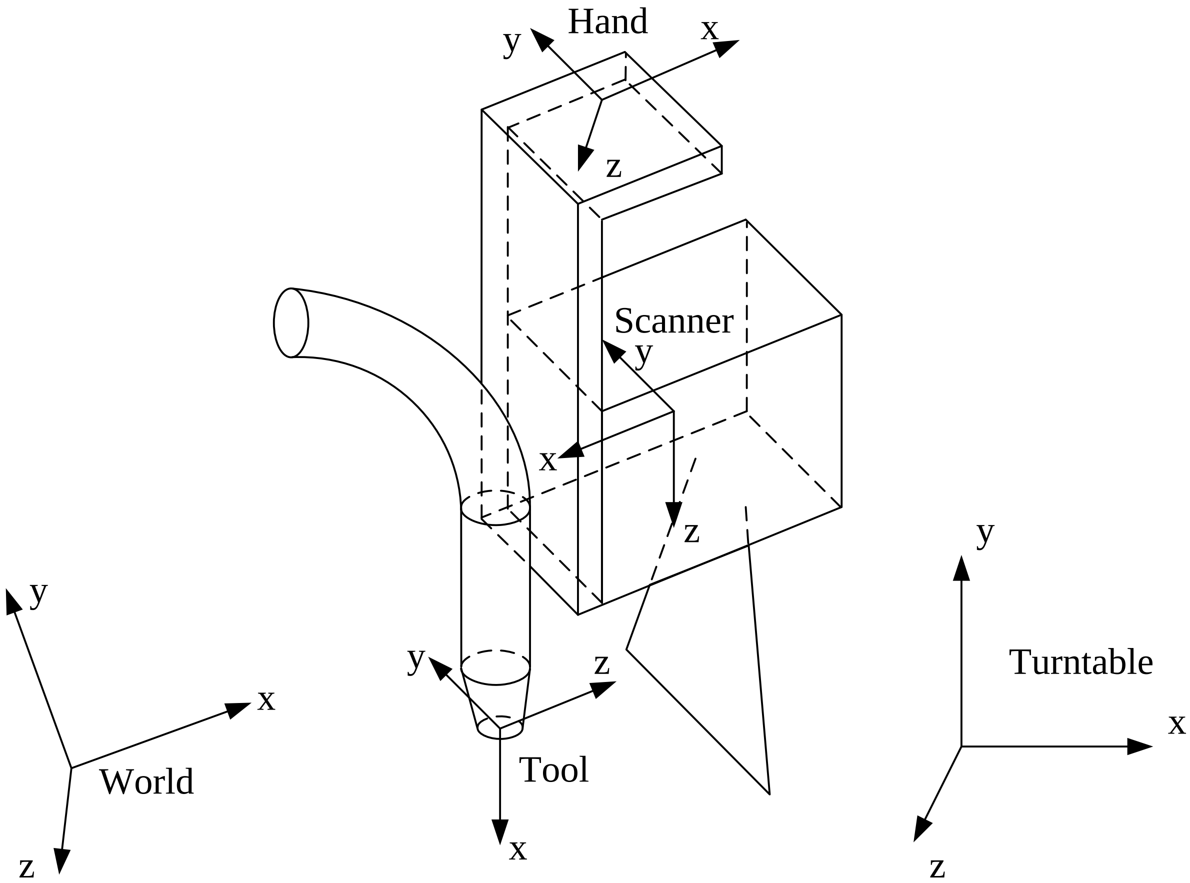


Figure D.12: Frames for world, turntable, tool, scanner, and hand. The hand frame of the robot is fixed to the tool fixture where the laser scanner with the scanner frame and welding torch with the tool frame are mounted.

World-frame was located in the world with a relation to the base of the robot.
Turntable-frame was located at the turning part at turntable and followed its movements.
Tool-frame (defined in chapter 3) was affixed to the tool center point, which here was the tip of the nozzle on the welding gun.
Scanner-frame (defined as sensor-frame in chapter 4) was affixed to the camera inside the laser scanner.
Hand-frame was affixed at the end of the robot arm where the tool fixture was mounted.

D.2.1 Calibration

Determination of $^{world}T_{hand}$ and $^{turntable}T_{hand}$.

When the robot is calibrated the Cartesian coordinates of the hand frame are known in either world frame $^{world}T_{hand}$ or the turntable frame $^{turntable}T_{hand}$. It was chosen to use the turntable frame because some of the parts require a laser scanning on the backside. To make the laser scanning on the backside of the part was the turntable rotated 180º and by using the turntable frame was the turning of the table represented in the $^{turntable}T_{hand}$.

Calibration of $^{hand}T_{tool}$ and $^{hand}T_{scanner}$

Calibration software was used to calibrate the tool and scanner frame according to the hand frame which was respectively $^{hand}T_{tool}$ and $^{hand}T_{scanner}$. The calibration procedure and software is described in [Nielsen et al., 2003]. In figure D.13 is shown the result of the calibration program.

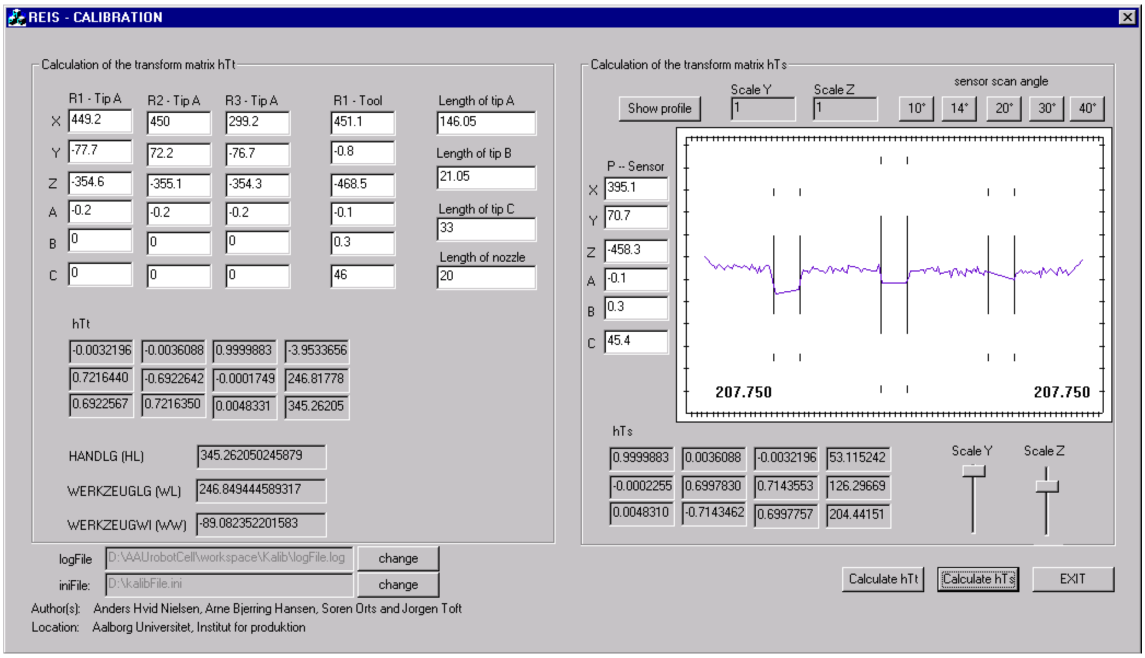


Figure D.13: Screen dump of the calibration program showing the calibration result.

A setup file was made by the calibration program and it was split up into three parts to calibrate:

- The neutral robot interface.
- The process control and data collection tool.
- The REIS robot.

The three parts are described and shown in figure D.8, figure D.14 and figure D.15 respectively. The process control and data collection tool made the planning as if the tool frame were laying in the hand frame. This was done because the process control and data collection tool plans in the hand frame and the changes of welding parameters should be executed as if they were in the tool frame.

Calibration of neutral robot interface

The setup file for the neutral robot interface shown in figure D.8 contains the transformation ${}^{hand}T_{tool}$. The neutral robot interface uses this transformation to transform locations in hand frame to tool frame.

Calibration of the process control and data collection tool

In the setup file for the process control and data collection tool is ${}^{hand}T_{tool}$ and ${}^{hand}T_{scanner}$ shown in figure D.14. Because the process control and data collection tool made the planning where the hand and tool frame both were in the hand frame was the ${}^{hand}T_{tool}$ zero and the ${}^{hand}T_{scanner}$ was the transformation from tool frame to scanner frame.

```
<facility TYPE="AAUHead">
  <att NAME="id" VALUE="AAUhead" />
  <att NAME="facilityType" VALUE="head" />
  <att NAME="Xtorch" VALUE="0" />
  <att NAME="Ytorch" VALUE="0" />
  <att NAME="Ztorch" VALUE="0" />
  <att NAME="Atorch" VALUE="0" />
  <att NAME="Btorch" VALUE="0" />
  <att NAME="Ctorch" VALUE="0" />
```

```
  <att NAME="Xsensor" VALUE="-184.688" />
  <att NAME="Ysensor" VALUE="-18.395" />
  <att NAME="Zsensor" VALUE="56.4084" />
  <att NAME="Asensor" VALUE="2.41838" />
  <att NAME="Bsensor" VALUE="-1.57075" />
  <att NAME="Csensor" VALUE="0.733686" />
</facility>
```

Figure D.14: Setup file for the process control and data collection tool based on IPAC.

The description of the transformation in figure D.14 is using the process control tool notation with a position and a orientation described by yaw, pitch and roll.

Calibration of REIS robot

The REIS robot can be equipped with different tools, which have different tool centre points. The transformation from the hand to the tool centre point was specified by ${}^{hand}T_{tool}$. For the REIS robot it is described by three values: HANDLG (HL), WERKZEUGWI (WW) and WERKZEUGLG (WL). From these values the hand to tool transformation can be calculated the following way.

$${}^{hand}T_{tool} = \begin{bmatrix} \cos(WW) & -\sin(WW) & 0 & WL \cdot \cos(WW) \\ \sin(WW) & \cos(WW) & 0 & -WL \cdot \sin(WW) \\ 0 & 0 & 1 & HL \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

The setup file used for the Reis robot to specify the ${}^{hand}T_{tool}$ is shown in figure D.15.

```
HL:        345.262
WW:         -89.082
WL:        246.849
```

Figure D.15: Setup for the REIS robot in the program “ADPROG” in the REIS robot controller.

Different setup of tool positions can be used but because the neutral robot interface made the ${}^{hand}T_{tool}$ was the tool used defined in the REIS controller and it was TNULL with HL = 0, WW = 0 and WL = 0.

D.2.2 Task path

The experiment task was assembled from three types of subtasks: inter task motion, scanning task and welding task. They were described in XML files which are shown in appendix E. The task locations were manually programmed and comes from readings of the robot teach box. When teaching the locations was the TNULL tool used and described as ${}^{turntable}T_{hand}$. A program was developed to transform the taught locations in the XML files, described in appendix E, from ${}^{turntable}T_{hand}$ to ${}^{turntable}T_{tool}$. The program used the following transformation.

$${}^{turntable}T_{tool} = {}^{turntable}T_{hand} \cdot {}^{hand}T_{tool}$$

D.2.3 Process control and data collection tool

The process control and data collection tool made all the calculations as if the tool frame was in the same position and orientation as the hand frame.

Laser scanning

The process control and data collection tool controls the laser scanning by moving the tool to the locations specified in the XML scanning file described in appendix E. For each location was made a scanning as illustrated in figure D.16. The scanning gives two types of measured points:

- Raw points which lays on the grey lines in figure D.16
- Breakpoints which describes the seam shape and is marked as the grey dots in figure D.16

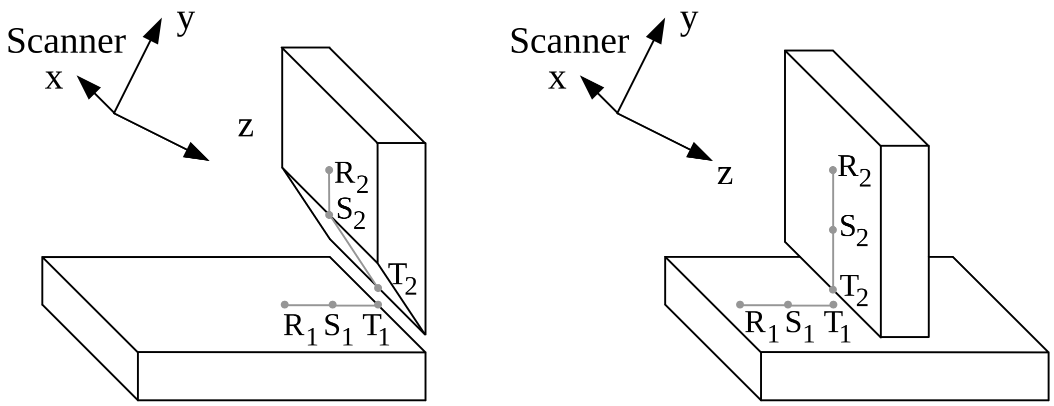


Figure D.16: The part on the left is a HalfV-Joint and on the right is a T-Joint. The plane made by the laser scanning is perpendicular to x-axis of the scanner frame. This results in laser scanner measurements which are in the y-z plane. The laser scanner measurements are raw points along the grey lines and breakpoints in the grey dots.

The process control and data collection tool generated an output file for each laser scanning task. The file had the transformation ${}^{tool}T_{scanner}$ written in the head of the file. For each laser scanning was written the tool transformation ${}^{turntable}T_{tool}$ and all the raw and breakpoints in scanner frame.

Welding

The process control and data collection tool plans the welding based on the laser scanning file from the pre welding scanning. During welding the process control and data collection tool writes an output file with a specified frequency. For each welding measurement was written the tool transformation ${}^{turntable}T_{tool}$ together with measured values from the welding process.

Appendix E

Task sequence

In this appendix is a description of the files to set up a sequence of tasks for making a welding experiment in the experimental system. All the files used for setting up an experiment are shown for the HalfV-Joint, but for the T-Joint are only shown the files there differ from the HalfV-Joint.

E.1 HalfV-Joint

The sequence of tasks is illustrated in figure E.1.

```
<Sequence>
  <Task Type="InterTask" FileName="subtasks\\interTaskSubTask001.xml" />
  <Task Type="SprofileSensing" FileName="subtasks\\openLoopScanningSubTaskFacePre001.xml"
    OutputFileName="RawPreWeldScanFace001.xml" />
  <Task Type="InterTask" FileName="subtasks\\interTaskSubTask002.xml" />
  <Task Type="ProfileSensing" FileName="subtasks\\openLoopScanningSubTaskBackPre001.xml"
    OutputFileName="RawPreWeldScanBack001.xml" />
  <Task Type="InterTask" FileName="subtasks\\interTaskSubTask003.xml" />
  <Task Type="WeldingExperiment" FileName="NN" OutputFileName="Data.xml"
    InputFileName="RawPreWeldScanFace001.xml" />
  <Task Type="InterTask" FileName="subtasks\\interTaskSubTask004.xml" />
  <Task Type="ProfileSensing" FileName="subtasks\\openLoopScanningSubTaskFacePost001.xml"
    OutputFileName="RawPostWeldScanFace001.xml" />
  <Task Type="InterTask" FileName="subtasks\\interTaskSubTask005.xml" />
  <Task Type="ProfileSensing" FileName="subtasks\\openLoopScanningSubTaskBackPost001.xml"
    OutputFileName="RawPostWeldScanBack001.xml" />
  <Task Type="InterTask" FileName="subtasks\\interTaskSubTask006.xml" />
</Sequence>
```

Figure E.1: Sequence for a HalfV-Joint.

Making a welding experiment can be pieced together of experimental parameters from three kinds of tasks:

- Inter task motion
- Profile sensing
- Welding experiment

HalfV-Joint sequence was made from 6 inter task motion, 4 profile sensing and 1 welding experiment. These 11 tasks were preformed the following way:

- Move laser scanner to start position of the laser scanning at the pre weld face
- Scan workpiece weld face pre welding
- Move robot away from the turntable and turn the table 180° and move the laser scanner to the start position of the laser scanning at the pre back bead
- Scan workpiece back bead pre welding
- Move robot away from the turntable and turn the table -180° and move the welding torch to the start position of the welding task
- Make welding experiment based on the pre weld face laser scanning
- Move laser scanner to start position of the laser scanning at the post weld face

- Scan workpiece weld face post welding
- Move robot away from the turntable and turn the table 180° and move the laser scanner to the start position of the laser scanning at the post back bead
- Scan workpiece back bead post welding
- Move robot away from the turntable and turn the table -180° and move the robot to the end position of the task

The tasks are described in the following sections.

E.1.1 Inter task motion

The experimental parameters inter task motion files are illustrated in figure E.2, figure E.3, figure E.4, figure E.5, figure E.6 and figure E.7. The experimental parameters inter task motion is composed of locations defined from a position by x, y and z, from an orientation by yaw, pitch and roll and from the angles of the turntable theta 1 and theta 2. The speed of the inter task motion is described in the bottom of the files.


```
<IPACSubTask Type="InterTask" Id="MoveTOStartPoint" SubTaskStatus="waiting">
  <InterTaskPositions>
    <RobotPosition x="193.82812" y="-366.03735" z="-252.28389" a="-45.6022" b="30.623524" c="32.96491"
      theta1="0.312" theta2="-7.913" />
    <RobotPosition x="201.03217" y="-365.93173" z="72.81698" a="-41.37646" b="15.921775" c="43.93697"
      theta1="0.312" theta2="-7.913" />
  </InterTaskPositions>
  <InterTaskSpeed Speed="50.0" />
</IPACSubTask>
```


Figure E.2: interTaskSubTask001.xml


```
<IPACSubTask Type="InterTask" Id="MoveTOStartPoint" SubTaskStatus="waiting">
  <InterTaskPositions>
    <RobotPosition x="597.9062" y="-1108.0082" z="650.6255" a="-3.8844082" b="-30.450686" c="100.082146"
      theta1="0.312" theta2="-7.913" />
    <RobotPosition x="597.9062" y="-1108.0082" z="489.62546" a="-3.8844082" b="-30.450686" c="100.082146"
      theta1="0.312" theta2="-7.913" />
    <RobotPosition x="1114.012" y="586.31146" z="489.62546" a="85.51556" b="-30.450682" c="100.082146"
      theta1="0.312" theta2="82.087" />
    <RobotPosition x="-603.61" y="1104.558" z="489.62543" a="176.41551" b="-30.450686" c="100.08214"
      theta1="0.312" theta2="172.087" />
    <RobotPosition x="-842.65857" y="1233.7351" z="391.76868" a="175.97853" b="-12.712486" c="101.6765"
      theta1="0.312" theta2="172.087" />
    <RobotPosition x="-875.15857" y="1238.7351" z="391.76868" a="175.97853" b="-12.712486" c="101.6765"
      theta1="0.312" theta2="172.087" />
  </InterTaskPositions>
  <InterTaskSpeed Speed="50.0" />
</IPACSubTask>
```


Figure E.3: interTaskSubTask002.xml

```
<IPACSubTask Type="InterTask" Id="MoveTOStartPoint" SubTaskStatus="waiting">
  <InterTaskPositions>
    <RobotPosition x="-384.71918" y="614.0744" z="352.78455" a="159.32901" b="-57.60792" c="158.19792"
      theta1="0.312" theta2="172.087" />
    <RobotPosition x="-198.01959" y="661.12726" z="298.47583" a="146.20688" b="-74.59523" c="172.21362"
      theta1="0.312" theta2="172.087" />
    <RobotPosition x="664.26544" y="187.73602" z="298.47586" a="55.306892" b="-74.59523" c="172.21364"
      theta1="0.312" theta2="82.087" />
    <RobotPosition x="194.64279" y="-662.4602" z="298.47586" a="-34.093086" b="-74.59523" c="172.21364"
      theta1="0.312" theta2="-7.913" />
    </InterTaskPositions>
    <InterTaskSpeed Speed="50.0" />
</IPACSubTask>
```


Figure E.4: interTaskSubTask003.xml


```
<IPACSubTask Type="InterTask" Id="MoveTOStartPoint" SubTaskStatus="waiting">
  <InterTaskPositions>
    <RobotPosition x="-74.1168" y="-677.7308" z="486.07516" a="-127.8482" b="-82.55972" c="-93.18092"
      theta1="0.312" theta2="-7.913" />
    <RobotPosition x="194.64279" y="-718.16016" z="298.47586" a="-34.093086" b="-74.59523" c="172.21364"
      theta1="0.312" theta2="-7.913" />
    <RobotPosition x="194.64279" y="-485.1602" z="298.47586" a="-34.093086" b="-74.59523" c="172.21364"
      theta1="0.312" theta2="-7.913" />
    <RobotPosition x="244.2428" y="-486.9602" z="477.4759" a="-34.093086" b="-74.59523" c="172.21364"
      theta1="0.312" theta2="-7.913" />
  </InterTaskPositions>
  <InterTaskSpeed Speed="20.0" />
</IPACSubTask>
```


Figure E.5: interTaskSubTask004.xml


```
<IPACSubTask Type="InterTask" Id="MoveTOStartPoint" SubTaskStatus="waiting">
  <InterTaskPositions>
    <RobotPosition x="194.64279" y="-662.4602" z="459.4759" a="-34.093086" b="-74.59523" c="172.21364"
      theta1="0.312" theta2="-7.913" />
    <RobotPosition x="194.64279" y="-662.4602" z="298.47586" a="-34.093086" b="-74.59523" c="172.21364"
      theta1="0.312" theta2="-7.913" />
    <RobotPosition x="664.26544" y="187.73602" z="298.47586" a="55.306892" b="-74.59523" c="172.21364"
      theta1="0.312" theta2="82.087" />
    <RobotPosition x="-198.01959" y="661.12726" z="298.47583" a="146.20688" b="-74.59523" c="172.21362"
      theta1="0.312" theta2="172.087" />
    <RobotPosition x="-400.21918" y="786.0744" z="352.78455" a="159.32901" b="-57.60792" c="158.19792"
      theta1="0.312" theta2="172.087" />
    <RobotPosition x="-432.71918" y="791.0744" z="352.78455" a="159.32901" b="-57.60792" c="158.19792"
      theta1="0.312" theta2="172.087" />
  </InterTaskPositions>
  <InterTaskSpeed Speed="50.0" />
</IPACSubTask>
```


Figure E.6: interTaskSubTask005.xml

```
<IPACSubTask Type="InterTask" Id="MoveTOStartPoint" SubTaskStatus="waiting">
  <InterTaskPositions>
    <RobotPosition x="-384.71918" y="614.0744" z="352.78455" a="159.32901" b="-57.60792" c="158.19792"
      theta1="0.312" theta2="172.087" />
    <RobotPosition x="-198.01959" y="661.12726" z="298.47583" a="146.20688" b="-74.59523" c="172.21362"
      theta1="0.312" theta2="172.087" />
    <RobotPosition x="664.26544" y="187.73602" z="298.47586" a="55.306892" b="-74.59523" c="172.21364"
      theta1="0.312" theta2="82.087" />
    <RobotPosition x="194.64279" y="-662.4602" z="298.47586" a="-34.093086" b="-74.59523" c="172.21364"
      theta1="0.312" theta2="-7.913" />
  </InterTaskPositions>
  <InterTaskSpeed Speed="50.0" />
</IPACSubTask>
```

Figure E.7: interTaskSubTask006.xml

E.1.2 Profile sensing

The experimental parameters profile sensing files are shown in figure E.8, figure E.9, figure E.10 and figure E.11. The profile sensing is described as a scanning from its current location to an end locations defined from a position by x, y and z, from an orientation by yaw, pitch and roll and from the angles of the turntable theta 1 and theta 2. The distance between each scanning is defined by a length in millimetres. The speed of the robots tool centre point between the scanning is described in the bottom of the files.

```
<IPACSubTask type="RawPreWeldScanWeldFace" id="AAUpipeTest 0" subTaskStatus="waiting"
  template="outerFlange">
  <InterTaskPositions>
    <RobotPosition x="218.44278" y="-662.4602" z="477.4759" a="-34.093086"
      b="-74.59523" c="172.21364" theta1="0.312" theta2="-7.913">
      <StepLength Length="2.5" />
    </RobotPosition>
  </InterTaskPositions>
  <InterTaskSpeed Speed="2.0" />
</IPACSubTask>
```

Figure E.8: openLoopScanningSubTaskFacePre001.xml

```
<IPACSubTask type="RawPreWeldScanBackBead" id="MoveTOStartPoint" SubTaskStatus="waiting"
  template="outerFlange">
  <InterTaskPositions>
    <RobotPosition x="-457.71918" y="614.0744" z="352.78455" a="159.32901"
      b="-57.60792" c="158.19792" theta1="0.312" theta2="172.087">
      <StepLength Length="2.5" />
    </RobotPosition>
  </InterTaskPositions>
  <InterTaskSpeed Speed="2.0" />
</IPACSubTask>
```

Figure E.9: openLoopScanningSubTaskBackPre001.xml

```
<IPACSubTask type="RawPostWeldScanWeldFace" id="MoveTOStartPoint" SubTaskStatus="waiting"
  template="outerFlange">
  <InterTaskPositions>
    <RobotPosition x="218.44278" y="-662.4602" z="477.4759" a="-34.093086"
      b="-74.59523" c="172.21364" theta1="0.312" theta2="-7.913">
      <StepLength Length="2.5" />
    </RobotPosition>
  </InterTaskPositions>
  <InterTaskSpeed Speed="2.0" />
</IPACSubTask>
```

Figure E.10: openLoopScanningSubTaskFacePost001.xml

```
<IPACSubTask type="RawPostWeldScanBackBead" id="MoveTOStartPoint" SubTaskStatus="waiting"
  template="outerFlange">
  <InterTaskPositions>
    <RobotPosition x="-457.71918" y="614.0744" z="352.78455" a="159.32901"
      b="-57.60792" c="158.19792" theta1="0.312" theta2="172.087">
      <StepLength Length="2.5" />
    </RobotPosition>
  </InterTaskPositions>
  <InterTaskSpeed Speed="2.0" />
</IPACSubTask>
```

Figure E.11: openLoopScanningSubTaskBackPost001.xml

E.1.3 Welding experiment

The experimental system carries out the welding operation from a file with sensing profiles and the welding control vector described in appendix D. A file format is prepared (but not used) for the experimental system to carry out the welding experiment from the experimental parameters welding experiment, which are specified in the file. The specification of the file is shown in figure E.12.

```
<IPACSubTask Type="InterTask" Id="MoveTOStartPoint" SubTaskStatus="waiting">
  <InterTaskPositions>
    <RobotPosition x="-400.0" y="245.0" z="-293.0" a="-99.6" b="0.1" c="-27.7" theta1="89.66" theta2="172.23">
      <InterTaskSpeed Speed="8.0" />
      <Oscillation On="FALSE" Width="5" Frequency="1" HoldingTime="35" VectorX="1" VectorY="0"
        VectorZ="0" />
      <Welding On="FALSE" WireFeedSpeed="4.7" Voltage="20" />
    </RobotPosition>
    <RobotPosition x="-429.0" y="45.0" z="-293.0" a="-99.6" b="0.1" c="-27.7" theta1="89.66" theta2="172.23">
      <InterTaskSpeed Speed="8.0" />
      <Oscillation On="FALSE" Width="5" Frequency="1" HoldingTime="35" VectorX="1" VectorY="0"
        VectorZ="0" />
      <Welding On="FALSE" WireFeedSpeed="4.7" Voltage="20" />
    </RobotPosition>
  </InterTaskPositions>
</IPACSubTask>
```

Figure E.12: weldingExperimentSubTask001.xml

E.2 T-Joint

The sequence of tasks is illustrated in figure E.13.

```
<Sequence>
  <Task Type="InterTask" FileName="subtasks\\interTaskSubTaskBox001.xml" />
  <Task Type="ProfileSensing" FileName="subtasks\\openLoopScanningSubTaskFacePreBox001.xml"
    OutputFileName="RawPreWeldScanFace001.xml" />
  <Task Type="InterTask" FileName="subtasks\\interTaskSubTaskBox002.xml" />
  <Task Type="WeldingExperiment" FileName="NN" OutputFileName="Data.xml"
    InputFileName="RawPreWeldScanFace001.xml" />
  <Task Type="InterTask" FileName="subtasks\\interTaskSubTaskBox003.xml" />
  <Task Type=" ProfileSensing " FileName="subtasks\\openLoopScanningSubTaskFacePostBox001.xml"
    OutputFileName="RawPostWeldScanFace001.xml" />
  <Task Type="InterTask" FileName="subtasks\\interTaskSubTaskBox004.xml" />
</Sequence>
```

Figure E.13: Sequence for a T-Joint.

T-Joint sequence was made from 4 inter task motion, 2 profile sensing and 1 welding experiment. These 11 tasks were preformed the following way:

- Move laser scanner to start position of the laser scanning at the pre weld face
- Scan workpiece weld face pre welding
- Move the welding torch to the start position of the welding task
- Make welding experiment based on the pre weld face laser scanning
- Move laser scanner to start position of the laser scanning at the post weld face
- Scan workpiece weld face post welding
- Move the robot to the end position of the task

The files describing the operations were constructed the same way as for the HalfV-Joint and by that reason are they not shown.

Appendix F

Making and analysing experiments

In this appendix the implementation is described for a HalfV- and T-Joint, used for exemplification, of the architecture in section 4.3 “Architecture of making and analysing experiments”. The tasks in the system for making and analysing experiments are shown in figure F.1.

Experiment and measurements (Automatic and manual) →	Observations and measurements (Manual) →	Data processing (Automatic) →	Create specific welding data-base record (Automatic)
• Insert workpiece • Perform pre-profile sensing(s) • Carry out welding • Perform post-profile sensing(s) • Take out workpiece	• Manual inspection • Manual tests	• Load data • Transform data to common co-ordinate system • Find datasets closest at each other • Project closest dataset to 2D record • Analyse 2D records • Examine validity of analysed data • Make visualisation • Make welding experiment record	• Load data • For selected parameter find minimum and maximum • Discretise data to manually defined intervals • Make welding experiment record
System for making experiments		System for analysing experiments	

Figure F.1: Overview of the tasks, listed as points, in the system to produce empirical knowledge. The system is divided into a system for making experiments and a system for analysing experiments.

F.1 Experiment and measurements

The tasks for making experiment and measurement, in figure F.1, are exemplified in the following sub sections.

F.1.1 Insert workpiece

The workpiece was manual inserted in the welding fixture at a fixed location as illustrated in figure F.2. The welding fixture was constructed so the seam was accessible for profile sensing from both the weld face and back bead side.

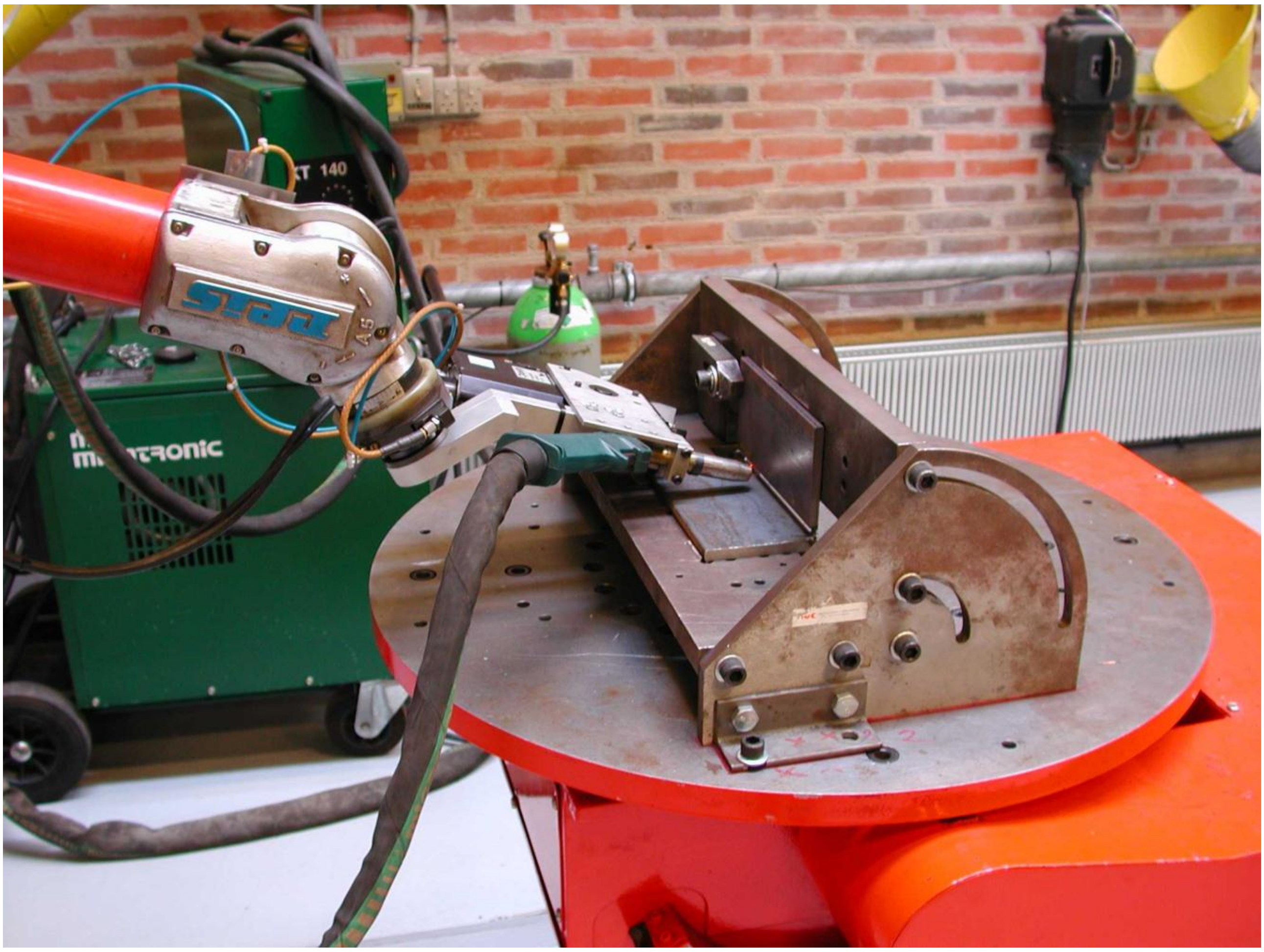


Figure F.2: Workpiece with HalfV-Joint inserted in the welding fixture mounted at the turntable. At the robot arm is mounted a welding torch and a laser scanner.

F.1.2 Perform pre-profile sensing(s)

The profile sensing was not made in a continuous motion but with a stop for each laser scanning to make sure that the robot location is known when the laser scanning is carried out. The start and stops are not desirable because the robot can start to vibrate if the motion speed is too high, which causes a bad laser scanning result.

A template in the laser scanner interface was selected to detect breakpoints for the given joint type. The method: “Detect second order derivatives of sensing profile”, presented in appendix C, was used and the setup for the actual equipment is explained in appendix D. Figure F.3 shows graphically the output of a laser scanning.

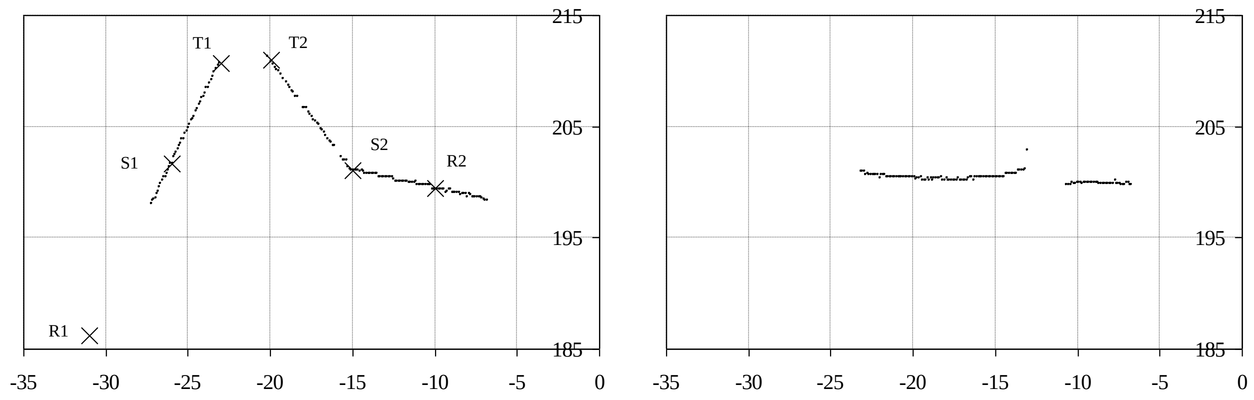


Figure F.3: Example of the laser scanner raw point (dots) for a HalfV-joint in scanner frame. Left; is weld face including breakpoints (crosses), right; is back bead. The axes of the graphs are respectively the y- and z-axis in the sensor frame measured in millimetres.

F.1.3 Carry out welding

The welding experiment is planned in the process control and data collection software as explained in appendix D. The process control and data collection tool calculates the tool location using the sensing data from the task “Perform pre-profile sensing data” and the welding control variables. This was done with a frequency set in the process control and data collection tool and for each step the process control and data collection tool sends the tool location to the neutral robot interface and welding variables to the neutral welding machine interface, which made sure that they were executed on the physical equipment. With a frequency specified in the process control tool and data collection tool were data sampled and saved as welding data.

Manual observation were made of irregularities during the welding process and equipment condition were observed and recorded so the later analysis of the data could give an explanation of phenomena’s in the welding data. Examples of irregularities to document were e.g. if the contact nozzle melted or if the equipment had a collision.

F.1.4 Perform post-profile sensing(s)

This task is done in a similar fashion as “Perform pre-profile sensing(s)” in section F.1.2. It was difficult to achieve robust breakpoints after welding applying the method: “Detect second order derivatives of sensing profile” explained in appendix C. The reason was the soft curves, so breakpoints were not detected. Figure F.3 shows graphically the output of a laser scanning.

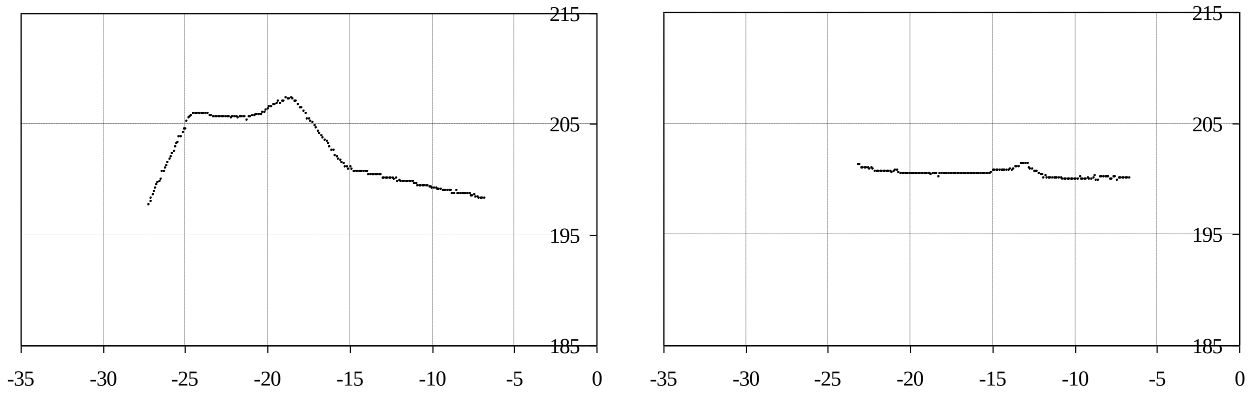


Figure F.4: Example of the laser scanner raw point (dots) for a HalfV-joint in scanner frame. Left; is welded weld face and right; is welded back bead. The axes of the graphs are respectively the y- and z-axis in the sensor frame measured in millimetres.

F.1.5 Take out workpiece

After completing the automatic experiment the workpiece was taken out of the welding fixture for manual inspection.

F.2 Observations and measurements

The tasks for observations and measurements, in figure F.1, are exemplified in the following sub sections.

F.2.1 Manual inspection

The welding operator was visually inspecting and grading the welded seam, which exemplifies looks like the T-Joint shown in figure F.5. The grades were for weld face undercut plate 1 and 2 and if visible cracks and holes given for both the T- and HalfV-Joint. Parameters as depth of fusion plate 1 and 2 could not be measured by inspection but require testing. The same can be the case for cracks and holes.

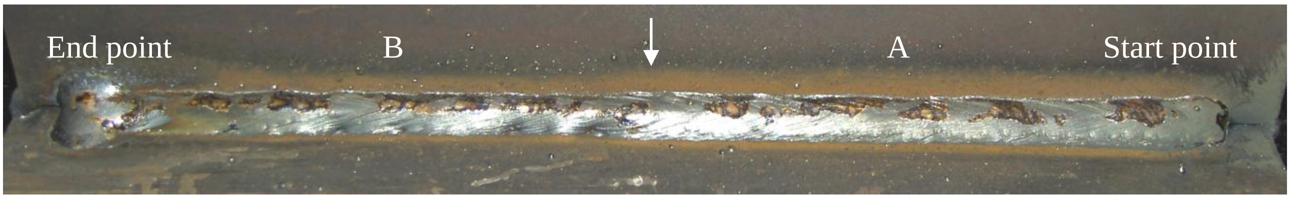


Figure F.5: Picture of a welded T-Joint for manual inspection. Two experiments are made by changing welding parameters halfway at the arrow. Individual grades were given for the experiment at section A and the experiment at section B.

F.2.2 Manual tests

In this thesis was metallography and inspection penetrants used. Metallography was used for selected welds to investigate interfusion, internal cracks and holes. An example of the test is shown at the polished section in figure F.6. Because metallography was not carried out on all workpieces were the depth of fusion plate 1 and 2 missing for some welding experiment.

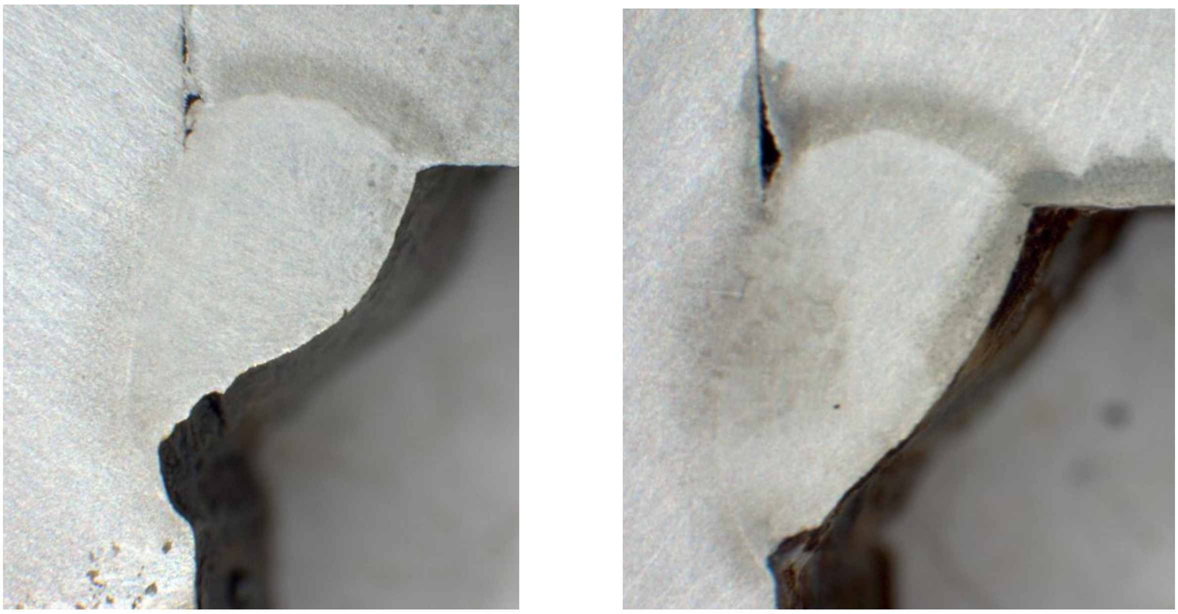


Figure F.6: Polished section of the T-Joint for gathering information about depth of fusion and defects such as holes, cracks and under cut. Experiment A is to the right and B is to the left. From the inspection of the polished section can the interfusion and under cut be measured because the scale of the picture is known.

Inspection penetrants [Rocol] were used on all the parts to detect cracks and holes and the standard was used to determine the grade.

F.3 Data processing

The tasks for data processing, in figure F.1, are exemplified in the following sub sections.

F.3.1 Load data

The data produced from one experiment were read and the validity was checked.

F.3.2 Transform data to common coordinate system

For each experiment the data had to be merged together and represented in the same frame and it was for this setup the turntable frame attached to the turntable in figure F.2 and specified in appendix D.

Visualising in 3D the breakpoints for a weld face profile sensing with the tool position for welding is illustrated in figure F.7.

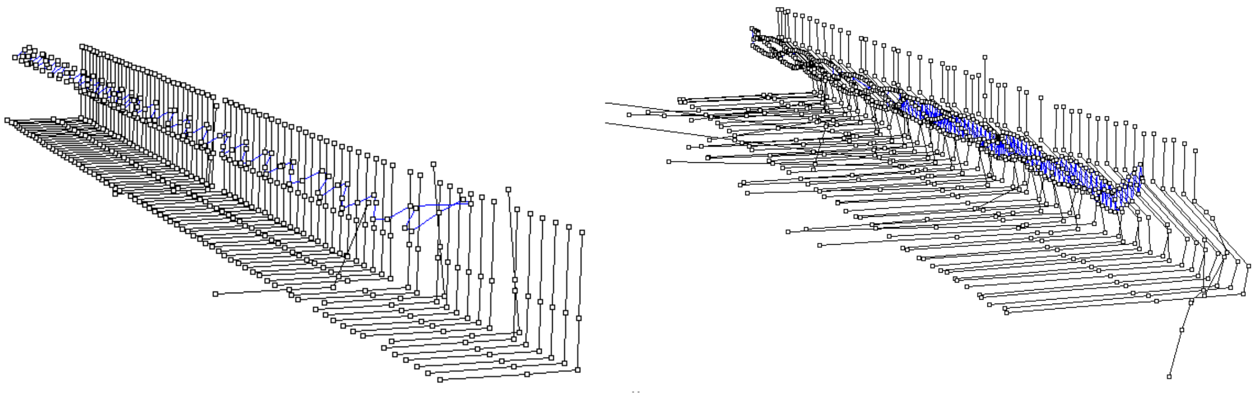


Figure F.7: Weld face of a T-Joint seam to the left and HalfV-Joint seam to the right. The breakpoints from pre-profile sensing of weld face are merged to the same frame as the tool centre point (blue line) from the welding experiment. Noise causes that some of the measured breakpoints are out layers. For both welding experiments oscillation are used, which causes the weaving of the tool centre point.

For the specific setup, specified in appendix D, the welding data was stored in turntable frame and the scanned data was stored as points in scanner frame. During welding and making laser scanning the ${}^{turntable}T_{hand}$ was changed by manipulating the robot and turntable. To merge the welding data with the sensing data in a reference frame, which was selected to be the turntable frame, were the following transformations required. For the welding data:

$$ {}^{turntable}T_{tool} = {}^{turntable}T_{hand} \cdot {}^{hand}T_{tool} $$

For the sensing data, consisting of both raw points and breakpoints:

$$ {}^{turntable}P = {}^{turntable}T_{hand} \cdot {}^{hand}T_{scanner} \cdot {}^{scanner}P $$

Further specification of the frames and calibration of the transformation matrices are in appendix D.

F.3.3 Find datasets closest at each other

This task is made as in the general system. The sample position for records was selected to be the position for sensing data for pre weld face. Attaching of the other experimental data was made after the two principles:

- Attach to the nearest record: used for sensing and welding data.
- Attach to the following record: used for welding control variables.

F.3.4 Project closest dataset to 2D record

This task is made as in the general system. The principle is illustrated in figure F.8.

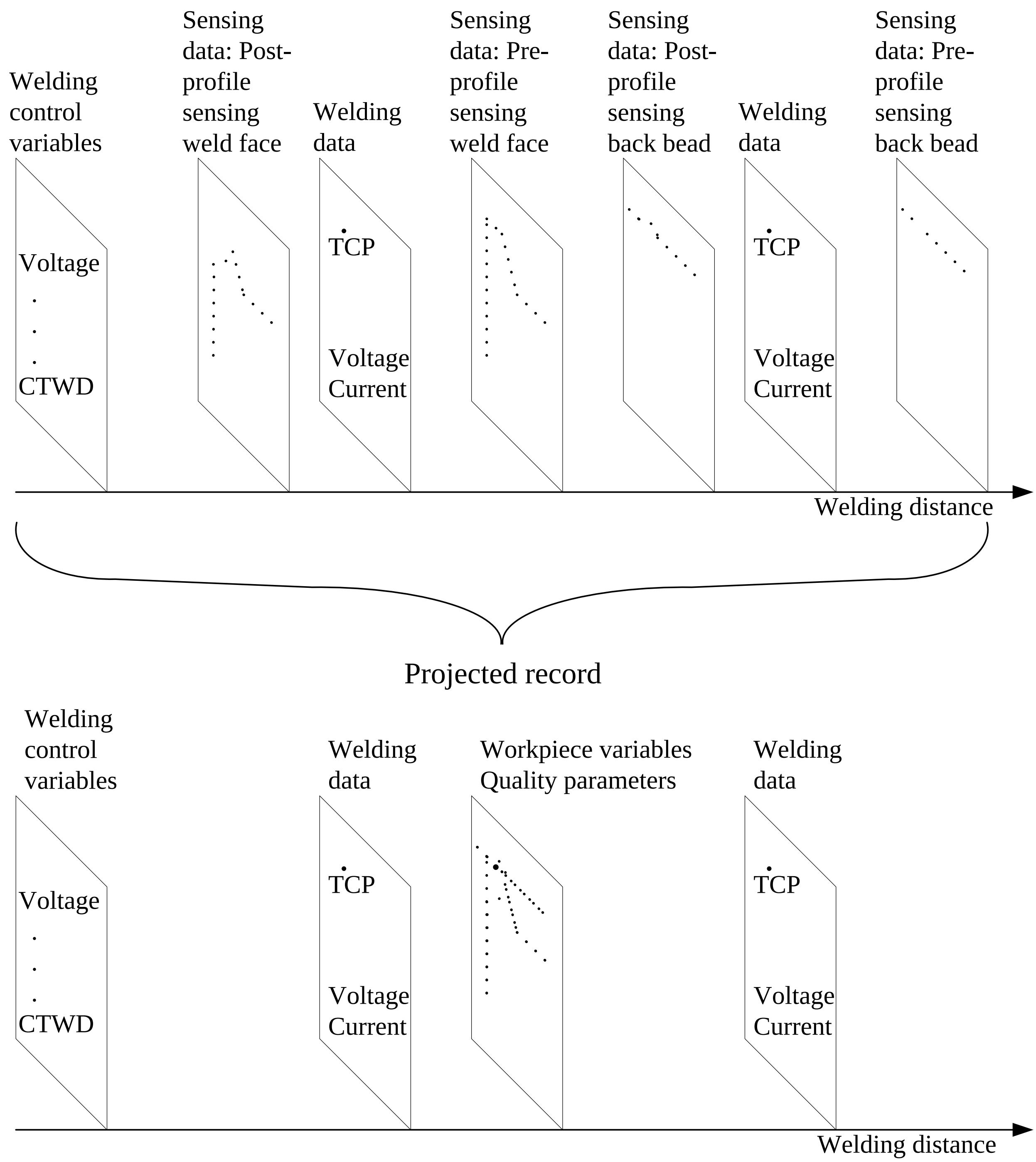


Figure F.8: The top; the selected experiment data must be projected to the position of sample data, which is at the position of the sensing data of the pre-profile sensing weld face. The bottom; experimental data are merged to the position of sample data and is made into a projected record.

F.3.5 Analyse 2D records

The analysis of the T-Joint and HalfV-Joint was carried out according to the specification in appendix C.

Determine breakpoints, weld face and root vector for pre-profile sensing

The breakpoints were calculated for the sensing data from the pre-profile sensing using the method “Detect distance and direction from point to point of sensing profile” described in appendix C. The reason was that the best robustness was achieved with this method and especially for the welded bead. Breakpoint placement on the T-Joint and HalfV-Joint are illustrated in figure F.9 and figure F.10.

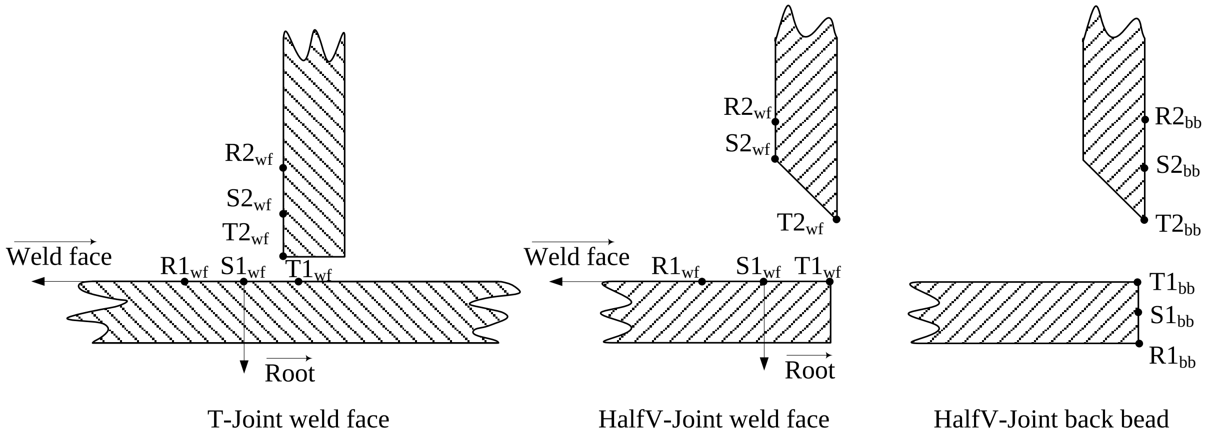


Figure F.9: Breakpoints before welding the T-Joint and HalfV-Joint.

Determine workpiece variables

From the analysis of the sensing data from the pre-profile sensing was the workpiece variables in table F.1 calculated. Root gap back bead is calculated additional as a check of consistency between root gap weld face and root gap back bead.

Table F.1: Workpiece variables determined for the T- and HalfV-Joint.

	T-Joint	HalfV-Joint
Plate angle	X	X
Root gap	X	X
Root gap back bead		X
Off-set		X
Thickness plate 1		X
Thickness plate 2		X
Depth of bevel		X
Bevel angle		X

Determine breakpoints for post-profile sensing

The breakpoints were calculated for the sensing data from the post-profile sensing, but compared to the sensing data from the pre-profile sensing had the post-profile sensing distortion factors as an unknown weld seam geometry, which may contain spatter, undercuts and distortions. With these factors was smoothing of raw data in some cases required to make the breakpoint detection more noise resistant.

The breakpoints for the weld face of the welded HalfV-Joint were not placed according to the specification in appendix C because $T2_{wwf}$ are located inside the groove. It causes that some of the equations for analysis cannot be applied.

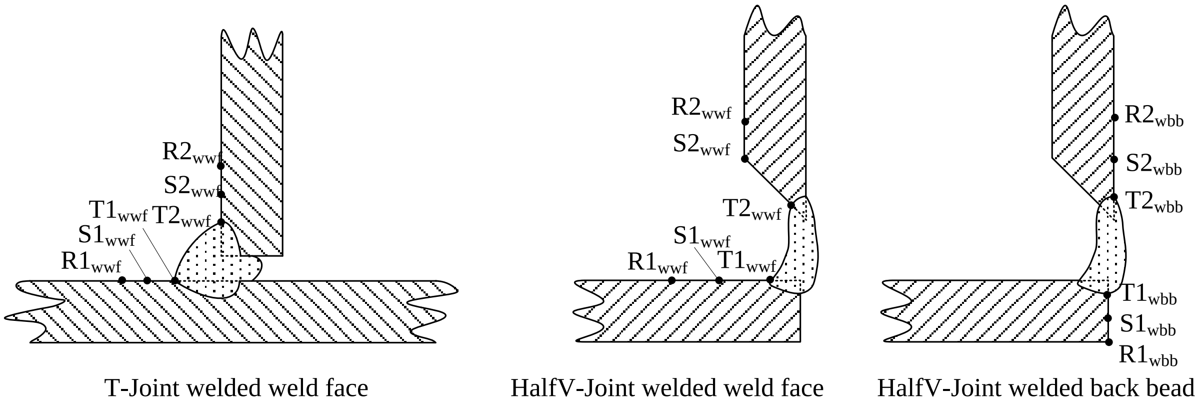


Figure F.10: Position of breakpoints for the post scanning of the T-Joint and HalfV-Joint.

Determine quality parameters

From the analysis of sensing data from the post-profile sensing was the quality parameters in table F.2 calculated. Additional quality parameters were defined and they are described in the following. For the HalfV-Joint the theoretical throat, equal legs and convexity cannot be calculated because the welded seams are too small to exceed the groove. The determination of the leg length plate 1 and 2 are not following the ISO standard. Instead a measurement is made of the welded bead distance along the surface of the workpiece, before welding, inside the groove and it is named contact length plate 1 and 2. For the T-Joint the plate angel post welding was determined to investigate a potential distortion. Height of seam is defined in the ISO standard [ISO 5817] number 1.10 and calculated to give a grade for the convexity. Fill area was defined as the area of the welded bead outside the groove and root gap and it is illustrated in figure F.11. It is determined by numerical integration using the raw point between $T1_{wwf}$ and $T2_{wwf}$ and the line spanned between $R1_{wwf}$ and $T1_{wwf}$.
The unit and measurement range of the defined quality parameters are below:

- Plate angle post welding [degrees] is > 0 and < 180 degrees.
- Contact length plate 1 [mm] is ≥ 0.
- Contact length plate 2 [mm] is ≥ 0.
- Height of seam [mm] is usually between -5 and 5 mm.
- Fill area [mm^2] is > 0.

Table F.2: Quality parameters determined for the T- and HalfV-Joint.

	T-Joint	HalfV-Joint
Leg length plate 1	X	
Leg length plate 2	X	
Back bead width		X
Back bead height		X
Theoretical throat	X	
Plate angle post welding	X	
Equal legs	X	
Convexity	X	
Contact length plate 1		X
Contact length plate 2		X
Height of seam	X	
Fill area	X	

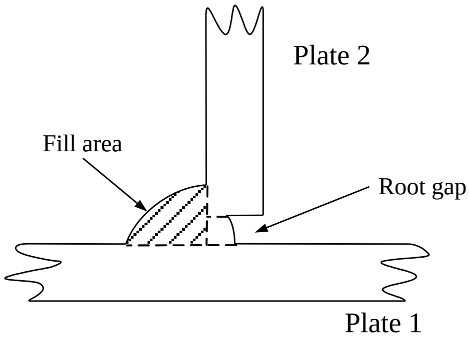


Figure F.11: Fill area is the area of the welded seam, which is outside the root gap and groove between the two plates. It is marked as the hatched area.

F.3.6 Examine validity of analysed data

The variables and parameters were examined to avoid using data which was wrongly analysed and with unrealistic values. The limits of the accepted values were set manually for the experiments and shown in table F.3 and table F.4.

Table F.3: Acceptance limits for T-Joint.

Workpiece variables				
85	<	Plate angle	<	95
0	≤	Root gap	<	4
Process variables				
5	<	Voltage	<	100
5	<	Current	<	500
Quality parameters				
0	<	Leg length plate 1	<	20
0	<	Leg length plate 2	<	20
80	<	Plate angel post welding	<	100

Table F.4: Acceptance limits for HalfV-Joint.

Workpiece variables				
80	<	Plate angle	<	90
0	≤	Root gap	<	6
2	<	Thickness plate 1	<	14
2	<	Thickness plate 2	<	14
0	≤	Bevel angle plate 1	<	90
Process variables				
5	<	Voltage	<	100
5	<	Current	<	500
Quality parameters				
0	<	Contact length plate 1	<	20
0	<	Contact length plate 2	<	20
80	<	Plate angel post welding	<	100

F.3.7 Make visualisation

The specific visualisation for each experiment was made to show the recorded raw data for each projected record.

Furthermore was the visualisation also to present the result of the welding experiment shown in four different graphs with selected process variables, workpiece variables, quality parameters and welding control variables along the weld seam. A simplification was made for the oscillation holding at side 1 and 2 because they were identical. By this reason they were specified by one variable and calculated the following way.

$$Oscillation\ holding = Oscillation\ holding\ 1 + Oscillation\ holding\ 2$$

T-Joint

An example of recorded raw data for a projected record is illustrated in figure F.12. For the pre-profile sensing of the weld face the root gap is clearly illustrated. For the welding process is the position of the tool frame illustrated and because more tool positions were measured within this projected record are more dots illustrated and the oscillation gives them different position. Comparing the pre-profile sensing and the post-profile sensing for the weld face shows distortion of the workpiece. In section B is the volume of the welded seam larger than in section A caused by the change of welding control variables.

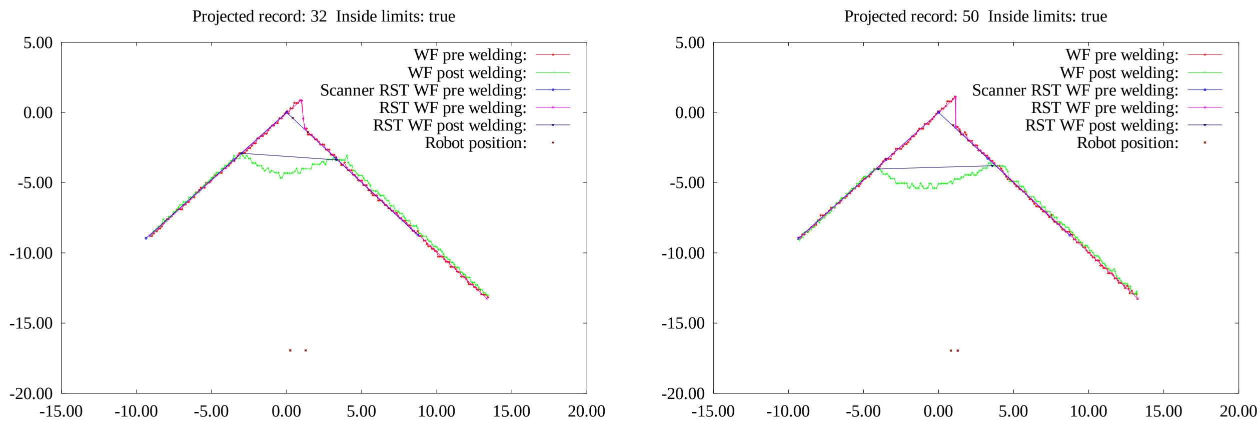


Figure F.12: Projected record for T-Joint experiment (number 01). To the left is a projected record from section A, 80 millimetres from the start point, and to the right is a projected record from section B, 150 millimetres from the start point. WF is an abbreviation of weld face.

Parameters and variables of a welding experiment are illustrated in figure F.13. It shows how the change of travel speed influences the quality parameters. Furthermore, the distortion of the plates, which were observed in figure F.12, is also measured as the difference between plate angle and plate angle post welding.

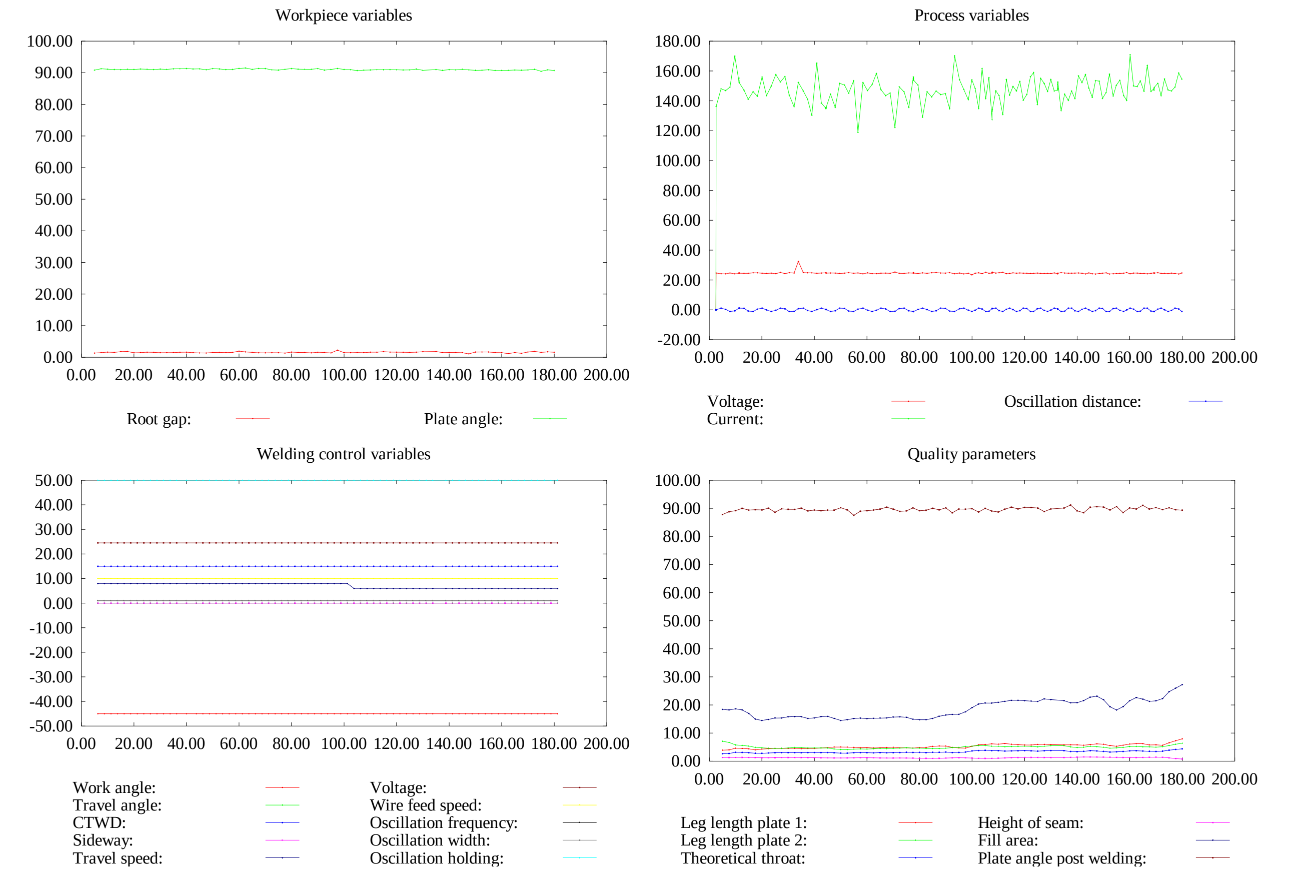


Figure F.13: For T-Joint experiment (number 01) is shown with the parameters and variables to each projected record along the weld seam. The x-axis is measured in millimetre. The measuring unit of each parameter is as specified in chapter 3 and in section F.3.5 "Analyse 2D records". After 100 millimetres were the travel speed decreased.

HalfV-Joint

In a similar way as for the T-Joint is an example of the HalfV-Joint illustrated in figure F.14. The plots were constructed the same way just with additional sensing data added from the back bead. Section A and B have a different shape of the welded seam caused by the change of welding control variables.

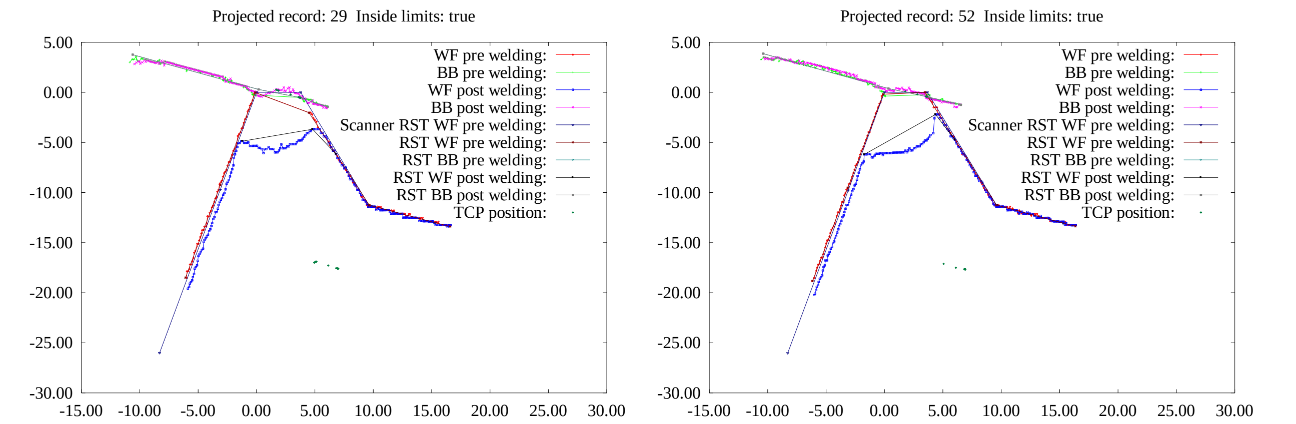


Figure F.14: Projected record for halfV-Joint experiment (number 49). To the left is a projected record from section A, 72.5 millimetres from the start point, and to the right is a projected record from section B, 130 millimetres from the start point. WF and BB are abbreviations of weld face and back bead respectively.

Parameters and variables of a welding experiment for a HalfV-Joint are illustrated in figure F.15 in a similar way as for the T-Joint.

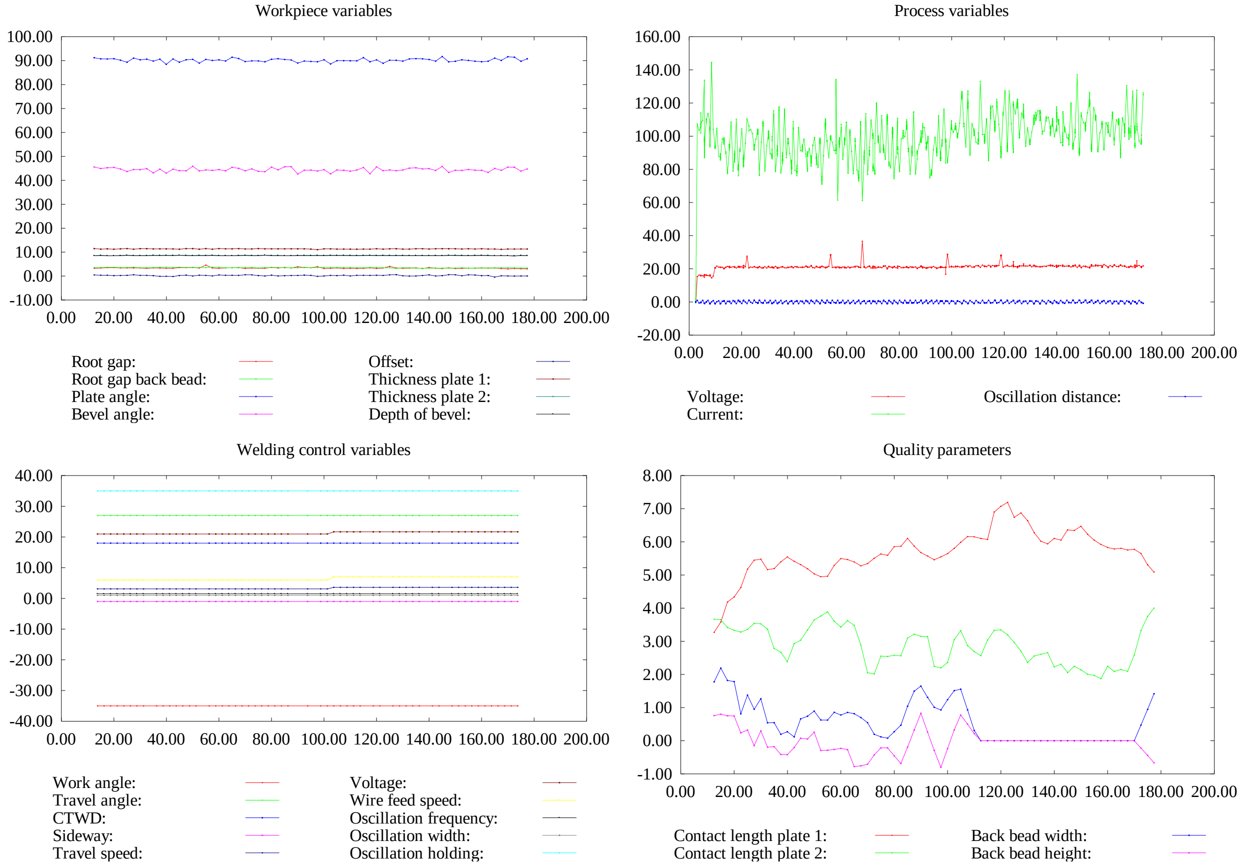


Figure F.15: HalfV-Joint experiment (number 49) is shown with the parameters and variables to each projected record along the weld seam. The x-axis is measured in millimetre. The measuring unit of each parameter is as specified in chapter 3 and in section F.3.5 “Analyse 2D records”. After 100 millimetres were the voltage, wire feed speed and travel speed increased. The voltage is only increased 0.7 volt so it is difficult to see it at the process variable graph.

With the visualisation can a welding operator judge if the data processing is delivering a trustworthy result and view the result for changing the specific settings, which is input to the data processing.

F.3.8 Make welding experiment record

After data processing were the accepted welding experiment samples written to a welding database record. An example of one accepted welding experiment sample is illustrated for the T-Joint in figure F.16 and the HalfV-Joint in figure F.17. For the specific system the welding experiment samples are extended with some more parameters which were shown in table F.1 and table F.2.

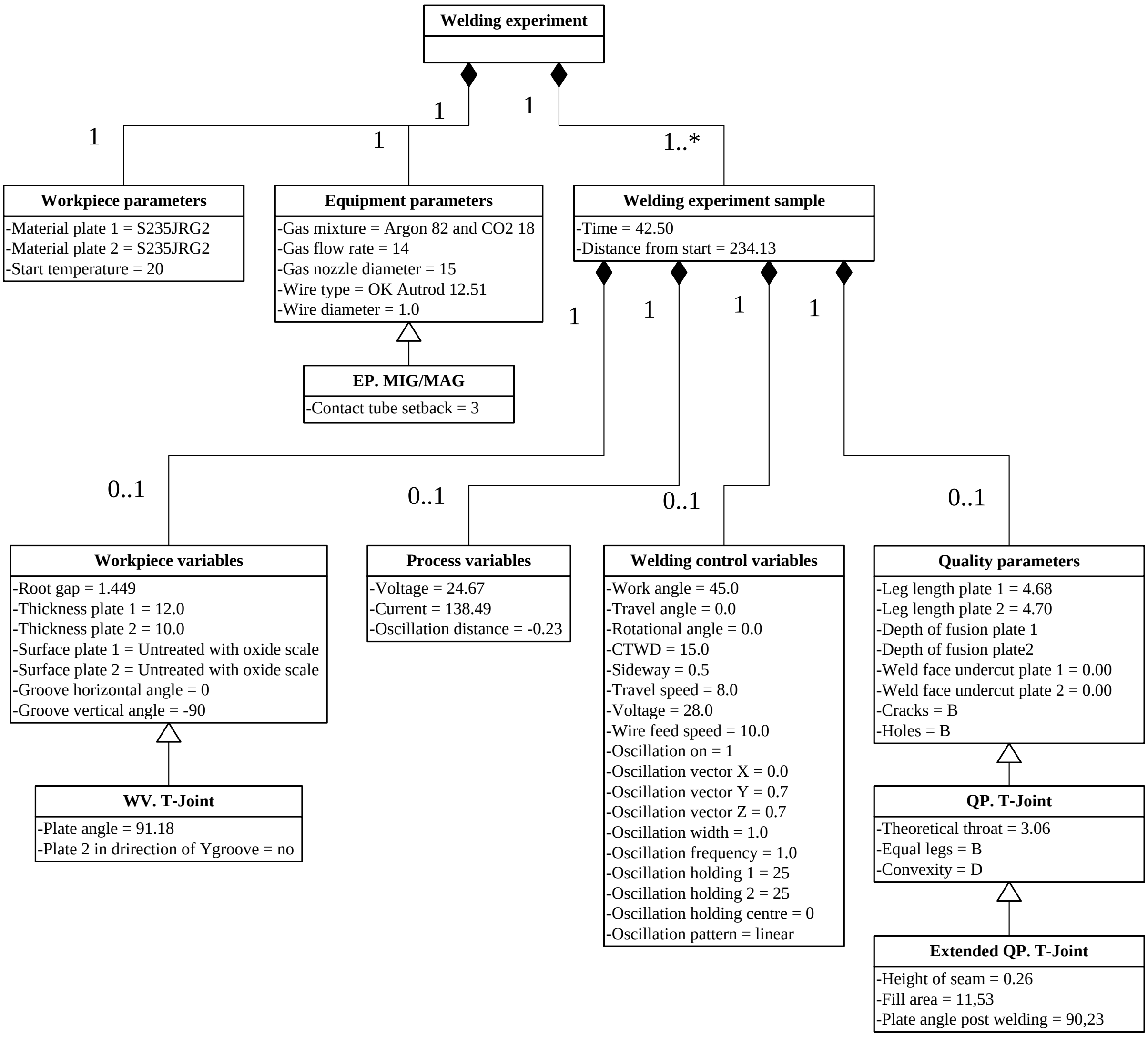


Figure F.16: Illustration of a welding experiment sample for a T-Joint. The additional quality parameters specified in section F.3.5 "Analyse 2D records" are in the class "Extended QP. T-Joint".

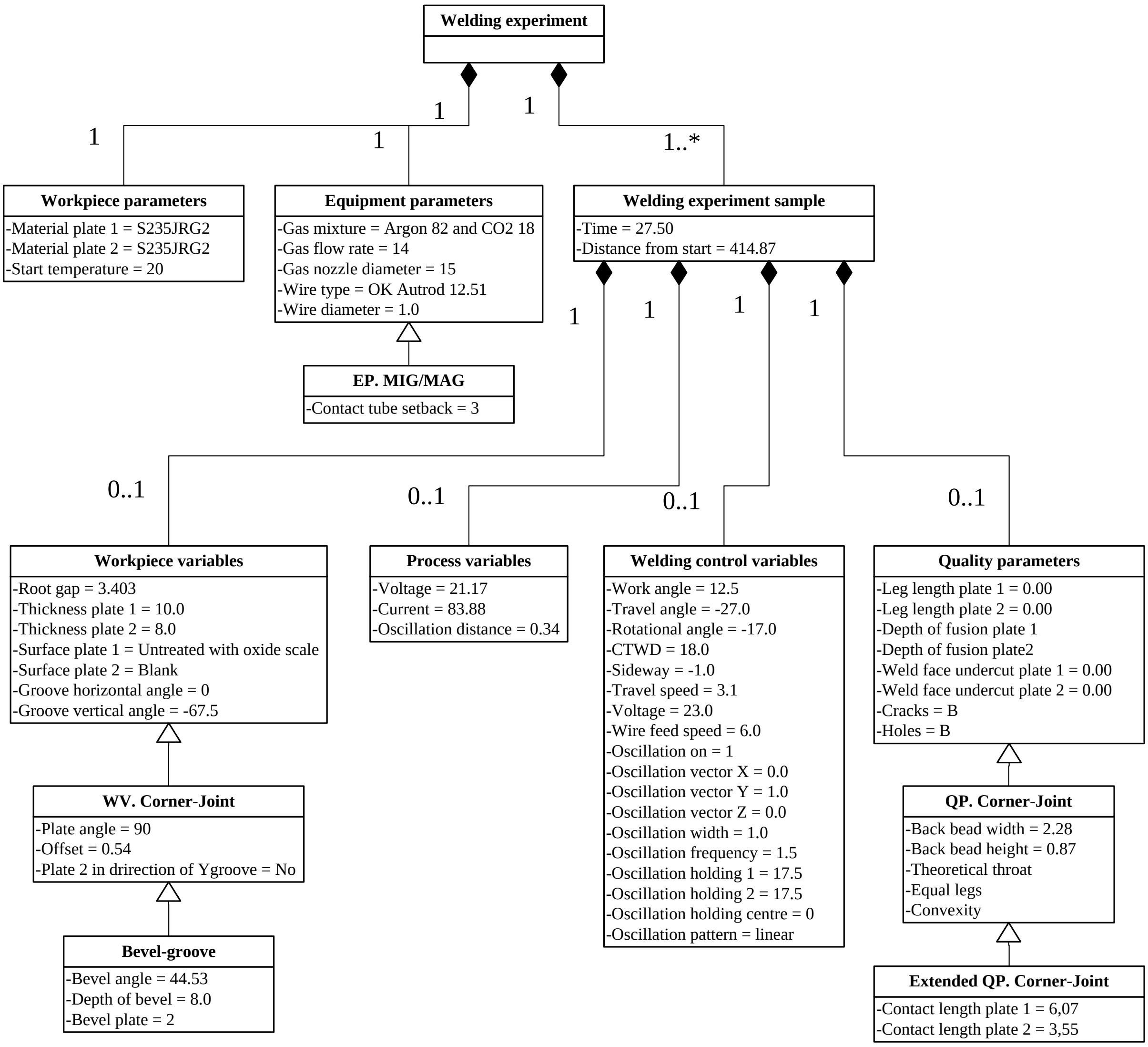


Figure F.17: Illustration of a welding experiment sample for a HalfV-Joint. The additional quality parameters specified in section F.3.5 "Analyse 2D records" are in the class "Extended QP. Corner-Joint".

F.4 Create specific welding database record

The tasks for create specific welding database record, in figure F.1, are exemplified in the following sub sections. In this specific case was the purpose to create an empirical welding database to the process-planning models in chapter 6 and appendix H and I. The requirement was a tab delimitated text file only including static welding data for the T-Joint.

F.4.1 Load data

The selected welding experiment records from a welding database record were input to this task and the validity of the input structure and types was checked if they were legal.

Only static welding experiment samples were required for the model in chapter 6. The welding process were not considered stable around start point, end point and change of welding control variables after 100 millimetres welding. So intervals were specified outside these areas were the welding experiment samples were accepted. The total welding distance was 180 millimetre and the intervals for the accepted welding experiment samples were 40-90 millimetre for experiment A and 120-170 millimetre for experiment B.

F.4.2 For selected parameter find minimum and maximum

This task is made as in the general system. The welding data for modelling the T-Joint in chapter 6 needs to be specified. Parameters and variables selected as output are showed in table F.5. The discritised intervals used are showed in table F.5.

Table F.5: The selected parameters and variables, for the T-Joint, with their discretisize interval size under each parameter or variable.

Workpiece variables
Root gap
0.2

Equipment parameters
Wire diameter
0.2

Welding control variables								
Work angle	Travel angle	CTWD	Travel speed	Oscil-lation width	Oscil-lation frequency	Oscil-lation holding	Wire feed speed	Voltage
5	5	2	1	0.2	0.2	10	1	1

Quality parameters										
Leg length plate 1	Leg length plate 2	Fill area	Theo-retical throat	Height of seam	Dept of fusion plate 1	Dept of fusion plate 2	Weld face under-cut plate 1	Weld face under-cut plate 2	Con-vexity	Equal legs
1	1	2	1	0.2	0.5	0.5	1	1		

F.4.3 Discritise data to manually defined intervals

This task is made as in the general system.

F.4.4 Make welding experiment record

The specific welding database record is written to a text file in a tab delaminated format.

Appendix G

Experiments for HalfV-Joint

In this appendix is the welding control vectors used for the 138 experiments for the halfV-Joint shown. They are illustrated in table G.1.

Table G.1: Welding control variables for the HalfV-Joint. Gray marking indicates change of welding control variable values according to previous experiment. Root gap were 3 millimetres for number 1 - 104, 2 millimetres for number 105 - 112, 4 millimetres for number 113 - 124 and 5 millimetres for number 125 - 138.

Experiment	Number	Work angle	Travel angle	CTWD	Side way X	Side way Y	Travel speed	Oscillation on	Oscillation width	Oscillation frequency	Oscillation holding 1	Oscillation holding 2	Wire feed speed	Voltage
HalfV-Joint001A	1	-35	0	15	0	0	1.94	1	1.5	1.5	17.5	17.5	4	17
HalfV-Joint001B	2	-35	0	15	0	0	1.94	1	1.5	1.5	17.5	17.5	6	17
HalfV-Joint002A	3	-35	0	15	0	0	1.94	1	2	1.5	17.5	17.5	4	19
HalfV-Joint002B	4	-35	0	15	0	0	1.94	1	2	1.5	17.5	17.5	6	19
HalfV-Joint003A	5	-35	0	15	0	0	1.94	1	1.7	1.5	17.5	17.5	4	20
HalfV-Joint003B	6	-35	0	15	0	0	1.94	1	1.7	1.5	17.5	17.5	5	20
HalfV-Joint004A	7	-35	0	15	0	0	1.94	1	1.7	1.5	17.5	17.5	4	22
HalfV-Joint004B	8	-35	0	15	0	0	1.94	1	1.7	1.5	17.5	17.5	5	22
HalfV-Joint005A	9	-35	0	15	0	0	1.94	1	1.7	1.5	17.5	17.5	6	22
HalfV-Joint005B	10	-35	0	15	0	0	1.94	1	1.7	1.5	17.5	17.5	8	22
HalfV-Joint006A	11	-30	0	15	0	0	1.94	1	1.7	1.5	17.5	17.5	8	24
HalfV-Joint006B	12	-35	0	15	0	0	1.94	1	1.7	1.5	17.5	17.5	8	24
HalfV-Joint007A	13	-30	0	15	0	0	1.94	1	1.7	1.5	17.5	17.5	8	25
HalfV-Joint007B	14	-30	0	15	0	0	2.1	1	1.7	1.5	17.5	17.5	8	25
HalfV-Joint008A	15	-30	0	13	0	0	1.94	1	1.7	1.5	17.5	17.5	8	24
HalfV-Joint008B	16	-30	0	10	0	0	1.94	1	1.7	1.5	17.5	17.5	8	24
HalfV-Joint009A	17	-30	0	13	0	0	1.94	1	2	1.5	17.5	17.5	8	25
HalfV-Joint009B	18	-30	0	10	0	0	1.94	1	2	1.5	17.5	17.5	8	25
HalfV-Joint010A	19	-30	0	12	0	0	1.94	1	2	1.5	17.5	17.5	8	26
HalfV-Joint010B	20	-25	0	12	0	0	1.94	1	2	1.5	17.5	17.5	8	26
HalfV-Joint011A	21	-30	0	13	0	0	1.94	1	2	1.5	17.5	17.5	8	25
HalfV-Joint011B	22	-30	0	13	0	0	1.8	1	2	1.5	17.5	17.5	8	25
HalfV-Joint012A	23	-33	0	15	0	0	1.94	1	2	1.5	17.5	17.5	6	19.6
HalfV-Joint012B	24	-33	0	12	0	0	1.94	1	2	1.5	17.5	17.5	6	19.6
HalfV-Joint013A	25	-31	0	12	0	0	1.94	1	2	1.5	17.5	17.5	6	19.6
HalfV-Joint013B	26	-31	0	12	0	0	1.94	1	2	1.5	17.5	17.5	5	19.6
HalfV-Joint014A	27	-31	0	12	0	0	1.94	1	2	1.5	17.5	17.5	6	20
HalfV-Joint014B	28	-31	0	12	0	0	1.94	1	2	1.5	17.5	17.5	7	20
HalfV-Joint015A	29	-30	0	15	0	0	1.94	1	1.6	1.5	17.5	17.5	8	24
HalfV-Joint015B	30	-30	0	15	0	0	1.8	1	1.6	1.5	17.5	17.5	8	24
HalfV-Joint016A	31	-25.5	-25	15	0	0	1.94	1	1.5	1.5	17.5	17.5	2.5	17
HalfV-Joint016B	32	-25.5	-25	15	0	0	1.5	1	1.5	1.5	17.5	17.5	2.5	17
HalfV-Joint017A	33	-25.5	10	15	2.2	0	1.94	1	1.5	1.5	17.5	17.5	2.5	17

HalfV-Joint017B	34	-25.5	10	15	2.2	0	1.5	1	1.5	1.5	17.5	17.5	2.5	17
HalfV-Joint018A	35	-25.5	10	12	3.4	0	1.94	1	1.5	1.5	17.5	17.5	2.5	17
HalfV-Joint018B	36	-25.5	10	8	3.4	0	1.94	1	1.5	1.5	17.5	17.5	2.5	17
HalfV-Joint019A	37	-25.5	10	8	3.4	0	1.94	1	1.5	1.5	17.5	17.5	2.5	17.7
HalfV-Joint019B	38	-25.5	10	8	3.4	0	1.5	1	1.5	1.5	17.5	17.5	2.5	17.7
HalfV-Joint020A	39	-25.5	10	8	3.4	0	1.94	1	1.7	1.5	17.5	17.5	2.5	17
HalfV-Joint020B	40	-25.5	10	8	3.4	0	1.94	1	1.7	1.5	17.5	17.5	2.5	17
HalfV-Joint021A	41	-25.5	25	8	3.6	0	1.94	1	1.5	1.5	17.5	17.5	2.5	17
HalfV-Joint021B	42	-25.5	25	8	3.6	0	1.8	1	1.5	1.5	17.5	17.5	2.5	17
HalfV-Joint022A	43	-25.5	25	8	3.4	0	1.94	1	1.5	1.5	17.5	17.5	2.5	17.3
HalfV-Joint022B	44	-28.5	25	8	3.4	0	1.94	1	1.5	1.5	17.5	17.5	2.5	17.3
HalfV-Joint023A	45	-30	0	20	-0.4	0	1.94	1	1.5	1.5	17.5	17.5	3	19
HalfV-Joint023B	46	-30	0	20	-0.4	0	1.94	1	1.5	1.5	17.5	17.5	4	19
HalfV-Joint024A	47	-30	0	20	-0.4	0	1.94	1	1.7	1.5	17.5	17.5	4	20
HalfV-Joint024B	48	-30	0	20	-0.4	0	1.94	1	1.7	1.5	17.5	17.5	5	20
HalfV-Joint025A	49	-27	0	20	-0.4	0	1.94	1	1.5	1.5	17.5	17.5	4	19
HalfV-Joint025B	50	-27	0	20	-0.4	0	2.1	1	1.5	1.5	17.5	17.5	4	19
HalfV-Joint026A	51	-27	0	20	-0.4	0	1.94	1	1.5	1	17.5	17.5	4	19
HalfV-Joint026B	52	-27	0	20	-0.4	0	1.7	1	1.5	1	17.5	17.5	4	19
HalfV-Joint027A	53	-27	10	20	-0.4	0	1.94	1	1.5	1	17.5	17.5	4	19
HalfV-Joint027B	54	-27	10	20	-0.4	0	1.94	1	1.5	1	17.5	17.5	3.5	19
HalfV-Joint028A	55	-26	10	20	-0.4	0	1.94	1	1.5	1	22.5	22.5	4	19
HalfV-Joint028B	56	-29	10	20	-0.4	0	1.94	1	1.5	1	22.5	22.5	4	19
HalfV-Joint029A	57	-27	10	20	-0.4	0	1.94	1	1.5	1	25	25	4	19.6
HalfV-Joint029B	58	-27	10	20	-0.4	0	2.1	1	1.5	1	25	25	4	19.6
HalfV-Joint030A	59	-27	10	20	-0.4	0	1.9	1	1.5	1	25	25	4	19.6
HalfV-Joint030B	60	-27	10	20	-0.4	0	1.75	1	1.5	1	25	25	4	19.6
HalfV-Joint031A	61	-27	10	20	-0.4	0	1.9	1	1.5	1	25	25	4	20
HalfV-Joint031B	62	-27	10	20	-0.4	0	1.7	1	1.5	1	25	25	4	20
HalfV-Joint032A	63	-27	10	18	-0.4	0	1.94	1	1.5	1	25	25	4	19.6
HalfV-Joint032B	64	-27	10	15	-0.4	0	1.94	1	1.5	1	25	25	4	19.6
HalfV-Joint033A	65	-35	25	19	0	0	2	1	0.5	1	20	20	4	21
HalfV-Joint033B	66	-35	25	19	0	0	2	1	0.5	1	20	20	4	21
HalfV-Joint034A	67	-30	25	16	0	2	2	1	0.5	0.8	20	20	4	21
HalfV-Joint034B	68	-30	25	16	0	2	2	1	0.5	0.8	20	20	4	21
HalfV-Joint035A	69	-30	27	16	0	1.5	2	1	0.3	0.8	20	20	4	21
HalfV-Joint035B	70	-28	27	16	0	1.5	2	1	0.3	0.8	20	20	4	21
HalfV-Joint036A	71	-30	27	16	0	1.5	2	1	0.3	0.8	20	20	4	21.7
HalfV-Joint036B	72	-30	27	16	0	1.5	2	1	0.3	0.8	20	20	4	22
HalfV-Joint037A	73	-30	27	16	0	1.5	2	1	0.3	0.8	20	20	4	25
HalfV-Joint037B	74	-30	27	16	0	1.5	2	1	0.3	0.8	20	20	4	24
HalfV-Joint038A	75	-32	27	17	0	0	1.94	1	1.2	1.5	17.5	17.5	4	17
HalfV-Joint038B	76	-32	27	17	0	0	1.94	1	1.2	1.5	17.5	17.5	4	19
HalfV-Joint039A	77	-32	27	17	0	0	1.94	1	1.2	1.5	17.5	17.5	4	20
HalfV-Joint039B	78	-32	27	17	0	0	2.1	1	1.2	1.5	17.5	17.5	4	20
HalfV-Joint040A	79	-32	27	18	0	0	1.94	1	1.2	1.5	17.5	17.5	4	19.6
HalfV-Joint040B	80	-32	27	18	0	0	2.1	1	1.2	1.5	17.5	17.5	4	19.6
HalfV-Joint041A	81	-34	27	18	0	0	1.94	1	1	1.5	17.5	17.5	5	19.6
HalfV-Joint041B	82	-34	27	18	0	0	2.2	1	1	1.5	17.5	17.5	5	19.6
HalfV-Joint042A	83	-35	27	18	0	0	2.2	1	1	1.5	17.5	17.5	5	20

HalfV-Joint042B	84	-35	27	18	0	0	2.4	1	1	1.5	17.5	17.5	5	20
HalfV-Joint043A	85	-35	27	18	-1	0	2.4	1	1	1.5	17.5	17.5	5	20
HalfV-Joint043B	86	-35	27	18	-1	0	2.6	1	1	1.5	17.5	17.5	5	20
HalfV-Joint044A	87	-35	27	18	-1	0	2.6	1	1	1.5	17.5	17.5	5	21
HalfV-Joint044B	88	-35	27	18	-1	0	2.8	1	1	1.5	17.5	17.5	5	21
HalfV-Joint045A	89	-35	27	18	-1	0	2.9	1	1	1.5	17.5	17.5	6	21
HalfV-Joint045B	90	-35	27	18	-1	0	3.1	1	1	1.5	17.5	17.5	6	21
HalfV-Joint046A	91	-35	27	18	-1	0	3	1	1	1.5	17.5	17.5	6	21
HalfV-Joint046B	92	-35	27	18	-1	0	3	1	1	1.5	17.5	17.5	6	21.7
HalfV-Joint047A	93	-35	27	18	-1	0	3.2	1	1	1.5	17.5	17.5	6	21
HalfV-Joint047B	94	-35	27	18	-1	0	3.2	1	1	1.5	17.5	17.5	6	21.7
HalfV-Joint048A	95	-35	27	18	-1	0	3.4	1	1	1.5	17.5	17.5	6	21.7
HalfV-Joint048B	96	-35	27	18	-1	0	3.8	1	1	1.5	17.5	17.5	7	21.7
HalfV-Joint049A	97	-35	27	18	-1	0	3.1	1	1	1.5	17.5	17.5	6	21
HalfV-Joint049B	98	-35	27	18	-1	0	3.6	1	1	1.5	17.5	17.5	7	21.7
HalfV-Joint050A	99	-35	27	18	-1	0	3.1	1	1	1.5	17.5	17.5	6	21.7
HalfV-Joint050B	100	-35	27	18	-1	0	3.6	1	1	1.5	17.5	17.5	7	22.4
HalfV-Joint051A	101	-35	27	18	-1	0	2.9	1	1	1.5	17.5	17.5	6	22
HalfV-Joint051B	102	-35	27	18	-1	0	3.4	1	1	1.5	17.5	17.5	7	22.4
HalfV-Joint052A	103	-35	27	18	-1	0	3.1	1	1	1.5	17.5	17.5	6	21
HalfV-Joint052B	104	-35	27	18	-1	0	3.6	1	1	1.5	17.5	17.5	7	22
HalfV-Joint053A	105	-35	27	18	-1	0	3.1	1	1	1.5	17.5	17.5	6	21
HalfV-Joint053B	106	-35	27	18	-1	0	3.6	1	1	1.5	17.5	17.5	7	22
HalfV-Joint054A	107	-35	27	18	-1	0	3.4	1	1	1.5	17.5	17.5	6	21
HalfV-Joint054B	108	-35	27	18	-1	0	4	1	1	1.5	17.5	17.5	7	22
HalfV-Joint055A	109	-35	27	18	-0.5	0	3.4	1	0.5	1.5	17.5	17.5	6	21
HalfV-Joint055B	110	-35	27	18	-0.5	0	4	1	0.5	1.5	17.5	17.5	7	22
HalfV-Joint056A	111	-35	27	18	-0.5	0	3.2	1	0.5	1.5	17.5	17.5	6	21
HalfV-Joint056B	112	-35	27	18	-0.5	0	3.7	1	0.5	1.5	17.5	17.5	7	22
HalfV-Joint057A	113	-35	27	18	-1	0	3.1	1	1	1.5	17.5	17.5	6	21
HalfV-Joint057B	114	-35	27	18	-1	0	3.6	1	1	1.5	17.5	17.5	7	22
HalfV-Joint058A	115	-35	27	18	-0.5	0	3.1	1	1.2	1.5	17.5	17.5	6	21
HalfV-Joint058B	116	-35	27	18	-0.5	0	3.6	1	1.2	1.5	17.5	17.5	7	22
HalfV-Joint059A	117	-35	27	18	-0.5	0	3.1	1	1.4	1.5	17.5	17.5	6	21
HalfV-Joint059B	118	-35	27	18	-0.5	0	3.6	1	1.4	1.5	17.5	17.5	7	22
HalfV-Joint060A	119	-35	27	18	-0.3	0	3.1	1	1.5	1.5	17.5	17.5	6	21
HalfV-Joint060B	120	-35	27	18	-0.3	0	3.6	1	1.5	1.5	17.5	17.5	7	22
HalfV-Joint061A	121	-35	27	18	-0.2	0	2.9	1	1.5	1.5	17.5	17.5	6	21
HalfV-Joint061B	122	-35	27	18	-0.2	0	3.3	1	1.5	1.5	17.5	17.5	7	22
HalfV-Joint062A	123	-35	27	18	0	0	2.8	1	1.5	1.5	17.5	17.5	6	21
HalfV-Joint062B	124	-35	27	18	0	0	3.2	1	1.5	1.5	17.5	17.5	7	22
HalfV-Joint063A	125	-35	27	18	0	0	2.8	1	1.5	1.5	17.5	17.5	6	21
HalfV-Joint063B	126	-35	27	18	0	0	3.2	1	1.5	1.5	17.5	17.5	7	22
HalfV-Joint064A	127	-35	27	18	0	0	2.6	1	2.5	1.5	17.5	17.5	6	21
HalfV-Joint064B	128	-35	27	18	0	0	3	1	2.5	1.5	17.5	17.5	7	22
HalfV-Joint065A	129	-35	27	18	0	0	2.3	1	2.5	1.5	17.5	17.5	6	21
HalfV-Joint065B	130	-35	27	18	0	0	2.7	1	2.5	1.5	17.5	17.5	7	22
HalfV-Joint066A	131	-35	27	18	0	0	2.1	1	2.5	1.2	17.5	17.5	6	21
HalfV-Joint066B	132	-35	27	18	0	0	2.5	1	2.5	1.2	17.5	17.5	7	22
HalfV-Joint067A	133	-35	27	18	0	0	2	1	2.6	1	17.5	17.5	6	21

HalfV-Joint067B	134	-35	27	18	0	0	2.4	1	2.6	1	17.5	17.5	7	22
HalfV-Joint068A	135	-35	27	18	0	0	2	1	2.6	1	17.5	17.5	6	21
HalfV-Joint068B	136	-35	27	18	0	0	2.4	1	2.6	1	17.5	17.5	7	22
HalfV-Joint069A	137	-35	20	18	0	0	2	1	2.6	1	17.5	17.5	6	21
HalfV-Joint069B	138	-35	20	18	0	0	2.4	1	2.6	1	17.5	17.5	7	22

Appendix H

Artificial neural network model

The artificial neural network is an often used method for making process planning models, which can be seen from the literature survey in appendix A. Artificial neural network, was studied to benchmark Bayesian network.

H.1 Historical background

Studies of the structure and mechanisms of the biological learning system have inspired the development of computational models. In 1943 Warren McCulloch and Walter Pitts made the first step towards artificial neural network [McCulloch et al., 1943] and described how a neuron might work. The research really started in the 1960s after a learning scheme for updating the neuron weights is proposed by [Hebb, 1949], and in [Rosenblatt, 1958] the first useful network called a Perceptron was developed. However most of the research in artificial neural networks stopped after [Minsky et al., 1969] determines that the Perceptron could never solve a XOR-problem and doubted whether a multilayer perceptron network, which could solve the problem, would ever have an efficient training algorithm developed. This meant that a large group of problems could not be solved by artificial neural networks. The research gained momentum again after [Rumelhart et al., 1986] described a training algorithm, which often with good result could be used on a multilayer perceptron network. Artificial neural networks have been applied to a wide range of problems in areas as e.g. function approximation, time series prediction, classification and pattern recognition.

A big variety of artificial neural network packages with different training algorithms are now available for both commercial and non-commercial use. The package used for implementation in this thesis is [Clementine].

The basic theory and definitions behind artificial neural networks are described below. For more thoroughly description and examples see e.g. [Mitchell, 1997].

H.2 General artificial neural network theory

A number of neural network models have been developed and some of the best known are perceptron networks, Hamming networks, Carpenter/Grossberg networks, Kohonen's feature maps and multilayer perceptron networks. They are together with more networks described in [Lippmann, 1987]. The networks have different characteristics for handling of continuous or binary input and dependent on whether they use supervised or unsupervised learning. [Lippmann, 1987] groups the networks after these characteristics. The network used in this thesis is the multilayer perceptron network, because this network fits the problem with continuous data and a supervised learning algorithm described in the section about training the model. This network was implemented in Clemmentine and [Clementine algorithms, 2004] was used to solve the problem. The theory for the multilayer perceptron network will be explained.

The neuron is the basic element in an artificial neural network and neurons are connected in a systematic way. For the multilayer perceptron network the neurons (N) are arranged in layers as in figure H.1. The layers are numbered from zero for the input layer to the number of layers for the output layer. The input vector ***x*** containing n variables is input to an input layer of input neurons. In the network there are one or more hidden layers of processing neurons and one output layer of processing neurons. The output layer gives an output vector, $\boldsymbol{y}_k$, where k is the output layer number and the vector has the size n_k. Inside the multilayer perceptron network each layer is fully interconnected from the preceding layer to the following layer with an output vector y_k, where k is the layer number. For the input layer $\boldsymbol{y}_0 = \boldsymbol{x}$ and the input vector is propagated forward through the network layer-by-layer and mapping $\boldsymbol{y}_k = \boldsymbol{F}(\boldsymbol{x}) : \Re^{n_0} \mapsto \Re^{n_k}$.

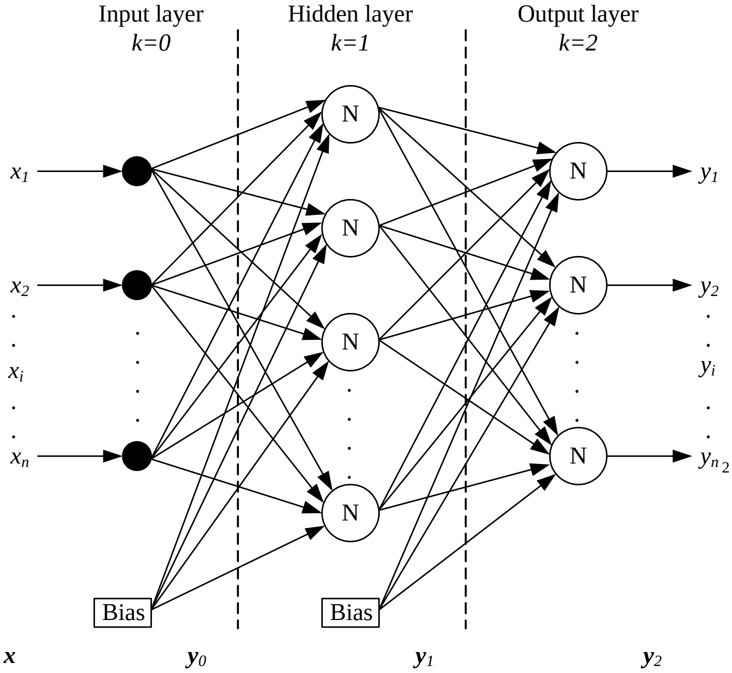


Figure H.1: Multilayer perceptron network with one hidden layer.

The input to the processing neurons, in figure H.2, is the output from all neurons in the last layer and a bias value, which is a background value to the neuron function.

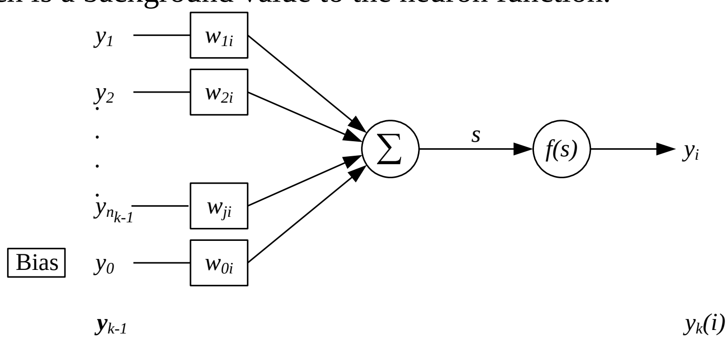


Figure H.2: The processing neuron consists of a summing function of all the input and a transfer function.

The feed forward calculus of the network for neuron j is:

$$y_j = f\left(\sum_{i=0}^{n_{k-1}} w_{ji} y_i\right)$$

For neuron j in layer k is applied:

y_i is the ith input to neuron j.
w_{ji} is the weight, which is associated with the ith input to neuron j.
y_j is the output of neuron j.

The transfer function, also called activation function, transforms the sum of the input to an output and for this transformation different transfer functions can be applied. The Sigmoid function, with the characteristic function in figure H.3, was used and calculated as follows.

$$f(s) = \frac{1}{1+e^{-s}}$$

The Sigmoid function is a non-linear function and it is useful for many types of problems. Other types of transfer functions such as a linear or a tangent hyperbolic function in figure H.3 can be applied to certain types of problems. E.g. the linear function is good in approximating linear functions. The linear function is calculated by *f(s) = s* and the tangent hyperbolic function is calculated by *f(s) = tanh(s)*.

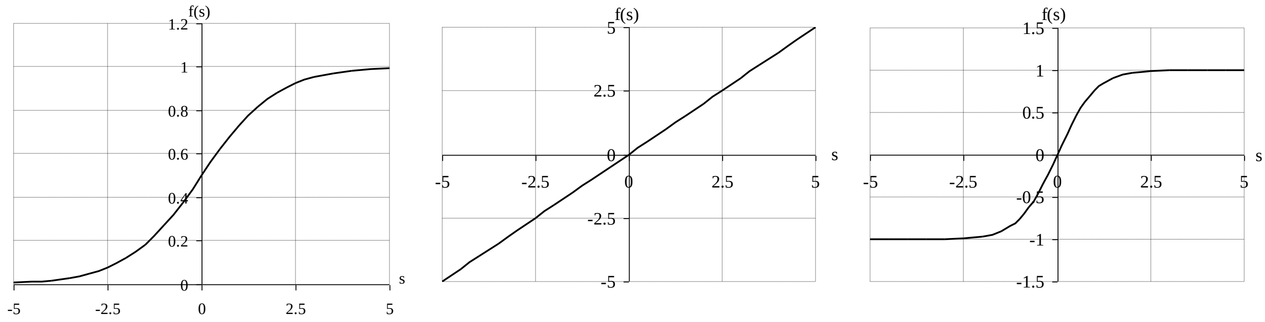


Figure H.3: From the left, the characteristic of a Sigmoid, a linear and a hyperbolic tangent transfer function.

H.2.1 Creating the model structure

Modelling an artificial neural network starts by defining the input and output vector. For the implementation in Clementine these vectors can contain continuous and discrete data. To give the same weight for all the input and output variables, the data is rescaled to a value between 0 and 1 by the transformation:

$$x_i^* = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$$

For record *i* the minimum, x_{min}, and maximum, x_{max}, value is found of all the *i* records and the record x_i is rescaled to x^*_i.

Constructing the artificial neural network can either be made manually or automatically.

Manually

The manual construction of the network structure is based on decision about the number of hidden layers and the number of neurons within in each hidden layer. Only approximate rules exist about estimating how many hidden layers and how many neurons there should be in each hidden layer for a certain problem. The method for finding the network size is to experiment with different network sizes and compare the result to find the model which best fits the problem. In practice it is advisable to start with a small network and then extend it as long as it gives a better fit to the problem.

Automatically

The network size can also be decided by some training algorithms, where the algorithm searches different network structures and for each structure calculates the accuracy of the network. Then a stop criteria for the algorithm is the network structure with the best accuracy within a certain training period or number of cycles or an achieved accuracy of the network with, which is manually decided. These algorithms are described further below.

H.2.2 Training the model

Supervised learning is used for the multilayer perceptron network where the network is presented to training records with associated input and output vectors. When training the multi-layer network the weights w_{ji} in the network are adjusted to minimize error between the training records and the corresponding response from the network. Training of the artificial neural network is an optimization problem, where the weights are adjusted to minimize the error. The error backpropagation training algorithm introduced by [Rumelhart et al., 1986], is an often applied algorithm for adjusting the weights. Slightly modification of the original algorithm was made and the algorithm implemented in Clementine will be explained.

Before the training of the neural network starts, all the weights are set to a random value in the interval $-0.5 \leq w_{ji} \leq 0.5$. The training data is presented in cycles where each cycle contains n randomly selected training datasets. This method means that some datasets are used several times and some might never be used. For each training dataset a forward pass is made in the network and prediction of the output y_j, which is compared to the target value t_j for the current dataset. The difference between y_j and t_j is the error and it is propagated backwards through the network and the weights w are updated. It is illustrated in figure H.4.

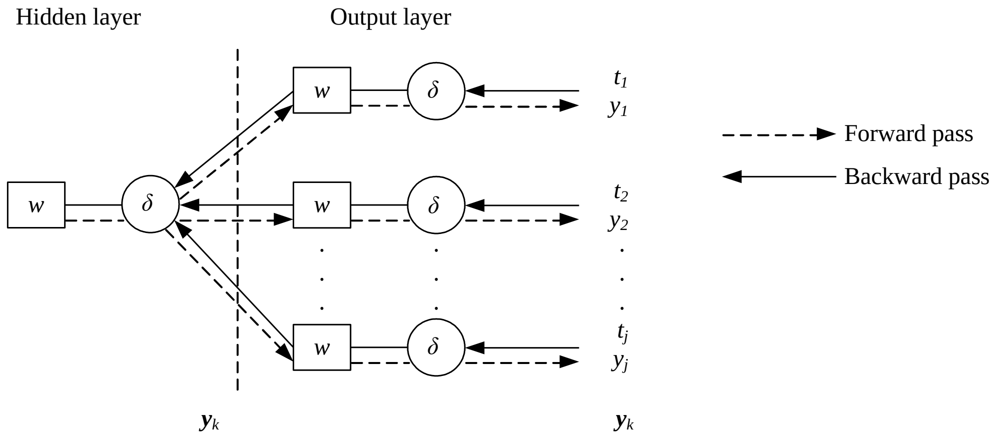


Figure H.4: The flow of the backpropagation training algorithm for the output layer and a hidden layer.

The backpropagation calculus of the network for neuron j is calculated from the learning rate parameter η, the propagated error δ_j, the input of the neuron y_i, the momentum parameter α and the weight change Δw_{ji} from the previous cycle. The updated weight is calculated as the learning rate parameter multiplied with the propagated error and the neuron input plus the weight change from the previous cycle. The momentum parameter α, $0 \leq \alpha \leq 1$, is fixed to a value before training and it is in the interval between zero and one. The effect of the momentum multiplied with the previous cycles weight change gives the artificial neural network momentum to jump out of local minima, across flat surfaces and gradually increases the step size in regions with equal gradient when training.

$$\Delta w_{ji}(n+1) = \eta \delta_j y_i + \alpha \Delta w_{ji}(n)$$

For the output layer the propagated error δ_j for the j neuron is calculated as shown below.

$$\delta_j = (t_j - y_j) y_j (1 - y_j)$$

For all internal layers the propagated error δ_j for the j neuron is calculated where y_j is the output, w_{pj} is the weight from this layer to neuron p in the next layer and δ_p is the propagated error for that neuron.

$$\delta_j = y_j(1 - y_j) \cdot \sum_{p \in outputs} \delta_p w_{pj}$$

The learning rate parameter η varies its value across the cycles of training. The value of η starts at a user specified initial value and decreases logarithmically to η_{low} and then it goes to the value of η_{high} and starts a new cycle again. It can be explained as if η (t-1)<η_{low} then $\eta(t)$ is set to η_{high}. The value of d specifies the decays each cycle contains. The value of η_{low} and η_{high} is user specified.

$$\eta(t) = \eta(t-1) e^{\left(\log\left(\frac{\eta_{low}}{\eta_{high}}\right) \Big/ d \right)}$$

Training the artificial neural network can be made with different stop criteria to train an accurate network without starting overtraining and thereby loosing accuracy. Overtraining occurs when the network is too well trained on specifics of the training data and thereby looses its ability to generalise.

To achieve a good trained artificial neural network, where the error between the network's prediction and the target output for all the training datasets is minimized, experiments were carried out with different network sizes, training algorithms and adjustable setting of the training algorithms.

H.3 Artificial neural network implementation for T-Joint

An artificial neural network was utilised as the tool to build a process-planning model for the T-Joint. To build the model, the input and output vector has to be specified first. Building a direct and an inverse process-planning model requires building of two models. For the direct and inverse process-planning model the specified input and output are shown in figure H.5. Both models have 10 nodes for the input vector and 9 nodes for the output vector.

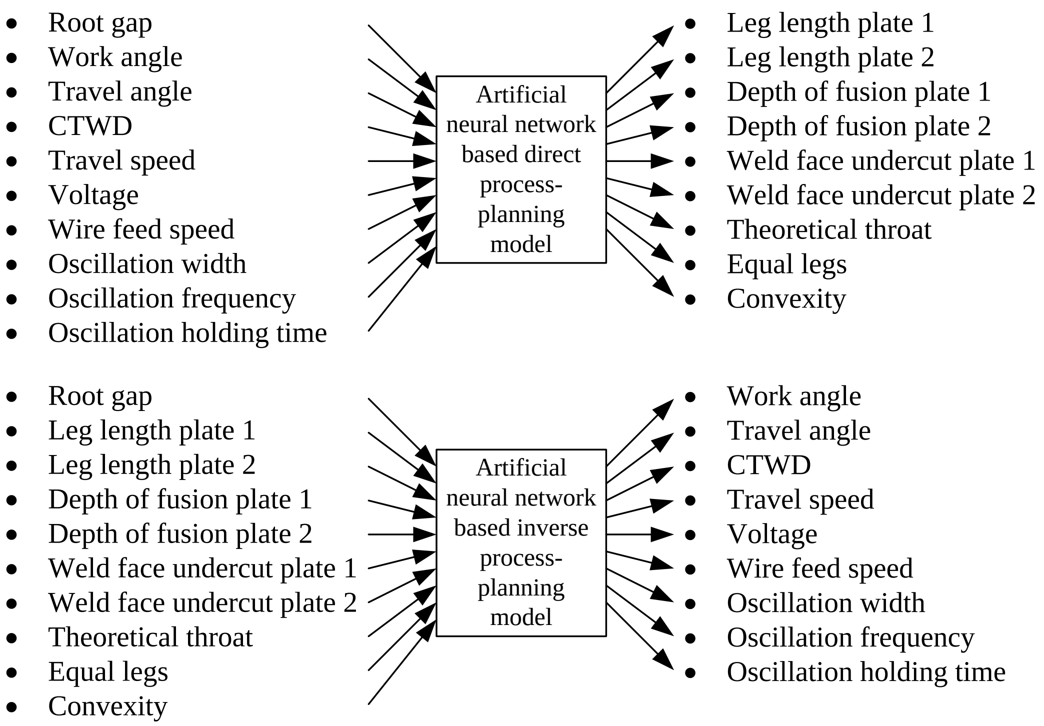


Figure H.5: Input and output vector for the direct artificial neural network model for the T-Joint welding.

Finding the number of hidden layers and the number of nodes in each hidden layer was investigated manually by making a number of training trials, where training algorithms were used with different setting. The goal of the training was to find the smallest network with a high accuracy, because a network with the same accuracy but a larger number of hidden neurons probably contains some neurons which have weakly trained weights. Different algorithms to train an artificial neural network were investigated and the following were tested using Clemmentine:

- Quick
- Dynamic
- Multiple
- Prune
- Exhaustive prune

A detailed description of the algorithms and their adjustable settings can be found in [Clementine algorithms, 2004].

The knowledge source for automatically modelling and training of the artificial neural network was empirical datasets since an artificial neural network is a completely black box model. Analytical knowledge and knowledge from a welding operator can be used for modelling by producing artificial empirical data.

For creating and training the model is used empirical data from 44 experiments and these experiments contained 802 datasets.

The common training procedure is to carry out a number of training trials and compare the result for different settings and algorithms. For all the network were used 1500 training cycles and afterwards were the network with the best fit selected.

H.3.1 The direct process-planning model

From trying out the different algorithms to train an artificial neural network was found that the best fit for the direct process-planning model was made with the dynamic algorithm. The distributions of the neurons were:
Input layer: 10
Hidden layer 1: 2
Hidden layer 2: 2
Output layer: 23

No parameters are set when using this algorithm.

H.3.2 The inverse process-planning model

From trying out the different algorithms to train an artificial neural network was found that the best fit for the inverse process-planning model was made with the prune algorithm. The distributions of the neurons were:
Input layer: 24
Hidden layer 1: 30
Hidden layer 2: 35
Hidden layer 3: 36
Output layer: 9

The parameters set when using this algorithm:
The momentum parameter $\alpha = 0.9$
The initial learning rate parameter $\eta = 0.3$
The low learning rate parameter $\eta_{low} = 0.01$
The high learning rate parameter $\eta_{high} = 0.1$
The decay parameter $d = 30$

Appendix I

Regression model

A classical and widely utilised modelling technique to construct empirically based models is regression. It is studied to benchmark Bayesian network for making process-planning models.

I.1 Historical background

The first publications, [Legendre, 1805] and [Gauss, 1809], concerns linear regression based on least square method. The theory is further developed by [Gauss, 1821]. Regression has been applied to a big variety of applications and it is common in pocket calculators and standard in computer spreadsheet.

Because spreading of regression to different applications there is an extensive supply of software packages available. The program for implementing a regression model in this thesis is the [Clementine] software package.

The fundamental theory about regression and different regression models is described below. A more detailed description can be found in [Walpole et al., 2002].

I.2 General regression theory

Regression analysis covers statistical methods for making curve fitting to find the curve that fits a given dataset best. The regression analysis gives a relatively simple mathematical formula for generating predictions. For a single output variable *y*, which is dependent on *k* independent variables x_i, the functional relation can be written as:

$$y = f\left(x_1, x_2, ..., x_i\right)$$

Different mathematical equations can be used to make the function curve for approximation of the given dataset. The equations can both be linear and nonlinear and they are selected dependent on the nature of dataset to approximate. A linear regression model can be described as:

$$y = a + bx_1 + cx_2 + ... + gx_i + \varepsilon$$

The right hand side of the equation can be changed to another form according to the data it shall model. The model parameters are *a, b, c,…, g* and the error ε represents unpredicted or unexplained variation and is conventionally expected to be equal to zero. Finding the model parameters is an optimization problem; one has to find a solution where the error between the approximation function and the dataset is at a minimum. Least square is the most common error measure and to solve the optimization problem the gradient decent algorithm, the Gauss-Newton algorithm or the Levenberg-Marquardt algorithm are normally utilised.

I.2.1 Creating the model structure

Modelling of a regression model starts by defining the input and output vector. For each element in the output vector a regression model is made. A linear regression model is not suitable because welding is a nonlinear process and because a process-planning model covers a large interval of the parameters and variables of the process. A non linear regression model handles these nonlinearities. To make an equation which fits the dataset well, the equation can be constructed manually by a welding expert, who has a good experience in writing the relation between the input and output parameters and variables. A number of training trials can be preformed to verify the model because training of this type of model is relatively fast.

I.2.2 Training the model

Training of the regression model to determine the model parameters is made automatically by the training algorithm.

I.3 Regression implementation for T-Joint

Regression is used as the tool to build a process-planning model for the T-Joint. To build the model, the input and output vector has to be specified first. Building a direct and an inverse process-planning model requires building of two models. For the direct and inverse model the specified input and output vectors are shown in figure I.1. Both process-planning models have 10 nodes for the input vector and 1 output node. A separate model was build for each output node. So, for the T-Joint case 9 models were required in total.

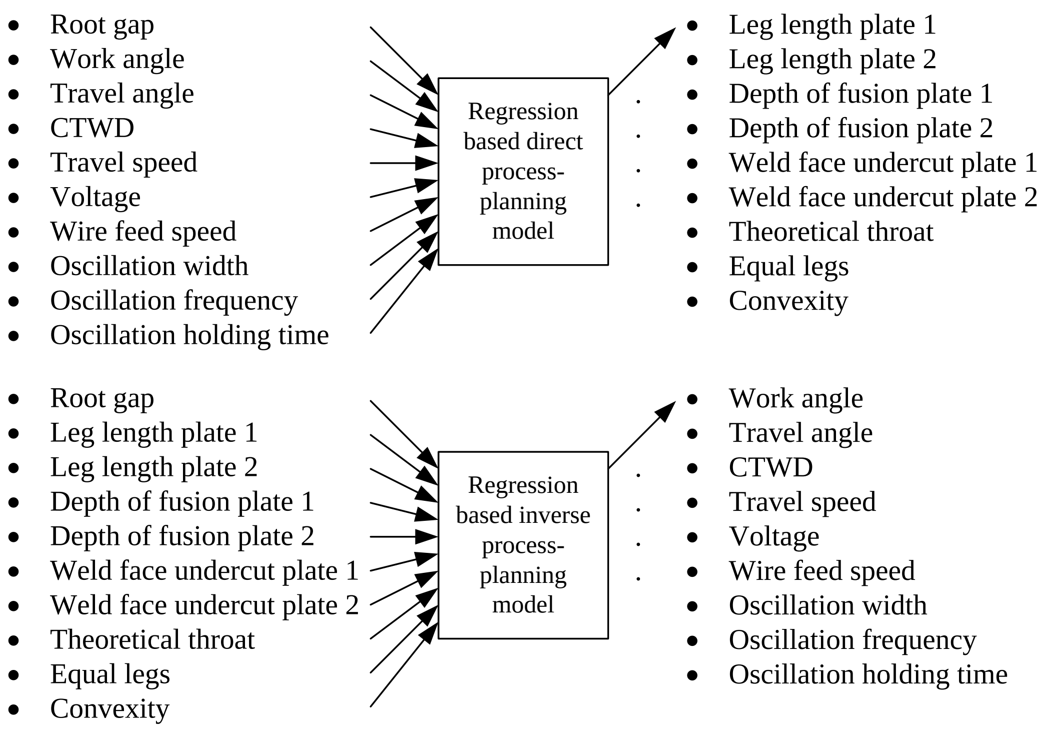


Figure I.1: Input vector and output node for the direct regression model.

The knowledge source for making a regression model is empirical datasets. Analytical knowledge cannot be used for building large regression models of welding, because analytical knowledge for welding is not yet developed to explain the relation between the amount of parameters and variables. Knowledge from welding operators is utilisable for building an expression in a regression model e.g. the method with an approximated equation, but for large model the relations between the amount of parameters and variables are complex to be handled by a welding operator.

For creating and training the model is used empirical data from 44 experiments and these experiments contained 802 datasets.

The common procedure for building a regression model is to try with different regression models, make a training trial for each model and compare the result to find out which regression model gives the best fit. Clemmentine was use to build the regression models and a detailed description of the algorithms and their adjustable settings can be found in [Clementine algorithms, 2004].

The constructed regression models are highly approximating models of the welding process because the empirical dataset used for training and modelling is very limited in size compared to the number of input variables and parameter. It causes that a linear regression model with no reciprocal effects included are used.

I.3.1 The direct process-planning model

The resulting direct process-planning model is as follows:

$$\begin{aligned}
\textit{Leg length plate 1} = {} & -0.299 \cdot \textit{Root gap} + 0.1977 \cdot \textit{Work angle} + 0.0399 \cdot \textit{Travel angle} \\
& - 0.3621 \cdot \textit{Travel speed} + 0.1153 \cdot \textit{Voltage} + 0.1461 \cdot \textit{Wire feed speed} \\
& + 1.484 \cdot \textit{Oscillation width} - 0.01815 \cdot \textit{Oscillation holding} \\
& - 0.1624 \cdot \textit{Oscillation frequency} + 12.6 \\
\textit{Leg length plate 2} = {} & -0.1237 \cdot \textit{Work angle} - 0.0232 \cdot \textit{Travel angle} - 0.1758 \cdot \textit{CTWD} \\
& - 0.729 \cdot \textit{Travel speed} + 0.0847 \cdot \textit{Voltage} + 0.3563 \cdot \textit{Wire feed speed} \\
& - 0.5509 \cdot \textit{Oscillation width} + 0.0053 \cdot \textit{Oscillation holding} + 1.074 \\
\textit{Depth of fusion plate 1} = {} & 0.0691 \cdot \textit{Root gap} + 0.0314 \cdot \textit{Travel angle} + 0.0462 \cdot \textit{CTWD} \\
& + 0.0580 \cdot \textit{Travel speed} + 0.0307 \cdot \textit{Voltage} + 0.1095 \cdot \textit{Wire feed speed} \\
& + 0.5609 \cdot \textit{Oscillation width} - 0.0032 \cdot \textit{Oscillation holding} \\
& - 0.1001 \cdot \textit{Oscillation frequency} - 3.261 \\
\textit{Depth of fusion plate 2} = {} & 0.4803 \cdot \textit{Root gap} + 0.1084 \cdot \textit{Travel angle} - 0.2056 \cdot \textit{CTWD} \\
& - 0.2051 \cdot \textit{Travel speed} + 0.4182 \cdot \textit{Wire feed speed} - 0.5162 \\
\textit{Weld face undercut plate 1} = {} & -0.139 \cdot \textit{Root gap} + 0.0275 \cdot \textit{Work angle} + 0.0194 \cdot \textit{Travel angle} \\
& - 0.117 \cdot \textit{CTWD} - 0.1437 \cdot \textit{Travel speed} - 0.171 \cdot \textit{Voltage} \\
& + 0.1662 \cdot \textit{Wire feed speed} + 0.6427 \cdot \textit{Oscillation width} \\
& - 0.0169 \cdot \textit{Oscillation holding} - 0.3536 \cdot \textit{Oscillation frequency} + 11.88 \\
\textit{Weld face undercut plate 2} = {} & 0.1283 \cdot \textit{Root gap} + 0.0680 \cdot \textit{Work angle} + 0.0242 \cdot \textit{Travel angle} \\
& - 0.0817 \cdot \textit{CTWD} + 0.1285 \cdot \textit{Travel speed} - 0.115 \cdot \textit{Voltage} \\
& + 0.0390 \cdot \textit{Wire feed speed} - 0.2417 \cdot \textit{Oscillation width} \\
& - 0.0099 \cdot \textit{Oscillation holding} - 0.2348 \cdot \textit{Oscillation frequency} + 12.02 \\
\textit{Theoretical throat} = {} & -0.0837 \cdot \textit{Work angle} - 0.0203 \cdot \textit{Travel angle} - 0.1052 \cdot \textit{CTWD} \\
& - 0.5126 \cdot \textit{Travel speed} + 0.0744 \cdot \textit{Voltage} + 0.1787 \cdot \textit{Wire feed speed} \\
& - 0.4937 \cdot \textit{Oscillation width} + 0.111 \cdot \textit{Oscillation frequency} + 0.9283 \\
\textit{Convexity} = {} & 0.0917 \cdot \textit{Root gap} + 0.0255 \cdot \textit{Work angle} + 0.0160 \cdot \textit{Travel angle} \\
& + 0.0894 \cdot \textit{Travel speed} - 0.0331 \cdot \textit{Voltage} + 0.2843 \cdot \textit{Wire feed speed} \\
& - 0.0104 \cdot \textit{Oscillation holding} + 1.145
\end{aligned}$$

I.3.2 The inverse process-planning model

The resulting inverse process-planning model is as follows:

$$\begin{aligned}
\textit{Work angle} &= 0.8961 \cdot \textit{Root gap} + 1.981 \cdot \textit{Leg length plate } 1 - 0.7921 \cdot \textit{Leg length plate } 2 \\
&- 0.5265 \cdot \textit{Theoretical throat} - 0.7001 \cdot \textit{Weld face undercut plate } 1 \\
&+ 1.489 \cdot \textit{Weld face undercut plate } 2 - 54.92 \\
\textit{Travel angle} &= 2.184 \cdot \textit{Root gap} + 1.689 \cdot \textit{Leg length plate } 1\text{-}2.596 \cdot \textit{Convexity} \\
&- 2.244 \cdot \textit{Weld face undercut plate } 1 + 2.222 \cdot \textit{Weld face undercut plate } 2 \\
&- 54.92 \\
\textit{CTWD} &= 0.6243 \cdot \textit{Root gap} + 0.8949 \cdot \textit{Leg length plate } 1 \\
&+ 0.2767 \cdot \textit{Leg length plate } 2 + 0.5164 \cdot \textit{Theoretical throat} \\
&- 0.4787 \cdot \textit{Convexity} - 1.464 \cdot \textit{Weld face undercut plate } 1 \\
&+ 0.4422 \cdot \textit{Weld face undercut plate } 2 + 11.82 \\
\textit{Travel speed} &= -0.4301 \cdot \textit{Root gap} - 0.6681 \cdot \textit{Leg length plate } 1 \\
&- 0.4446 \cdot \textit{Leg length plate } 2 - 0.394 \cdot \textit{Theoretical throat} \\
&+ 1.503 \cdot \textit{Convexity} - 0.5625 \cdot \textit{Weld face undercut plate } 2 - 13.43 \\
\textit{Voltage} &= 2.959 \cdot \textit{Leg length plate } 1 - 0.8719 \cdot \textit{Theoretical throat} \\
&+ 2.959 \cdot \textit{Convexity} - 0.9508 \cdot \textit{Weld face undercut plate } 1 \\
&- 1.351 \cdot \textit{Weld face undercut plate } 2 - 24.39 \\
\textit{Wire feed speed} &= 0.3888 \cdot \textit{Root gap} - 0.1649 \cdot \textit{Leg length plate } 1 \\
&+ 0.2452 \cdot \textit{Leg length plate } 2 - 0.2461 \cdot \textit{Theoretical throat} \\
&+ 2.172 \cdot \textit{Convexity} - 1.159 \cdot \textit{Weld face undercut plate } 2 + 10.22 \\
\textit{Oscillation width} &= -0.0552 \cdot \textit{Root gap} - 0.0907 \cdot \textit{Leg length plate } 1 \\
&- 0.0780 \cdot \textit{Leg length plate } 2 - 0.1483 \cdot \textit{Theoretical throat} \\
&- 0.1519 \cdot \textit{Convexity} - 0.1601 \cdot \textit{Weld face undercut plate } 1 \\
&- 0.2979 \cdot \textit{Weld face undercut plate } 2 + 3.16 \\
\textit{Oscillation frequency} &= 0.1086 \cdot \textit{Root gap}\text{-}0.2213 \cdot \textit{Leg length plate } 1 - 0.2478 \cdot \textit{Leg length plate } 2 \\
&- 0.2829 \cdot \textit{Theoretical throat} - 0.2757 \cdot \textit{Convexity} - \\
&- 0.4984 \cdot \textit{Weld face undercut plate } 2 - 7.525 \\
\textit{Oscillation holding time} &= -3.879 \cdot \textit{Leg length plate } 1 - 11.61 \cdot \textit{Theoretical throat} - 7.022 \cdot \textit{Convexity} \\
&- 4.5 \cdot \textit{Weld face undercut plate } 1 - 6.476 \cdot \textit{Weld face undercut plate } 2 \\
&+ 154.2
\end{aligned}$$

Appendix J

Article 1

Morten Kristiansen, Ole Madsen, “Experimental data and operator knowledge used for classifying welding quality”, Proceedings of IASTED International Conference on Artificial Intelligence and Applications - AIA 2004, Vol. 2, pages 712-717, 2004, ISBN 0889864047

EXPERIMENTAL DATA AND OPERATOR KNOWLEDGE USED FOR CLASSIFYING WELDING QUALITY

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Abstract

Automation of many manufacturing processes requires a process-planning model. These models are hard and time consuming to construct because they are often non-linear and the physics of the process is not completely understood. In the literature these models are usually constructed from experiments. However, the operator possesses a lot of knowledge about the process, but it is rarely used because it is hard to formalize. This paper presents the results of a feasibility study in the use of the operator knowledge for building a process-planning model. A method is presented in which operator knowledge in the construction of process-planning models is used. The method consists of three steps: 1) Generating knowledge from operator interviews, 2) Construction of training data, 3) Construct process-planning models. Use of operator knowledge compared with use of experiments shows that the same precision of the process-planning modes is achieved but the time consumption is reduced considerably.

Key Words

Knowledge acquisition, automation, artificial neural networks, Bayesian network, welding, process-planning models.

1. Introduction

Industry is very interested in automation of the welding process using e.g. robots. Through automation, production costs can be reduced and workers can be removed from unhealthy working situations. In order to save costs and make it beneficial to install a welding robot the programming of the robots needs to be fast and/or automatic. This is in particular important for small batch manufacture. One task when making the robot programming automatic is to select the variables of the welding process. In order to select appropriate variables a model of the welding process is needed. This model is called a process-planning model. A process-planning model is difficult to build for the welding process because it is influenced by many factors, is non-linear and the physics of the process is not completely understood. Two different approaches are used to construct these models.

One approach is empirical, i.e. models are made from experiments with different parameter settings. For each experiment the input parameters and the output, described by the quality of the process, are used. Examples of this method are described by [1], [2] and [3]. Different methods from machine learning have also been used to create process-planning models where experimental data is used. Examples of this are described by [4], [5], [6] and [7], which use experimental data to train an artificial neural network. [8] use rule-based reasoning and case-based reasoning, and [9] use decision trees to construct process-planning models.
Another approach is analytical, i.e. mathematical models made from physical laws describing the physics of the process. The physical laws are based on empirical experiments, which have been formalised on mathematical form. The knowledge of the analytical process-planning models lies in this description of the physics and it can be used to control the process if it is a sufficiently precise description. An example of an analytical method is described by [10] where a finite element model including heat conduction and weld pool surface tension is constructed.

A lot of experimental data is required for empirical process-planning models, and it is very time consuming and thereby expensive to make these models. A lot of time is also required for building analytical process-planning models and they are limited because the physics of some production processes is not well described.
In this paper the result of a feasible strategy is presented in order to investigate the possibility and feasibility of building process-planning models based on operator interviews. In the paper operator-built models are compared with conventional models based on experiments.
The use of interviews of experienced operators to make process-planning models is investigated, but it is only described few places in the literature. [11] describes a method for controlling the quality of production processes using historical data and the experience of the operator.

2. Materials and Methods

To investigate if knowledge from operator interviews can be used for process-planning models they are compared with the use of experiments. Tests with the three following knowledge sources were carried out in this investigation:

- Experiments.
- Operator.
- Experiments and operator combined.

The process-planning model built and tested is for butt welding without backing of thin plates. The model has four input variables, four output quality parameters and the rest of the parameters are fixed. See figure 1 and table 1.

Input variables:

- Welding speed (WS).
- Voltage (VO).
- Wire feed speed (WF).
- Gap (GA).

Output quality parameters:

- Weld-face width.
- Weld-face height.
- Back-bead width.
- Back-bead height.

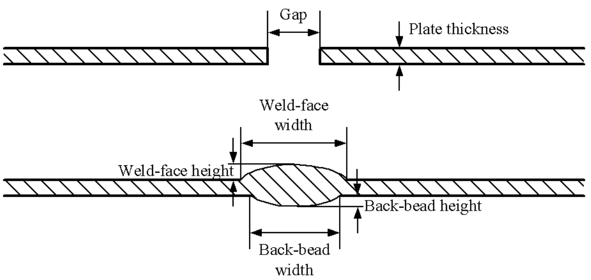


Figure 1: Measurement on the plates before and after welding. Welding is made from above.

Plate material:	S235
Plate thickness:	3 mm
Plate dimensions (L x W):	330 x 50 mm
Power supply:	Constant voltage machine
Wire type:	EN440 – G3SI1
Wire diameter:	Ø1.2 mm
Shielding gas:	Mixture 92 % Ar and 8 % CO_2
Gas flow rate:	15 l/min
CTWD:	10 mm
Welding torch orientation:	Work angle 0° & travel angle 0°

Table 1: Specifications for the experiments conducted.

To compare operator knowledge with experimental knowledge it was chosen to discretisize the variables and parameters to three states: small, medium and large. The discretization made it possible to compare the result and because it was a feasibility study the introduced reduced resolution could be accepted.

2.1 Generating knowledge from operator interviews

The operator's knowledge of the relationship between the input variable and the quality parameter has to be formalized. The first step in the formalization was an interview where the operator was informed about the welding task. Then, for each input/output combination, the operator was asked to indicate whether the result was:

- Direct or inverse proportional.
- How much weight the input parameter had on the output parameter.

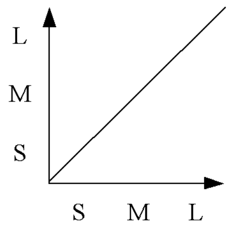
Table 2 shows the result of the interview and the operator's arguments are listed below in appendix.

Quality parame-ter	Input variable	Influence: Direct proportional Inverse proportional	Weight: (1-4) 1 = low 4 = high
Weld-face width	Welding speed	Inverse	2
	Voltage	Direct	3
	Wire feed speed	Direct	4
	Gap	Inverse	1
Weld-face height	Welding speed	Inverse	2
	Voltage	Inverse	3
	Wire feed speed	Direct	4
	Gap	Inverse	1
Back-bead width	Welding speed	Inverse	1
	Voltage	Direct	2
	Wire feed speed	Direct	3
	Gap	Direct	4
Back-bead height	Welding speed	Inverse	1
	Voltage	Direct	2
	Wire feed speed	Direct	3
	Gap	Direct	4

Table 2: The operators answer to the questionnaire.

2.2 Construction of training data

The second step of the formalization was the transformation of answers into data of the same format as the result of the welding experiments. Probability was used to transform the influence. Figure 2 shows the transformation to probabilities determined according to the uncertainties in the interpretations of operator's answers.



State (s)				
	L	0.0	0.1	0.9
	M	0.1	0.8	0.1
	S	0.9	0.1	0.0
		S	M	L
		Input (i)		

Figure 2: A direct proportional influence is transformed to a direct probability table. S = Small. M = Medium. L = Large. The probability was calculated by the function f(i,s).

For the inverse proportional influence, the probability matrix was transposed. A program converts the following:

- Probability table. A probability is calculated by *f*(i,s).
- Influence. A direct or inverse probability is chosen.
- Weight. A weight *w*(x) is determined from table 2 column 4.

These three are converted into discrete training sets of small, medium or large for each of the four quality parameter. A Java program converts the data and the pseudo code at figure 3 converts each of the four quality parameters.

$$W = \frac{w(WS) + w(VO) + w(WF) + w(GA)}{4}$$

for $(WS = S, M, L)$
for $(VO = S, M, L)$
for $(WF = S, M, L)$
for $(GA = S, M, L)$
Probability of small (PS) $= P(State = S \mid WS, VO, WF, GA) =$

$$\frac{w(WS)\cdot f(WS,S) + w(VO)\cdot f(VO,S) + w(WF)\cdot f(WF,S) + w(GA)\cdot f(GA,S)}{W}$$

Probability of medium (PM) $= P(State = M \mid WS, VO, WF, GA) =$

$$\frac{w(WS)\cdot f(WS,M) + w(VO)\cdot f(VO,M) + w(WF)\cdot f(WF,M) + w(GA)\cdot f(GA,M)}{W}$$

Probability of large (PL) $= P(State = L \mid WS, VO, WF, GA) =$

$$\frac{w(WS)\cdot f(WS,L) + w(VO)\cdot f(VO,L) + w(WF)\cdot f(WF,L) + w(GA)\cdot f(GA,L)}{W}$$

if $(PS > PM$ and $PS > PL)$ return Small
else if $(PM > PS$ and $PM > PL)$ return Medium
else if $(PL > PS$ and $PL > PM)$ return Large
else return NotClassified

Figure 3: Pseudo code for transformation of operator answer to discrete training data for a given quality parameter.

2.3 Construct process-planning models

Two methods from machine learning are used to make the process-planning models:

- Artificial neural network method
- Bayesian network method

The methods were chosen, because classification of the process-planning model can be made according to them, and they can both handle discrete input. Two methods were used to investigate their differences.

Artificial neural network
Artificial neural network is a widely used method for classification of discrete and continuous valued functions. The artificial neural network consists of an input layer, a number of hidden layers and an output layer and one layer is connected with the next layer. Training data is used to set the weights in the artificial neural net. The way the neural net describes the relation between the input and output data is by the function of a number of polynomials. The artificial neural network was built with 2 hidden layers and the following number of initial nodes 12-20-15-3. Back-propagation was used for training with a "Prune" algorithm to reduce the number of network nodes. Clementine 7.2 [12], [13] was used to build the network and perform the training. The default opportunity was used to stop training, and it stops when the network seemed to have reached the optimally trained state. In cases where pure operator data was used, the training was set to stop after 10,000 iterations because these data do not contain contradictory results, and therefore the default training algorithm does not stop.

Bayesian network
A Bayesing network is a probabilistic method for taking decisions, and it is based on a causal network and uses a graphical representation of the problem. Probabilistic information was entered into the network nodes from training sets or from experts. The network was then able to calculate the probabilities for hypotheses. A graphical model was built using the NPC (Necessary Path Condition)- algorithm. [14] Because enough training data was not available for the NPC-algorithm to predict all the relations between the nodes the operator was used to build the model in figure 4 for all the experiments. Hugin Researcher 6.2 was used to build the Bayesian network model.

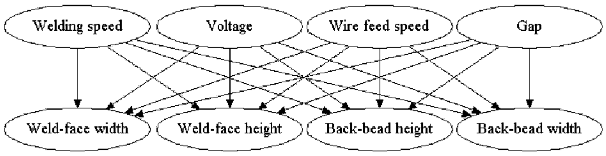


Figure 4: The Bayesian network model used.

2.4 Generation of knowledge from experiments

To generate knowledge from experiments an experimental setup was made on a xy-table, see figure 1, with the parameters listed in table 1. The plates are tack-welded to keep a fixed gap. Before welding, the position of the part and the gap size was measured by a laser scanner. The welding was carried out with fixed parameters except for the input variables, which were changed between the welding experiments. After welding, a laser scanning was carried out on the front and the back side of the plate, and from the scanning the four quality parameters were found. From each experiment one data set was stored. See table 4 in appendix. The experiments were carried out by Kim Hardam Christensen, DTU.

2.5 The test procedure

The procedure of testing different knowledge sources to build process-planning models was carried out in two steps. The first step generates the training sets and trains the learning methods. Figure 5 illustrates the sequence of operations.

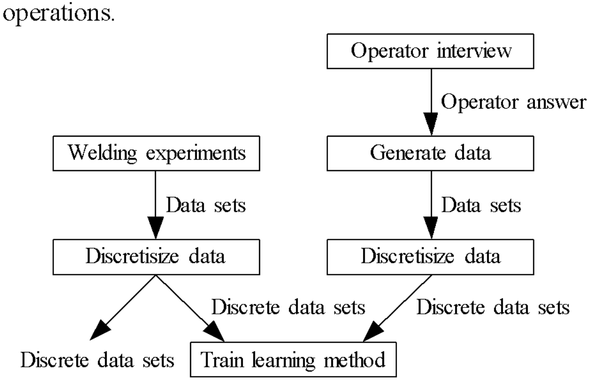


Figure 5: Generating training data and training learning methods.

From the welding experiments 39 data sets were made where 26 were used for training and 13 were used as test data. Each third data set illustrated in table 4 was used as test data. The data was discretisized, so each input was in equal sized intervals with approximately 1/3 of the data in each interval. Table 4 shows the result of the discretization. The discrete data sets were used to train the three learning methods. The following training sets were used:

- Experiments: With 26 data sets.
- Operator: With 77 data sets.

The trained learning methods were then tested to see how exact they were in predicting the quality parameter of the 13 data sets with experimental data. Figure 6 shows the process of testing the trained data.

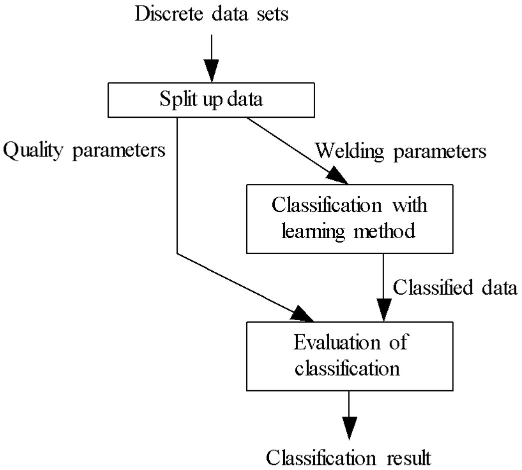


Figure 6: Classifying test data using learning methods.

The 13 test data sets were split up and the welding parameters were entered into the learning method, which acts as a process-planning model predicting the quality parameters. Afterwards, quality parameters from the experiment and the predicted quality parameters were evaluated if they fitted. The evaluation of the fit of the quality parameters was then written in per cent.

3. Results

The results of the test in figures 7 and 8 show that use of operator knowledge can predict the quality very close to the use of experiments.

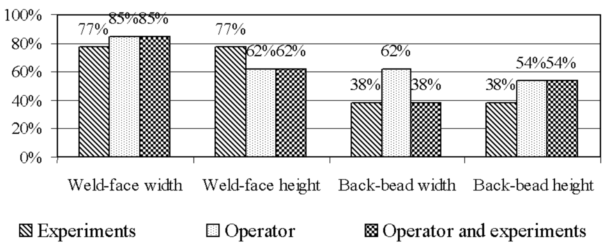


Figure 7: Classification result using artificial neural network.

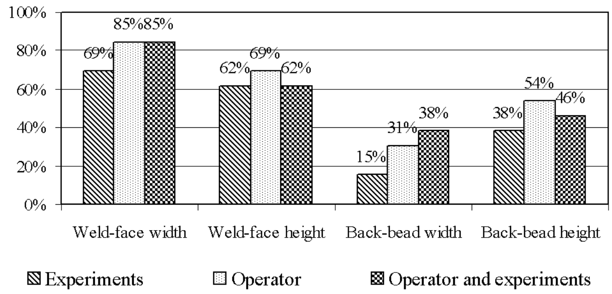


Figure 8: Classification result using Bayesian network.

It was not possible to make a 100 per cent correct classification because the test data contained some sets of input vectors which were equal, but they gave a different output vector. Making a guess will in average give a classification rate of 33 per cent so the classification of back-bead width, figure 8, gives a much poorer result.

The time consumption for the welding experiments was about 30 minutes for each experiment. For the 26 training examples in this paper it was 13 hours. Time was also used to make the experimental setup and to adjust and calibrate the system. The operator interview lasted 30 minutes for filling out table 2, and the rest of the process was made automatically by a computer program.

To check the level of details, necessary from the operator interviews, a comparison of the different models was made. The use of influence and weight from the questions was compared with use of influence only. The level of correctly predicted quality parameters decreased only slightly when the question of weight was not used in making the process-planning model. Nothing general can be predicted when taking uncertainties into account.

	Bayesian network		Artificial neural network	
Influence	X	X	X	X
Weight		X		X
Weld-face width	85%	85%	85%	85%
Weld-face height	54%	69%	46%	62%
Back-bead width	38%	31%	54%	62%
Back-bead height	54%	54%	69%	54%
Average	58%	60%	63%	65%

Table 3: The amount of questions for the operator interview is compared.

The decision tree method was also tested in building process-planning models from the three knowledge sources. This method showed the same tendency as the Bayesian network and the artificial neural network.

4. Conclusion

Comparing the use of operator knowledge with the use of experiments gives the same classification rate. Combining the experimental data with operator knowledge does not show an increased classification rate. Reducing the

number of questions of the interview did not show a marked rice of the classification rate.
Industry's wish to go from on-line programming towards automatic programming is shown in figure 9. The use of operator knowledge instead of experiment is a step towards making automatic programming profitable because a lot of time is saved.

On-line programming → Off-line programming → Automatic programming

Figure 9: More knowledge is required in the robot programming systems when going from on-line towards automatic programming.

In this work welding is used as case, but it can be applied for other production processes as for instance painting.

From the framework of this paper it is strongly believed that process-planning models can be made with input from operator interviews and thus the time consumption for making the models is reduced. Further work will be carried out within building of larger process-planning models including more parameters. The models will be based on the Bayesian network because it is believed that creating the graphical model of a large-scale process-planning model can be carried out in cooperation with the operator.

5. Acknowledgement

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References

[1] P. E. Murray, Selecting parameters for GMAW using dimensional analysis, *Welding Journal, 81*(7), 2002, 125-131.
[2] I. S. Kim, W. H. Kwon & E. Siores, An investigation of a mathematical model for predicting weld bead geometry, *Canadian Metallurgical Quarterly, 35*(4), 1996, 385-392.
[3] O. Madsen, J. Lauridsen, H. Holm, J. Boelskifte & I. Hafsteinsson, Model of root-bead welding for off-line programming and control, *Computer applications in production engineering, Proceedings of CAPE '95*, 1995, 847-855.
[4] G. E. Cook, R. J. Barnett, K. Andersen & A. M. Strauss, Weld modeling and control using artificial neural network, *IEEE Transaction on Industry Applications, 31*(6), 1995, 1484-1491.
[5] H. S. Moon & S. J. Na, Optimum design based on mathematical model and neural network to predict weld parameters for fillet joints, *Journal of Manufacturing Systems, 16*(1), 1997, 13-23.
[6] O. Madsen & V. Karri, Neural networks to estimate welding velocity for control of root-bead welding, *Advanced Manufacturing Processes, Systems, and Technologies*, 1996, 183-192.
[7] K. H. Christensen & T. Sørensen, A Neural Network Approach for GMA Butt Joint Welding, *Proceedings of 11th International Conference on the Joining of Materials - JOM-11*, 2003.
[8] P. Peng, J. Tian, L. Wu & M. Da, An intelligent hybrid system of welding parameters for robotic arc welding task-level off-line programming, Proc. of SPIE Intelligeng Systems in Design and Manufacturing III, Bhaskaran Gopalakrishnan, 2000, 440-445.
[9] W. Yanhong, Z. Xiuzhi & T. Xitang, An expert system for generating welding procedures of boilers and pressure vessels, *Welding in the World/Le Soudage dans le Monde, 34*, 1994, 381-388.
[10] H. Holm, P. Jeberg & C. Bro, Applications of numerical model for off-line programming of posture robot welding, *Preceding for 12th International TWI Computer Technology in Welding and Manufacturing Conference*, 2002, Paper no. 81.
[11] G. Yi, J. Shin, H. Cho & K. Kim. Quality-oriented shop floor control system for large-scale manufacturing processes: Functional framework and experimental results, *Journal of Manufacturing Systems, 21*(3), 2002, 187-199.
[12] Clementine® 7.0 User's Guide, 2002. www.spss.com
[13] T. Khabaza & C. Shearer, Data mining with Clementine, *Knowledge Discovery in Databases*, 1995, 1/1-1/5
[14] Hugin Help, Hugin Researcher 6.2, 2003. www.hugin.com

Appendix

The operator's arguments for the choices

Weld-face width:

Increasing of welding speed gives less input material per area and the weld-face width decreases. (Inverse)
Increasing of voltage gives more heat input so more material melts and the weld-face width increases. (Direct)
Increasing of wire feed speed gives more material per area and more heat input so more material melts and the weld-face width increases. (Direct)
Increasing of gap gives more space in the gap for material and material from the weld-face is used and the weld-face width decreases. (Inverse)

Weld-face height:

Increasing of welding speed gives less input material per area and weld-face height decreases. (Inverse)
Increasing of voltage gives more heat input so more material melts and the weld-face height decreases. (Inverse)
Increasing of wire feed speed gives more material per area and more heat input so more material melts and the weld-face height increases. (Direct)
Increasing of gap gives more space in the gap for material and material from the weld-face is used and the weld-face height decreases (Inverse)

Back-bead width:
Increasing of welding speed gives less input material per area and back-bead width decreases. (Inverse)
Increasing of voltage gives more heat input so more material melts and the back-bead width increases. (Direct)
Increasing of wire feed speed gives more material per area and more heat input so more material melts and the back-bead width increases. (Direct)
Increasing of gap gives more space in the gap for material and the material can float through the gap from the weld-face and the back-bead width increases. (Direct)

Back-bead height:
Increasing of welding speed gives less input material per area and back-bead height decreases. (Inverse)
Increasing of voltage gives more heat input so more material melts and the back-bead height increases. (Direct)
Increasing of wire feed speed gives more material per area and more heat input so more material melts and the back-bead height increases. (Direct)
Increasing of gap gives more space in the gap for material and the material can float through the gap from the weld-face and the back-bead height increases. (Direct)

Weights:
For the weld-face, the factors with biggest influence are the heat input and input of material because they control the size of the weld pool and the amount of material going to the weld pool. Therefore, the two most important factors are the wire feed speed, which influences both factors, and voltage, which influences the heat input. The third factor is the welding speed because it influences the material input. The last factor is the gap, which influences how much space there is for the material input but the space is dependent on the heat input to melt the material.
For the back-bead the gap has the biggest influence because the material to make the back-bead has to parse through the gap. The second factor is the wire feed speed, which gives both heat input and material input. The third factor is voltage, which gives heat input necessary to melt the material. The fourth factor is welding speed and it is the last factor because gap size and heat input are required before the extra material can parse.

Welding speed [mm/min]		Voltage [V]		Wire feed speed [m/min]		Gap [mm]		Weld-face width [mm]		Weld-face height [mm]		Back-bead width [mm]		Back-bead height [mm]	
375	L	22	L	5.8	L	0	S	9.3	L	2.28	L	3	M	0.65	S
365	L	22	L	5.8	L	0	S	9.22	L	2.23	L	3.2	M	1.3	L
370	L	22	L	5.8	L	0	S	9.2	L	2.12	L	3.5	M	1.4	L
300	S	18	S	3	S	1.85	L	5.3	S	1	S	2.7	S	0.55	S
300	S	18	S	3.3	S	1.45	L	6.3	S	1.37	S	3.4	M	0.9	M
325	S	18	S	3.3	S	1.8	L	5.5	S	1.18	S	3.7	L	0.85	M
300	S	18	S	3	S	1.1	M	5.9	S	1.5	M	1.8	S	0.25	S
325	S	19	M	3.8	M	1	M	7	M	1.5	M	3.7	L	1	M
300	S	18	S	3	S	1.2	M	6.1	S	1.45	M	2.2	S	0.3	S
350	M	20	M	4	M	0.85	M	6.9	M	1.75	M	1.7	S	0.45	S
325	S	20	M	4.5	L	0.4	S	7.6	M	1.42	M	4.3	L	1.95	L
375	L	20	M	4.5	L	0.6	M	7.5	M	1.85	L	3.3	M	0.95	M
325	S	18	S	2.8	S	1.55	L	5.3	S	0.73	S	2.7	S	0.43	S
350	M	18	S	3.2	S	1.55	L	5.4	S	1.08	S	3	M	0.55	S
375	L	21	L	5	L	0.4	S	8.2	L	2.15	L	2.8	S	0.6	S
360	M	22	L	5.5	L	0.2	S	9.2	L	2	L	3.85	L	1.35	L
370	L	21	L	4.2	M	0.8	M	7.8	L	1.7	M	2.7	S	0.95	M
360	M	21	L	4.2	M	0.5	S	7.6	M	1.9	L	2.6	S	0.8	M
300	S	19	M	3.6	M	0.7	M	7.2	M	2.05	L	2.9	M	0.75	M
340	M	19	M	3.5	M	1.4	L	7.2	M	1.35	S	3.2	M	0.9	M
350	M	20	M	4	M	1	M	6.9	M	1.6	M	3.7	L	1.1	L
325	S	18	S	3	S	1.3	L	6.1	S	1.45	M	2.7	S	0.5	S
310	S	18	S	2.8	S	2	L	4.5	S	0.8	S	3.7	L	0.85	M
350	M	18	S	3	S	1.6	L	6	S	1.25	S	2.8	S	0.4	S
300	S	18	S	2.8	S	1.7	L	6	S	1.3	S	2.5	S	0.5	S
350	M	19	M	3.5	M	1.55	L	5.5	S	1.2	S	3.4	M	0.8	M
350	M	18	S	3	S	2.1	L	3.2	S	0.55	S	3.6	L	0.8	M
375	L	20	M	4.3	M	0.9	M	7.4	M	1.7	M	3.3	M	1	M
375	L	22	L	5.2	L	0.5	S	7.6	M	1.1	S	5.1	L	2.7	L
360	M	20	M	4	M	0.7	M	6.8	M	1.85	L	3.1	M	0.85	M
350	M	20	M	4	M	0.9	M	7.2	M	1.5	M	3.5	M	1.1	L
375	L	20	M	4.3	M	0.6	M	7.7	L	1.7	M	3.4	M	1.1	L
350	M	19	M	3.7	M	0.8	M	6.9	M	1.9	L	2.8	S	0.85	M
350	M	20	M	4.3	M	0.4	S	7.9	L	2.2	L	2.7	S	0.5	S
325	S	21	L	4.8	L	0.3	S	8	L	1.3	S	3.9	L	1.55	L
375	L	21	L	4.8	L	0.4	S	7.6	M	1.85	L	3.7	L	1.2	L
325	S	19	M	3.8	M	0.7	M	7.1	M	1.9	L	1.5	S	0.35	S
325	S	20	M	4.8	L	0.3	S	7.8	L	2.1	L	3.5	M	1.15	L
300	S	20	M	4.5	L	0.5	S	8	L	1.7	M	4.3	L	1.65	L

Table 4: Original data and discretization of data to S (small), M (medium) and L (large).

Appendix K

Article 2

Morten Kristiansen, Ole Madsen, “Process-planning models for welding using Bayesian network”, Proceedings of the 7th International Conference on Trends in Welding Research, pages 635-640, 2006, ISBN 978-0-87170-842-7

Process-Planning Models for Welding Using Bayesian Network

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Abstract

A process-planning model has been developed for welding of T-joints. The model has been used for computing control variables on a T-joint with varying root gap. This research investigates how different sources of knowledge can be produced, acquired, integrated and formalised in process-planning models. The knowledge sources investigated are empirical knowledge from welding experiments, analytical knowledge from literature and knowledge obtained from interviews with welding operators and experts. A Bayesian network is selected as the tool for making the process-planning model. It is selected because it is a graphical model and it uses probabilities, which enables use of welding operator and expert knowledge. Welding made using the designed process-planning model shows good results on a T-joint with varying root gap. A benchmark with artificial neural networks for a direct process-planning model shows an advantage of the model based on a Bayesian network

Introduction

The industry requests solutions for automation of the welding process to reduce the production costs, improve weld quality and to increase the standard of the working conditions. One of the obstacles, which prevent many industries from utilizing robots is the cumbersome work, associated with the programming of robots. For manufacture of small batch sizes, it is especially important to make the programming more effective.

Automation of the programming task requires models of processes. A process-planning model is illustrated in figure 1.
The direct model relates the welding control variables, workpiece parameters and equipment parameters to the quality parameters. The welding control variables can be adjusted during the process execution. Workpiece parameters, which describe the workpiece are given during the product design and cannot be changed. The Equipment parameters are settings of the equipment used and can be changed before process execution but are fixed during process execution. Quality parameters define the quality of the welding by geometrical and metallurgical parameters.

To plan a robotic welding task the inverse process-planning model is used to compute welding control variables. Reliable direct and inverse process-planning models are difficult and expensive to build for the welding process because they are influenced by many factors, the physics of the process is not understood completely, and the process is non-linear.
The two different approaches used to construct the process-planning modes are analytically and empirically based.

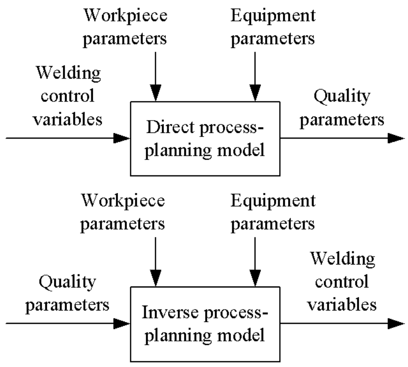

Figure 1: The input and output to the direct and inverse process-planning model. [1]

The analytical method uses general physical laws verified and formalised on a mathematical form. Using these mathematical equations and physical laws, a description of the welding process is made. Examples are [2] and [3] who model the heat- and mass flow and surface tension of the weld pool using the finite element method.
Empirical methods use experimental data that contains sets of welding control variables, workpiece-, equipment- and quality parameters. Different methods are used to model the relation between the input and output. [4] and [5] use regression and curve fitting methods. Methods from the area of machine learning are used in [5-10]. Artificial neural network is a frequently described method in the literature and is described by [5], [6] and [7]. [8] describes the use of rule- and case based reasoning, [9] describes use of decision trees, and [7] describes the use of genetic algorithms used with artificial neural network. For the spot welding process [10] has made a direct process model using Bayesian network.

Building process-planning models using the analytical method is time consuming and not possible because the physics of the process is not completely understood. Empirically based process-planning models require many experimental data and taking more variables and parameters into the model increases drastically the number of required experiments. Furthermore, empirical models have limited range of application since they can only be applied to tasks, which are carried out under the same conditions as those used for the experiments.

An available knowledge source rarely used for making welding process-planning models is the welding operator. The welding operator has experience from many hundreds of hours of welding and can quickly find the settings of the welding parameters giving the decided quality and this even for new geometries and materials. In the literature only very few examples can be found with use of operators knowledge. [11] describes how historical data and experience of operators can be used for controlling quality of production processes. Combinations of different knowledge sources are also very rarely used. [12] describes, in a pre-study for the work presented in this paper, how empirical data and experience of welding operators can be combined.

This paper describes the result of an investigation of how the different knowledge sources can be combined and used in one process-planning model. The knowledge sources are analytical knowledge, empirical knowledge, and experience from operator and expert. The investigated modelling technique is Bayesian networks, which have some good facilities for combining knowledge by having a graphical representation and using probabilities to represent data. The objectives of using Bayesian networks are to combine and integrate different knowledge sources in one model. The objectives are also to be able to use the same model as a direct and an inverse process-planning model. Another objective of using the Bayesian network compared with many other types of machine learning tools as e.g. artificial neural network is that the model is not a total black box model because it can be visualised, understood and the physics of the process can be modelled to some extent.

Materials and methods

Welding task
A T-joint with varying root gap is used as case and shown in figure 2.

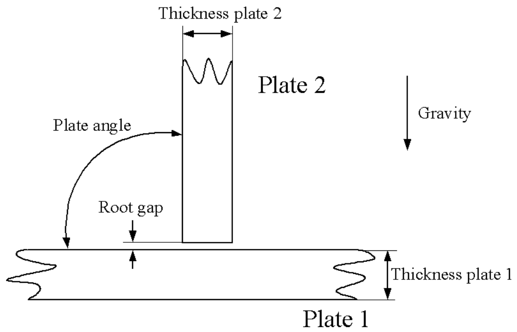

Figure 2: T-joint to be welded showing geometrical workpiece parameters.

After welding the quality parameters are measured and the geometrical quality parameters are defined in figure 3.

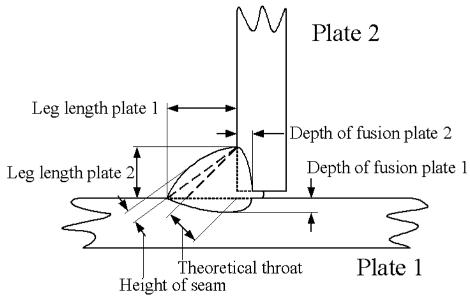

Figure 3: Welded T-joint showing the measured geometrical quality parameters.

The measurement of leg length plates 1 and 2, height of seam and theoretical throat are determined by non-destructive methods. Depth of fusion plates 1 and 2 are determined from destructive test. The used materials and equipment are described in table 1.

Table 1: Specifications of task and setup.

Part	
Plate 1 dimensions (T x L x W):	12 x 200 x 100 mm
Plate 2 dimensions (T x L x W):	10 x 200 x 100 mm
Root gap:	0-3 mm
Plate angle	90°
Plate material plates 1 and 2:	S235
Plate surface plates 1 and 2:	Untreated with oxide scale
Equipment	
Power supply:	Migatronic BDH550 constant voltage machine
Wire type:	ESAB OK Autrod 12.51
Shielding gas:	82 % Ar and 18 % CO_2
Shielding gas flow:	14 l/min
Nozzle cup diameter:	Ø15 mm

Sources of knowledge
The sources of knowledge for the modelling are:

- Empirical knowledge from experiments
- Analytical knowledge from equations and rules
- Operator and expert experience from interviews.

Empirical knowledge
Empirical knowledge is created from 58 welding experiments where 44 experiments are used for training and 14 for testing. Each experiment is made with different settings of the welding control variables, variations of the root gap and the quality parameters are measured different. The weld groove is scanned before and after welding with a laser scanner to measure respectively the initial geometry shown in figure 2 and the seam geometry of the weld face shown in figure 3. For each experiment, more data sets are made from laser scanning measurement because the geometry is scanned with an interval of 2.5 mm. For 36 of the experiments the depth of fusion are measured. The data from the experiments are stored in a database with an example showed in table 2. The experiments

are reproducible and made using a robot. The data logging is made by the welding machine and by a laser scanner, which scans the part before and after welding.

Table 2: Example of two empirical data sets discretized to fit to the states of the Bayesian network.

Gap	Wire diameter	Work angle	Travel angle	Stickout	Travel speed
0.8	1	-45	0	14	8
1.2	1	-45	0	18	8
Oscillation width	Oscillation frequency	Oscillation holding	Wire feed speed	Voltage	
1	2	50	12	28	
1	2	40	15	36	
Fill area	Height of seam	Leg length plate 1	Leg length plate 2	Theoretical throat	Depth of fusion plate 1
20	1.4	5	5	3	0.5
30	1.8	7	6	4	1.5
Depth of fusion plate 2	Weld face undercut plate 1	Weld face undercut plate 2	Convexity	Appearance	
0.5	4	4	3	3	
1	2	2	3	2	

Analytical knowledge

Analytical knowledge from physical laws where the following are used:

$$\text{Material deposit} = \frac{\text{Wire feed speed} \cdot \frac{1}{4} \cdot \text{Wire diameter}^2 \cdot \pi}{\text{Travel speed}}$$

$$\text{Energy} = \text{Voltage} \cdot \text{Current}$$

$$\text{Heat input} = \frac{\text{Energy}}{\text{Travel speed}}$$

A constitutive equation is also used:

$$\text{Voltage} = \alpha \cdot \text{Current} + \beta$$

From the empirical training data it is found that $\alpha = 0.0869$ and $\beta = 15.237$.

From welding standard [13] rules are used to classify the welding quality.

Operator and expert knowledge

Operator and expert experience is gathered from interviews and formalised into relations, interactions and descriptions.

Relations tell which variables in the process have an effect on each other, e.g. that wire feed speed influences the current.

Interaction tells what interaction one variable has with a related variable when the state of the variable is changed. E.g. when wire feed speed increases then the current increases.

Descriptions describe phenomena in the process, which can be made into a variable, which describes the intermediating process state variables between welding control variables, workpiece and equipment parameters and the quality parameters of the process-planning model in figure 1. E.g. that an energy variable can be made from the voltage and current variable.

Using operator and expert experience is often difficult because different operators and experts have different ways of describing things. In addition, the descriptions of e.g. interactions are not so precise that a fixed value can be specified. Although, the knowledge is not very precise it is still useful to build the model structure where the general view is more important than the precision.

Modelling

A Bayesian network is a directed acyclic graph having a set of nodes (variables) and a set of directed edges between them. Each node has a set of mutually discrete states and each state is associated with a probability measure. The probability measures are written in a table and for node A with the parent nodes $B_1,\dots,B_n$ is $P(A| B_1,\dots,B_n)$. [14]

A process-planning model is modelled using a Bayesian network describing a T-joint welding task. The modelling is made by making a graphical representation describing the physics and/or the relations of the system and by giving probabilistic information to the nodes.

The principle of creating the process-planning model is to identify and make relations between the three node categories of welding control variables, workpiece and equipment parameters and the node category of quality parameters see figure 4. Each node category can be split up into one or more nodes with different characteristic:

The workpiece parameter describes the workpiece to weld.

The equipment parameter describes the adjustment of the welding equipment.

The control variables describe the controllable variables.

The quality parameters describe the quality of the welding.

Between the three categories of welding control variables, workpiece and equipment parameters and the category of quality parameters are an intermediating node category of process state variables, describing the relations shown in figure 4.

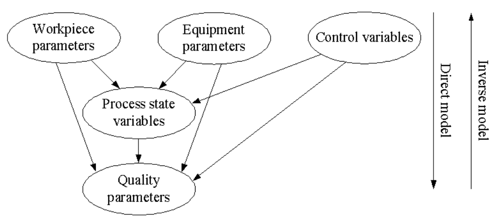

Figure 4: The node categories of variables and parameters in the model.

From the general model in figure 4 the dedicated model for the T-joint in figure 5 is constructed. The process of constructing the model has taken many iterations where knowledge from operators and experts is used together with the analytical knowledge. The edges are defined by operator and expert descriptions of relations together with analytical knowledge.

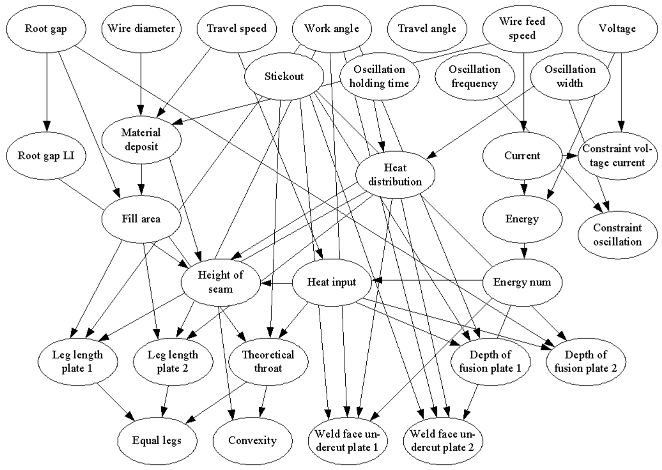

Figure 5: Model dedicated to T-Joint welding.

The nodes in the process-planning model in figure 5 are described in table 3 together with a description of how the node tables are generated. The number of states in each node is for the welding control variables, workpiece, equipment and quality parameter nodes decided by the resolution of the empirical experiment and by the operators and experts knowledge of how big effect a node give on its edges. For the process state variable nodes are the number of states decided so a precise probability of the node is achieved.

*Table 3: Nodes in the model. No sensor variables are used in the model. The methods for table generation are described by a two letter abbreviation and can be found below the table. * States described by an interval.*

Node	Unit	Stat-es	Reso-lution (min-max)	Table genera-tion
Workpiece parameters:				
Root gap	mm	21	0-4	
Equipment parameters:				
Wire diameter	mm	1	1	
Control variables:				
Travel speed	mm/min	11	3-13	
Work angle	degrees	4	-50--35	
Travel angle	degrees	13	-30-30	
Wire feed speed	m/min	6	10-15	
Voltage	volt	20	17-36	
Stickout	mm	8	8-22	
Oscillation holding time	%	6	0-50	
Oscillation frequency	Hz	8	0+0.8-2	
Oscillation width	mm	6	0-1	
Process state variables:				
Root gap LI	mm	9	0-4	RE
Material deposit	mm^2	31*	8-68	EQ
Fill area	mm^2	31	8-68	LS+EM
Heat distribution	mm^2	4*	0-0.2	AP
Current	amp	10	150-240	CE
Energy	J/sec	70*	2050-8950	EQ
Energy num	J/sec	70	2050-8950	CN
Heat input	J/mm	30	50-2950	EQ
Height of seam	mm	17	-0.6-2.6	LS+EM
Constraint voltage current	boolean	2	0-1	CE+RU
Constraint oscillation	boolean	2	0-1	RU
Quality parameters:				
Leg length plate 1	mm	11	2-12	LS+EM
Leg length plate 2	mm	11	2-12	LS+EM
Theoretical throat	mm	4	2-5	LS+EM
Depth of fusion plate 1	mm	9	0-4	LS+EM
Depth of fusion plate 2	mm	9	0-4	LS+EM
Equal legs	grade	4	1-4	RU
Convexity	grade	4	1-4	RU
Weld face undercut plate 1	grade	4	1-4	LS+EM
Weld face undercut plate 2	grade	4	1-4	LS+EM

LS: Least square polynomial approximation
From the empirical data, a least square approximation is made to fit a polynomial curve through the data. The welding operator and expert decide the order of the equation and a verification of the fit is made from the residuals. More fits of the function are often evaluated to find the best fit and the lowest deviation of the residuals. The approximated equations are used to generate a probability table for the nodes. As an example is the fill area fitted by:

$$\text{Fill area} = -3.155 \cdot \text{root gap} + 1.096 \cdot \text{material deposit} + 2.008$$

This equation generates a probability table for the fill area.

EM: EM-learning
The EM-learning algorithm described in [15] trains the Bayesian network from the empirical training data. The algorithm reads the training data file, and for each training set is evidence from the training set modelled into the Bayesian network. The algorithm updates the probability in the actual column in the nodes table for the nodes with training data.

EQ: Analytical equation
From the analytical equation describing the node a probability table is generated.

CE: Constitutive equation
The parameters in the constitutive equation are calculated from empirical data and from the constitutive equation a probability table is generated.

AP: Approximation
The nodes are described by an approximation. As an example, is the heat distribution approximated by the area, which the oscillation motion covers. From calculating all the possible combinations, a probability table is generated.

RE: Reduction
The node has a reduced number of states compared to the number of states of its parent. It is done to reduce the size of the tables in the model to ease computing.

CN: Convert to numbered
The node states are converted to a numbered value when the parent states are an interval.

RU: Rule
Rules from e.g. welding standards [13] are converted to Boolean probabilities for the node table.

Constraint nodes are used in the model and [14] describes the principle. They are inserted in the network as a child to nodes where a relation between them should be expressed. This relation could be a rule or a relation given by an equation or operator and expert knowledge. The constraint node removes all the impossible combinations between the parents nodes. That is for example for the oscillation nodes where there is either oscillation or no oscillation, so the oscillation frequency and width should be either zero or a value.

Operating the model
When using the Bayesian network as an inverse process-planning model evidence based on workpiece, equipment and quality parameters is entered into the model nodes. For the inverse process-planning model the evidence would look like:
e = {Gap = 1.0, Wire diameter = 1.0, Constraint voltage current = 1, Constraint oscillation = 1, Theoretical throat = 3, Depth of fusion plate 1 = 0.5, Depth of fusion plate 2 = 0.5, Equal legs = 4, Convexity = 4, Weld face undercut plate 1 = 4, Weld face undercut plate 2 = 4}
The prediction of the wire feed speed is found and described by probabilities, which can be between 10 and 15 m/min:
P(Wire feed speed | e) = (10 = 16.9%, 11 = 20.6%, 12 = 19.8%, 13 = 19.1%, 14 = 15.5%, 15 = 8.1%)
The highest probability is selected and this state is entered as evidence to the network. This is calculated for all the control variables, and the desired control variables are found and used to control the welding process. The selected order of the control variables for selecting and entering evidence influences the result. This is because every time evidence is entered into a node then the network is updated and this may result in another probability distribution in the rest of the network nodes.

Results

The process-planning model can be used as a direct or an inverse model.

Direct model
The direct model is tested with the 14 experimental testing data sets with the result shown in figure 6. A benchmark with an artificial neural network trained in Clementine [16] with a dynamic training method shows a slightly lower correct prediction, which is shown in figure 7. In figure 6 and figure 7 is correct prediction zero at the x-axis and e.g. -1 is when the prediction is one state too low. E.g. means -1 for the theoretical throat that the Bayesian network model estimated the theoretical throat 1 mm to short.

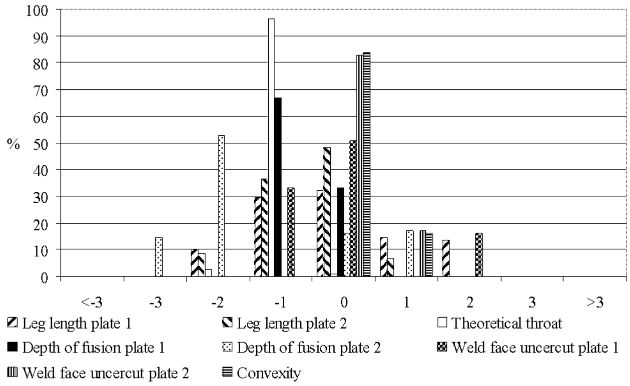

Figure 6:Results for Bayesian network. The average correct prediction is 44% and the average correct prediction +-1 state is 85%.

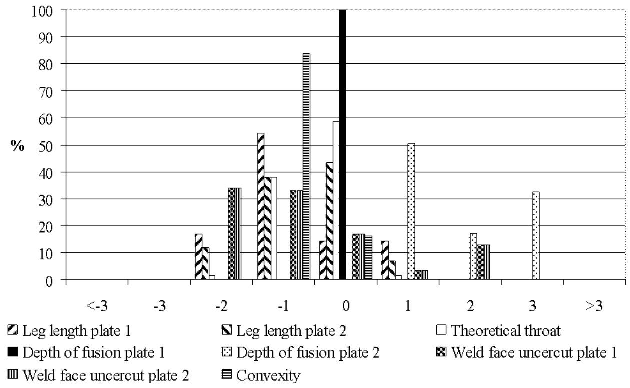

Figure 7: Result for artificial neural network. The average correct prediction is 33% and the average correct prediction +-1 state is 84%

Inverse model
When the process-planning model is used inverse, the model is tested and verified by making a sensitivity analysis and by making experiments. The sensitivity analysis is made for each quality parameter separately where one quality parameter is selected. Evidence is given to each state individually of the quality parameter and the control variables are observed and plotted. The result of the sensitivity analysis for changing the root gap is shown in figure 8.

An experimental verification is made where a part with a root gap changing from 0 to 4 mm is welded using the developed process-planning model. The part is first scanned by a laser scanner, and based on the scanning the root gap is found and the control variables generated. The result of the welding experiment was that the quality parameters convexity and the weld face undercut for plate 1 and 2 were set to a class 4 [13] and that was achieved. The quality parameters leg length plate 1 and 2 were set to 6 mm and it was achieved to lay between 6.5 mm ± 1 mm for the weld seam.

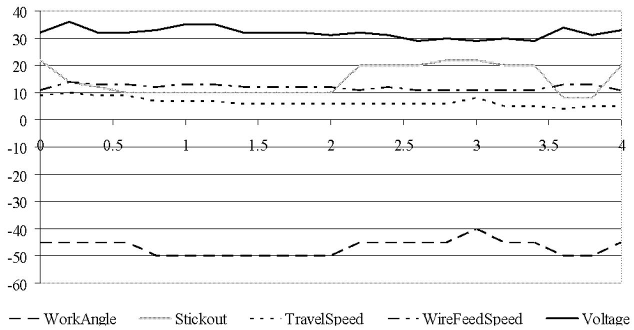

Figure 8: The control variables when changing the root gap from 0 to 4 mm.

Conclusion

It is shown that a process-planning model, which combines different sources of knowledge, can be constructed and gives a satisfactory welding result for a T-joint. The Bayesian network with the graphical and probabilistic representation is a good way to use the different knowledge sources. The network is built so welding operator and experts together with analytical knowledge are the main sources of the casual experience to build the edges of the network. Analytical and empirical knowledge is the main sources of making the probability tables. The model based on Bayesian networks shows in a benchmark with an artificial neural network a slightly better prediction for the Bayesian network. A welding experiment using the Bayesian network process-planning models gives a quality according to the decided quality.
The perspective of using the Bayesian network is that dynamic models can be developed where the effect of changing conditions and changing welding variables can be modelled. The model can be used for both process-planning and process-control where feedback during welding process execution is given as evidence to the model. Future work will be done to figure out how big models are required to different welding tasks and how much of a model can be reused for another welding task.

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References

1. Madsen O., *Sensor based robotic multi-pass welding*, Ph.D. thesis, Department of Production, Aalborg University, Denmark, ISBN 87-89867-02-5 (1992)
2. Holm H., Jeberg P. V. and Bro C., *Applications of numerical model for off-line programming of posture robot welding*, In proceedings of 12th International TWI Computer Technology in Welding and Manufacturing Conference, Paper no. 81, (2002)
3. Jeberg P., Holm H. and Lambaek S., *Planning of Dynamic Trajectories for Weld Process Control Variables by Finite Element Simulation and Iterative Learning*, In proceedings of 7th International Conference on Trends in Welding Research, (2005)
4. Murray P. E., *Selecting parameters for GMAW using dimensional analysis*, Welding Journal, 81(7), pp. 125-131, (2002)
5. Kim I. S., Son J. S., Park C. E., Kim I. J., Kim H. H., *An investigation into an intelligent system for predicting bead geometry in GMA welding process*, Journal of Materials Processing Technology, Vol. 159 Issue. 1, 113-118, ISSN 09240136, (2005)
6. Christensen K. H. and Sørensen T., *A Neural Network Approach for GMA Butt Joint Welding*, Proceedings of 11th International Conference on the Joining of Materials - JOM-11, (2003)
7. Dilthey U. and Heidrich J., *Using AI-methods for parameter scheduling, quality control and weld geometry determination in GMA-welding*, ISIJ International, Vol. 39 Issue. 10, pp. 1067-1074, ISSN 09151559, (1999)
8. Peng P., Tian J., Wu L., Da M., *An intelligent hybrid system of welding parameters for robotic arc welding task-level off-line programming*, Intelligent Systems in Design and Manufacturing III, Proceedings of SPIE Vol. 4192, ISSN 0277-786, (2000)
9. Yanhong W., Xiuzhi Z. and Xitang T., *An expert system for generating welding procedures of boilers and pressure vessels*, Welding in the World, Vol. 34, pp. 381-388, ISSN 0034-2288, (1994)
10. Laurinen P., Junno H., Tuovinen L., Röning J., *Studying the quality of resistance spot welding joints using Bayesian networks*, Proceedings of IASTED International Conference on Artificial Intelligence and Applications, pp. 705-711 Vol. 2, (2004)
11. Yi G., Shin J., Cho H. and Kim K., *Quality-oriented shop floor control system for large-scale manufacturing processes: Functional framework and experimental results*, Journal of Manufacturing Systems, 21(3), pp. 187-199, (2002)
12. Kristiansen M., Madsen O., *Experimental data and operator knowledge used for classifying welding quality*, Proceedings of IASTED International Conference on Artificial Intelligence and Applications, pp. 712-717 Vol. 2, (2004)
13. ISO 5817, *Arc-welded joints in steel – Guidance on quality levels for imperfections*, 1st edition, (1994)
14. Jensen F. V., *Bayesian Networks and Decision Graphs*, Springer-Verlag, ISBN: 0-387-95259-4, (2001)
15. Hugin Help, Hugin Researcher 6.4, www.hugin.com, (2004)
16. Clemmentine® 7.0 User´s Guide. www.spss.com, (2002)

Appendix L

Taxonomy of generic information model

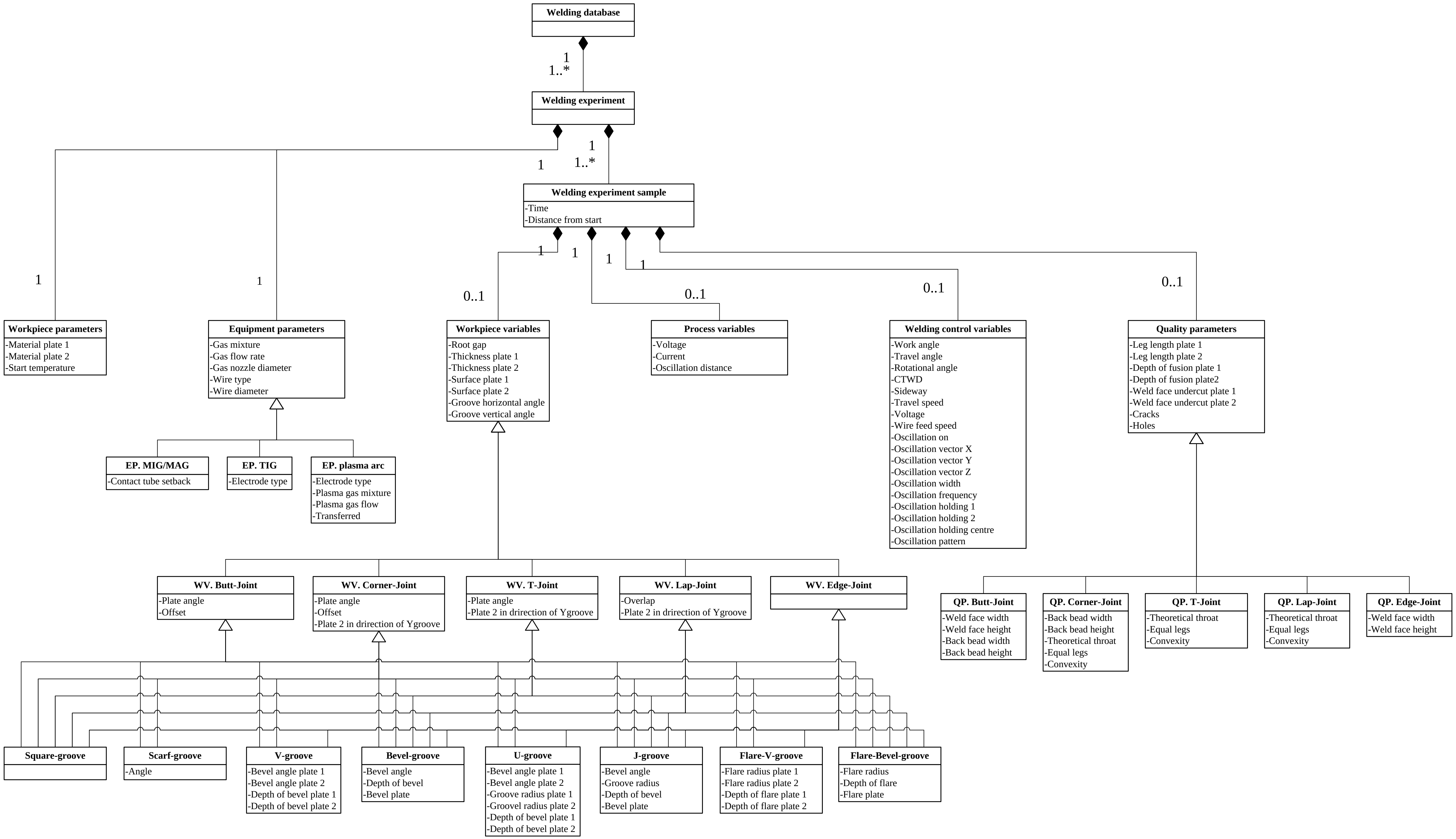

Figure L.1: Taxonomy of the generic information model.

The background for the thesis arises from the fact that process models are required to perform automatic planning and control of the welding process. Reliable quantitative models of the welding process are rarely available, and the lack of process models is a major obstacle for automation of industrial processes. To improve upon this methods from machine learning and knowledge sources about welding are identified and investigated.

This thesis contribution on this problem can be described by the following three areas.

- A generic information model is developed to store dynamical empirical welding data and a system is made to produce the welding data from experiments.

- Techniques are developed to formalise operator knowledge and it is applied as a knowledge source to produce process-planning models.

- A process-planning model based on Bayesian network is produced combining sources of operator, empirical and analytical knowledge and it is showing promising results for future work.

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