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Plant Information Modelling, Using Artificial Intelligence, for Process Hazard and Risk Analysis Study

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgement has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Behrouz Khabbaz Beheshti

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Abstract

Accidents in process plant industry, loss of lives and damages to the environment are all showing the deficiencies of traditional design methods in process plant industry. Numerous research in this area shows human-error, lack of knowledge, late analysis on process safety, and improper usage of process data as some of the major causes in triggering these accidents.

In this research, the application of Information modelling, mathematical modelling, and Artificial intelligence to reduce the risk in different phases, including design, to the operation of process plants, were investigated. First, Semantic web and knowledge engineering was used to create knowledge bases of process engineering diagrams. Then, new query methods were used to study the safety in the design. Second, automation of equipment arrangement design was investigated, using mathematical modelling of process equipment. An algorithm was developed to study and validate all possible design scenarios. Third, an algorithm was developed to develop all possible piping and support design in process plants. Also, machine learning classification algorithm was used to automate the stress analysis activity. Finally, information modelling was used to collect the data from 3D models of process plants. An algorithm was developed to shift the 'field weld locating' activity, from the construction phase to design phase and the benefits were illustrated.

This thesis makes significant contributions to applying Artificial Intelligent-based methods in the automation of design, safety analysis, and data management in process plant industry. The contributions includes the development of machine-readable knowledge bases, mathematical modelling and automation of equipment arrangement and piping design, application of machine learning in stress analysis of piping design, and shifting field-weld joint selection to the design phase. This is the first time that each of these methods have been used in process plant design and they all have been tested on case studies and the results have been analysed and discussed in each chapter.

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Chapter 1 Introduction

1.1 Background of process plant accidents, prevention approaches, and integrating computer and data science

The process industry is considered a hazardous industry for both human lives and the environment. Accidents in process plants occur in different stages of the plant lifecycle: construction, pre-commissioning, commissioning, operation, shutdown, and maintenance.

There are various traditional methods for preventing accidents, depending on the nature of the potential hazards. Process hazard analysis (PHA) is one of the major approaches to accident prevention. A review of catastrophic process plant accidents from the past two decades reveals the importance of applying PHA in the early stages of the project (i.e., basic design).

Studies in this area show that limited time, budget, human resources, and knowledge are some of the obstacles facing a comprehensive analysis in the early stages of design. Because there is a near-zero chance in increasing the available time and budget, new technologies should be sought and integrated to assist in this area.

With new improvements in computer hardware and software systems, artificial intelligence (AI), knowledge engineering (KE), and expert systems (ESs) are developing and emerging in different fields. These new technologies can be used to increase the safety of process plants in the different stages of their lifecycle.

A more recent definition of AI is about creating models to understand the past and predict the future. New core aspects of AI, including machine learning (ML), are introducing smarter ways of creating models, in which the algorithms are not generated by human beings, but by the machine itself. This approach has the capability to replace traditional methods in which predicting the accidents in process plant requires a time-consuming approach and developing algorithms is difficult.

One of the new transitions in technology is from the information/data science field to KE. Although proper use of data and their analysis provides powerful tools, KE is able to create new leverage in different fields and it is not possible to develop them with pure data science approaches. On the contrary, human knowledge, in the form of human language, is required to be used for any machine-based analysis. Ontology-based platforms in KE are the basis for converting human knowledge into machine-readable knowledge. Different software systems in the process plant industry are constantly generating data, which presents the opportunity to use KE in this field, to create knowledge-based systems toward a more advanced PHA.

The powerful reasoning capabilities of KE systems, integrated with the automated programming possibilities of ML, are paving the way toward developing ESs to enrich safety analysis in the basic design phases of a process plant project. These ESs can be useful in preventing accidents in the commissioning, construction, operation, shutdown, and maintenance of process plants, by reviewing the design in the basic stages.

The link between the process plant industry and AI, KE, and finally, ES, is established through the proper use of data, information, and knowledge in this field. Owing to a new set of software systems for different design stages of process plants (e.g., process analysis, plot plan development, detailed design 3D modeling, and mechanical stress analysis), it is now possible to access the required data in the early stages of a new project or to use data from existing projects. Extracting, exporting, saving, and importing the data from the first stages of the project is the key in developing ESs in this industry.

1.2 Motivation for this work

Recent accidents in the process plant industry, the loss of many lives, and irreparable damage to the environment demonstrate the unfortunate failure of human beings and the traditional methods of designing safe process plants for their whole lifecycle. The lessons learnt from these accidents and numerous studies in this area reveal some major causes triggering these accidents; for example, human-error, lack of knowledge, late analysis of process safety, and improper usage of process data. Integrating new technologies in AI with existing design methodologies, especially in the basic design phase, could be a proper approach to dealing with safety concerns in process plant industry.

However, following challenges face the development of this method:

- In order to use AI and KE in the methods of process safety analysis, all the data from the different process analysis platforms should be converted into one similar format. Additionally, human knowledge, in the form of human-natural-language, should be changed into a machine-readable language. The combination of process data and the machine-readable language (i.e., knowledge) should be the input for an analysis platform. This analysis platform will be a knowledge-based ES for PHA.
- With a knowledge-based system for process safety analysis, a parallel query system is required to check different safety aspects in the piping and instrument diagram (P&ID) or process flow diagram (PFD) of the plant in the basic design/conceptual phase of the project. The query language should be able to interpret safety questions in the form of human language, verify the knowledge base, and answer the query in a human-readable format.

- Along with the PFD, the plot plan and equipment arrangement are the most important deliverable documents in the basic phase of the project. They can also have a vital role in reducing the potential for hazard in the lifecycle of the plant. With a limited time in this phase, the equipment arrangement drawing should be developed as the basis for the architecture of the plant. In developing this important drawing, a combination of human knowledge and the project specifications is crucial. Additionally, with the number of equipment and the process plant area, there are thousands of possible equipment arrangement combinations for each plant. This is again the human knowledge and project specifications that filter out the approved combinations. In order to have a parallel safety analysis system, an ES is required to automatically design all the possible options for the equipment arrangement in a 2D environment and verify the human knowledge and specifications simultaneously. Developing such an automated system requires a platform to automatically design each equipment arrangement option. Data from the PFD should be used as a database for this platform. Moreover, safety knowledge and specifications (knowledge-base) should be imported as a part of the platform. Finally, an automated loop is required to read data from the PFD database, design the equipment arrangement, check the design with the knowledge base, and filter out the approved arrangements.
- Because automation in the design of the equipment arrangement and parallel safety checking is proposed here, automation in the other design and analysis stages should be considered to reduce the design time and provide opportunities to perform the PHA on different design options. Piping route design, piping supporting, and mechanical stress analysis are the activities linked to the equipment arrangement. Any change in the equipment arrangement drawing implies that the piping route and piping support should be changed, and the mechanical stress/pipe flexibility should be checked for critical lines (i.e., piping lines with high temperature, pressure, or connected to rotary equipment). Engineering software (e.g., CAESAR II) has been used for stress analysis activities in process plant design for approximately 10 years. This process requires the piping route and piping supports to be modeled in the analysis software after any change in the design of the plant. Achieving the main goal, which is to develop different design options and parallel safety analysis, is in contradiction with the time-consuming nature of this analysis method. Therefore, a better method is required to replace the design–analysis loop and the traditional use of analysis software. Existing databases of analyzed routes provide the opportunity to consider ML approaches to develop a predictive model to solve this issue and to reduce the amount of time required for design-analysis purposes.

- One of the other major potential sources of accidents in the process plant industry is its complex construction process, especially in piping installation. The traditional method involves generating a piping isometric drawing from a 3D model and sending it to the construction office. As in the design stage, there is a constraint time specified for the construction process. A lack of time, resources, software platform, and improper use of data are the reasons for accidents during piping installation and erecting the necessary scaffoldings. The "design for construction safety" concept, which is used in other construction fields, can be used here to prevent accidents. Applying this safety concept requires the schedule to be shifted back to the design phase. In other words, it requires the planning for piping installation to be shifted to the detailed design phase of the project. In order to achieve this, a knowledge-based ES should be integrated into the detailed design platform. Additionally, construction knowledge and safety concerns should be imported to this platform as the knowledge base. This combination should generate piping isometric drawings, which are ready for a safe assembly and scaffolding process.

These challenges pose the following questions:

- What type of machine-readable format is suitable to represent process data?
- How can human knowledge and engineering specifications be converted into a machine-readable format?
- What is the platform to combine process data with human knowledge and engineering specifications to create a knowledge-based system?
- What is the query language to verify the safety of process design?
- How can the data from the P&ID and PFD be used in an automatic generation of the equipment arrangement?
- What is the platform and programming language to automatically generate equipment arrangements?
- How is human knowledge integrated as a part of the programming algorithm to check the equipment arrangement design?
- What is the database (i.e., "training" data) for creating the ML platform and a predictive model?
- How is the piping design and piping support information automatically analyzed in the predictive model?
- How can the "design for construction safety" concept be applied in the process plant industry?

This research was conducted to address these questions.

1.3 Research methodology

The overall goal of this project is to increase safety in the process plant lifecycle by integrating automation tools and AI methods in basic design, hazard analysis, KE, and data gathering. To achieve this goal, the following studies were carried out:

1) Automation in P&ID safety analysis/HAZOP study:
   - Developing a machine-readable source for human knowledge and engineering specification: to be able to use human knowledge and engineering specification in a knowledge-based ES and for the machine to compare the process design with the traditional human-readable knowledge.
   - Developing conversion tools for process engineering data: to make process data readable for the machine in the knowledge base system.
   - Integrating machine-readable knowledge base and process data in an expert system: to combine both data and knowledge in one platform for safety analysis purposes.
   - Developing a query platform for automatic safety analysis: to make enquiries about safety concerns in the design of the PFD or P&ID.
2) Automation of equipment arrangement and piping design:
   - Developing a database from process diagrams: to have the required input data for automatic design platform.
   - Mathematical modeling of each process equipment: to have a mathematical model of each equipment.
   - Mathematical modeling of all possible equipment arrangements: to identify different possible equipment arrangements.
   - Converting human knowledge and project specifications to applicable rules on mathematical models of arrangements: to be able to automatically apply human knowledge and project specifications to different mathematical models of arrangements.
3) Automation of pipe routing and stress analysis:
   - Mathematical modeling of pipe routes: to identify different possibilities of pipe routes between two equipment in the arrangement.
   - Developing a machine-learning-based predictive model for stress analysis: to automatically check the safety and operability of the pipe under high temperature and pressure.

4) Design for safe construction in process plants:
    - Data collection from 3D detail design models: to create a database for construction safety analysis in the design phase.
    - Mathematical modeling of 3D model data: to have a model for applying construction safety rules.
    - Applying construction safety rules to the mathematical model: to reject the models with low safety aspects within them.

The detailed research methodology to target the above objectives is outlined below:

1) Machine-readable human knowledge

This involves the conversion of human-readable knowledge and specifications into a machine-readable format for automation purposes in safety analysis. Human knowledge and engineering specifications have traditionally been stored in a human-readable format. Current research on natural language processing (NLP) and KE is proposing new methods on generating machine-readable knowledge. Creating ontologies for the machine to understand the semantics of this field is the first major step in this phase. An approved knowledge and the latest engineering specifications can be generically generated and used in other projects without the necessity for regeneration. The interoperability of this knowledge base can be set as one of its features by following ISO 15926 chapters.

2) Process design data

The PFD and P&ID are not simply process engineering drawings, they can also be considered as engineering databases, which can be linked to other datasets or used for analysis purposes. This part of the study addresses the automatic generation of databases from these diagrams. It not only creates a database for linkage and analysis but also saves the time for future references and prevents human error in reading and interpretation the diagram, which could lead to disastrous decision-making in different phases of the project.

3) Integrating process data and machine-readable knowledge

Automation of safety analysis with respect to engineering specifications and human knowledge is impossible without combining the machine-readable process data and knowledge base. In this part of study, an ontology-based platform is used for combining these two datasets. This platform is where these datasets are linked and communicate with each other. Because this dataset follows a standard format, interoperability is one of its features and is able to link to other datasets from other projects.

4) Query platform

Safety analysis of process diagrams and data extracted from the knowledge base is possible through using a query language that can read and interpret it. The nature of this query language is essentially similar to traditional database query languages, such as SQL. The difference is in the power of this language in understanding semantics. This query language has been used to compare the process data and knowledge base to identify possible flaws in the design.

5) Mathematical models of process equipment

Automation of equipment arrangement requires a mathematical model of each process equipment. The basic data for this modeling is gathered from the process diagrams. Process equipment models are spatial point-based matrices of each equipment and they include all the required data about each equipment for equipment arrangement purposes. The benefit of converting the process equipment to these mathematical models is that it allows their use in the automation algorithms.

6) Human knowledge, project specification, and automation of equipment arrangement

This stage is about developing automation algorithms for equipment arrangement. Mathematical models of all process equipment and the process layout are the input data for the algorithm. The developed algorithm generates mathematical models of all possible equipment arrangements and the knowledge base, as a part of the algorithm and the resulting code, filters the approved list of equipment arrangement models. The algorithm then converts the approved equipment arrangements from mathematical models into human-readable engineering diagrams for other uses in the lifecycle of the plant.

7) Automation of piping design

Extending the automation capabilities in process plants requires the automation of piping design to be added to the automation of equipment arrangement design. At this stage, an algorithm is developed to design all the possible 3D routes between two points. It generates the number of elbows, and their location in each possible route. It should be considered that it is not possible to filter the “best” pipe routes without pipe supporting and mechanical stress analysis. This algorithm should be combined with another automation platform for stress analysis (especially for critical lines with high pressure and temperature during testing and operation) to be able to generate the best list of possible piping routes.

8) *Automation of stress analysis:*

Stress analysis is another major activity that should follow each equipment arrangement, piping, and support design. This especially is the case for the lines that are under high pressure and temperature during testing or operation. Overlooking this part of the design may lead to catastrophic accidents during the operation or hydro-testing of lines. Because this activity creates a time-consuming loop in the design phase, and it is normally considered an expensive task, this part of the study is dedicated to developing an automatic method of stress analysis. To achieve this, a number of different pipe routes and their stress analysis are used as the training dataset of an ML algorithm and a predictive model is developed to predict the analysis result of any change in the existing routes. For any changes in the equipment arrangement, the route, and the location of pipe supports, the predictive model provides an analysis to determine whether route remodeling is needed. This avoids running the model on the analysis software. Automaton of piping stress analysis is the last step in the automation process, from equipment arrangement to piping design.

9) *Design for safe construction*

Shifting the planning activities from the construction phase to the design phase of the project is one of the recent approaches in reducing casualties in the construction of a process plant. One major time-consuming activity during the construction is planning the field-fit-up welding. At this stage of the study, a mathematical model of piping routes is developed form the 3D model data. An algorithm generates a mathematical model of the required scaffolding for the piping model. Safety criteria are input as a knowledge base to the algorithm. The algorithm then generates all possible field-fit-up weld options and chooses the safest set of field weld points in the design phase.

1.4 Research contributions

This thesis makes significant contributions to applying AI-based methods and cutting-edge technologies in the automation of design, safety analysis, and data management in the process plant industry.

The first contribution is the development of machine-readable knowledge bases for safety analysis in the process industry. This is the first time that such a new field in computer and data science (semantic technology and KE) is used in safety analysis in the chemical engineering field. Combining process data, human knowledge, and engineering specifications in a knowledge-base and developing a query platform to automate/assist in the safety analysis minimizes the required time for safety analysis, minimizes human error, and also provides the opportunity for process engineers to try different sets of process diagrams.

Another contribution is the development of mathematical models of process equipment and algorithms to automatically design equipment arrangements, piping routes, and supporting, and to choose the best models according to the knowledge and engineering specifications integrated with the algorithms. There have been very few attempts to automate the design in this field and there has been no success in developing a comprehensive algorithm that fully integrates human knowledge, best engineering practices, and project specifications in its flow. The type of mathematical models and the number of details therein, as well as the combination of knowledge-base in the flowchart in this study minimize the time required for trying different equipment arrangements and piping designs in the process plant, maximize the time for safety analysis (e.g., hazard and operability (HAZOP) study), and can add other variables (e.g., economic variables) into the list of variables in the design automation process.

The third contribution is the application of an ML algorithm in mechanical stress analysis. Automation of equipment arrangement, piping, and support design without the automation of stress analysis would be a no-value-added attempt in this field. Every design should go through stress analysis (especially for high-pressure/temperature services) before approval for construction or operation. This is the first time that an AI-based automatic stress analysis method with ML is introduced in the process industry. The success of this method, along with the automation of equipment arrangement and piping design will optimize the material use, reduce human error, and increase the time for process safety analysis, which are all highly significant benefits to the process industry.

Another contribution is the shift of a series of activities from the construction to the design phase to increase safety in construction. The traditional method of specifying field-weld points in the process industry includes the usage of piping isometric drawings in the construction phase of the project. A lack of data and usual shortage of time in the construction phase normally lead to human errors and loss of lives during piping assembly, as well as low-quality welding, which may lead to future leaks of dangerous materials during operation. This is the first time that such activity is proposed to be shifted to the detailed design phase of the project. This method benefits from the 3D model data in the detailed design phase, and it can reduce the human error and number of casualties during the construction phase and increase the quality of the piping installation for safe operation in the lifecycle of the plant.

1.5 Outline of the thesis

The structure of the thesis is summarized in Figure 1-1. Each chapter in Chapters 3–6 covers one of the four research contributions. The interactions of the sections are shown by arrows. The thesis is organized into a total of seven chapters.

Chapter 1 provides introductory material and gives the perspective of using AI-based methods in the process industry and motivations of the study. This chapter also discusses the problems and required investigations, and finally highlights the contributions of this thesis.

In ***Chapter 2***, a literature review of the accidents in the lifecycle of process plants, human error, importance of data, automation of design, and new application of AI-based methods in the process plant industry is presented. This chapter also thoroughly covers the gaps in the current state of research on AI in the process plant industry and the plan for further needed research.

The challenges in developing applications with KE and semantic web technology to automate safety analysis in process plants are discussed in ***Chapter 3***. An application has been developed on two different platforms and it is tested on a real case study, which highlights the contribution of this chapter and illustrates the potential for industrial usage of these platforms for automatic safety analysis in the basic phases of the process plant design.

In ***Chapter 4***, an algorithm for the mathematical modeling of process equipment, integration of human knowledge and engineering specifications, and finally, automation of equipment arrangement is discussed. The algorithm is implemented and tested to automatically design a part of a naphtha hydro-treater process plant as a case study. The accuracy of the design and its conformity to the human knowledge and project specifications is discussed; moreover, its possible contribution to the design automation of other larger process plants and its error detection capabilities in existing designs are illustrated.

Developing an algorithm for piping design automation and using ML for the automation of stress analysis is discussed in ***Chapter 5***. The algorithm verifies all the possible routes and piping supports between two points (equipment nozzles) in 3D space and automatically verifies the analysis without any analysis software. In developing this prediction model for stress analysis, a database of piping routes with their analysis results was used along with the gradient boosting algorithm to identify the statistically important features in the stress analysis. Additionally, the possible integration of this method in real industrial scenarios was discussed in this chapter to reduce the required design time and the human error.

Chapter 6 is about developing an algorithm to shift some of the activities in the construction of process plants to the design phase. This algorithm gathers data from 3D information models and provides the best approach for scaffolding and pipe fit-up welding for the construction phase of the project. A case study is used to illustrate the benefits of using this algorithm to increase safety and efficiency in process plant construction.

***Chapter** 7* concludes the research based on the results from each chapter and makes suggestions for future research.

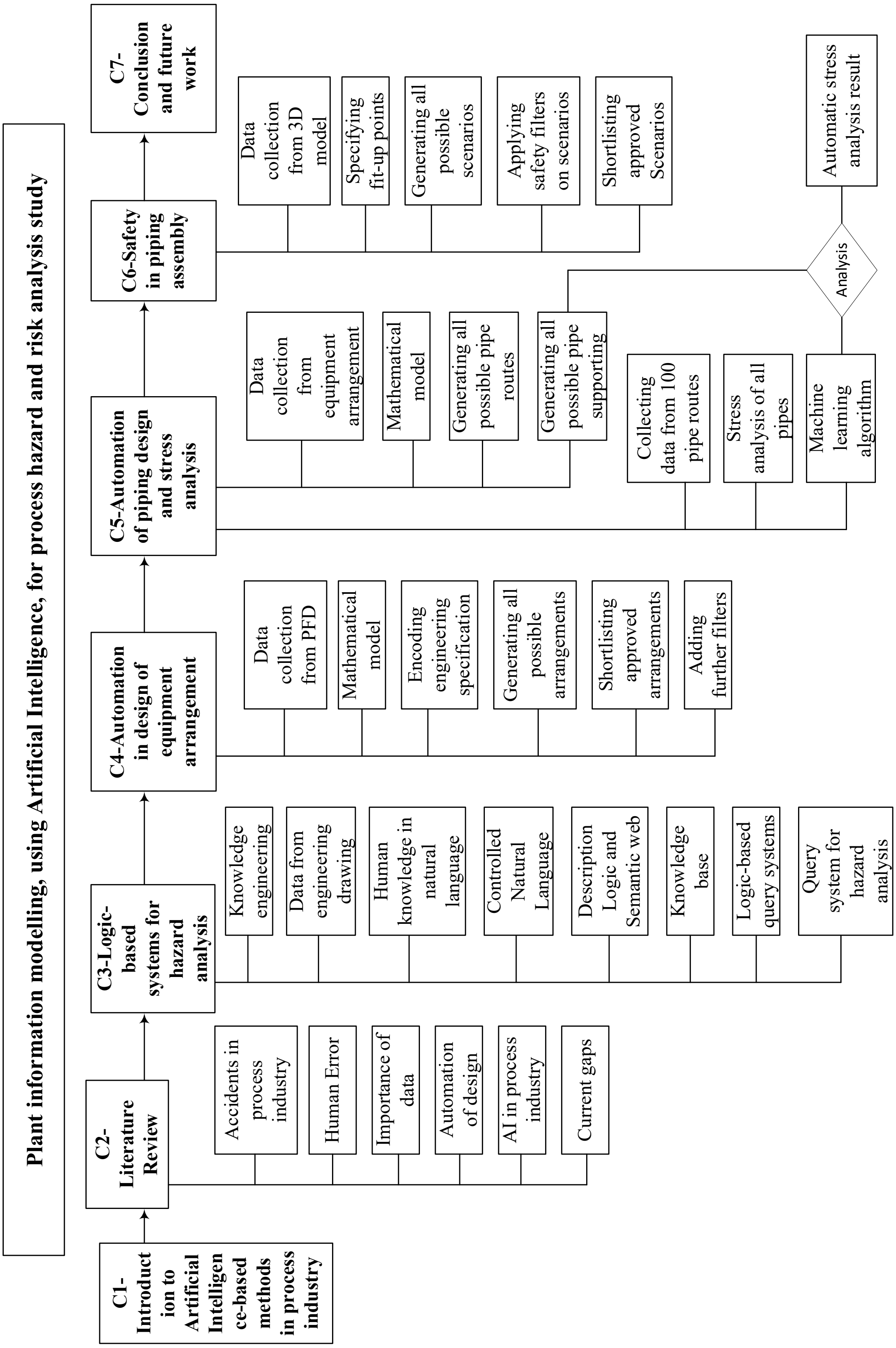


Figure 1-1: Thesis structure

Chapter 2 Literature review

The process plant industry faces catastrophic accidents with irreversible consequences for human beings and the environment. The number of casualties and the cost of damage resulting from incidents in the process plant industry have been significant. Some of examples area follows: the Flixborough incident in 1974 with 450 million dollars lost and 28 deaths, Piper Alpha accident in 1987 with 300 million dollars in damage and 167 deaths, and the BP disaster in 2005 in the US with 1.5 billion dollars in damage, 15 deaths, and 180 people injured.

In this chapter, a literature survey is conducted to review the impact of human error in PHA and in the design of process plants. The importance of equipment arrangement and pipe routing/analysis is also discussed. Subsequently, previous efforts in automating equipment arrangement and pipe routing/analysis are highlighted and the application of AI in the design and safety analysis of process plants is presented.

2.1 Human error and data handling in plant accidents

Human error has been identified as the root cause for many process plant accidents, such as Esso Australia's gas plant and Piper Alpha on the British continental shelf (Murphy, 2009). This factor has been thoroughly discussed by (Skogdalen & Vinnem, 2012) for the oil and gas industry. Human error can be traced as the cause in all these industrial disasters (Lundteigen & Rausand, 2008; Skogdalen & Vinnem, 2011, 2012). Studies on human reliability (Rasmussen, 1997) and human factors (Gould, Ringstad, & van de Merwe, 2012) in such a vulnerable industry are of great value (Skogdalen & Vinnem, 2011). Human error probability and human reliability can be quantified (Kujath, Amyotte, & Khan, 2010) and estimated by referring to operational experiences (Abbassi et al., 2015), dynamic Bayesian networks (Preischl & Hellmich, 2013), and databases (Cai et al., 2013).

Data communication and communication among members of the team are important activities in different parts of the lifecycle of a process plant. It is crucial for the safety of the plant to use the proper means of communication and data transfer in every stage of the project. Many accidents in the process plant industry occur because of a lack of proper communication among teams involved in the design of the plant (Kariuki & Löwe, 2007). A shortage of time for error detection and modification is another factor of process plant accidents (Kletz, 2009). It has also been considered as a major reason for incomplete application of health and safety management in the industry (Williams, 2015).

Data play a major role in every step of decision-making (Berg, Gersinska, & Sievers, 2010). However, inappropriate handling of data during querying, integrating, and interpreting causes human error.

Proper interoperability has a critical role in the competitive environment in which owners of capital facilities try to achieve lower costs in managing their facilities during their lifecycles (Gallaher, O'Connor, Dettbarn, John L, & Gilday, 2004). Different parties typically use different sets of words, terminology, and data formats (Eweje, Turner, & Müller, 2012), which prevents information interoperability. It is important for everyone involved in the information network to use the same "ontology" for the sake of interoperability.

Vendors and manufacturers involved in the design and construction of process plants use their own specific software to produce engineering drawings and documents. These drawings are only human-readable and cannot be considered as a database. It is the responsibility of the end user to read and interpret data from these drawings, reach a reasonable conclusion, and make correct decisions.

Traditional database systems (relational databases in particular) choose different schemas according to their database management system (DBMS). Every time users change the data, the database is updated, but it does not guarantee the change in any other databases, as they do not use the same database schema. It should also be noted that a major change in the data requires the whole schema to be changed. (Chapman, 2005) shows that relational database systems currently face major challenges in an era in which every industry is using big data with dynamic entry and access.

There is always great potential for human error in traditional data capturing (Murphy, 2009). Traditional database systems, especially relational databases, use SQL-based query languages. However, these databases cannot cope with the nature, amount, and variety of data in the process plant industry. Moreover, such databases are not capable of storing human knowledge (in the form of human natural language) for querying and reasoning purposes. The lack of this capability is the reason for their weak reasoning platforms. A good database requires the whole set of knowledge to achieve the best results when queried.

2.2 Process hazard analysis methods in different parts of the process plant lifecycle

(Shariff & Zaini, 2013) have thoroughly reviewed the history of process plant accidents and discussed previous and future studies to reduce/mitigate the incidents in this field.

Depending on the phase of the project, there are different methods in the hazard analysis of a plant. One of the most common methods is PHA, which has various sub methods. HAZOP is a well-known method of PHA that is still widely used in various existing and new process plants, and a thorough literature review has been presented by (Hinze & Teizer, 2011).

Another method of safety checking, especially for the operation of high-temperature/pressure pipes, is using analysis software during the plant design. Common software packages for piping stress analysis in the industry include CAESAR II (by coade), AutoPIPE (by Bentley), and CAEPIPE (by sstusa).

Although methods such as HAZOP (Dunjó, Fthenakis, Vílchez, & Arnaldos, 2010a) and systemic safety management system (SSMS) (Dunjó, Fthenakis, Vílchez, & Arnaldos, 2010b) have been applied or proposed to increase safety in process plants, they are still not able to prevent accidents from occurring (Santos-Reyes & Beard, 2009). Traditional methods consider safety after the completion of the design (Fabiano & Currò, 2012); moreover, PHA lacks rule-based human experience from previous studies and accident analysis information in their databases (Hurme & Rahman, 2005). Market competition is forcing industries to balance the investments in safety with productivity (Suardin, Mannan, & El-Halwagi, 2007). A study has shown it is cheaper to apply safety in the early stages of the design (Houssin & Coulibaly, 2011).

Traditional PHA and HAZOP studies are time-consuming methods (Wang, Gao, & Wang, 2012). The success of hazard analysis depends on the skill of the team members (Dunjó et al., 2010a), and it is prone to failure because of the lack of skill, proper communication, and data (Qureshi, 1988). Other downfalls of HAZOP study were discussed by other researchers (Bullock, Mitchell, & Skelton, 1991). PHA also requires the input of lessons learned from real cases of accidents in the process industry (Jones, 1992).

One of the first attempts at developing a rule-based platform for HAZOP was HAZOPEX (Parmar & Lees, 1987). (Heino, Suokas, & Karvonen, 1988) continued the trend and developed more knowledge-based systems for hazard analysis. (Venkatasubramanian & Preston, 1996) also illustrated a rule-based method for automation in HAZOP. AHA (Kang, Lee, Kang, Suh, & Yoon, 1999; Kang, Yoon, & Suh, 2001) is another automated hazard identification tool, in which three different knowledge bases were developed and used. Using logical statements and cause–effect relations in HAZOP study was introduced in literature (Galluzzo, Bartolozzi, & Rinaudo, 1999). HAZOPExpert (Venkatasubramanian & Vaidhyanathan, 1994) and the following modifications (Srinivasan & Venkatasubramanian, 1996; Vaidhyanathan & Venkatasubramanian, 1995, 1996) were efforts at developing an ES and a support tool for HAZOP study. OptHAZOP (F. I. Khan & Abbasi, 1997a), TOPHAZOP

(F. I. Khan & Abbasi, 1997b), COMHAZOP (F. I. Khan & Abbasi, 1997b), and HAZOPTool (Karvonen, Heino, & Suokas, 1990) are other support systems using knowledge bases in PHA.

(S. Rahman, Khan, Veitch, & Amyotte, 2009) introduced a knowledge-based system to automatically run HAZOP in the process design. (Bragatto, Monti, Giannini, & Ansaldi, 2007) developed a knowledge-based software application in which HAZOP study is integrated with the CAD/PLM systems. Using signed directed graphs (SDG) in computer-aided HAZOP was introduced by (Lü & Wang, 2007). Another example of using data in the P&ID was presented by (S. Rahman et al., 2009). Other attempts include a fuzzy inference system in HAZOP (Guimaraes & Lapa, 2006) and PROCOS (Guimaraes & Lapa, 2006), which analyzed error prevention and recovery in operation. Using ontologies in HAZOP studies were discussed in the literature (Cui, Zhao, & Zhang, 2010; Zhao, Cui, Zhao, Qiu, & Chen, 2009).

2.3 Role of design in the safety of new process plant

Although many accidents have been claimed to be rooted back to the operation (Mahnken, 2001), they can still be traced further back to the design phase of the project. The design phase can be divided into the "basic" and "detailed" phases. Figure 2-1 shows the role of design in a cause–effect diagram.

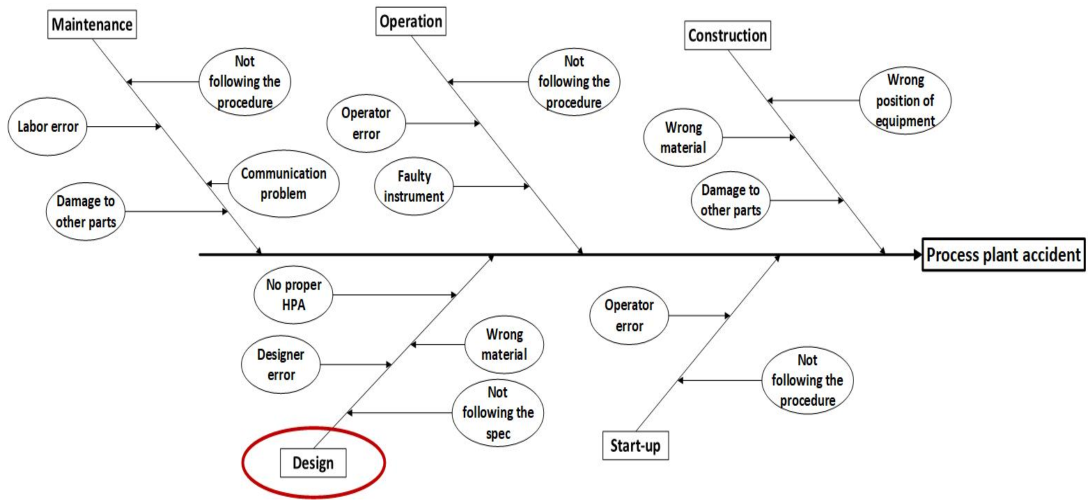


Figure 2-1: Cause-and-effect diagram: role of design in process plant accidents

"Design for safety" or "inherently safe design" is a concept that can be applied to the basic stages of the project to prevent future accidents. Inherent safety is based on the decision-making in the conceptual/basic phase of the project. It is proven to be an economically attractive tool to reduce the risk of accidents in process plants (Chang & Lin, 2006).With the lack of information and with no proper design at this stage, decision-making is difficult (R Rusli, Shariff, & Khan, 2013) The inherent safety and design for safety concepts are responses to major disasters in the process plant industry and are proposed as alternative methods to reduce the complexity of design. This complexity was increased by the number of add-on protection layers (M. Rahman, Heikkilä, & Hurme, 2005). This concept can be used in preventing accidents at different stages of the lifecycle of a process plant. Unfortunately, with the lack of tools and methodologies, inherent safety has not yet been fully applied in the process industry (Schupp, Hale, Pasman, Lemkovitz, & Goossens, 2006).

Studies show the effect of the environment on human performance (F. I. Khan & Amyotte, 2002; Kidam, Sahak, Hassim, Shahlan, & Hurme, 2016; Risza Rusli & Shariff, 2010). Decisions made in process plant construction sites can be affected by its challenging environment and lead to fatal injuries and losses. Figure 2-2 illustrates the roots of accidents during field fit-up weld. One common cause is the project being behind schedule.

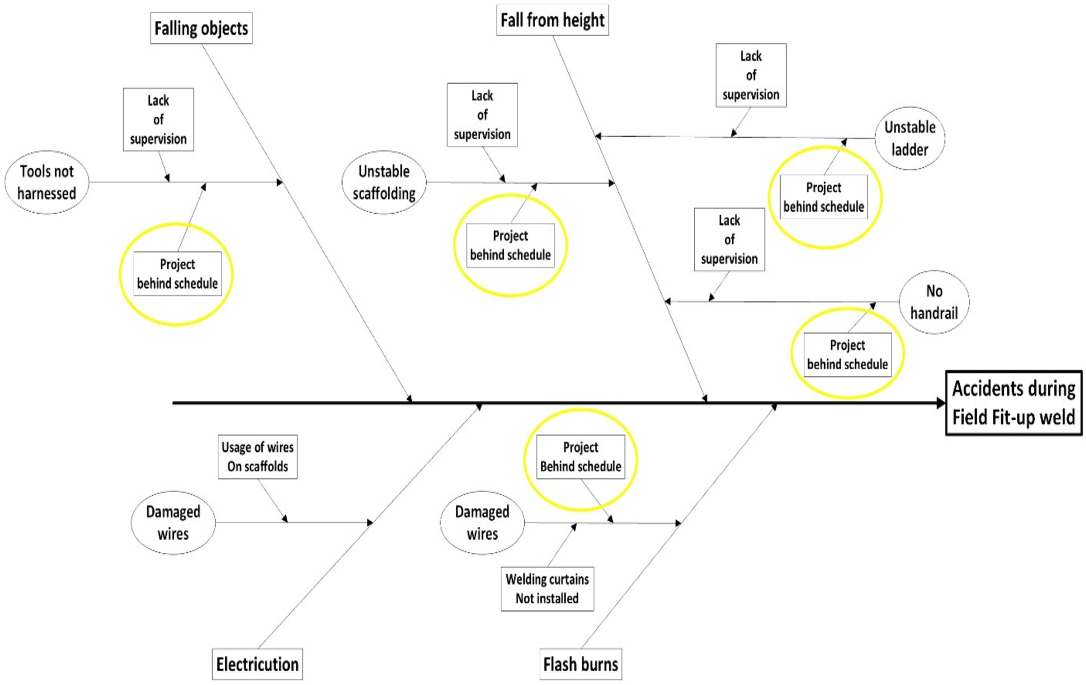


Figure 2-2: Cause-and-effect diagram: accidents during field fit-up welding

Figure 2-3 illustrates the causes/sub-causes of delays in a project. Shifting the activities from the construction to the design phase could be an alternative to eliminate this delay and ultimately increase the safety in the construction during the field fit-up weld.

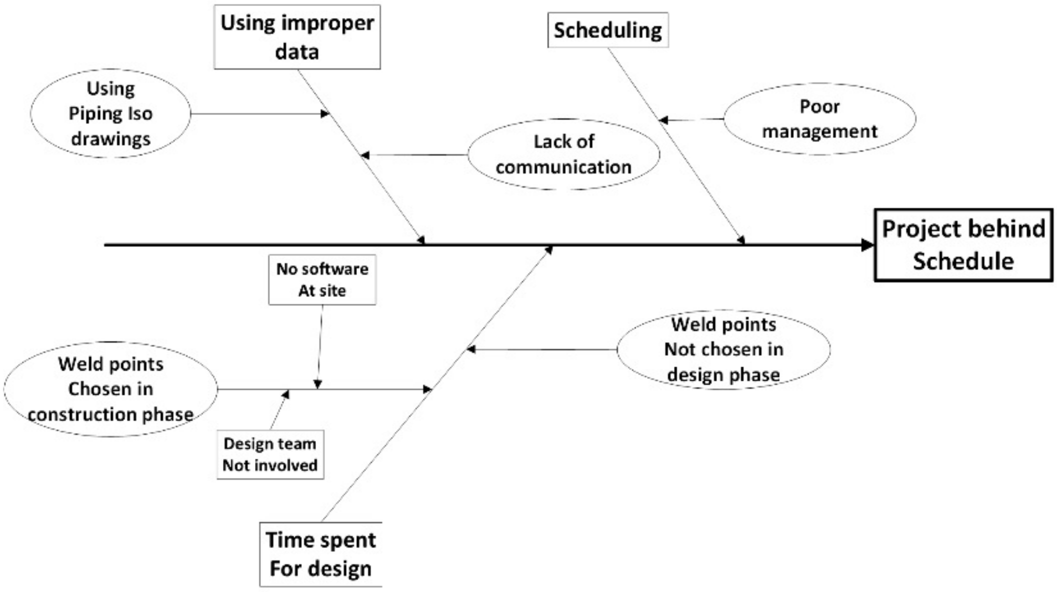


Figure 2-3: Cause-and-effect diagram: project behind schedule

Two major parts of a process plant design are "equipment arrangement" and "piping" design. Both of these play an important role in the safety of the plant. The role of these design stages and drawbacks of traditional design methods are discussed below.

2.3.1 Design of equipment arrangement

A proper equipment arrangement is vital for avoiding domino effects and increasing safety (Darbra, Palacios, & Casal, 2010). It is considered the basis for the detailed equipment arrangement and also leads to other design activities, including civil, structure, piping, electrical, and instrumentation. Studies have shown that proper spacing, equipment arrangement, and following specifications can minimize the number of casualties and the degree of environmental disturbance (D I Patsiatzis, Knight, & Papageorgiou, 2004; Xu & Papageorgiou, 2009). Additionally, (Taylor, 2007) discussed the importance of the economical and safety aspects of layout design and proposed a method of automating this process.

Although equipment arrangement design is an important part of the design and plays a major role in the lifecycle of the plant, traditional project scheduling allocates a very limited time for this document (Guirardello & Swaney, 2005). It is mostly based on experience and lessons learned from previous plant designs (Dimitrios I Patsiatzis & Papageorgiou, 2002) Moreover, there are hundreds of options under which equipment can be arranged in the plant. The traditional methods of equipment arrangement need hundreds of trial-and-error cycles to find the best fit that considers all the project specification requirements and best practices. This is not viable with the typical limitations in time and budget. Efforts to solve this problem through applying computer algorithms have been focusing on object-based method. Because all the meta-data required for a comprehensive list of scenarios cannot be achieved in this way; a point-based method must be developed.

Equipment arrangement study is a part of the famous facility layout problem (FLP) (Singh & Sharma, 2006), which is not limited to the chemical engineering field. Many research efforts have implemented optimization methods on single- and multiple-floor layouts (Ahmadi, Pishvaee, & Jokar, 2017), such as using mathematical optimization (Anjos & Vieira, 2017) to reduce the energy usage (Y. Wu, Wang, & Feng, 2016) or to minimize the sum of distances between facilities (Paes, Pessoa, & Vidal, 2017). In order to ensure safety and minimize costs, (Dimitrios I Patsiatzis & Papageorgiou, 2002) introduced a mathematical model to optimize the plant layout design in the basic stages of the project. A chemical plant layout can be designed to reduce risk (Alves, de Medeiros, & Araújo, 2016; Caputo, Pelagagge, Palumbo, & Salini, 2015). However, there is still lack of safety implementation in this research area (Neghabi & Ghassemi Tari, 2016).

(Eini, Abdolhamidzadeh, Reniers, & Rashtchian, 2015) developed a tool to optimize the integration of inherent safety in the design of a process plant and also combined the cost linked to each method. An object-oriented method in the automation of process models was proposed by (Barth, Strube, Fay, Weber, & Greifeneder, 2009). The importance of the integrating knowledge and incomplete data at the conceptual phase of the project was emphasized by (Burdorf, Kampczyk, Lederhose, & Schmidt-Traub, 2004) and an automatic tool to generate a process model for making necessary decisions at the early stages of the project was therefore developed. Integrating data into a process design simulator was proved to be possible (Shariff & Leong, 2009). Some suggested to considering the design of process plants as a mathematical programming activity (Westerberg, 2004).

2.3.2 Piping design and piping stress analysis

Another major design activity is the piping design. Figure 2-4 shows the traditional workflow in the piping design and stress analysis loop. Piping and piping support failure is one of the root causes for accidents in the process plant industry (Persson, Santos, Tavares, & de Andrade, 2009). Ignoring a comprehensive stress analysis in the design increases the probability of pipes failures and leaks, which could be a risk to human beings (Brown, Seker, Revankar, & Downar, 2012; Kidam & Hurme, 2012; Kidam et al., 2016) and could be a triggering point for domino accidents following the leak of hazardous materials.

To minimize human error, maximize the time for safety analysis, and reduce piping and support material costs, the design team should be provided with the opportunity to test different equipment arrangements, pipe routings, and choose various support locations and types. Considering the time and budget limitations of the project in the design phase, it is not possible to try all the design possibilities. Moreover, every change in the piping design requires the stress analysis for high-pressure or high-temperature lines. The loop of "design change to stress analysis" is not only a bottleneck in the way of creativity and testing new designs but also prone to human error with respect to updating the design, revising the data for analysis, and communication among team members.

The piping cost in a process plant can reach as high as 80% of the equipment cost (Peters, Timmerhaus, West, Timmerhaus, & West, 1968) which shows the necessity of applying new methods to reducing its cost (Akbarnia, Amidpour, & Shadaram, 2009). Automation of pipe route design with automation algorithms can save up to 50% of the total detailed design costs (Park & Storch, 2002). Some of the existing piping automation algorithms are as follows: Maze (Lee, 1961), Escape (Hightower, 1988), Network optimization (Nicholson, 1966), and GA (Ito, 1999). New methods of pipe routing and optimization have been proposed by other researchers (Montalvo et al. 2008; Kang & Lee 2017; Kim et al. 2013; Guirardello& Swaney 2005). What is missing in all these automation and optimization methods is the integration of stress analysis. Although many pipe routes may be cost effective or able to detect obstacles in a fixed environment, there is no guarantee that they pass the stress analysis test. Additionally, it should be noted that the automation of design creates a dynamic environment in which obstacles (i.e., equipment and structures) constantly move in each proposed arrangement.

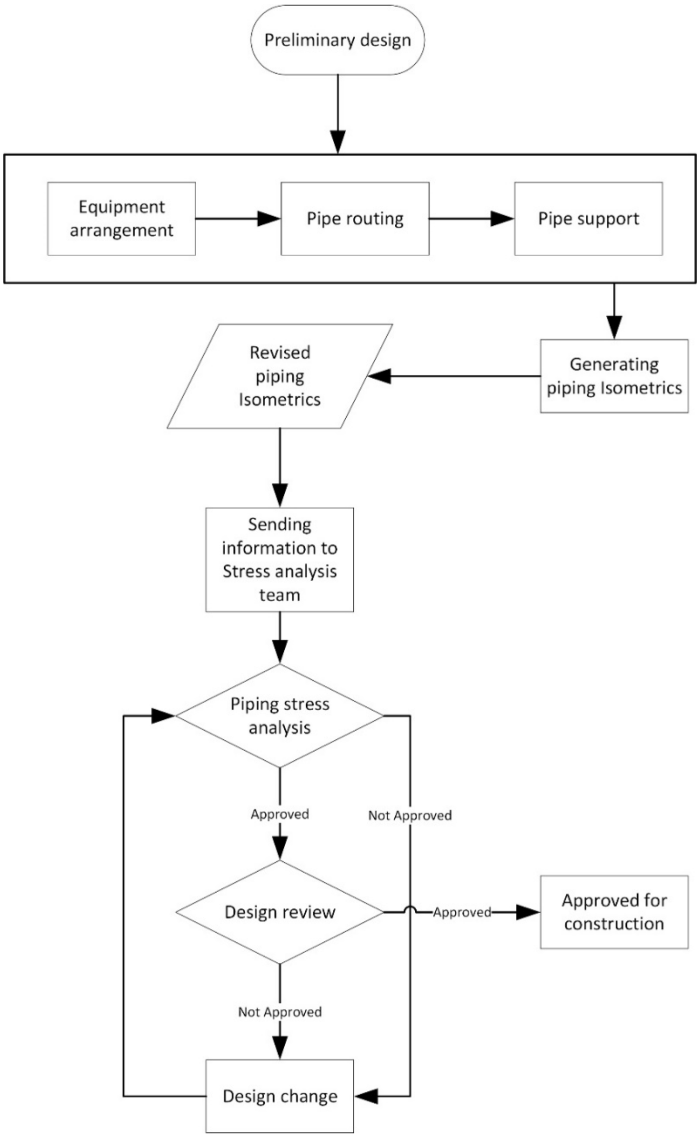


Figure 2-4: Piping design and stress analysis workflow

As illustrated in the flowchart shown in Figure 2-4, piping design requires stress analysis of the piping, especially for critical lines with high temperature and pressure in the testing and operation. Considering the amount of time required for changing the design and the required stress analysis after that, an automation method for stress analysis should be added to the pipe routing automation algorithm.

The automation of this loop removes this burden and helps by providing time for testing new equipment arrangements, piping design and supports, safety analysis, and material cost minimization, without going over budget during the design or falling behind schedule.

Supervised ML algorithms can be used to find structure and correlations in data, which are normally imperceptible to humans, and the patters of which are impossible to simulate through traditional programming in computer science (Ayodele, 2010). The gradient-boosting machine (GBM) algorithm could be helpful for this purpose.

2.3.3 Design for construction safety

Accidents in the process plant industry are not limited to the incidents during operation and maintenance. The construction of process plants claims many lives each year. Table 1 shows the number of construction fatalities from 2003 to 2009.

Table 2-1: Number of fatalities in construction (F. Khan, Rathnayaka, & Ahmed, 2015)

Year	Fatalities
2003	1131
2004	1272
2005	1224
2006	1226
2007	1204
2008	969
2009	607

New technologies are being applied in construction industry to increase safety. Some of these technologies include visualization (Guo, Yu, & Skitmore, 2017), making prediction models (Zhu et al., 2016), using unmanned aerial systems (de Melo, Costa, Álvares, & Irizarry, 2017), and psychological monitoring of workers (Guo, Yu, Xiang, Li, & Zhang, 2017). Even robotics (Lundeen, Kamat, Menassa, & McGee, 2017) are currently being used to increase safety in construction.

A better design can effectively increase the construction safety (Weinstein, Gambatese, & Hecker, 2005). "Design for safety" is a new proposed approach to increase safety in construction (Hongling, Yantao, Weisheng, & Yan, 2016). A study showed that 42% of the reviewed fatality cases were linked to the concept design for construction safety (Behm, 2005). Building information modeling (BIM) models can be highly beneficial in this approach (Malekitabar, Ardeshir, Sebt, & Stouffs, 2016). The aim of this study is to bring a part of construction into design and apply the "design for safety" concept.

2.4 Artificial intelligence in process plant industry

Considering the possibility of human error in making critical decisions, new methods of decision-making should be sought, using the capabilities of computers (i.e., AI) because it has become clear that smarter industry processes require new models of information (Gallagher, Underhill, & Rimmer, 2003). In other words, facing the challenges in the process industry and the consequences of human error (Bou-ghannam, 2013) requires innovative methods

(Sheridan, 2008) and innovation in every industry requires a new look at knowledge management (Noroozi, Khakzad, Khan, MacKinnon, & Abbassi, 2013).

Although ML has been seen for years as merely a subset of AI, the truth is that ML is the core of AI (Du Plessis, 2007). The use of ML algorithms has gained momentum in different industries to increase productivity, quality, prediction capabilities, as well as reduce cost, and more. For example, reducing the cost of testing and personnel supervision by using ML methods has been thoroughly discussed in (Plasek, 2016). Integrating ML tools in industry is another challenge, which is the topic of much discussion (Shadravan, Tarrahi, & Amani, 2015).

Ontology is a knowledge representation for a specific domain. It can list the most important concepts and instances, describes the relation between objects, and is currently causing revolution on the World Wide Web (Rana, Staron, Hansson, Nilsson, & Meding, 2014). In order to create a machine-readable format of an ontology, it is written in Web ontology language (OWL). (C. Wu, Xu, Zhang, & Na, 2013) showed an example of using ontologies in HAZOP studies and (Mohammadfam, Kalatpour, Golmohammadi, & Khotanlou, 2013) have illustrated the usage of ontologies and knowledge bases in process equipment failures. As discussed by (Verhagen, Bermell-Garcia, van Dijk, & Curran, 2012), it is important to use ontologies to deal with interoperability issues in industry. OntoCAPE (Morbach, Yang, & Marquardt, 2007) is one of the ontologies developed in the process engineering field.

OWL is a W3C standard language to represent ontologies in semantic technology and is an AI tool. OWL integrates two areas of data science and AI. Some branches of OWL (including OWL DL) are based on description logic, which itself is rooted from first-order logic. As defined by W3C, OWL is Web ontology language and ontology is a term that describes the entities in a specific domain and the relation between these entities. OWL includes classes, properties, and instances to respectively define the entities in the domain, their relations, and individuals. OWL DL is the most expressive sublanguage of OWL and is directly related to description logic, which makes it easy to create a machine-readable format of human knowledge in any specific domain and is used in this study as the language for knowledge representation in process engineering. It is worth mentioning that ISO 15926 is a standard being developed for data modeling of information in the process plant industry ("OWL - Semantic Web Standards," 2012). One example for the data modeling of engineering drawings, by using ISO 15926, has been presented by (Leal, 2005).

2.5 Summary

The complexity of design and safety analysis results in human error and catastrophic accidents in the lifecycle of plants. Although specifications suggest a thorough guideline for PHA, the competitive market is pushing for the design of these plants to be ready in a short time. Publications do not suggest a completely automated method in the design of important parts such as equipment arrangement, pipe routing, and piping stress analysis. Traditional design and safety analysis methods fail to simultaneously provide a complete set of drawings for safe operation and construction in the basic phases of the project. Additionally, with the rise of AI, publications still do not suggest a practical method of integrating it into the design and safety analysis of process plants. In this study, systematic research has been conducted to develop practical uses of information modeling, KE, ML, and design automation, for safety analysis as well as the development of equipment arrangement, pipe routing, and piping stress analysis.

Chapter 3 Logic-based knowledge representation for hazard identification in process plants

Hazard identification in the process industry is one of the activities that relies on the integration of human knowledge and data from engineering documents. One of the main factors resulting in human error and improper hazard identification is the nature of data and data management, including issues regarding interoperability, data formats, database schema, query systems, and the lack a system integrating human knowledge into the current databases. In this chapter, to develop a smarter dataset, a machine-readable format of human knowledge and logical inferences from the knowledge base for hazard identification is proposed. This knowledge base includes machine-readable formats of engineering drawings and human knowledge and is a base for a knowledge-based ES for hazard identification. This method was applied to two case studies and the results are discussed. Finally, other benefits of using the knowledge base and future usages of this method in the process plant industry are discussed.

3.1 Introduction

Traditional hazard identification in the basic design of process plants requires many brainstorming sessions for experts in the field to discuss the basic engineering documents and identify the hazards according to their experiences, engineering specifications of the project, and the lessons learnt from previous incidents in the industry. The methodology is based on logical inferences based on general knowledge for an individual plant.

The success of hazard analysis depends on the skill of the team members (Dunjó et al., 2010a) and it is prone to failure because of a lack of skill, human error, and lack of knowledge (Qureshi, 1988). Human error has been identified as the root cause for many process plant accidents, including Esso Australia’s gas plant and Piper Alpha on the British continental shelf (Murphy, 2009). A shortage of time for error detection and modification is also considered one of the other reasons for process plant accidents (Kletz, 2009).

With new improvements in computer hardware and software systems, AI, KE, and ES are developing and emerging in different fields. These new technologies can be used in increasing the safety of process plants in their different lifecycle stages. The link between the process plant industry and AI, KE, and finally, ES, is established through the proper use of data, information, and knowledge in this field.

The proposed ES uses a machine-readable combination of engineering drawings, engineering specifications, and human knowledge, to automatically detect hazards in P&IDs. Figure 3-1 shows its simplified algorithm.

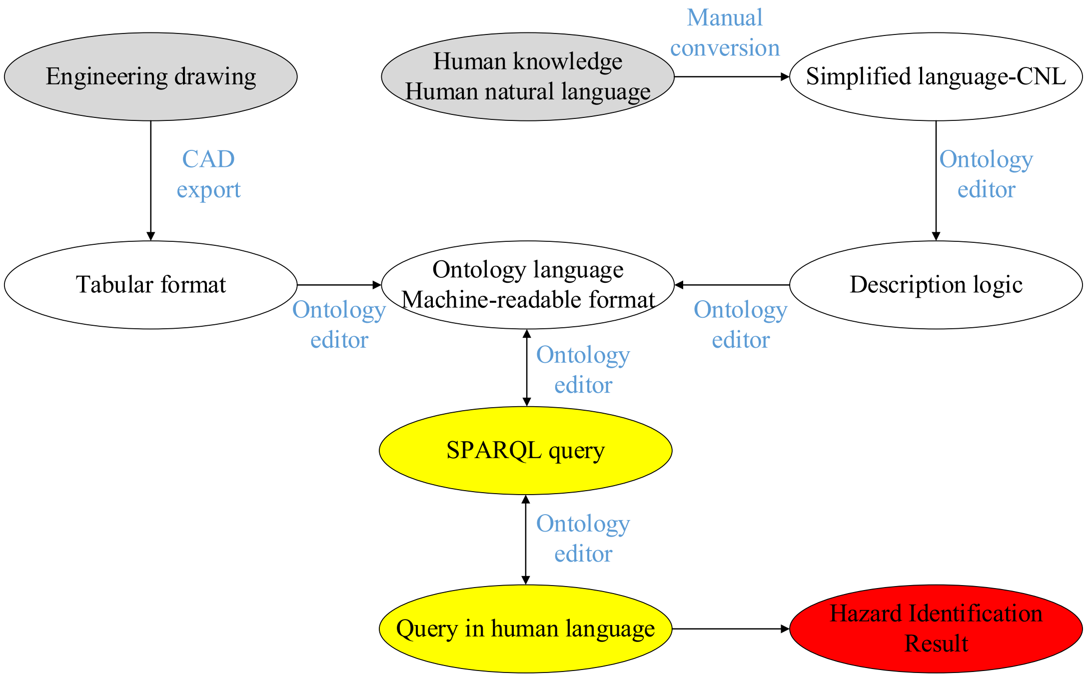


Figure 3-1: Expert System for hazard identification

The P&ID plays a major role in the process plant industry. It is developed from the PFD into a diagram that is used from the basic design, into the detailed design, and then during procurement, construction, testing, pre-commissioning, commissioning and operation. P&ID documents are generally developed by the process engineering team by using process analysis software (e.g., Aspen Hysys). Figure 3-2 shows an example of this diagram.

All sources of data, including P&ID documents, have their own format. The process engineering department normally uses specific software to analyze the process from the PFD and provides the information required for the design of the plant. This information includes the pipe size, material, pressure, and temperature. The design and drafting department produces P&ID engineering drawings using computer aided design (CAD) software. P&ID drawings normally show the flow and the relation between equipment in a human-readable format. At present, certain software development companies offer “smart” P&ID documents, which are data-enriched. Engineering drawings are not only human-readable but also require an expert to follow a specific pattern in reading the data, integrating them with human knowledge and providing reasoning.

In order to create a machine-readable format of a P&ID, three layers of information should be considered: engineering symbols, human interpretation of a P&ID, and individual data in each P&ID. In other words, in order for the machine to "understand" a P&ID drawing, all these layers should be converted into a unique knowledge base.

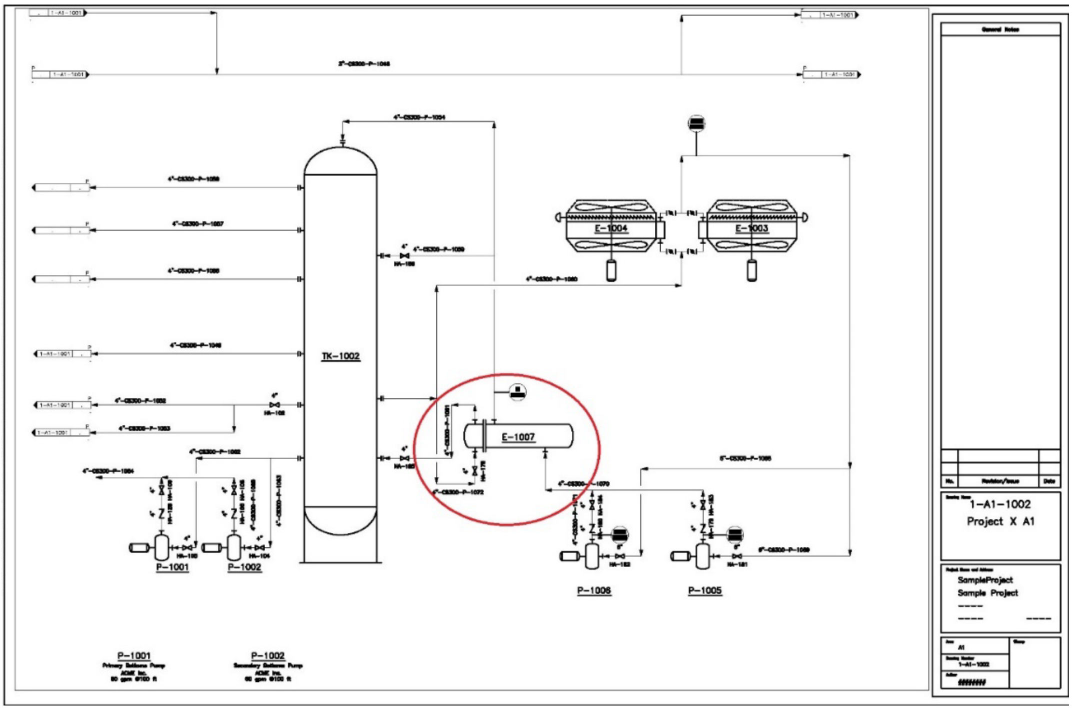


Figure 3-2: Sample P&ID ("Autodesk AutoCAD Plant 3D" 2014)

Recent computer-aided drawing (CAD) software packages, which are used in process engineering as well as other industries, are able to include data through adding attributes to each part of the drawings. These data can be extracted in a comma separated format (.CSV), which is a tabular format for basic databases. Moreover, there are other databases in each process plant project in tabular format. Examples of these databases include line lists, equipment lists, and valve lists.

3.2 Creating machine-readable formats of P&IDs

In computer and information science, an ontology is defined as a set of representational basics to model a domain of knowledge (Gruber, Ontology, & Özsu, 2009). Ontology languages (e.g., OWL and RDF/XML) are used to develop ontologies in different domains. An ontology can be used as a knowledge base in process engineering and may include extracted data from engineering drawings. Ontology editors such as Protégé and Fluent Editor are used to develop the ontologies in each domain. There are certain existing ontologies in the process engineering and oil/gas industries, but for the purpose of adding more data from other sources (which are described in other sections), a new ontology is developed here.

The first part of the ontology development is using the schema in the extracted tabular data from engineering drawings. Ontology languages following a "triple" concept (subject-predicate-object). Because the tabular data are convertible to triples, it is possible to create an ontology from all the extracted data from P&ID drawings. Figure 3-3 shows an example of the conversion from tabular to triple format.

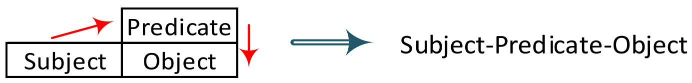


Figure 3-3: Tabular to triple conversion

A proper ontology requires a better list of "predicates" to be provided. For interoperability reasons, the chosen predicates can be based on ISO 15926 and POSC Caesar (Topping, 2011). Figure 3-4 shows the conversion of column headers into proper predicates to be used in the ontology editor and its usage in converting tabular format to proper triple format. Figure 3-5 shows the ontology developed for the equipment E-1s, discussed above, in the Protégé ontology editor.

Schema column	Ontology editor
Equipment tag	hasEquipmentTag
Pressure	hasDesignPressure
Pressure unit	hasDesignPressureUnit
Material	hasMaterialOfConstruction

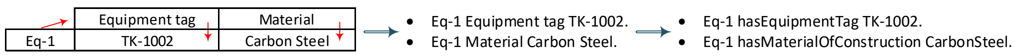


Figure 3-4: Conversion of header titles to proper ontology predicates

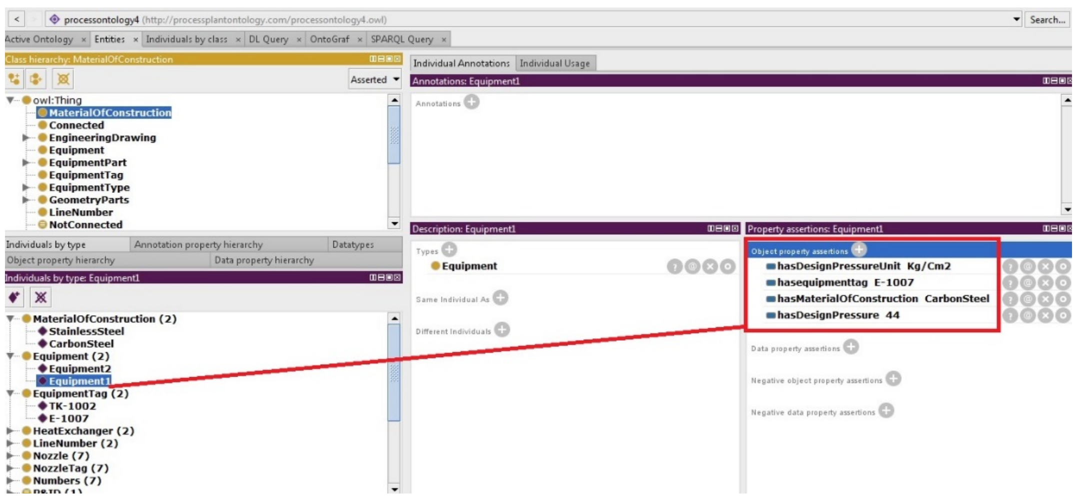
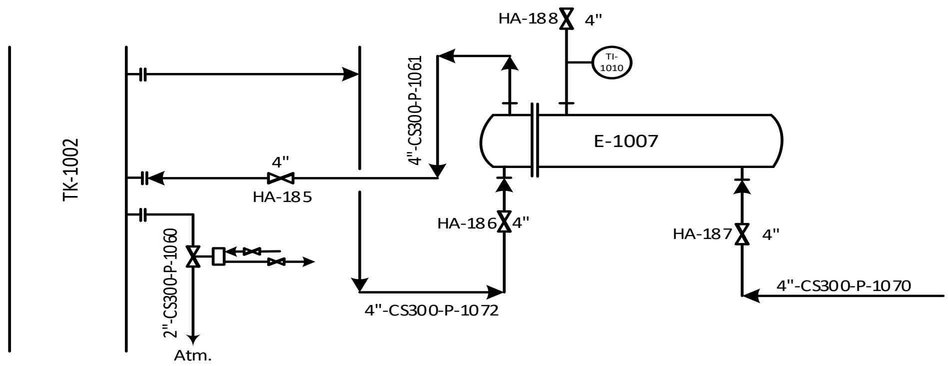


Figure 3-5: Ontology development in Protégé

Figure 3-6 shows a part of the P&ID, extracted data into related tabular data, and the graphical representation of a part of the ontology.



Equipment List

Eq. number	Eq. ID	Type	P&ID No.	Number of nozzles
Eq-1	E-1007	Heat exchanger	P&ID-100	4
Eq-2	TK-1002	Tank	P&ID-100	6

Line List

Line No.	Line ID	From	To	Des. Temp.	Des. Pressure	P&ID No.
Spool-1	4-CS300-P-1061	E-1007	TK-1002	120	10	P&ID-100
Spool-2	4-CS300-P-1072	TK-1002	E-1007	70	10	P&ID-100
Spool-3	2-CS300-P-1060	TK-1002	Atm.	70	10	P&ID-100

Valve List

Valve No.	Valve TAG No.	Type	Size (inch)	Line No.	Material
Valve-1	HA-185	Gate valve	4	4-CS300-P-1061	CS
Valve-2	HA-186	Gate Valve	4	4-CS300-P-1072	CS
Valve-3	HA-187	Gate Valve	4	4-CS300-P-1070	CS

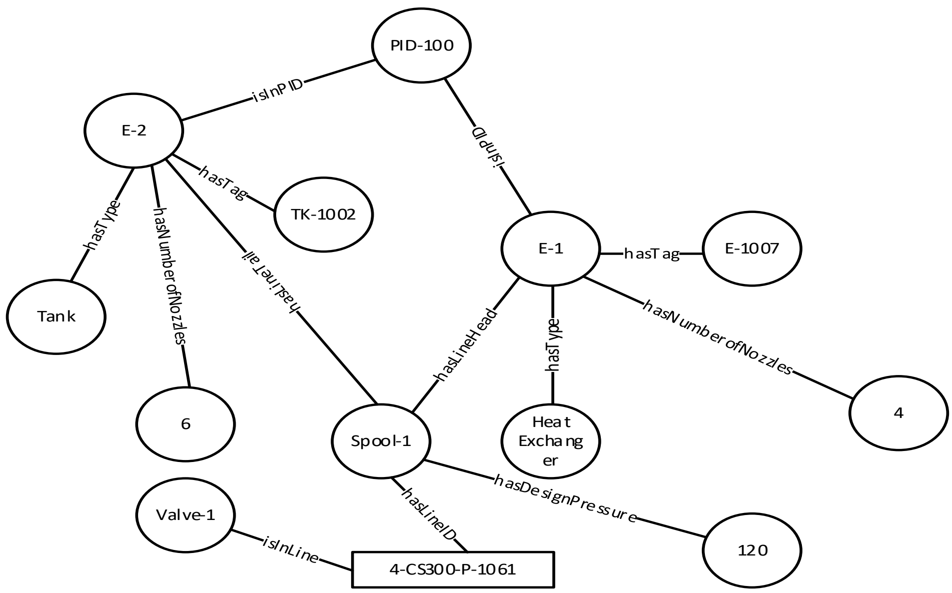


Figure 3-6: P&ID, extracted data tabular data, and the ontology diagram

In addition to developing the ontological knowledge base from P&ID drawings, human knowledge, which is used in interpreting P&ID drawings, can be a part of this knowledge base. Integrating these two gives the machine the capability to interpret the data, which is conceptually converting this knowledge base into an interpreting system, and not solely another platform for storing data.

Human knowledge for the interpretation of P&IDs is developed in an ontology editor by using "classes" and "predicates/properties." For example, "Equipment" can be a class and has the property of "hasEquipmentTag." "hasEquipmentTag" is defined as an "Asymmetric," "Functional," and "non reflexive" property between "Equipment" and "EquipmentTag" in order to set the concept in the ontology that an equipment should have an equipment tag, and each equipment has one, and only one tag. Figure 3-7 shows this concept in Protégé.

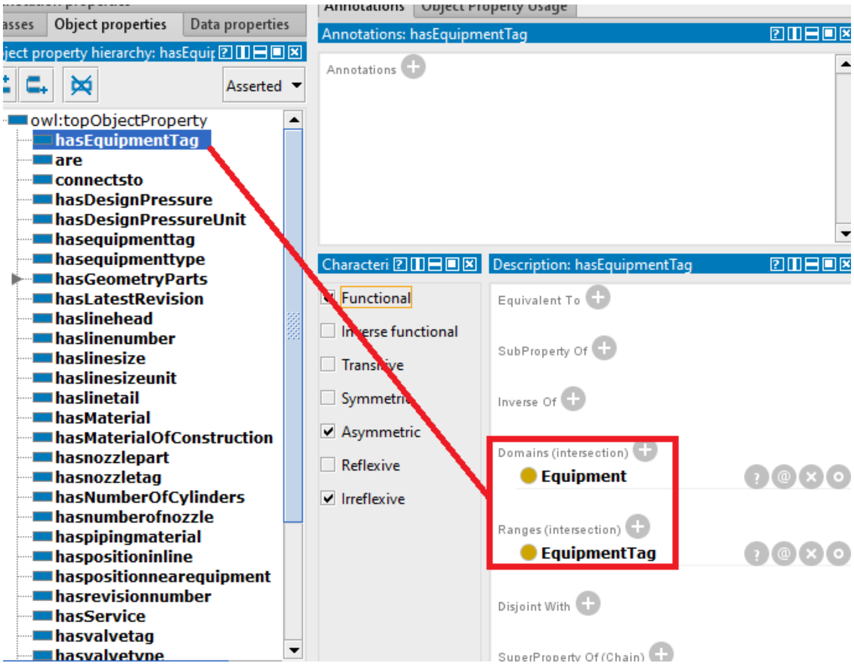


Figure 3-7: Setting rules for the properties

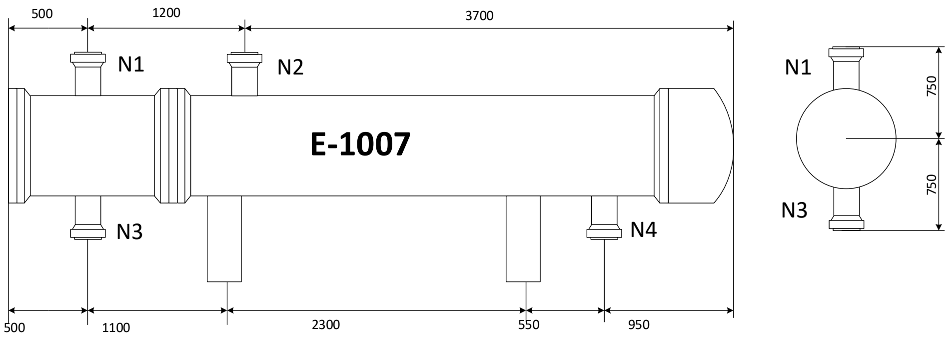
More human knowledge, in natural language format, can be added to the ontology. Below is a list of some examples that can be integrated into the ontology.

- P&ID is an engineering drawing, including at least one equipment and one piping spool.
- Shell and Tube Heat-Exchanger is a heat-exchanger type of equipment.
- Heat-Exchanger is an equipment type.
- Every nozzle is an equipment-part.
- Nozzle can only be a part of an equipment.
- "connect-to" is a symmetric relation.
- A valve can only be in one piping spool. When a pipe "includes" a valve, it means the valve "is in" the pipe.

3.3 Developing the knowledge base-inclusion of other drawings

In order to have a reliable database, all the new data should be integrated into the existing knowledge base. The knowledge base will be a platform to add other types of data from other sources. In the case of process plants, different forms of data are developed, depending on the phase of the project. In the detailed design phase, for example, mechanical datasheets are drawings that are normally developed in other departments than process engineering. Integrating the data from these drawings extends the capabilities of query and reasoning from the knowledge base, by linking the data from two sources. Such an integration will be helpful in applying model-based definition (MDB) (Kaufmann & Bernstein, 2010) in process plants.

Therefore, the next step is to integrate information from the mechanical datasheet and the tabular data (shown in Figure 3-8) into the knowledge base. Classes such as “NumberOfNozzles” and relations such as “hasNumberOfNozzles” have been developed to cover the knowledge representation required for an “individual” such as “Equipment-1.”



Nozzle ID	Size(DN)	Pressure(lb)	Dist-Base	Dist-Centre	Orientation
N1	100	150	500	750	Up
N2	100	150	1700	750	Up
N3	100	150	500	750	Down
N4	100	150	4450	750	Down

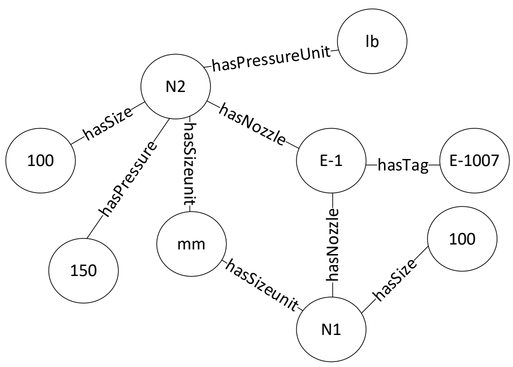


Figure 3-8: Sample mechanical datasheet, extracted data, and ontology graph

Because two machine-readable knowledge bases are available from the P&ID and mechanical datasheet, it is now possible to combine them into one knowledge base. Figure 3-9 below shows the linked graph data that illustrate the developed knowledge base and the classes and relations by combining the P&ID and mechanical datasheet. It shows how different sources of data and information are now linked together in one unique knowledge base.

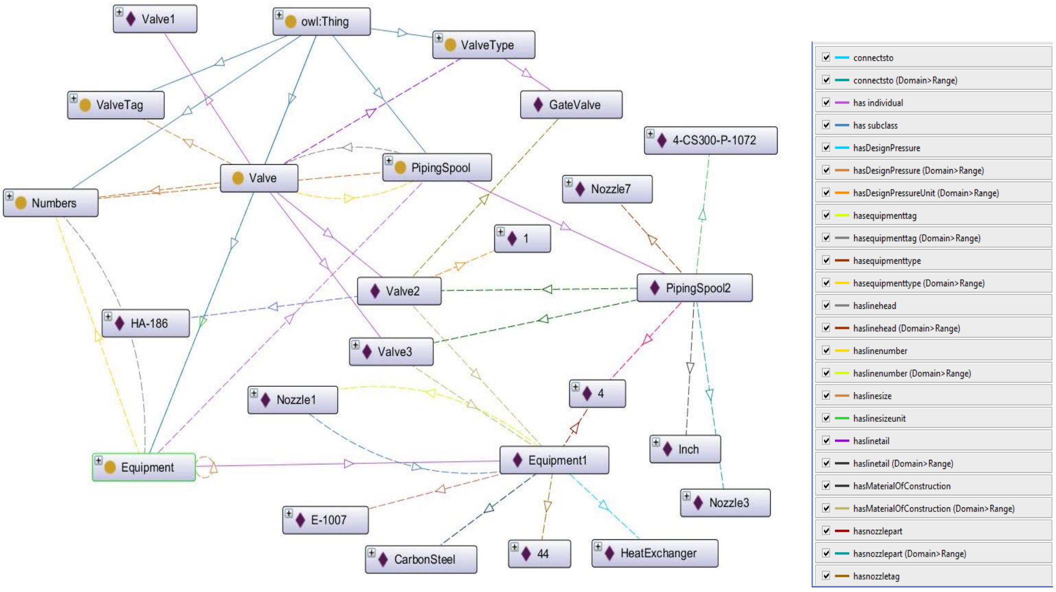


Figure 3-9: Linked data graph

3.4 Developing the knowledge base-Integrating of human knowledge

The final step in creating a complete knowledge base for hazard identification is integrating human knowledge into this knowledge base. In order to achieve that, this knowledge should be converted into the ontology format. This conversion requires a brief introduction to DL and OWL.

DLs are a family of logic-based languages for knowledge representation in different domains (Baader, Horrocks, & Sattler, 2008). DLs have reasoning capability and OWL is based on DL languages (Horrocks, Patel-Schneider, & Van Harmelen, 2003). Simplified sentences in human natural language can be illustrated in DL; Table 3-1 below shows some examples.

Table 3-1: Natural language to description logic

Natural language	DL format
Gate-valve is a type of valve.	gate−valve valve
Ethylene is considered a highly-flammable hydrocarbon.	{_Ethylene} highly−flammable−hydrocarbon
Kpa is one of the units for pressure.	{_Kpa} pressure−unit

It is clear that manual conversion of human language into DL would not be possible, especially in the case that a huge number of sentences should be converted to DL. One possible approach is a combination of controlled natural language (CNL) grammar and an ontology editor that can support it. Figure 3-10 shows the process:

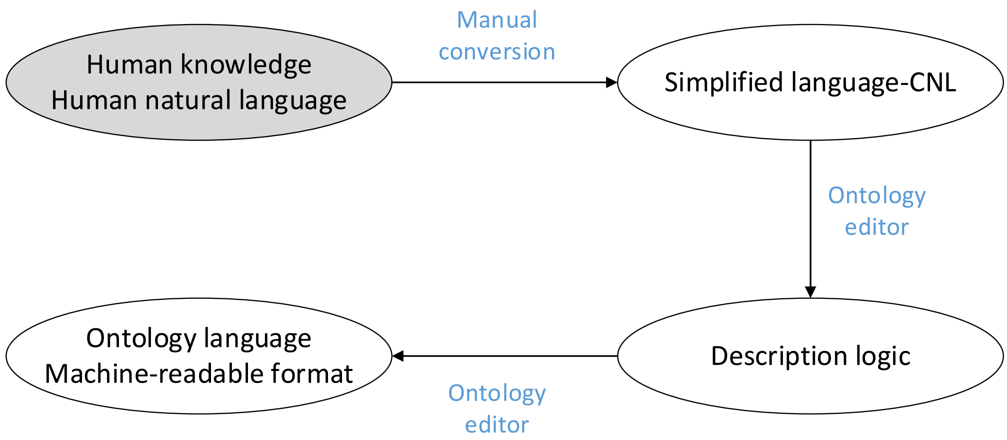


Figure 3-10: Machine-readable knowledge base from human natural language

Although CNL is still a fuzzy term and there is no precise definition for it, it can be defined as a restrictive version of natural language and it has been used in different environments and disciplines (Kuhn, 2014). One of the examples is Attempto controlled English (Fuchs, Schwertel, & Schwitter, 1998). Another example is Ontorion Controlled Natural Language (OCNL), which is designed to be compatible with OWL (Seganti, Kapłański, & Zarzycki, 2015). Table 3-2 shows some examples.

Table 3-2: OCNL and DL conversions of natural language

Natural language		OCNL format		DL format
Gate-valve is a type of valve.	↔	every gate-valve is a valve.	↔	gate−valve valve
Ethylene is considered a highly-flammable hydrocarbon.	↔	Ethylene is a highly-flammable-hydrocarbon.	↔	{_Ethylene} highly−flammable −hydrocarbon
Kpa is one of the units for pressure.	↔	Kpa is a pressure-unit.	↔	{_Kpa} pressure−unit

Semantic Web (SW) is considered the next generation of the Web and ontology languages such as RDF and OWL are used as its language (Lucanu, Li, & Dong, 2006). OWL was developed by the World Wide Web Consortium (W3C) to overcome the limited expressiveness of RDF Schema (Antoniou & Van Harmelen, 2004). Because OWL is based on DL (Yang, Dong, & Miao, 2008), all the simplified sentences above will be converted to OWL. Table 3-3 shows the ontology (OWL/XML encoded) version of DL formats.

Table 3-3: OWL format from OCNL and DL formats

OCNL format		DL format		Ontology format(OWL/XML)
every gate-valve is a valve.	↔	⊑ gate−valve valve	↔	<SubClassOf xmlns="http://www.w3.org/2002/07/owl#"> <Class IRI="GateValve" /> <Class IRI="Valve" />
Ethylene is a highly-flammable-hydrocarbon.	↔	⊑ {_Ethylene} highly−flammable−hydrocarbon	↔	<ClassAssertion xmlns="http://www.w3.org/2002/07/owl#"> <Class IRI="HighlyFlammableHydrocarbon" /> <NamedIndividual IRI="Ethylene" />
Kpa is a pressure-unit.	↔	⊑ {_Kpa} pressure−unit	↔	<ClassAssertion xmlns="http://www.w3.org/2002/07/owl#"> <Class IRI="PressureUnit" /><NamedIndividual IRI="Kpa" <NamedIndividual IRI="Kpa" /></ClassAssertion>

Both data from engineering drawings and human knowledge are in a unique format, because both have been encoded into ontology/OWL format. These two knowledge bases can now be combined to form a unique knowledge base, which is illustrated in Figure 3-11.

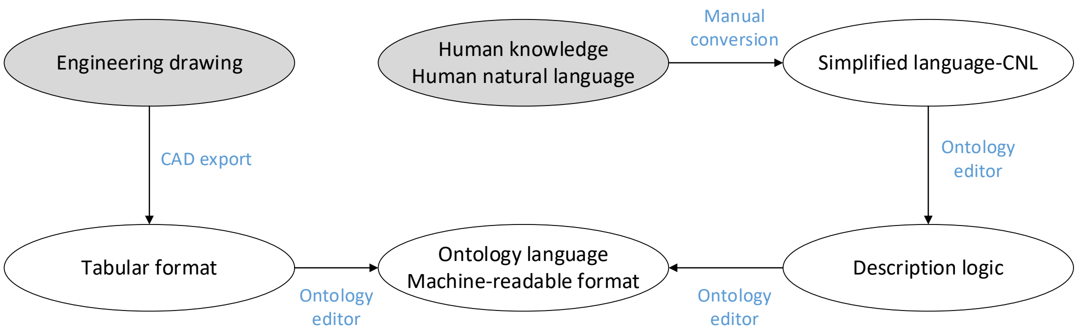


Figure 3-11: Combination of knowledge bases

Another part of human knowledge is the conditional relations. A conditional relation in logic is expressed as pair of propositions, where one of the propositions is expressed to be true if the other is true. This part is more sophisticated than triple-made sentences. Some examples of conditional relations in the process industry are presented here:

If a valve is a part of a line, then the same fluid passes through the line and the valve.

If a valve is open, then it is not closed.

Although these expressions seem simple, they are essential parts of a knowledge base for accurate logical inferences.

Part of the engineering knowledge and project specifications can be introduced to the knowledge base through these conditional relations. Here is an example:

If a tank is open and the tank does not have high-level control, then it may overflow. If the tank overflows, then humans are exposed to the material in the tank. If the material in the tank is hazardous material, then the site is not safe.

In the SW, these conditional relations are defined as Semantic Web Rule Language (SWRL). Adding this part of the human knowledge is essential to create a knowledge base for accurate inferencing. As with other parts of the human knowledge, it is possible to convert the OCNL format of SWRL into DL and use them as part of the ontology/knowledge base. Table 3-4 shows an example in which two engineering expressions are converted into the OCNL and DL format. As discussed, the DL format can be integrated as a part of the knowledge base, in OWL language.

Table 3-4: SWRL from natural language to DL format

Natural language format	OCNL format	DL format
When a pipe is connected to a nozzle, which ia a part of an equipment, then the pipe is connected to the equipment. →	If a process-pipe(1) is-connected-to a nozzle(1) and the nozzle(1) belongs-to an equipment(1) then the process-pipe(1) is-connected-to the equipment(1). →	⌂○process−pipe(?process−pipe−1) ○nozzle(?nozzle−1) be−connected−to(?process−pipe−1,?nozzle−1) ○nozzle(?nozzle−1) ○equipment(?equipment−1) belong−to(?nozzle−1,?equipment−1)→be−connected−to(?process−pipe−1,?equipment−1)
A vertical tank with pressre more than 1000 Kpa is considerred a high-pressure tank. →	if a vertical-tank(1) has-operating-pressure an operating-pressure(1) and the operating-pressure(1) has-value greater-than 1000 and the operating-pressure(1) has-pressure-unit Kpa then the vertical-tank(1) is a high-pressure-tank. →	⌂○vertical−tank(?vertical−tank−1) ○operating−pressure(?operating−pressure−1) have−operating−pressure(?vertical−tank−1,?operating−pressure−1) ○operating−pressure(?operating−pressure−1) °have−value(?operating−pressure−1,?:value−tmp−1) °>1000(?:value−tmp−1) ○operating−pressure(?operating−pressure−1) have−pressure−unit(?operating−pressure−1,_Kpa)→○high−pressure−tank(?vertical−tank−1)

3.5 NO-SQL inferencing

It is now possible to make a query from this knowledge base. Because this knowledge base is based on DL, a logical inference can be a part of the query. The query language for this OWL-based knowledge base is SPARQL, which is a No-SQL query language and is the W3C-recommended query language for SW. Figure 3-12 shows where the query can be made from the knowledge base.

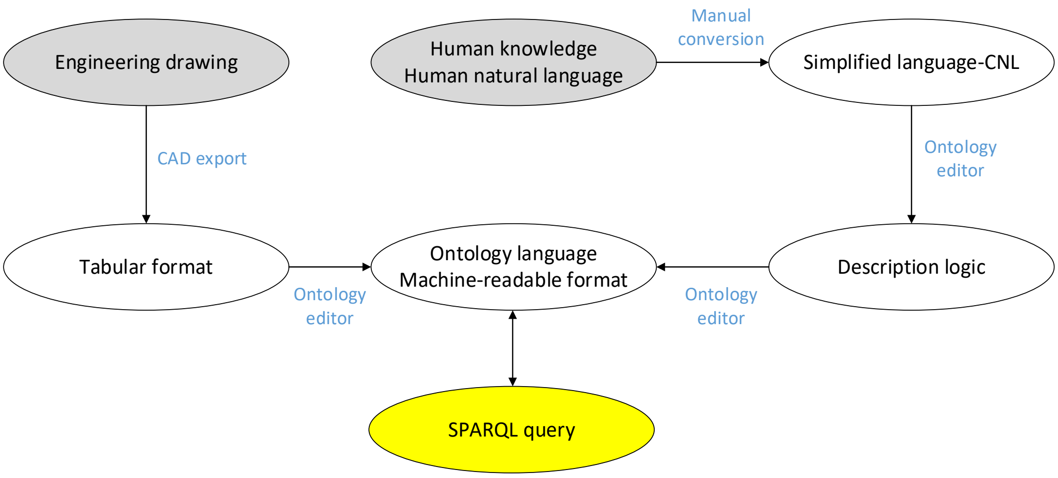


Figure 3-12: SPARQL query from knowledge base

Table 3-5 shows two examples:

Table 3-5: Query in natural language and SPARQL

Query(Natural language)	**SPARQL format**
Equipment tag of Equipment1	PREFIX pro: <http://processplantontology.com/processontology20.owl#> SELECT ?EquipmentTag WHERE { pro:Equipment1 pro:hasequipmenttag ?EquipmentTag.}

list of equipment tags which the equipment material is carbon steel	PREFIX pro: <http://processplantontology.com/processontology20.owl#>
	SELECT ?EquipmentTag
	WHERE
	{
	?Equipment pro:hasMaterialOfConstruction ?CarbonSteel.
	?Equipment pro:hasequipmenttag ?EquipmentTag.
	}

It is also possible to use CNL to convert simplified queries, in human natural language, into SPARQL format queries. The CNL grammar is used in this case is again OCNL, which was used for the content of the knowledge base. FE ontology editor can convert the OCNL format of the query into SPARQL, as illustrated in Table 3-6.

Table 3-6: Query from natural language to SPARQL, using OCNL

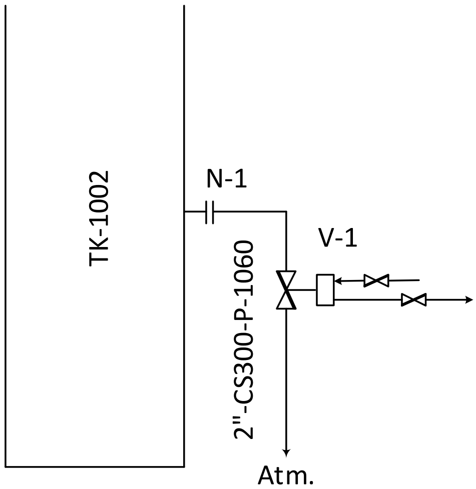
Query(Natural language)	**OCNL format**	**SPARQL format**

list of equipment tags which the equipment material is carbon steel.	Who-Or-What has-material-of-construction Carbon-Steel?	PREFIX pro: <http://processplantontology.com/processontology20.owl#>
		SELECT ?EquipmentTag
		WHERE
		{
		?Equipment pro:hasMaterialOfConstruction ?CarbonSteel.
		?Equipment pro:hasequipmenttag ?EquipmentTag.
		}

3.6 Case studies

3.6.1 Phillips disaster

Figure 3-13 shows a part of a P&ID in which a two-inch line is connected to a high-pressure tank (TK-1002) at its head and connected to the atmosphere at its tail. A logic-based knowledge representation is used to identify hazard(s) in the process design. First, an ontology is extracted from this part of the P&ID. In the next step, the engineering specification, in the form of human knowledge is presented in DL and OCNL formats. Finally, a combination of these two knowledge bases is used for a SPARQL/OCNL query about the safety of the design.



Valve	hasType	isInLine	hasMaterial	hasManufacturer
V-1	SingleBlockValve	PipingSpool 1	…	…

Piping	hasID	hasHead	hasTail	hasMaterial
PipingSpool 1	2-CS300-P-1060	Nozzle 1	Atmosphere	…

Nozzle	hasTag	isInEquipment	hasMaterial	hasSize
Nozzle-1	N-1	Equipment-1	…	…

Equipment	hasTag	hasPressure	hasMaterial	isinPID
Equipment-1	TK-1002	1200	…	P&ID-100

Figure 3-13: P&ID100 for case study 1: Line connected to high-pressure tank

The ontology editor is used to convert these tables into a part of the knowledge base. A part of this encoding is shown in Table 3-7 in two formats: OCNL and DL.

Table 3-7: Triples converted to DL format

Triple-OCNL format	**DL**
V-1 has-type Single-Block-Valve.	{_V−1} (have−type).({_Single−Block−Valve})
Piping-Spool-1 has-valve V-1.	{_Piping−Spool−1} (have−valve).({_V−1})
Piping-Spool-1 has-line-number "2-CS300-P-1060".	{_Piping−Spool−1} (have−line−number).("2−CS300−P−1060")

A graphical ontology is shown in Figure 3-14 below:

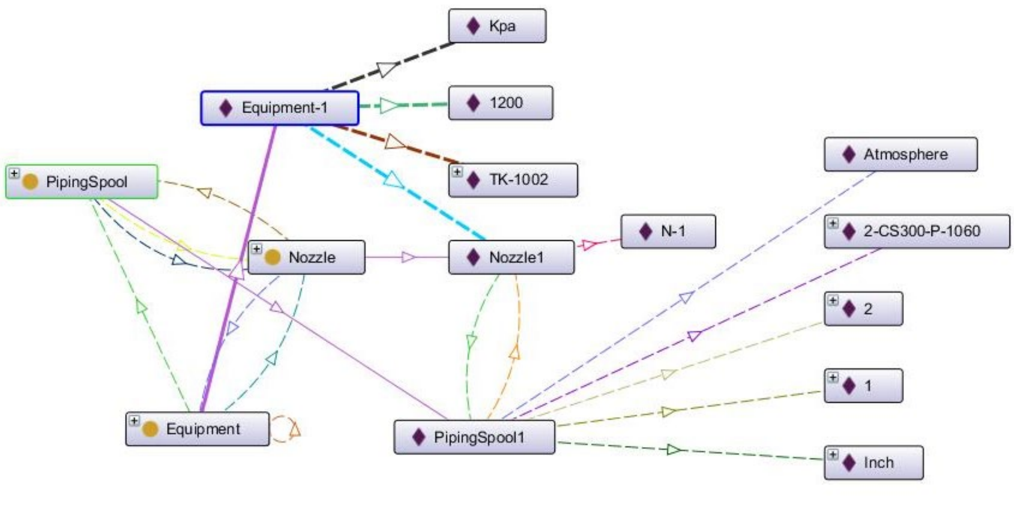


Figure 3-14: Graphical representation of the P&ID Ontology

There is also general engineering knowledge that should be added to the knowledge base for accurate reasoning (shown in Table 3-8). This part of the knowledge base is not limited to any specific project and can be applied to any P&ID:

Table 3-8: Encoding general knowledge-from OCNL to DL

OCNL format	**DL**
Every single-block-valve is a valve.	single−block−valve valve
If a process-pipe(1) is-connected-to a nozzle(1) and the nozzle(1) belongs-to an equipment(1) then the process-pipe(1) is-connected-to the equipment(1).	⌂○process−pipe(?process−pipe−1) ○nozzle(?nozzle−1) be−connected−to(?process−pipe−1,?nozzle−1) ○nozzle(?nozzle−1) ○equipment(?equipment−1) belong−to(?nozzle−1,?equipment−1)→be−connected−to(?process−pipe−1,?equipment−1)
Open is a valve-status. Close is a valve-status.	{_Open} valve−status {_Close} valve−status

Another layer that should be added here is the engineering specification, originally in the form of human natural language, into OCNL, and then DL format. The sentence below is the natural language format of the engineering specification.

"If a vertical tank's operating pressure is above 1000 kPa, a connected pipe to this tank which leads to atmosphere on the other side MUST have a double block valve."

Table 3-9 below shows the conversion into the OCNL and DL format.

Table 3-9: From SWRL in natural language to DL format

Knowledge Natural language	**SWRL-OCNL format**	**DL**
"If a vertical tank's operating pressure is above 1000 Kpa, a connected pipe to this tank which leads to atmosphere on the other side MUST have a double block valve."	if a vertical-tank(1) has-operating-pressure an operating-pressure(1) and the operating-pressure(1) has-value greater-than 1000 and the operating-pressure(1) has-pressure-unit Kpa then the vertical-tank(1) is a high-pressure-tank.	⌂○vertical–tank(?vertical–tank–1) ○operating–pressure(?operating–pressure–1) have–operating–pressure(?vertical–tank–1,?operating–pressure–1) ○operating–pressure(?operating–pressure–1) °have–value(?operating–pressure–1,?:value–tmp–1) °>1000(?:value–tmp–1) ○operating–pressure(?operating–pressure–1) have–pressure–unit(?operating–pressure–1,_Kpa)→○high–pressure–tank(?vertical–tank–1)
	If a process-pipe(1) has-line-tail Atmosphere and the process-pipe(1) is-connected-to a vertical-tank(1) and the vertical-tank(1) is a high-pressure-tank then the process-pipe(1) must-have Double-Block-Valve.	⌂○process–pipe(?process–pipe–1) have–line–tail(?process–pipe–1,_Atmosphere) ○process–pipe(?process–pipe–1) ○vertical–tank(?vertical–tank–1) be–connected–to(?process–pipe–1,?vertical–tank–1) ○vertical–tank(?vertical–tank–1) ○high–pressure–tank(?vertical–tank–1)→must–have(?process–pipe–1,_Double–Block–Valve)
	If a process-pipe(1) is-in-drawing a piping-and-instrument-diagram-drawing(1) and the process-pipe(1) has-line-tail Atmosphere and the process-pipe(1) is-connected-to a vertical-tank(1) and the vertical-tank(1) is a high-pressure-tank and the process-pipe(1) does-not-have Double-Block-Valve then the piping-and-instrument-diagram-drawing(1) has-design-status Unsafe and Recommendation-1 have-status Applicable.	⌂○process–pipe(?process–pipe–1) ○piping–and–instrument–diagram–drawing(?piping–and–instrument–diagram–drawing–1) be–in–drawing(?process–pipe–1,?piping–and–instrument–diagram–drawing–1) ○process–pipe(?process–pipe–1) have–line–tail(?process–pipe–1,_Atmosphere) ○process–pipe(?process–pipe–1) ○vertical–tank(?vertical–tank–1) be–connected–to(?process–pipe–1,?vertical–tank–1) ○vertical–tank(?vertical–tank–1) ○high–pressure–tank(?vertical–tank–1) ○process–pipe(?process–pipe–1) doe–not–have(?process–pipe–1,_Double–Block–Valve)→have–design–status(?piping–and–instrument–diagram–drawing–1,_Unsafe)
	Recommendation-1 has-content Line-Connected-To-High-Pressure-Tank-And-Atomosphere-Must-Have-A-Double-Block-Valve.	{_Recommendation–1} (have–content).({_Line–Connected–To–High–Pressure–Tank–And–Atomosphere–Must–Have–A–Double–Block–Valve})

The SPARQL query for hazard identification is the reasoner that refers to the knowledge base, which is the DL combination of information from the P&ID and human knowledge. It is the reasoning engine/reasoner that can ultimately help with hazard identification. As discussed, the SPARQL query can be asked with the OCNL format. Table 3-10 below shows the question to check the safety of design in the P&ID above.

Table 3-10: Query about P&ID safety

Query Natural language	Query-OCNL format	Query result
Is P&ID design safe?	Who-Or-What has-design-status Unsafe?	P&ID-100

At this stage, the reasoner identifies the P&ID as "Unsafe," but it cannot help the designer to modify the design. In order to add this ability, a "Recommendation" part has been added to the knowledge base. For example, in this case, because the root cause of the "Unsafe" status is the lack of a double block valve, a recommendation is initially added to the original human knowledge. Table 3-11 shows the complete query result.

Table 3-11: Query result: Line connected to high-pressure tank

Query Natural language	Query-OCNL format	Query result
Is P&ID design unsafe? And if unsafe, what is recommended?	Who-Or-What has-design-status Unsafe?	P&ID-100
	Who-Or-What is a recommendation that has-status Applicable?	Recommendation-1 has-content Line-Connected-To-High-Pressure-Tank-And-Atomosphere-Must-Have-A-Double-Block-Valve.

This way, the knowledge base not only helps with hazard identification but also provides a recommendation to the process designer to modify it. In this case, the response to the query includes the recommendation: "*Line-Connected-To-High-Pressure-Tank-And-Atomosphere-Must-Have-A-Double-Block-Valve.*"

A revised P&ID, shown in Figure 3-15, considers two block valves for the line. This time, the reasoner approves the P&ID and identifies it as "Safe," because a double-block valve has been used instead of a single-block valve.

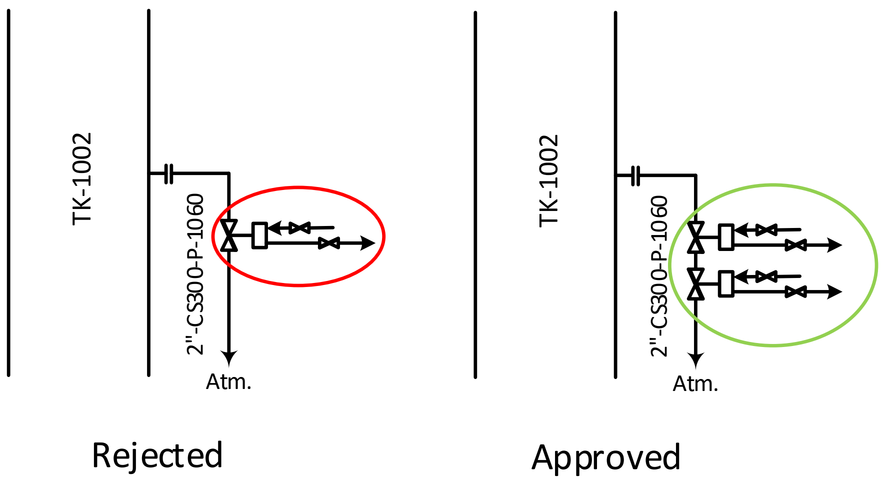
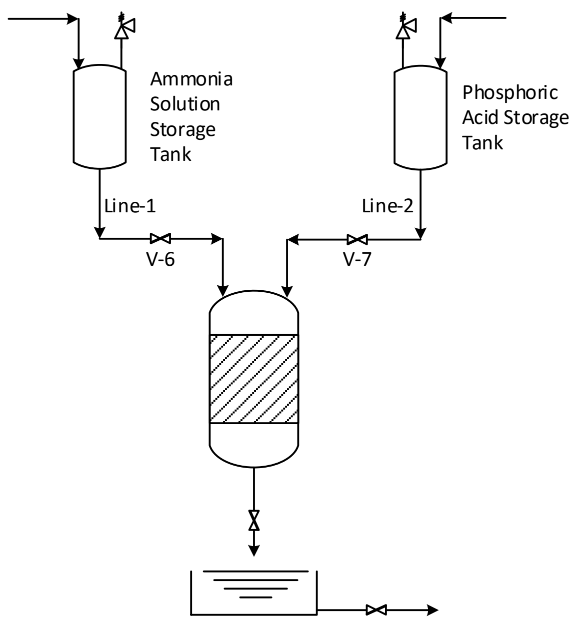


Figure 3-15: Revised P&ID

The case study discussed above was from the Phillips disaster in 1989 (F. I. Khan & Abbasi, 1999) in which 23 people died and 130 people were injured. A thorough review and better P&ID design could have prevented the incident from occurring.

3.6.2 Acid transfer line

Figure 3-16 shows a part of a P&ID in which a line transfers phosphoric acid from a storage tank to a reactor. A logic-based knowledge representation is used to identify hazard(s) in the process design. The same steps as in case study 1 are followed; first, an ontology is extracted from this part of the P&ID. In the next step, the engineering specification, in the form of human knowledge is presented in the DL and OCNL formats. Finally, a combination of these two knowledge bases is used for a SPARQL/OCNL query about the safety of the design.



Valve	hasType	isInLine	hasMaterial	hasManufacturer
V-7	GateValve	PipingSpool 1	CarbonSteel	…

Piping	hasID	hasHead	hasTail	Transfers	isInP&ID
PipingSpool 1	Line-2	Nozzle 1	Nozzle 2	PhosphoricAcid	P&ID-200

Figure 3-16: P&ID 200 and the extracted data for case study 2

The graphical ontology is shown in Figure 3-17 below:

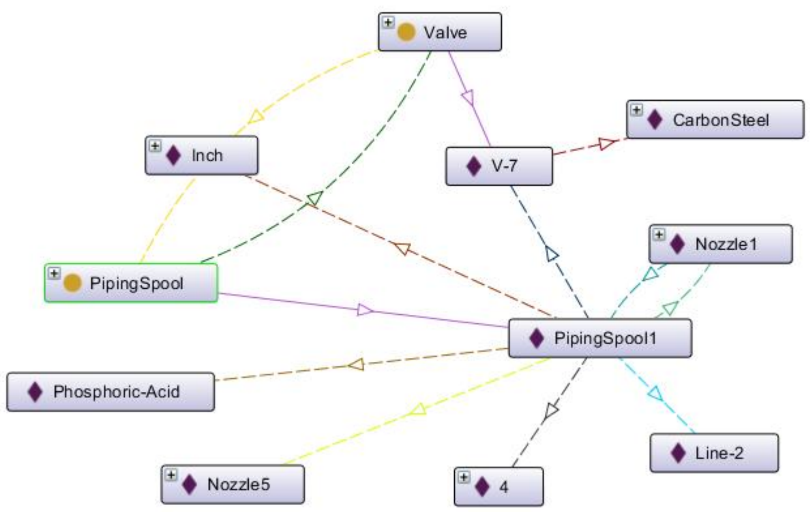


Figure 3-17: Graphical representation of the ontology

There is also general engineering knowledge that should be added to the knowledge base for accurate reasoning (shown in Table 3-12). This part of the knowledge base is not limited to any specific project and can be applied to any P&ID:

Table 3-12: Conversion of certain OCNL expressions into DL format

OCNL		DL
Phosphoric-Acid is an acidic-service.	→	{_Phosphoric−Acid} acidic−service
if a process-pipe(1) has-service a service(1) and the process-pipe(1) has-valve a valve(1) then the valve(1) has-service the service(1).	→	⌂○process−pipe(?process−pipe−1) ∧ ○service(?service−1) ∧ have−service(?process−pipe−1,?service−1) ∧ ○process−pipe(?process−pipe−1) ∧ ○valve(?valve−1) have−valve(?process−pipe−1,?valve−1)→have−service(?valve−1,?service−1)
Monel is a material-of-manufacturing.	→	{_Monel} material−of−manufacturing

Engineering Knowledge:

When a line is carrying acidic product, valve material should be Monel or 316 Stainless Steel and the flow rate should be checked at all time.

Table 3-13 below shows the conversion into the OCNL and DL formats.

Table 3-13: Engineering knowledge, from natural language to DL

Knowledge Natural language	SWRL-OCNL format	DL
When a line is carrying acidic product, valve material should be Monel or 316 Stainless Steel and the flow rate should be checked at all time.	if a valve(1) is-in-drawing a piping-and-instrument-diagram-drawing(1) and the valve(1) has-service a service(1) and the service(1) is an acidic-service and the valve does-not-have-material-of-manufacturing Monel then the piping-and-instrument-diagram-drawing(1) has-design-status Unsafe and Recommendation-4 have-status Applicable.	○valve(?valve−1) ○piping−and−instrument−diagram−drawing(?piping−and−instrument−diagram−drawing−1) be−in−drawing(?valve−1,?piping−and−instrument−diagram−drawing−1) ○valve(?valve−1) ○service(?service−1) have−service(?valve−1,?service−1) ○service(?service−1) ○acidic−service(?service−1) ○valve(?valve−x) doe−not−have−material−of−manufacturing(?valve−x,_Monel)→have−design−status(?piping−and−instrument−diagram−drawing−1,_Unsafe) have−status(_Recommendation−4,_Applicable)
	if a process-pipe(1) is-in-drawing a piping-and-instrument-diagram-drawing(1) and the process-pipe(1) has-service an acidic-service(1) and the process-pipe(1) does-not-have-flow-indicator a flow-indicator(1) then the piping-and-instrument-diagram-drawing(1) has-design-status Unsafe and Recommendation-5 have-status Applicable.	○process−pipe(?process−pipe−1) ○piping−and−instrument−diagram−drawing(?piping−and−instrument−diagram−drawing−1) be−in−drawing(?process−pipe−1,?piping−and−instrument−diagram−drawing−1) ○process−pipe(?process−pipe−1) ○acidic−service(?acidic−service−1) have−service(?process−pipe−1,?acidic−service−1) ○process−pipe(?process−pipe−1) ○flow−indicator(?flow−indicator−1) doe−not−have−flow−indicator(?process−pipe−1,?flow−indicator−1)→have−design−status(?piping−and−instrument−diagram−drawing−1,_Unsafe) have−status(_Recommendation−5,_Applicable)
	Recommendation-4 has-content Valve-Contains-Acid-Should-Be-From-Stainless-Steel-Or-Monel	{_Recommendation−4} (have−content).({_Valve−Contains−Acid−Should−Be−From−Stainless−Steel−Or−Monel})
	Recommendation-5 has-content Line-Contains-Acid-Must-Have-Flow-Indicator.	{_Recommendation−5} (have−content).({_Line−Contains−Acid−Must−Have−Flow−Indicator})

Table 3-14 below shows the question, by the SPARQL/reasoning engine, to check the safety of the design in the P&ID above.

Table 3-14: Query from P&ID-Acid transfer line

Query Natural language	Query-OCNL format	Query result
Is P&ID design safe?	Who-Or-What has-design-status Unsafe?	P&ID-200

At this stage, the reasoner identifies the P&ID as "Unsafe," but it cannot help the designer to modify the design. In order to add this ability, a "Recommendation" part is added to the knowledge base. For example, in this case, because the root cause of the "Unsafe" status is the wrong material of the valve and the lack of a flow indicator, two recommendations are initially added to the original human knowledge, as shown in Table 3-15 below:

Table 3-15: Query results: Acid transfer line

Query Natural language	Query-OCNL format	Query result
Is P&ID design unsafe? And if unsafe, what is recommended?	Who-Or-What has-design-status Unsafe?	P&ID-200
	Who-Or-What is a recommendation that has-status Applicable?	Recommendation-4 has-content Valve-Contains-Acid-Should-Be-From-Stainless-Steel-Or-Monel. Recommendation-5 has-content Line-Contains-Acid-Must-Have-Flow-Indicator.

This way, the knowledge base not only helps with hazard identification, but it can provide a recommendation to the process designer to modify it. In this case, response to the query will include the recommendation: "*Valve-Contains-Acid-Should-Be-From-Stainless-Steel-Or-Monel.*" and "*Line-Contains-Acid-Must-Have-Flow-Indicator*."

A revised P&ID, Figure 3-18, considers a Monel valve and a flow indicator for this line. This time, the reasoner approves the P&ID and identifies it as "Safe."

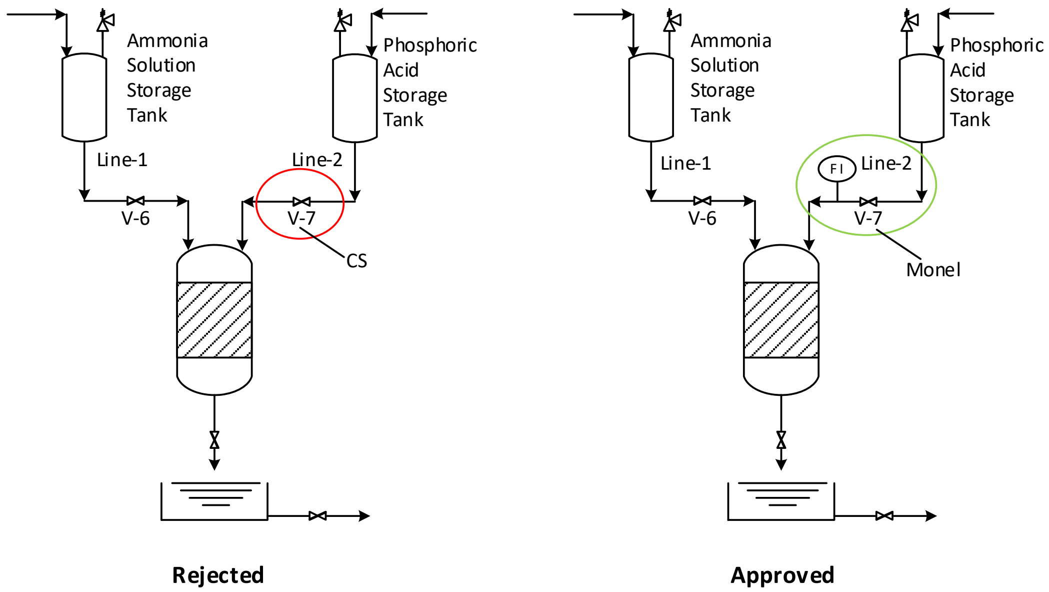


Figure 3-18: Original and revised P&ID

3.7 Discussion

With the development of data science, there are now alternatives to SQL, called No-SQL in general, which can boost the existing capabilities of SQL by introducing new formats of data. One of the main reasons for developing the knowledge base is to be able to query it by using No-SQL. As discussed, there are many situations in the process plant lifecycle in which it is critical to get the right answer for the query, and answering the query requires multiple documents, drawings, and documents, with their latest revisions, to be sought.

An example of that would be the hazard identification in process engineering diagrams (e.g., the P&ID). It is obvious that, without the knowledge base, answering this question would require the design validation team to refer to different drawings, specifications, lessons learnt from previous incidents, and find mistakes in the process diagram. This is actually the traditional method of hazard identification in the process engineering field, which is normally conducted by a group of experts in the field; it is not only time-consuming but also inevitably introduces human error. The two case studies in this chapter illustrate the accuracy and speed of using a knowledge base, and their reasoning engine for hazard identification.

It should be noted that developing such a knowledge base for a process plant requires a digital format of engineering drawings (e.g., the P&ID). Although a part of this ES requires the time and effort to convert human knowledge and engineering specifications into the CNL format, it should be that once this is complete, the knowledge base can be used in different projects, without the requirement that this part be done again.

Another major benefit in this method is the capability of using the ISO 15926 standard, which is a developing standard. Following ISO 15926 standardizes the assignment of "predicates" in the triples and data extraction from CAD platforms.

The idea is not limited to the design of new process plants, but with the current challenges of process plant owners in managing their facilities, while trying to keep their personnel safe and the environment intact, it is possible to model all types of information from existing plants (as shown in Figure 3-19) for the purpose of any reasoning during the operation and maintenance. Moreover, it may be used in conjunction with "Internet of Things" (IoT) technology (F. I. Khan & Abbasi, 1999).

The aim of ontology-based modelling and analysis is to reduce the amount of time, effort, and money that is required to do process hazard analysis in the future. It requires an investment in time and money, but the return of this investment is worth the time and effort since it is eliminating the repetitive (and unnecessary) activities. Besides, it minimizes the human error in future hazard analysis.

On the other hand, current advancements in Natural Language Processing is benefiting this process in converting natural language, into a machine-readable format. This research is aimed to apply NLP in converting human-readable scripts into semantic language in the next steps.

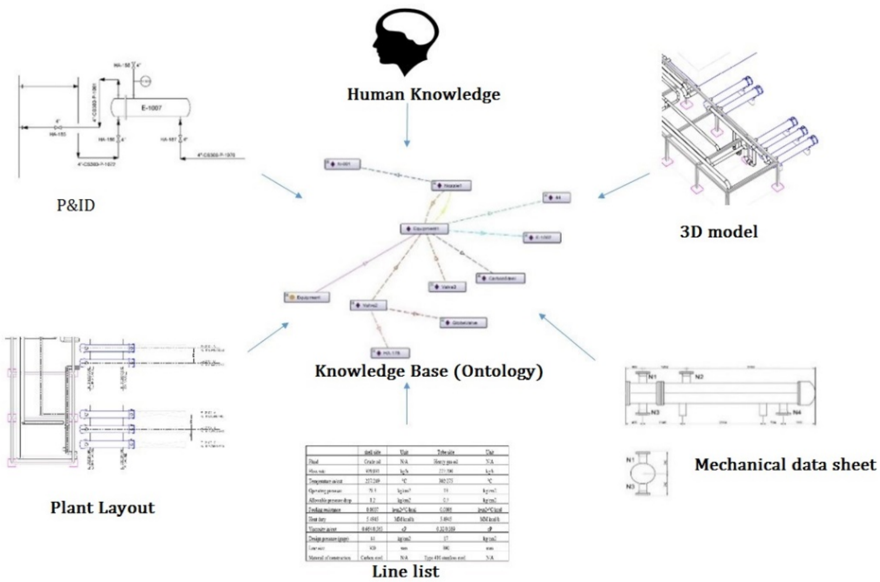


Figure 3-19: Creating a comprehensive knowledge base

3.8 Conclusions and future work

In this chapter, state-of-the-art semantic technology and ontology language were used to address safety issues in the process industry, and their roots in data query and reasoning and successful application to two case studies were illustrated. The contribution here lies in developing machine-readable knowledge bases for safety analysis in the process industry. This is the first time that such a new field in computer and data science (semantic technology and KE) is used in safety analysis in the chemical engineering field. Combining process data, human knowledge, and engineering specifications in a knowledge base and developing a query platform to automate/assist in the safety analysis minimize the required time for safety analysis, minimize human error, and also provide the opportunity for process engineers to try different sets of process diagrams.

Developing a knowledge base (ontology), including the data from engineering drawings (e.g., P&ID and mechanical datasheet), using CNL, DL, and OWL language was proposed. Using a No-SQL language (e.g., SPARQL) and built-in reasoners in ontology editors to gain accurate responses for complex questions during the lifetime of a plant were also illustrated. The flexibility of a knowledge base in integrating data from different sources and its data visualization and unique identifier features were also presented.

Because the roots of this methodology are a part of semantic technology and AI development, it can be linked to other AI systems and applications to create a type of process plant that acts smarter in each phase of the project (i.e. design, construction, operation, and shutdown and maintenance). The development of applications for design automation can be named as such futuristic applications because the machine stores human knowledge and it can read other formats of existing data. Therefore, the future of this research will be about using the human knowledge in a machine-readable format for reviewing the design, as well as automating the design.

Chapter 4 Automation of equipment arrangement and design validation in process plants

In this chapter, an algorithm for the automation of equipment arrangement in process plants is first developed. Mathematical models of equipment in the PFD are then established. The algorithm is applied to equipment models to generate multiple scenarios of equipment arrangement. Human knowledge and engineering specifications are integrated to the algorithm to check the scenarios and filter the best arrangements

4.1 Algorithm and preliminary data extraction

Figure 4-1 shows the algorithm flowchart. Data from the PFD and preliminary equipment dimensions are used in creating data matrices of the layout and equipment with mathematical modeling. All possible scenarios for the equipment arrangement are created and different matrices are developed for each scenario. The project specification and best engineering practices are then applied to each scenario model to filter the scenarios and choose the approved list.

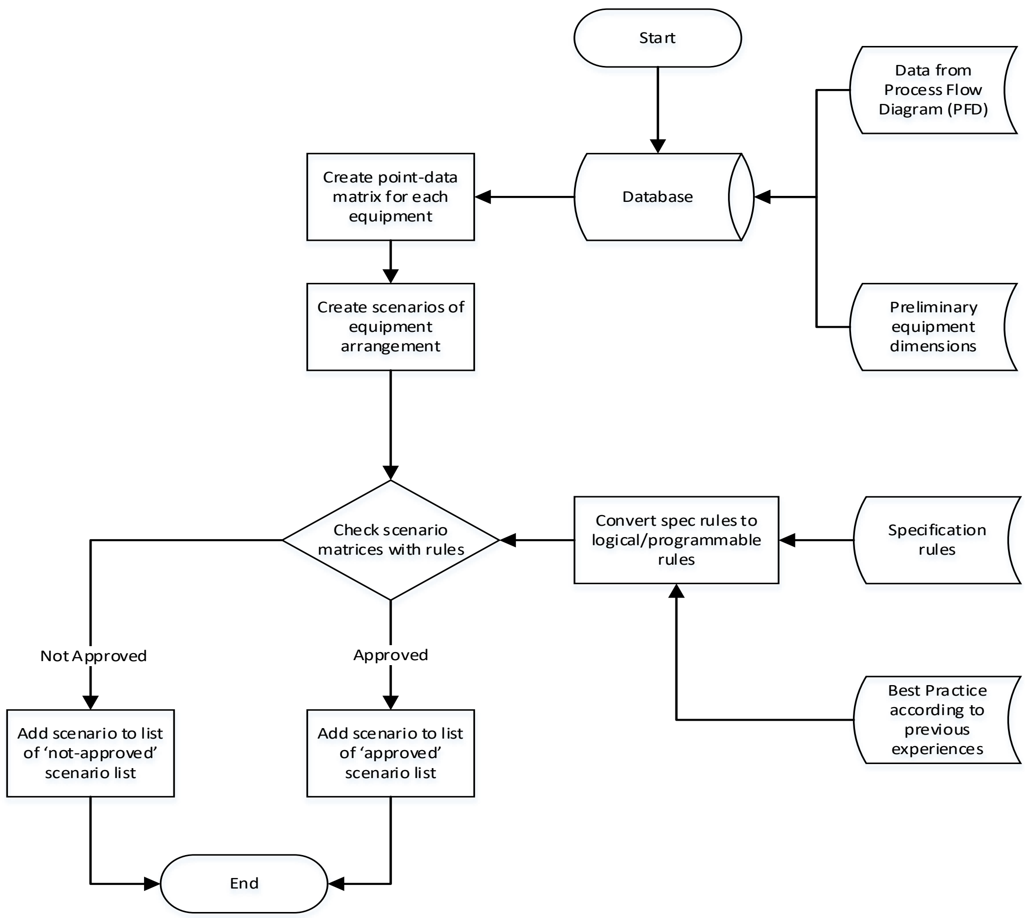


Figure 4-1: Flowchart for equipment arrangement and validation

At the first stage, a database is developed which includes the data from process flow diagram (PFD) and the preliminary equipment dimensions. It is worth mentioning that the equipment manufacturers in the process plant industry have preliminary dimensions, based on the process information. For example, a centrifugal pump with specific operation/test pressure and temperature and in/out nozzle dimensions has a rectangular shape with certain dimensions; these dimensions are normally in a (somehow) similar range among centrifugal pump manufacturers. The same concept is correct for other equipment in this field (i.e. heater, heat exchanger, towers).

In the next stage, the algorithm develops data models, in form of matrices, for each equipment, by converting each equipment into data-enriched nodes. Combination of these data models creates multiple scenarios for equipment arrangement.

Another part of the algorithm is about integrating the engineering specifications into the code; in other words, equipment arrangement rules (e.g. clash prevention, safe distance, and orientations) can become a part of the code script.

In the last stage, rules (included as a part of the code) are going to check each equipment arrangement scenario and approves its validity.

PFDs normally show the relation between the process equipment at the early stages of the project. PFDs are human-readable diagrams and include information about the relations among the equipment. It is a common practice in the process plant industry for, with the preliminary information in the PFD, the preliminary dimensions of the process equipment to be generated as a database for the preliminary design of the equipment arrangement. These data are based on the lessons learned and previous similar process plants. Figure 4-2 below shows an example of this.

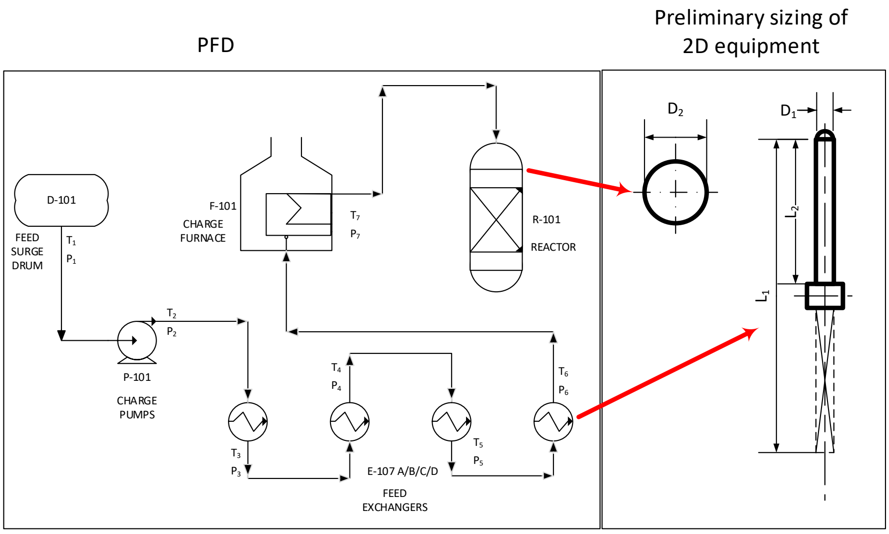


Figure 4-2: Preliminary equipment dimensions from PFD

4.2 Mathematical modeling of process equipment

In order to apply the design automation algorithm, each process equipment should be converted into a 2D spatial data matrix using mathematical modeling. This way, instead of a mere object, each equipment is illustrated as a matrix of spatial data points. Each point in each process equipment not only has a spatial data but is also linked to meta-data. A mathematical model defines the relation between the points in each equipment, and the algorithm generates different arrangements of these points and the knowledge base checks the validity of the design. Figure 4-3 below shows the basic conversion of a pump into spatial points.

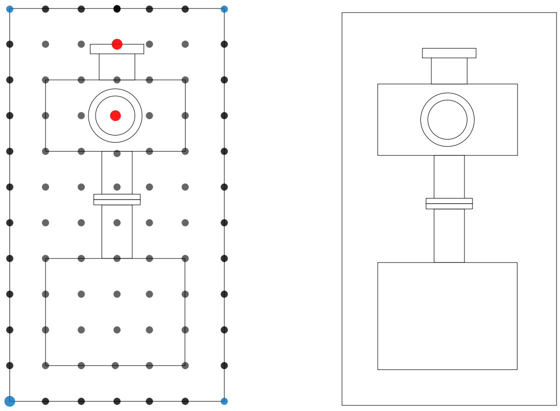


Figure 4-3: Spatial data points of a pump

4.2.1 Creating spatial point coordination

Two approaches have been investigated to create the mathematical model of the spatial points in each process equipment. The first is the “inward spiral guideline” and the second is the “coil-shaped guideline.” Figure 4-4 below shows both guidelines on a similar equipment.

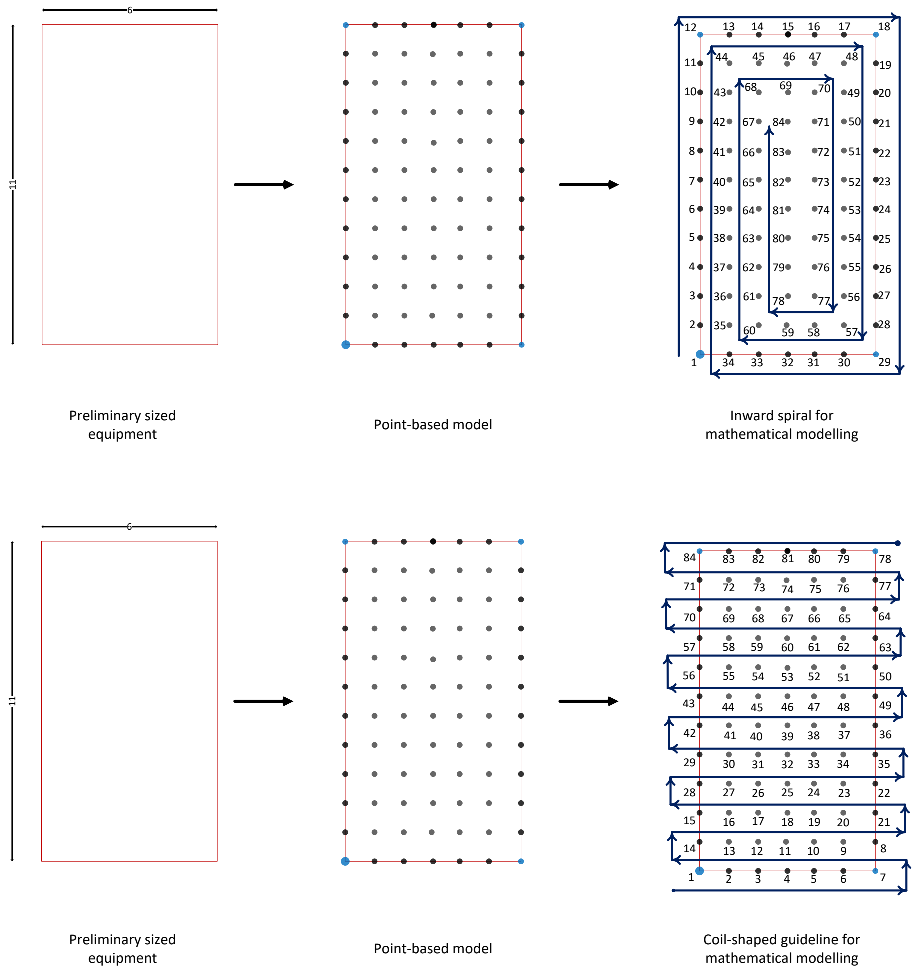


Figure 4-4: Inward spiral vs. coil-shaped guideline for mathematical modeling

Creating a mathematical model with the inward spiral guideline is a complex task. The coil-shaped guideline provides a simpler approach to develop a mathematical model that can predict the location of the points and other features from the number of each point. The coordination of each point $\left(X_{P\_No}, Y_{P\_No}\right)$ is based on the coordination of the base point $\left(X_0, Y_0\right)$ and the orientation of the equipment $\left(\alpha\right)$ in the layout area. Figure 4-5 illustrates the coordination of points for an equipment in four different rotations.

Following the coil-based guideline, each point's coordination can be expressed as follows:

$$L : Length$$
$$W : Width$$
$$\alpha : Rotation - Angle$$
$$X_{P\_No} = \left(Y_0 + \left(\left(P\_No\right) \operatorname{mod}\left(W+1\right)\right)\right) \times \sin\left(\alpha\right) + \left(X_0 + \left[\left(\left(P\_No\right) - \left(\left(\left(P\_No\right) \operatorname{mod}\left(W+1\right)\right) \times \left(W+1\right)\right)\right) - 1\right]\right) \times \cos\left(\alpha\right)$$
$$Y_{P\_No} = \left(Y_0 + \left(\left(P\_No\right) \operatorname{mod}\left(W+1\right)\right)\right) \times \cos\left(\alpha\right) - \left(X_0 + \left[\left(\left(P\_No\right) - \left(\left(\left(P\_No\right) \operatorname{mod}\left(W+1\right)\right) \times \left(W+1\right)\right)\right) - 1\right]\right) \times \sin\left(\alpha\right)$$

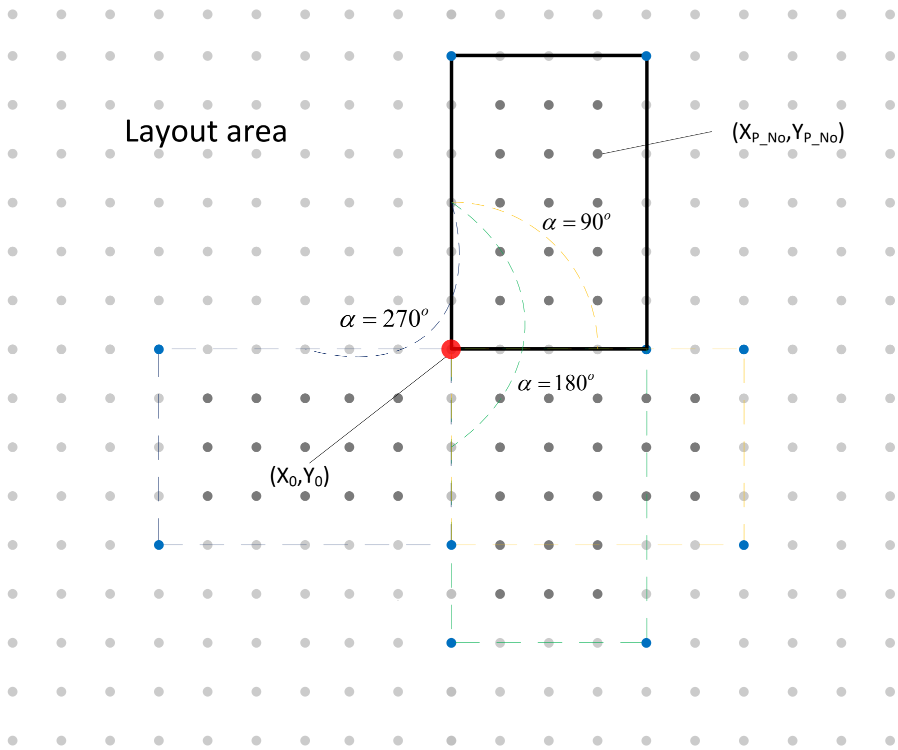
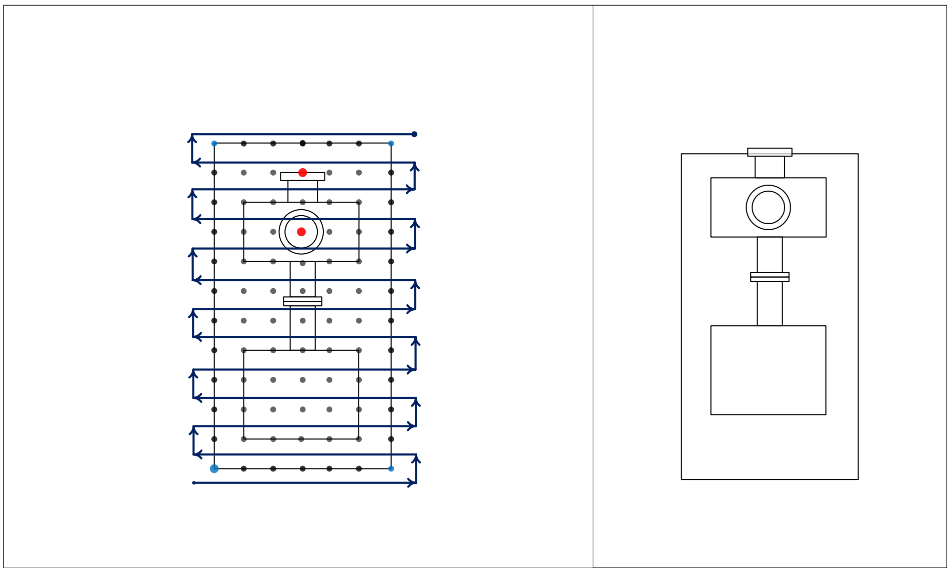


Figure 4-5: Process equipment spatial point coordination with respect to base point and rotation in the layout area

4.2.2 Creating equipment data matrix

As discussed above, creating a matrix from each process equipment gives us the opportunity of adding more meta-data to each point. Figure 4-6 shows the difference between the amount of data in a mere object and a matrix conversion of the same equipment. It shows limited data from the "object" when compared with the mathematical model.

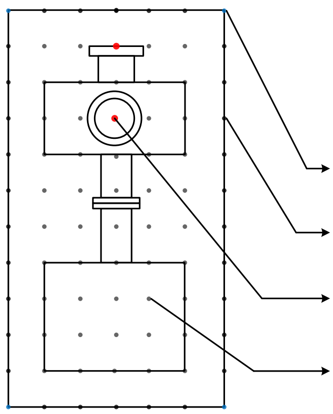


$$E1=\begin{bmatrix} X_{E1-1} & Y_{E1-1} & Corner & NA & NA & NA & E2 & N & E1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E1-10} & Y_{E1-10} & Operation & NA & NA & NA & E2 & N & E1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E1-50} & Y_{E1-50} & Nozzle_{E1-1} & Nozz-Conn & NA & Nozzle_{E2-1} & E2 & N & E1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E1-m} & Y_{E1-m} & Internal & NA & NA & NA & E2 & N & E1 \end{bmatrix}$$

$$E1=\begin{bmatrix} E_1 & Length & Width \end{bmatrix}$$

Figure 4-6: Data matrix vs. limited data of an object

An integrated knowledge base in the algorithm requires a reference to the meta-data of each point in the process equipment data matrix, such that the equipment arrangement design may be validated. This is a combination of different data matrices. Therefore, each equipment data matrix should have enough information in each row. Figure 4-7 below shows the nature of data in each column of the data matrix and each row refers to a point in the equipment.



$$\begin{array}{c} \begin{array}{ccccccccc} \text{X coordination} & \text{Y coordination} & \text{Point Location} & \text{Special feature1} & \text{Special feature2} & \text{Connected point} & \text{Equipment Name} & \text{Equipment Orientation} & \text{Connected Equipment on PFD} \end{array} \\ \begin{bmatrix} X_{E2-1} & Y_{E2-1} & Corner & NA & NA & NA & E1 & N & E2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E2-10} & Y_{E2-10} & Border & NA & NA & NA & E1 & N & E2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E2-50} & Y_{E2-50} & Nozzle_{E2-1} & Nozz-Conn & NA & Nozzle_{E1-1} & E1 & N & E2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E2-m} & Y_{E1-m} & Internal & NA & NA & NA & E1 & N & E2 \end{bmatrix} \end{array}$$

Figure 4-7: Points and matrix

4.2.3 Critical spatial points

Because some parts of the checklist in the algorithm are around the border, corner, and nozzle points of each process equipment, it is important to consider them in the data matrix and mathematical model of each equipment. The following rules should be considered in the mathematical modeling of the equipment:

Corners

$$Corner\_Points = \left[P_{Co\_1}, P_{Co\_2}, P_{Co\_3}, P_{Co\_4}\right]$$
$$P_{Co\_1} = P_1 \rightarrow P_{Co\_3} = P_{Co\_1} + \left(\left(L \times (W+1)\right)+1\right)$$
$$P_{Co\_2} = P_{W+1} \rightarrow P_{Co\_4} = P_{Co\_2} + \left(\left(L \times (W+1)\right)+1\right)$$

Border/perimeter points

Below is the rule for detecting the list of points positioned on the border/perimeter of the equipment:

$$Border\_Points = \left[P_{Bo\_1}, P_{Bo\_2}, \ldots, P_{Bo\_n}\right]$$
$$if\left(P_{Co\_1} \le (P\_No) \le P_{Co\_2}\right) \vee \left(P_{Co\_3} \le (P\_No) \le P_{Co\_4}\right) \vee$$
$$\left(\left((P\_No) \bmod (W+1)\right)-1\right) = 0 \vee \left((P\_No) \bmod (W+1)\right) = 0$$
$$\rightarrow P\_No \in Border\_Points$$

Nozzle points

Nozzle locations are also used in the algorithm and should be recorded as part of the data matrix.

$$Nozzle\_List = \left[Nozz_1, Nozz_2, \ldots\right]$$
$$if\left(X_{P\_No} = X_{Nozz\_1} \wedge Y_{P\_No} = Y_{Nozz\_1}\right) \rightarrow P\_No \in Nozzle\_List$$

Figure 4-8 below shows the location of two nozzles and their mirror points on the spatial point graph of the process equipment.

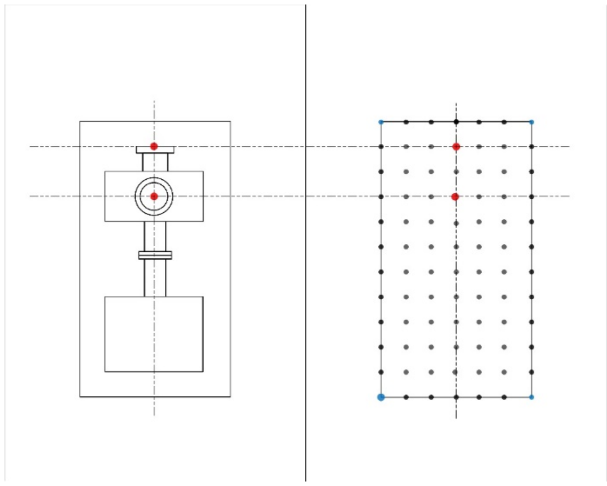


Figure 4-8: Nozzles on spatial point graph of the equipment

4.2.4 Adding more meta-data

As discussed, further details can be added to the mathematical models for equipment. This includes meta-data about the points in the operation, maintenance, and other required zones around each equipment. Assigning data rows to the matrix to cover these points will be helpful in future, because rules about each set of points will be added to the equipment arrangement algorithm. Figure 4-9 below shows "operation" and "maintenance" spaces added to the data matrix.

$$\begin{bmatrix} X_{E1-1} & Y_{E1-1} & \text{Corner} & NA & NA & NA & E2 & N & E1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E1-10} & Y_{E1-10} & \text{Operation} & NA & NA & NA & E2 & N & E1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E1-50} & Y_{E1-50} & \text{Maintenance} & NA & NA & NA & E2 & N & E1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E1-m} & Y_{E1-m} & \text{Internal} & NA & NA & NA & E2 & N & E1 \end{bmatrix}$$

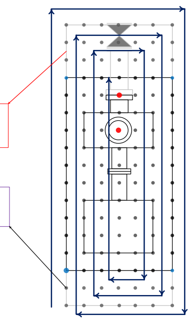


Figure 4-9: Operation and maintenance areas

4.2.5 Modeling scenarios

Now that the mathematical model for the process equipment data matrix is defined, it is possible to extend it to multiple pieces of equipment simultaneously and to create a data matrix of different scenarios. Each scenario represents a unique arrangement of all the process equipment in a PFD.

In order to cover all possible scenarios, the first step is to consider the process area as a spatial data matrix. The algorithm sets an order for the process equipment and assigns a point in the process area as the base point for one equipment at a time. Another degree of freedom in the algorithm for each equipment is the angle, or direction of the equipment with respect to the north of the plan. Therefore, each equipment not only has the freedom to choose its base point, but also can set its direction (North, South, East, or West). Figure 4-10 shows a process area with the specified length and width of L and W. It shows a possible coordination and direction for the base point of one simple equipment.

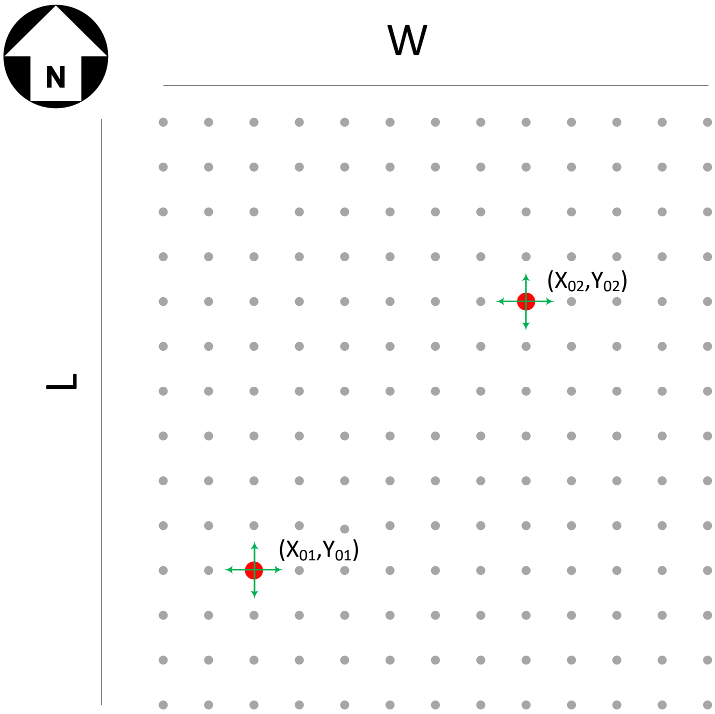


Figure 4-10: Sample scenarios for the base point of a process equipment

If the number of equipment in the PFD is K, then the number of scenarios is $\left(L \times W\right)^{K} \times 4$.

Figure 4-11 shows two different scenarios and the corresponding generated matrix. It shows two orientations and two different base points for the same equipment, which generates two different matrices of point data:

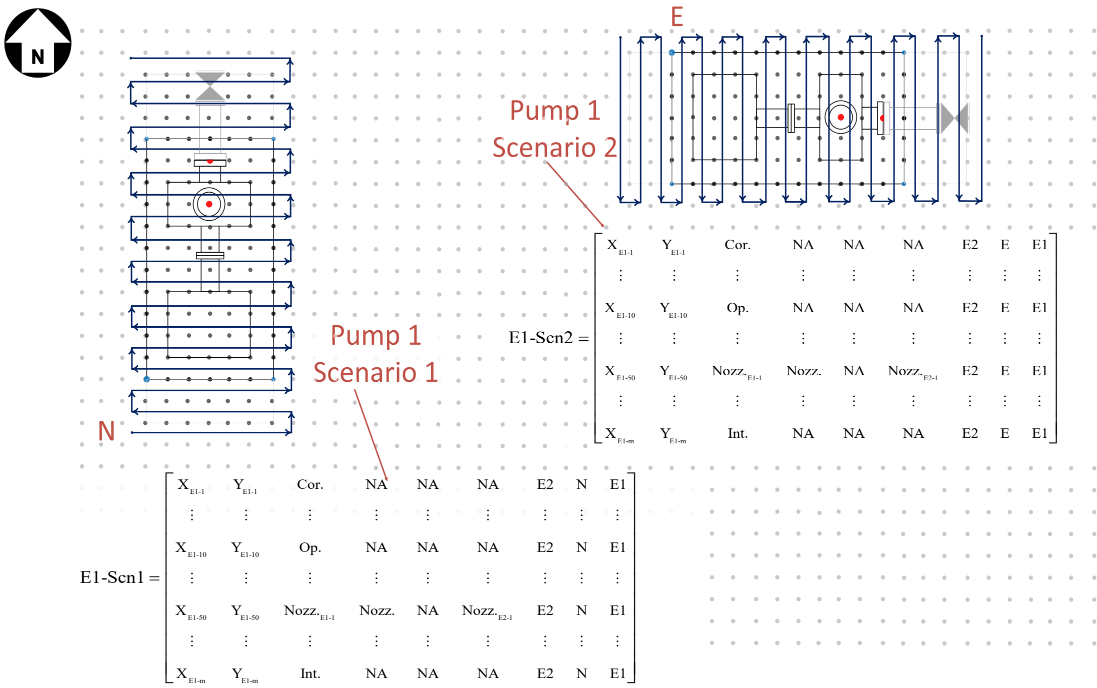


Figure 4-11: Two scenarios of the same equipment and their data matrices

Figure 4-12 below shows an example of a scenario (scenario n) with five equipment. Each equipment has the freedom to set its first point and orientation in the layout. Accordingly, five matrices are generated and the information of the specific scenario is recorded among other thousands of other possible scenarios.

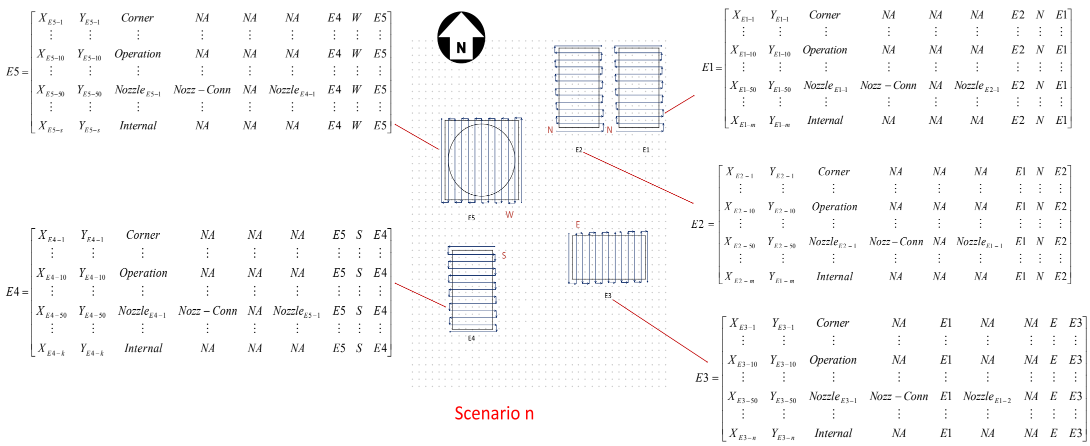


Figure 4-12: Sample scenario with five different process equipment

4.2.6 Combining matrices

In order to apply rules to each scenario, the separate matrices in each scenario should be concatenated as one mathematical model in the form of a matrix. Equation (4.1) below shows the concatenation of the matrices from the example above. This final matrix for each scenario has all the information about the process equipment in one place, which makes it possible to apply the knowledge base part of the algorithm to each scenario.

$$Scn-n=\left((E1)_{m4}\middle|(E2)_{m4}\middle|(E3)_{n4}\middle|(E4)_{k4}\middle|(E5)_{s4}\right) \tag{4.1}$$

The result would be as follows:

$$Scn-n=\begin{bmatrix} \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E1-i} & Y_{E1-i} & Loc_{E1-i} & SP1_{E1-i} & SP2_{E1-i} & Conn.Nozz_{E5-i} & Eq.Name_{E1-i} & Orientation_{E1-i} & Eq.Conn_{E1-i} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E2-i} & Y_{E2-i} & Loc_{E2-i} & SP1_{E2-i} & SP2_{E2-i} & Conn.Nozz_{E5-i} & Eq.Name_{E2-i} & Orientation_{E2-i} & Eq.Conn_{E2-i} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E3-i} & Y_{E3-i} & Loc_{E3-i} & SP1_{E3-i} & SP2_{E3-i} & Conn.Nozz_{E5-i} & Eq.Name_{E3-i} & Orientation_{E3-i} & Eq.Conn_{E3-i} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E4-i} & Y_{E4-i} & Loc_{E4-i} & SP1_{E4-i} & SP2_{E4-i} & Conn.Nozz_{E5-i} & Eq.Name_{E4-i} & Orientation_{E4-i} & Eq.Conn_{E4-i} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E5-i} & Y_{E5-i} & Loc_{E5-i} & SP1_{E5-i} & SP2_{E5-i} & Conn.Nozz_{E5-i} & Eq.Name_{E5-i} & Orientation_{E5-i} & Eq.Conn_{E5-i} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

4.3 Algorithm validation

As discussed, a part of the algorithm includes a knowledge base for human knowledge and engineering specifications of the process plant. Human knowledge and engineering specifications can be converted into a simplified version, and then into a logical format, in order to be included in the algorithm and to be applicable to the data matrices. Logical expressions have been used here to express the simplified knowledge. In order to show how the algorithm works with this knowledge and data matrices, three activities in validating the design have been conducted: clash checking, safety distances checking, and parallel equipment checks.

4.3.1 Clash check

Because the algorithm can provide all possible equipment arrangements, the first activity in checking the validity of the design should be clash checking. As discussed, that which is referred to here as a “design” is in fact a data matrix. In order to check the clash, the algorithm checks whether any two different equipment have any points in the same location (i.e., similar X and Y) and divide the complete list of scenarios into “Approved” and “Not-Approved” lists for this part of the validity check. The conditional statement in Equation (4.2) sets up the range and the statement. The logical expressions in Equation (4.3) set the hypothesis and check whether the validation refers to two different equipment and whether they have similar X and

Y coordination. Expressions (4.4) and (4.5) are the possible conclusions for the hypothesis checking and put the tested scenario into either the "Approved" or "Not-Approved" list of equipment arrangement scenarios.

$$\forall n \in \{1,2,\ldots,TotalScn\},\ p(n) \rightarrow q(n) \tag{4.2}$$

$$\begin{gathered} p(n): \exists i, j \in \{1,2,\ldots,m\}, \\ \left((Scn-n)_{i1} = (Scn-n)_{j1}\right) AND \left((Scn-n)_{i2} = (Scn-n)_{j2}\right) \\ AND\left((Scn-n)_{i9} \neq (Scn-n)_{j9}\right) \end{gathered} \tag{4.3}$$

$$q(n): \{NotApprovedScn\} \cup (Scn-n) \tag{4.4}$$

$$t(n): \{ApprovedScn\} \cup (Scn-n) \tag{4.5}$$

Figure 4-13 below shows a clash between two equipment and the overlapped area that creates similar (X, Y) coordinates in their corresponding matrices.

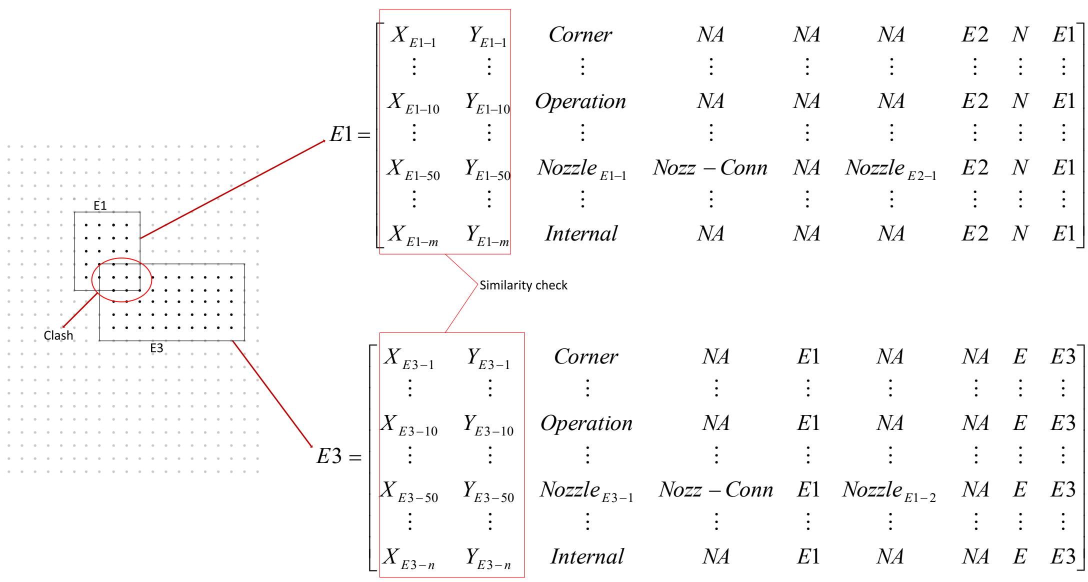


Figure 4-13: Clash between two equipment

4.3.2 Safety distance check

Checking safety distances is one of the most important activities in validating equipment arrangement design. Ignoring this may result in catastrophic accidents in process plants, as any failure may be a triggering point for a domino effect where fire or smoke in one equipment or part of the plant spreads to other parts of the plant without control.

An "equipment spacing" chart is normally a part of the engineering specifications of the project for any type of process plant. This chart can be included in the knowledge base of this automation algorithm as a matrix to check whether the safe distance between equipment in the arrangement is considered. Figure 4-14 shows a matrix for the list of equipment in a PFD and the required safety distance of equipment from each other. This matrix is developed along with the development of the PFD and obtains its values from the engineering specifications of the project.

$$
\begin{array}{ccccccc}
 & & \text{Eq. Num} & \text{Eq. Type} & \text{S.D. to reactor} & \text{S.D. to heater} & \text{S.D. to ...} \\
SD & = & \multicolumn{5}{c}{\left[\begin{array}{ccccc}
E_1 & Cent\ .Pump & SD_{E1-1} & SD_{E1-2} & \cdots \\
E_2 & \text{Re}\ actor & SD_{E2-1} & SD_{E2-2} & \cdots \\
E_3 & Heater & SD_{E3-1} & SD_{E3-2} & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
E_n & Eq\ .Type\ (E_n) & SD_{En-1} & SD_{En-2} & \cdots
\end{array}\right]}
\end{array}
$$

Figure 4-14: Equipment spacing (safe distance) matrix

In order to check the safe distance, the algorithm lists all possible distances between "border" points of each two equipment, finds the minimum, and compares that with the safe distance matrix. Figure 4-15 illustrates some of the distances between "border" points of two equipment.

In the mathematical description, the problem statement and logical check are represented by Equation 4.6 and 4.7. It also computes the minimum distance between "border" points and compares it with the safe distance matrix. In the case that the minimum distance is less than the identified safety distance in the safe distance matrix, the scenario is identified as "Not-Approved." Expressions (4.8) and (4.9) show the possible conclusions for the hypothesis checking and put the tested scenario in either the "Approved" or "Not-Approved" list.

$$\forall n \in \{1,2,...,TotalScn\}, p(n) \rightarrow q(n) \tag{4.6}$$

$$
\begin{aligned}
& p(n): \exists i, j \in \{1,2,...,m\}, \\
& \left(\min\left(\sqrt{\left((Scn-n)_{i1} - (Scn-n)_{j1}\right)^2 + \left((Scn-n)_{i2} - (Scn-n)_{j2}\right)^2} \right) \langle SD\left((Scn-n)_{i9}, (Scn-n)_{j9}\right) \right) \\
& AND\left((Scn-n)_{i3} = (Scn-n)_{j3} = 'Border'\right) \\
& AND\left((Scn-n)_{i9} \neq (Scn-n)_{j9}\right)
\end{aligned} \tag{4.7}
$$

$$q(n): \{NotApprovedScn\} \cup (Scn-n) \tag{4.8}$$

$$t(n): \{ApprovedScn\} \cup (Scn-n) \tag{4.9}$$

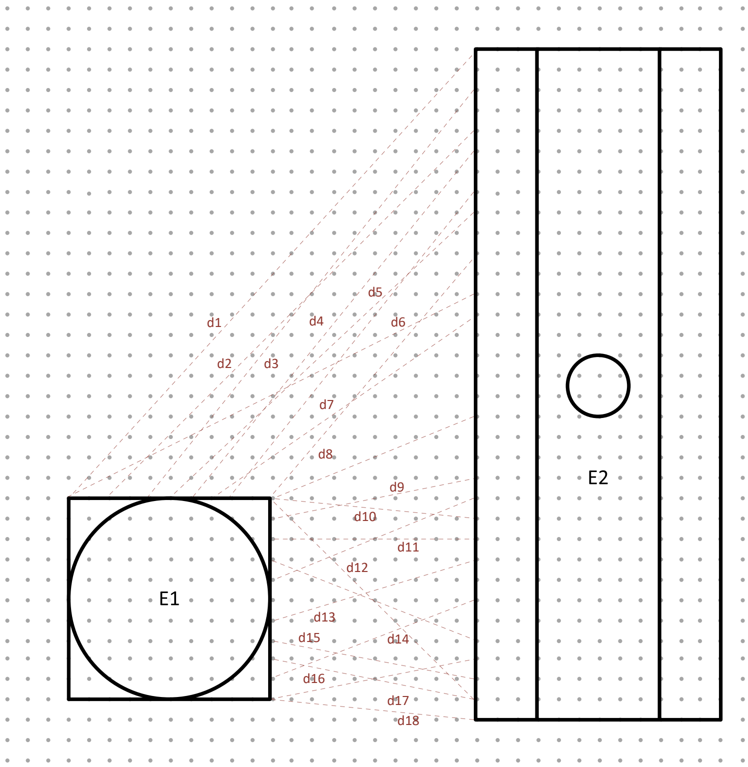
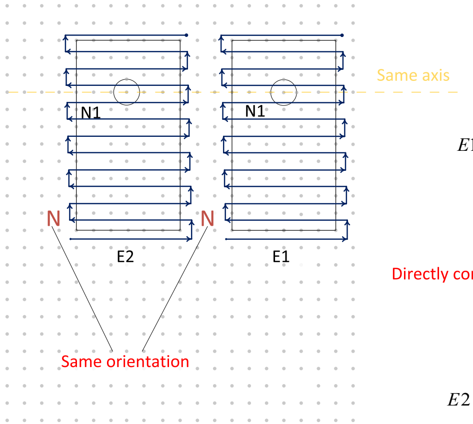


Figure 4-15: Distances between "border" points

4.3.3 Parallel equipment arrangement check

For some equipment in the equipment arrangement design, being parallel to each other is one of the major aspects of their positioning in the layout. This simplifies their operation, maintenance, and piping design. Some of these cases include stand-by pumps, compressors, or a series of shell-and-tube heat exchangers. Figure 4-16 shows an example of two parallel equipment and their corresponding matrices. For this equipment, being parallel is not only about the orientation of the equipment, but more importantly, it is about the location of connected nozzles in relation to each other. The algorithm checks the type of point, its connected nozzle on the PFD and the coordination of these two points in relation to each other. Statement (4.10) shows the logical expression for this rule.



$$E1=\begin{bmatrix} X_{E1-1} & Y_{E1-1} & Corner & NA & NA & NA & E2 & N & E1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E1-10} & Y_{E1-10} & Operation & NA & NA & NA & E2 & N & E1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E1-50} & Y_{E1-50} & Nozzle_{E1-1} & Nozz-Conn & NA & Nozzle_{E2-1} & E2 & N & E1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E1-m} & Y_{E1-m} & Internal & NA & NA & NA & E2 & N & E1 \end{bmatrix}$$

Directly connected nozzles

$$E2=\begin{bmatrix} X_{E2-1} & Y_{E2-1} & Corner & NA & NA & NA & E1 & N & E2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E2-10} & Y_{E2-10} & Operation & NA & NA & NA & E1 & N & E2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E2-50} & Y_{E2-50} & Nozzle_{E2-1} & Nozz-Conn & NA & Nozzle_{E1-1} & E1 & N & E2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{E2-m} & Y_{E1-m} & Internal & NA & NA & NA & E1 & N & E2 \end{bmatrix}$$

Figure 4-16: Parallel equipment

$$\begin{aligned} & p(n):\exists i,j\in\{1,2,\ldots,m\}, \\ & \left((Scn-n)_{i3}=(Scn-n)_{j5}\right) \\ & AND\left((Scn-n)_{i7}=(Scn-n)_{j9}\right) \\ & AND\left((Scn-n)_{i3}=(Scn-n)_{j3}='Nozzle'\right) \\ & AND\left(\left((Scn-n)_{i1}\neq(Scn-n)_{j1}\right)AND\left((Scn-n)_{i2}\neq(Scn-n)_{j2}\right)\right) \end{aligned} \tag{4.10}$$

4.4 Case study – process flow diagram

To validate the above activities (clash checking, checking safety distances, and parallel equipment checks), below are some of the rules that can be integrated into the knowledge base of the algorithm. This case study demonstrates the automation of a part of the equipment arrangement in a section of a naphtha hydro-treater plant (Bausbacher & Hunt, 1990).

Figure 4-17 shows the flow diagram used in this case study and Figure 4-18 shows the part for which the equipment arrangement will be applied. It should be noted that it is a common practice in the design of process plants to divide the PFD into separate parts and arrange the equipment in each part separately. Later in the design stage, these separate parts are combined to create a complete set of equipment arrangement for the entire PFD.

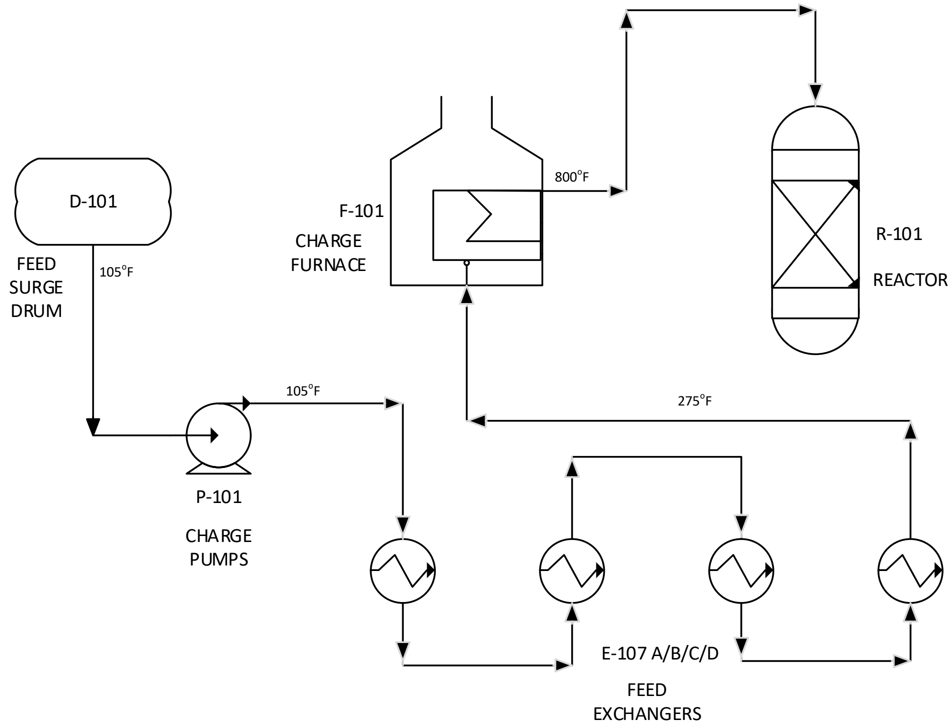


Figure 4-17: Process flow diagram

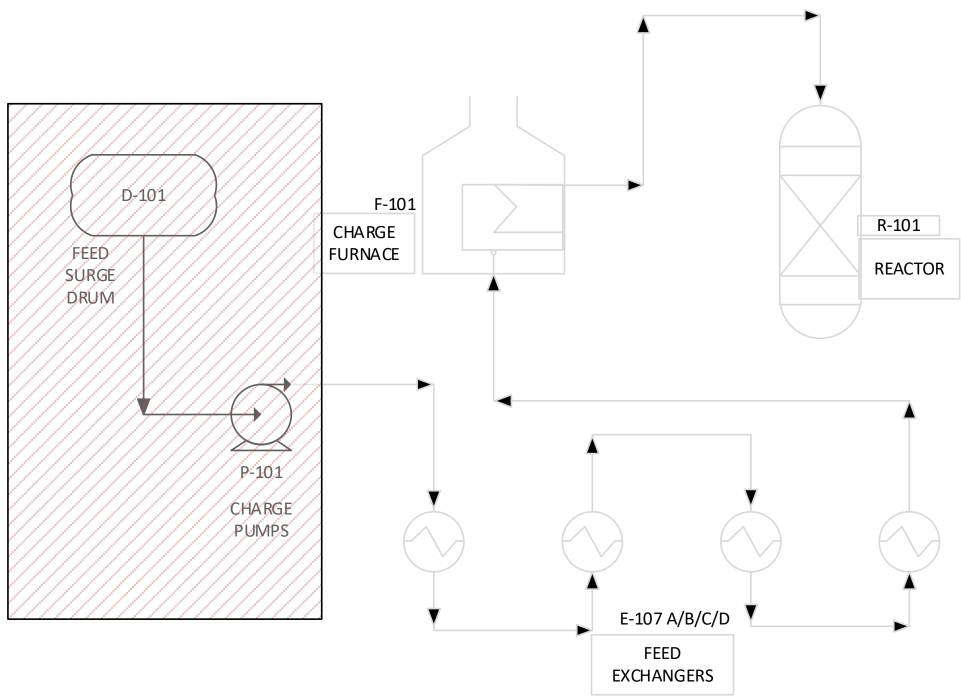


Figure 4-18: Selected part of the PFD for automatic equipment arrangement

As shown in Figure 4-19, there are different sources for the knowledge base of the algorithm; one part of data comes from the PFD, which is helpful in specifying the preliminary dimensions of the process equipment. Another part is from the engineering specifications and human knowledge. As discussed, this part of knowledge can be simplified into logical rules and encoded as part of the algorithm. The algorithm is used to generate different possible scenarios for the equipment arrangement and to validate them with the knowledge base.

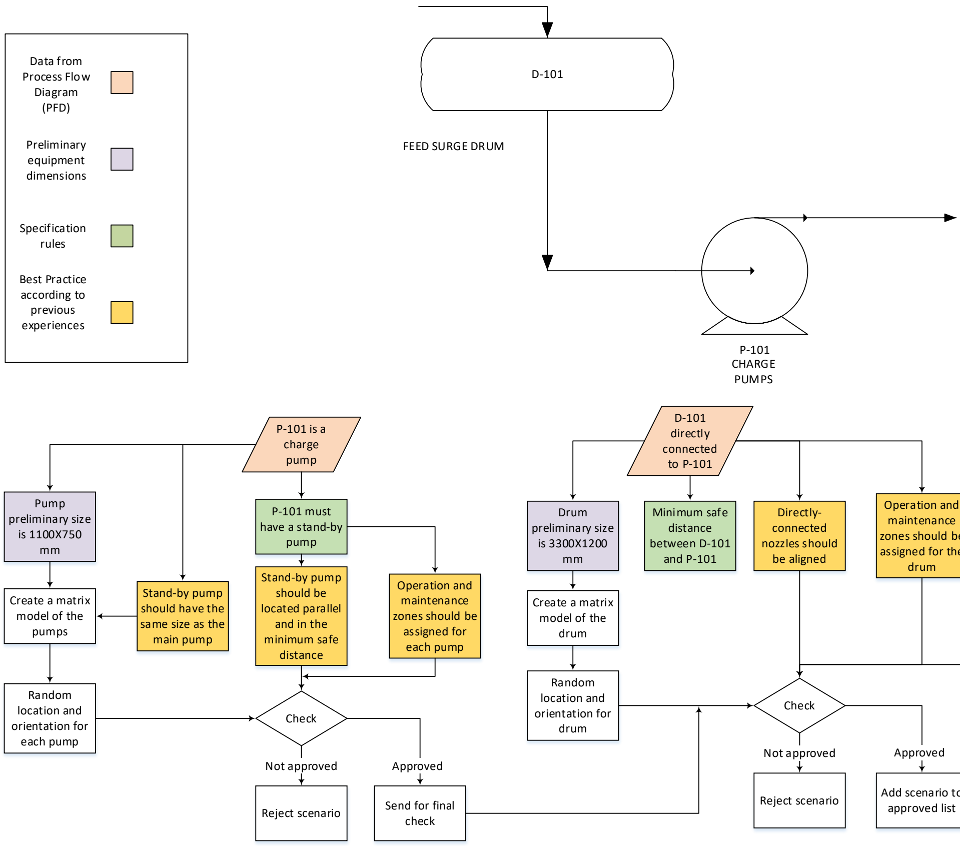


Figure 4-19: Data flow and algorithm

Figure 4-20 to Figure 4-22 show three different scenarios generated by the algorithm as well as the results of the validity check with the design knowledge base.

These figures show that scenario 1 is rejected for the clash, non-parallel positioning of the pumps, and for not considering the minimum safety distance between the pump and the drum. There is no clash in scenario 2 and the safety distance is considered, but the pumps are not in a parallel situation, as required in the knowledge base of the algorithm. Scenario 3 is approved for complying with all the necessary requirements.

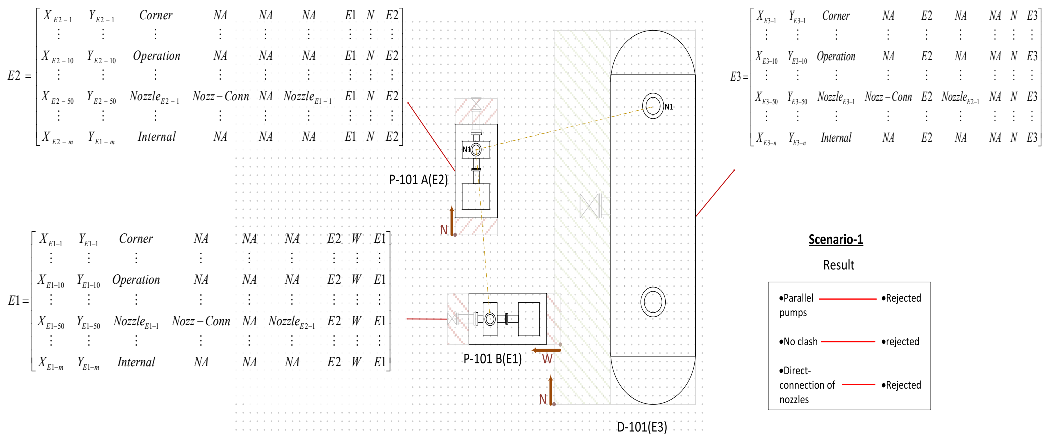


Figure 4-20: Scenario 1

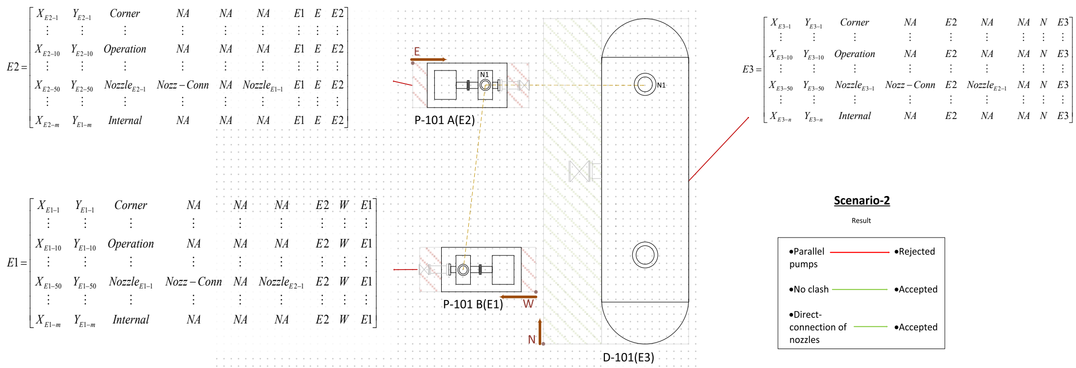


Figure 4-21: Scenario 2

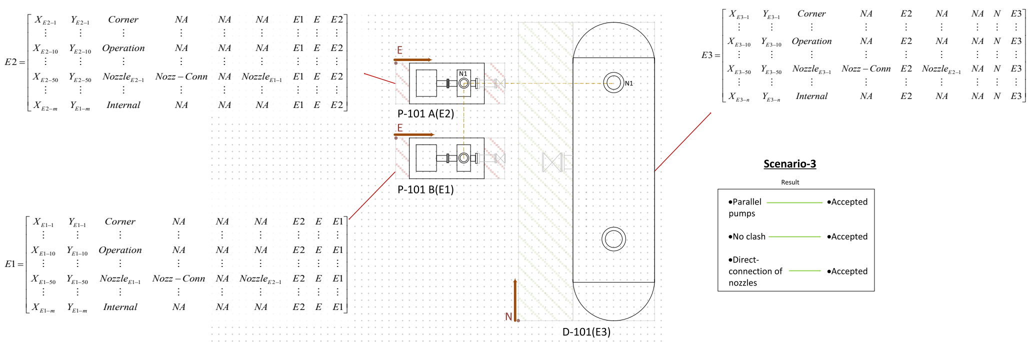


Figure 4-22: Scenario 3

4.5 Case study-complete plant

By expanding the rules and integrating them into the algorithm, it is possible to cover the entire process plant. Figure 4-23, Figure 4-24, and Figure 4-25 show three possible scenarios for the entire plant.

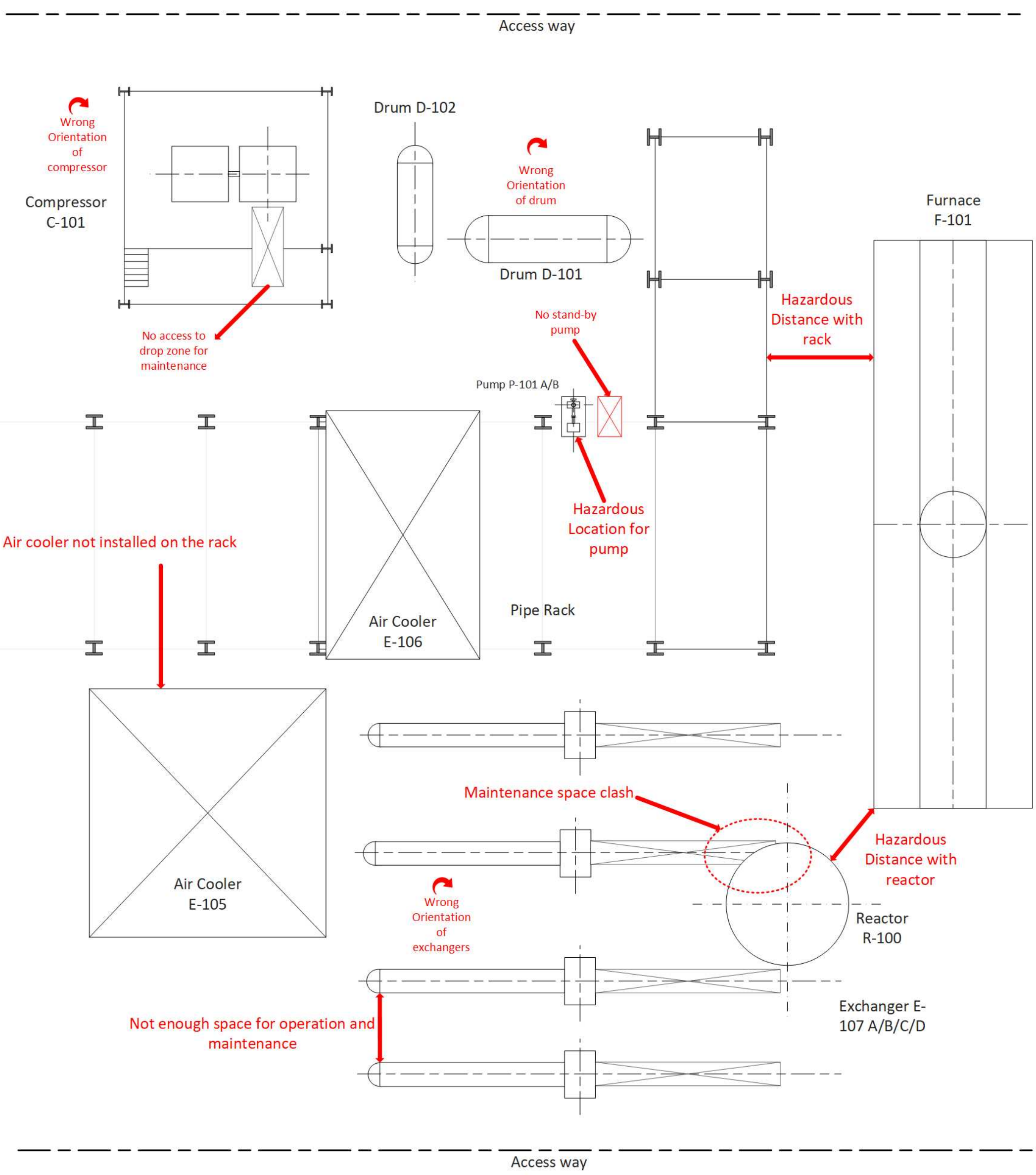


Figure 4-23: Complete plant scenario 1

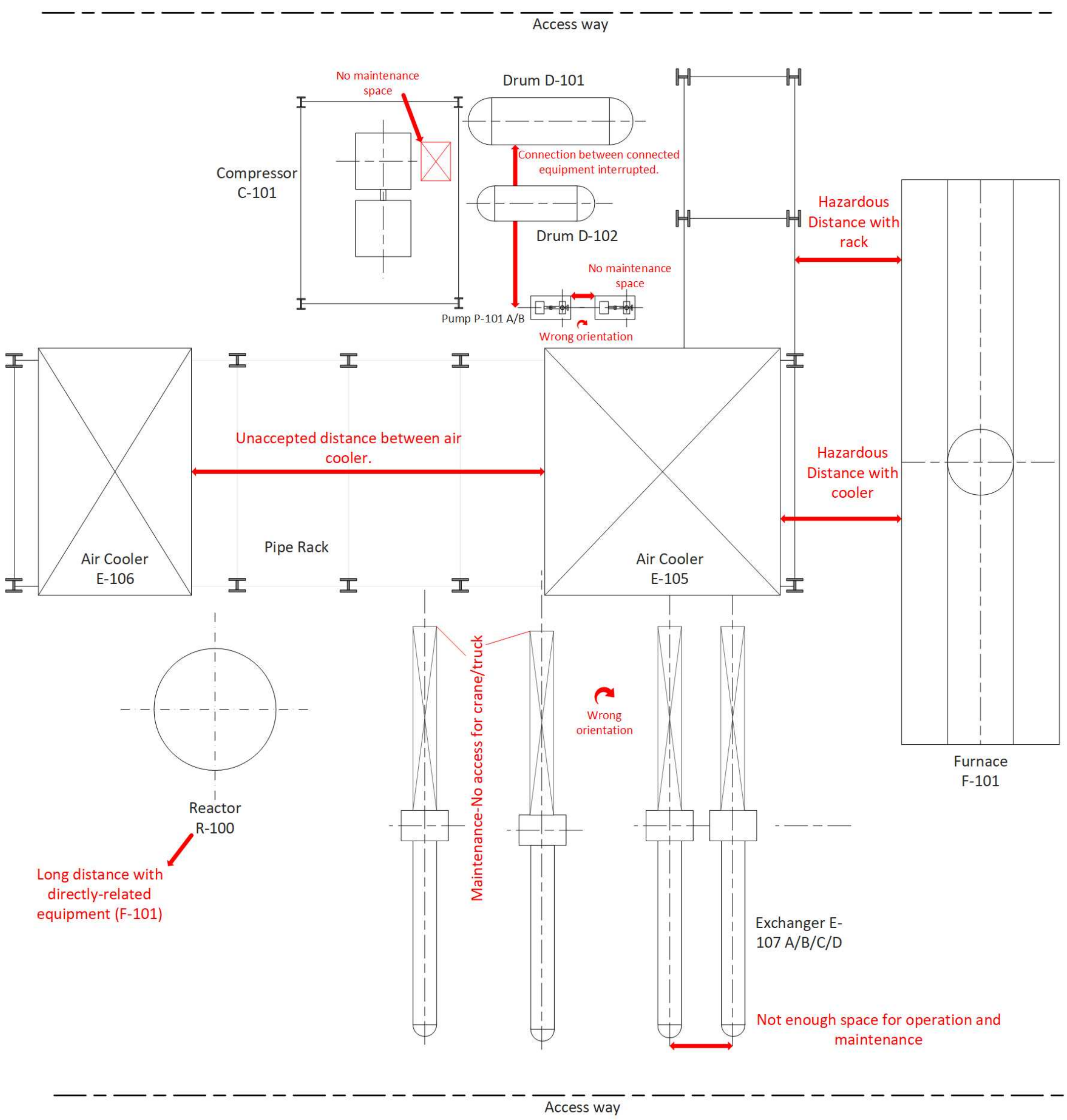


Figure 4-24: Complete plant scenario 2

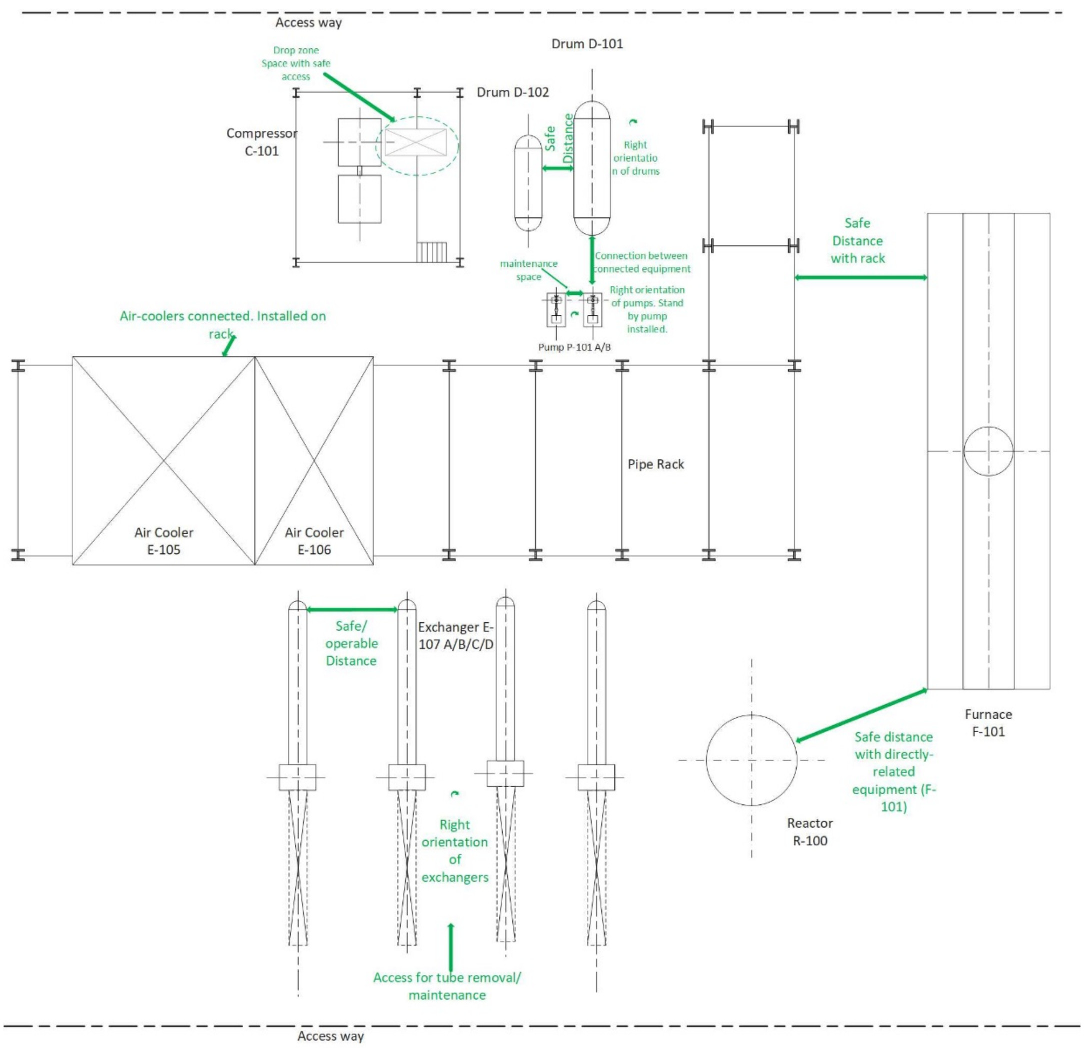


Figure 4-25: Complete plant scenario 3

The comments in red are the flaws in the equipment arrangement that were detected by the algorithm and its knowledge base. Incorrect orientation of equipment, clashes in the arrangement, incorrect location for installation, and ignoring safe distance and equipment spacing are some of the examples here. The last figure (scenario 3) with comments in green is one of the scenarios with no flaws detected by the algorithm. The equipment arrangement here considered the right location, right orientation, and safe distance between equipment. It should be emphasized that in the background, the algorithm worked on a large set of data matrices of 2D spatial points, with their associated meta-data, which is how it was able to try all the possible scenarios and validate each arrangement.

4.6 Summary and discussion

Considering the time/resource limitations for equipment arrangement, its important role for the safety of the plant, as well as the huge number of possible scenarios to arrange equipment in each process plant and large number of specifications and engineering practices that should be checked for each scenario, it is important to consider an automated method to assist in this case. In this chapter, a new algorithm was proposed to automate the equipment arrangement in the process industry. This algorithm created point-based mathematical models of each equipment and the plant area, created all the possible scenarios for equipment arrangement and checked the validity of the design in each scenario. Best practices and engineering specifications (e.g., safe distance between equipment) were encoded into the program environment for validation. The case studies show its accuracy in detecting arrangement faults and its ability to short-list the best scenarios.

the effectiveness of this algorithm is because it eliminates the time/resource limitations for equipment arrangement in the basic design of process plants. Besides, it adds another safety layer during the design stage. It provides the design team with the opportunity to check all possible equipment arrangement scenarios, without affecting the traditional routine in developing plot plans in process plants and works as a safe assistant in ensuring the safe and economic design, in a very limited time.

Chapter 5 Automation of piping and stress analysis

Piping design, pipe support design, and piping stress analysis are considered as some of the activities that are prone to human error in the process plant industry. A failure in a comprehensive analysis may result in the loss of human lives during pre-commissioning, commissioning, or operation, as well as catastrophic effects on the environment through the leakage of hazardous material.

A lack of communication between the design and analysis team members could be considered as one of the main drawbacks in the design process. Traditional methods of design require the designers to update the stress analysis team regarding any changes in the equipment arrangement, pipe routes, or pipe support locations and type. A failure in proper communication and updating the analysis team will result in a plant design, prone to failure due to a lack of a proper stress analysis. In this chapter, the automation of piping and pipe supporting design and piping stress analysis has been proposed to deal with current challenges in the industry. This chapter is divided into three main sections. Section 5.1 illustrates the details of the algorithm for piping design between two equipment and the algorithm for the automation of pipe support. Section 5.2 introduces an ML approach for the automation of stress analysis. Finally, in Section 3, the use of supervised ML for stress analysis and the results of the developed prediction model are further discussed in a case study.

5.1 Automation of piping design and supporting

Figure 5-1 illustrates the transformation from the traditional design–analysis workflow to the automated flow, in which ML is being used. It starts with capturing data from the equipment arrangement. These data are then used in creating all possible pipe routes and pipe supports between each two pieces of equipment. ML is then used in the automation of piping stress analysis.

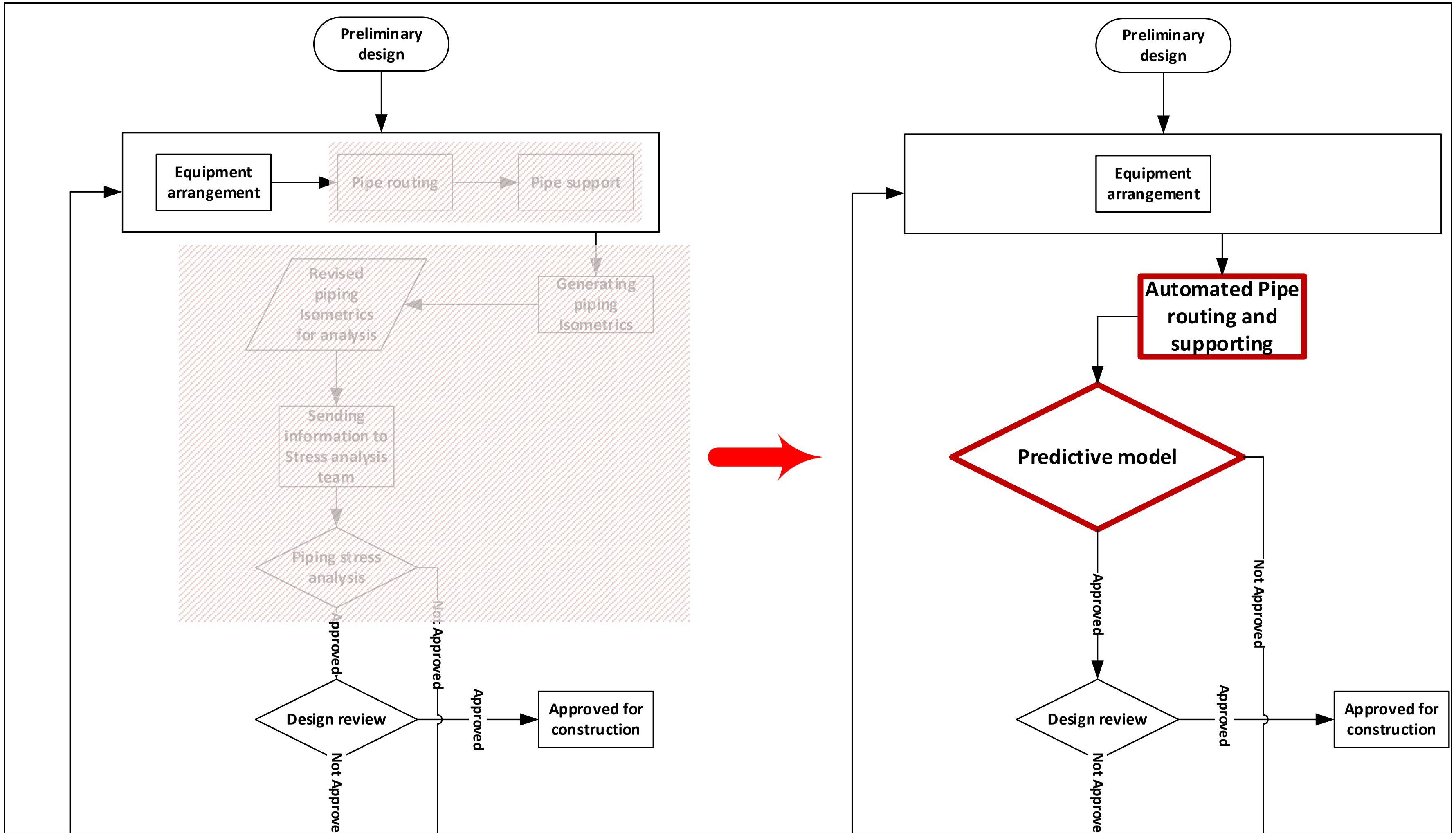


Figure 5-1: From traditional to automated design–analysis workflow

5.1.1 Generating possible pipe routes

The required data at this stage are the coordinates of the start and end points of the route of the pipe, and the direction of the route from each equipment. Figure 5-2 below is shows an example in a 3D environment:

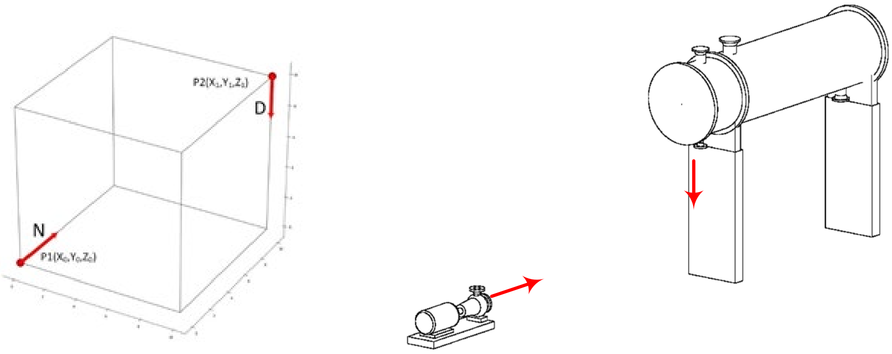


Figure 5-2: Two equipment, two nozzles in a 3D environment

A 3D grid pattern (Figure 5-3) is required to set the points in the space between two points.

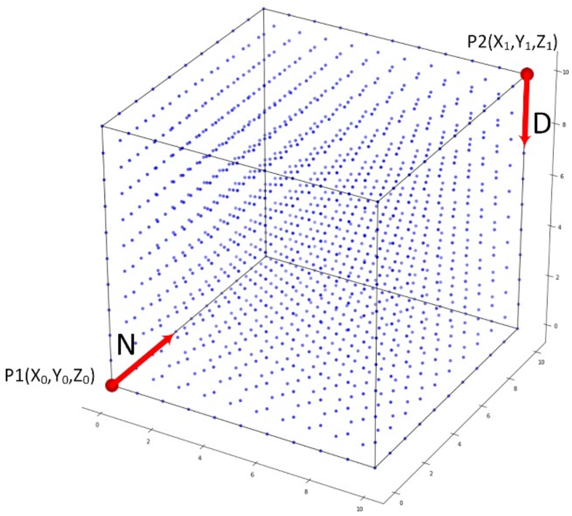


Figure 5-3: 3D grid pattern between two nozzles

Then, the distances in each direction are

$$DistEW = |X_0 - X_1|$$
$$DistNS = |Y_0 - Y_1|$$
$$DistUD = |Z_0 - Z_1|$$

The next step is to define the range for each of the distances in the different directions:

$$R_{EW} = [1, 2, 3, \ldots, DistEW]$$
$$R_{NS} = [1, 2, 3, \ldots, DistNS]$$
$$R_{UD} = [1, 2, 3, \ldots, DistUD]$$

Traveling from point 1 to point 2 for the pipe implies to complete the gap between two points in each axis. There could be thousands of route options from point 1 to point 2. A sub-list of routes that satisfy this condition is selected:

For EW axis, $R_{EW-k} \subset R_{EW}$ and $R_{EWi} \in R_{EW}$,

$R_{EW-k} = [R_{EW1}, R_{EW2}, \ldots, R_{EWn}]$ is accepted,

If: $\sum_{i=1}^{i=n} R_{EWi} = DistEW$

If approved, R_{EW-k} is renamed to $R_{EW-App-k}$.

For each axis, there exists a list of approved combinations:

$R_{EW-App} = \left[R_{EW-App-1}, R_{EW-App-2}, \ldots, R_{EW-App-m}\right]$ (for EW axis)

$R_{NS-App} = \left[R_{NS-App-1}, R_{NS-App-2}, \ldots, R_{NS-App-n}\right]$ (for NS axis)

$R_{UD-App} = \left[R_{UD-App-1}, R_{UD-App-2}, \ldots, R_{UD-App-p}\right]$ (for UD axis)

A combination of them is creates a pipe route that travels from point 1 to 2. That is:

For $R_{EW-App-i} \in R_{EW-App}$, $R_{NS-App-j} \in R_{NS-App}$ and $R_{UD-App-k} \in R_{UD-App}$:

$$Combination_t = \left[\left[R_{EW-App-i}\right], \left[R_{NS-App-j}\right], \left[R_{UD-App-k}\right]\right]$$

It should be noted that not all these combinations are approved. For example, in the case that both equipment nozzles are in the UD axis, the number of items in R_{UD-App} should be more than 2. The comprehensive list of logical conditions for approved combinations is as follows:

$$\forall App-Combination_t \subset Combination_t, R_{NS-App-i} \in App-Combination_t, P1\_Dir='NS' \wedge P2\_Dir='NS' \rightarrow len\left(R_{NS-App-i}\right) > 2$$
$$\forall App-Combination_t \subset Combination_t, R_{NS-App-i} \in App-Combination_t, P1\_Dir='EW' \wedge P2\_Dir='EW' \rightarrow len\left(R_{EW-App-i}\right) > 2$$
$$\forall App-Combination_t \subset Combination_t, R_{UD-App-i} \in App-Combination_t, P1\_Dir='UD' \wedge P2\_Dir='UD' \rightarrow len\left(R_{UD-App-i}\right) > 2$$
$$\forall App-Combination_t \subset Combination_t, R_{NS-App-i} \in App-Combination_t, P1\_Dir='NS' \vee P2\_Dir='NS' \rightarrow len\left(R_{NS-App-i}\right) > 1$$
$$\forall App-Combination_t \subset Combination_t, R_{EW-App-i} \in App-Combination_t, P1\_Dir='EW' \vee P2\_Dir='EW' \rightarrow len\left(R_{EW-App-i}\right) > 1$$
$$\forall App-Combination_t \subset Combination_t, R_{UD-App-i} \in App-Combination_t, P1\_Dir='UD' \vee P2\_Dir='UD' \rightarrow len\left(R_{UD-App-i}\right) > 1$$

An approved combination will be a set like the example below.

Because the algorithm works on the sequence of lists, in order to create other possible combinations, i.e., other routes, items inside each sub-list can be shuffled to its ultimate combination limit. Therefore, depending on the length of each sub-list, there are other combinations of points for each approved combination.

$$App-Combination_t = \left[\left[\underbrace{R_{EW-App1}, R_{EW-App2}, \ldots, R_{EW-Appm}}_{\text{EW points}}\right], \left[\underbrace{R_{NS-App1}, R_{NS-App2}, \ldots, R_{NS-Appn}}_{\text{NS points}}\right], \left[\underbrace{R_{UD-App1}, R_{UD-App2}, \ldots, R_{UD-Appp}}_{\text{UD points}}\right]\right]$$

After all approved combinations have been developed, depending on the direction of the first and end points, the first items of each related list are stored separately.

For example, for the case that we have P1_Dir = NS and P2_Dir = UD, the first items of both NS points and UD points are selected and used as the first and last sections of the pipe route:

$$App-Combination_t = \left[\underbrace{R_{NS-App1}}_{\text{First Section}}, \left[\underbrace{R_{EW-App1}, R_{EW-App2}, \ldots, R_{EW-Appm}}_{\text{EW points}}\right], \left[\underbrace{R_{NS-App2}, \ldots, R_{NS-Appn}}_{\text{NS points}}\right], \left[\underbrace{R_{UD-App2}, \ldots, R_{UD-Appp}}_{\text{UD points}}\right], \underbrace{R_{UD-App1}}_{\text{Last Section}}\right]$$

Figure 5-4 below shows the result of using the first and last section of the combination of which the length in NS axis is R_{NS_App1} and the length in UD axis is R_{UD_App1}.

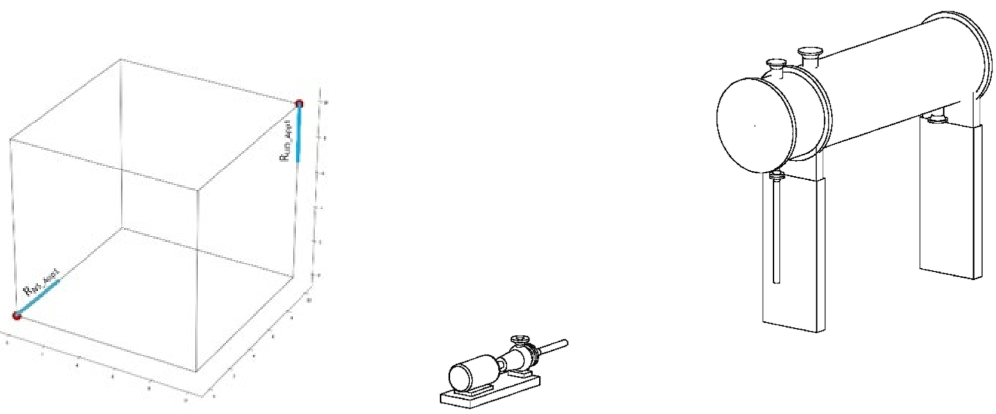


Figure 5-4: Specifying two pipe sections for two equipment: Constraint in axis and direction

In the next step, all three lists in the 3 axes are combined and shuffled to create another combination:

Creating combinations of the list

$$App-Combination_t=\left[R_{NS-App1},\left[R_{EW-App1},R_{EW-App2},\ldots,R_{EW-Appm},R_{NS-App2},\ldots,R_{NS-Appn},R_{UD-App2},\ldots,R_{UD-Appp}\right],R_{UD-App1}\right]$$

The final combination may look like the list shown below:

$$App-Combination_i=\left[R_{NS-App1},R_{EW-App2},R_{NS-App2},R_{EW-Appm},R_{UD-Appp},R_{NS-Appn},R_{UD-App2},R_{UD-App1}\right]$$

A 3D representation of the list above is shown in Figure 5-5 :

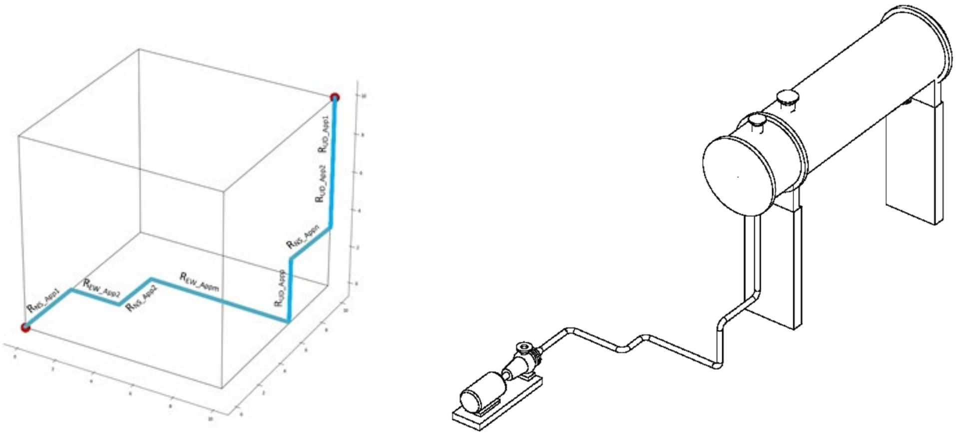


Figure 5-5: Possible route from exchanger to pump

Another possible combination can be represented as below:

$$App-Combination_j=\left[R_{NS-App1},R_{UD-App2},R_{NS-App2},R_{UD-Appp},R_{EW-App2},R_{NS-Appn},R_{EW-Appm},R_{UD-App1}\right]$$

A 3D representation of it is illustrated in Figure 5-6:

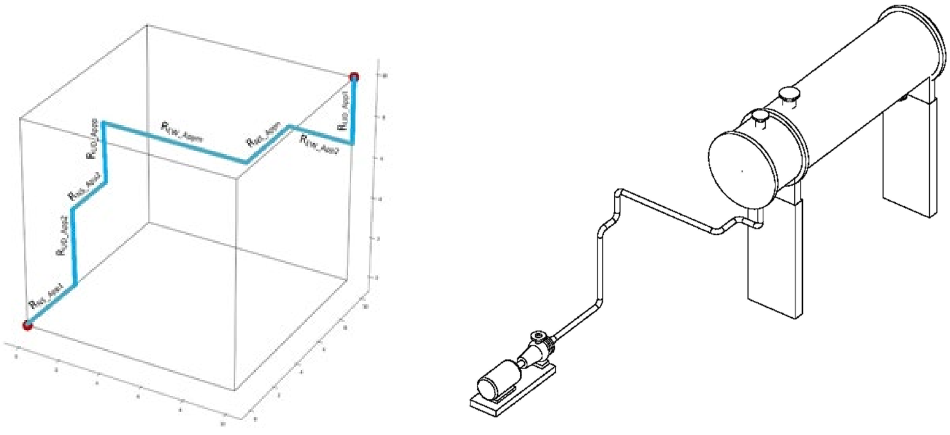


Figure 5-6: Another possible route from exchanger to pump

5.1.2 Determination of elbow number and location

One of the major types of input data for the stress analysis automation algorithm is the number of elbows and their location. In order to calculate the number and location of elbows in each combination, the algorithm iterates through the list and identifies the items that are different from the previous ones. Meanwhile, it creates a summary of each section's length to calculate the location of the elbow.

$$App-Combination_i=\left[R_{NS-App1},R_{EW-App2},R_{NS-App2},R_{EW-Appm},R_{UD-Appp},R_{NS-Appn},R_{UD-App2},R_{UD-App1}\right]$$

Dir change | Dir change | Dir change | Dir change | Dir change | Dir change | No Dir change

$$\left(X_0,Y_0+R_{NS-App1},Z_0\right)$$
$$\left(X_0+R_{EW-App2},Y_0+R_{NS-App1},Z_0\right)$$
$$\left(X_0+R_{EW-App2},Y_0+R_{NS-App1}+R_{NS-App2},Z_0\right)$$
$$\left(X_0+R_{EW-App2}+R_{EW-Appm},Y_0+R_{NS-App1}+R_{NS-App2},Z_0\right)$$
$$\left(X_0+R_{EW-App2}+R_{EW-Appm},Y_0+R_{NS-App1}+R_{NS-App2},Z_0+R_{UD-Appp}\right)$$
$$\left(X_0+R_{EW-App2}+R_{EW-Appm},Y_0+R_{NS-App1}+R_{NS-App2}+R_{NS-Appn},Z_0+R_{UD-Appp}\right)$$

From the coordination of the elbows, a list of coordination for all the points between the start and end points of the route can be developed. Figure 5-7 shows the graphical representation.

$$\text{Total\_Points}=$$
$$\left[(X_0,Y_0,Z_0),\ldots,\left(X_0,Y_0+R_{NS-App1},Z_0\right),\ldots,\left(X_0+R_{EW-App2},Y_0+R_{NS-App1},Z_0\right),\ldots,\left(X_0+R_{EW-App2},Y_0+R_{NS-App1}+R_{NS-App2},Z_0\right),\ldots,(X_1,Y_1,Z_1)\right]$$

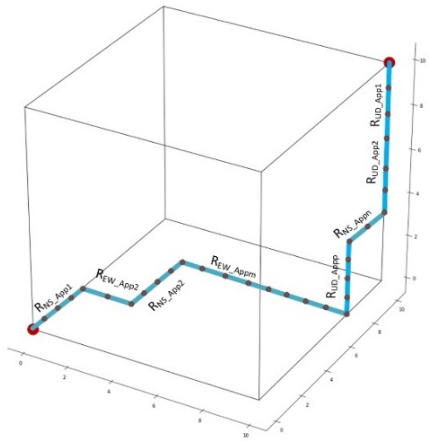


Figure 5-7: All the points on the pipe route

5.1.3 Piping support combination

If we consider "Shoe," "Guide," and "Anchor" as three main piping support types for any piping route, and set the maximum of n supports for each route, the possible combinations for support types are given by:

$$
\begin{aligned}
&n \langle \text{Total\_Points} \\
&\text{Support\_Types}(\text{ST}) = [Shoe, Guide, Anchor] \\
&\text{Possible\_Combinatons}(\text{m}) = len(Support\_Types)^{n} = 3^{n} \\
&\text{Support\_Combinations} = [[S_{11}, S_{12}, \ldots, S_{1n}], [S_{21}, S_{22}, \ldots, S_{2n}], \ldots, [S_{m1}, S_{m2}, \ldots, S_{mn}]]
\end{aligned}
$$

The next step is to randomly assign a pipe support to each point. Various combinations of point-supports can be developed and analyzed by this method. Below is an illustration of two combinations and Figure 5-8 shows the 3D model design for this configuration.

$$\text{Total\_Points} = [(X_0, Y_0, Z_0), \ldots, (X_0, Y_0 + R_{NS-App1}, Z_0), \ldots, (X_0 + R_{EW-App2}, Y_0 + R_{NS-App1}, Z_0), \ldots, (X_0 + R_{EW-App2}, Y_0 + R_{NS-App1} + R_{NS-App2}, Z_0), \ldots, (X_1, Y_1, Z_1)]$$

$$\text{Support\_Combinations} = [[S_{11}, S_{12}, \ldots, S_{1n}], [S_{21}, S_{22}, \ldots, S_{2n}], \ldots, [S_{m1}, S_{m2}, \ldots, S_{mn}]]$$

$$\text{Total\_Points} = [(X_0, Y_0, Z_0), \ldots, (X_0, Y_0 + R_{NS-App1}, Z_0), \ldots, (X_0 + R_{EW-App2}, Y_0 + R_{NS-App1}, Z_0), \ldots, (X_0 + R_{EW-App2}, Y_0 + R_{NS-App1} + R_{NS-App2}, Z_0), \ldots, (X_1, Y_1, Z_1)]$$

$$\text{Support\_Combinations} = [[S_{11}, S_{12}, \ldots, S_{1n}], [S_{21}, S_{22}, \ldots, S_{2n}], \ldots, [S_{m1}, S_{m2}, \ldots, S_{mn}]]$$

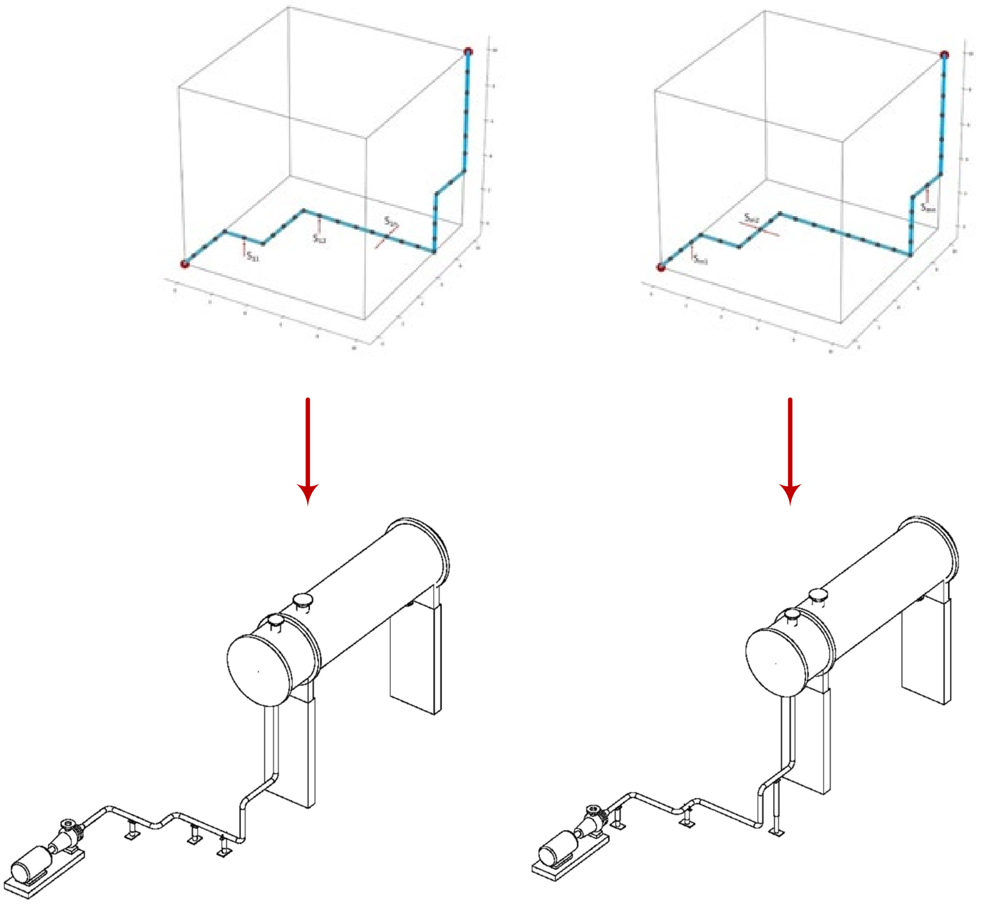


Figure 5-8: Two possible support design for the same pipe route

5.2 Machine learning for stress analysis

With the completion of the piping design and pipe support design, and with access to extracted data from both these activities, the piping stress analysis can begin. In order to automate the stress analysis, a supervised ML algorithm for classification, called GBM, is proposed. It should be noted that the classical supervised learning approach requires enormous (and often expensive) tasks in order to provide the explanatory and target variables in a specific domain. A database of 3D models and the resulting stress analysis helps in creating the predictive model to predict the failure/non-failure of the new pipe routes.

GBM is an ML process for regression and classification, in which new models are fitted in order to create a better estimate of the predicted variable. It uses an ensemble of weak learners (e.g., decision trees) to create a more complex prediction tool.

GBM has been very successful in industry and also in ML competitions (Bissacco, Yang, & Soatto, 2007; Hutchinson, Liu, & Dietterich, 2011; Johnson & Zhang, 2014; Pittman & Brown, 2011). The GBM algorithm starts with the process of computing the deviation of residuals for each partition and continues with determining the best data partitioning in each stage. Next, the successive model fits the residuals from the previous stage and develops a new model to reduce the residual variance. The reduction in the residual variance follows the functional gradient descent technique, in which it minimizes the residual variance by descending its derivatives.

Below is the algorithm GBM (Max Kuhn, n.d.):

```
Define sets of model parameter values to evaluate
For each parameter set do
    for each resampling iteration do
        Hold-out specific samples
        [Optional] Pre-process the data
        Fir the model on the remainder
        Predict the hold-out samples
    end
    Calculate the average performance across hold-out predictions
End
Determine the optimal parameter set
Fit the final model to all the training data using the optimal parameter set
```

5.2.1 Prediction model formulation

Because “supervised learning” is proposed, each pipe route should be modeled in stress analysis software (e.g., CAESAR II) along with the supports. Data about the pipe, including the material, thickness, diameter, and design and operation temperature and pressure, should be entered. After finalizing the analysis, the result (i.e., failure or non-failure) should be recorded along with the data for developing the prediction model. These data include the location of elbows, supports, type of supports, location of head and tail of the pipe, and all the other data that were previously entered into the analysis application. The result (i.e., failure or non-failure of the pipe route) is be considered as the “target variable” and the remaining variables (e.g., number of elbows and number of supports) are “explanatory variables” for the ML model and are used to predict new pipe routes, with new explanatory variables. The prediction model can be used to predict new pipe routes. Any route is introduced as a new “test” dataset and the stress analysis result can be predicted. Figure 5-9 shows the workflow.

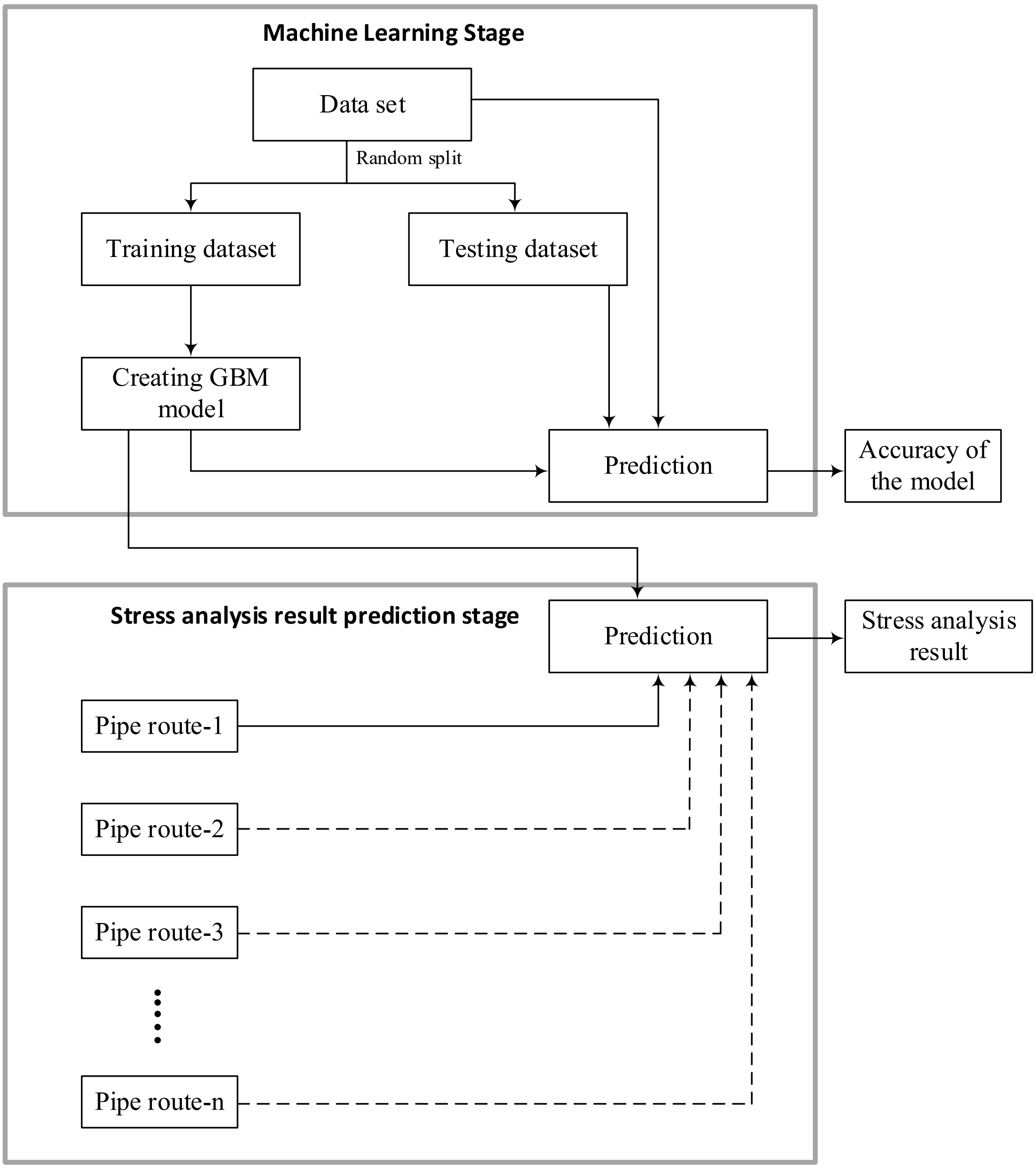


Figure 5-9: Creating prediction model with GBM and using it to predict the stress analysis result of new pipe routes

The variables for the GBM method are defined as follows:

p: predictive variable

r: response variable

M: number of iteration steps for optimization

θ: parameter estimation

$\hat{f}_0$: initial guess

$\left\{\hat{f}_i\right\}_{i=1}^{M}$: function increments (boosts)

λ : shrinkage parameter

$M_{\max}$: maximum number of iterations

K: cross-validation parameter

K: Number of data points

The result of the stress analysis is the dataset $(p,r)^{N}{}_{i=1}$, where $p=(p_1,\ldots,p_d)$ is the list of explanatory variables and y is the response variable label.

The explanatory variables $p=(p_1,\ldots,p_d)$, in the case of piping stress analysis and for this study, are those variables affecting the analysis report. They are listed below:

T_H: pipe tail location

n: number of elbows

m: number of supports

EL_i_P ($i \in \{1,\cdots,n\}$): elbow locations

EL_i_{cd} ($i \in \{1,\cdots,n\}$): elbow change in direction

SUP_j_P ($j \in \{1,\cdots,m\}$): support locations

SUP_j_{ty} ($j \in \{1,\cdots,m\}$): support types

The response variable r here is:

r: analysis result (failure or non-failure of pipe)

T_d: design temperature

T_o: operation temperature

P_d: design pressure

P_o: operation pressure

D_{nom}: nominal diameter of pipe

P_s: pipe service

5.2.2 Machine learning algorithm: gradient boosting method

The model training is carried out based on the theory of the GBM method (Natekin & Knoll, 2013) using the piping design data.

In the GBM method, an unknown functional dependence $p \xrightarrow{f} r$ is reconstructed with $\widehat{f}(p)$ in order to minimize the specified loss function $\psi(r, f)$:

$$\hat{f}(p) = r,$$
$$\hat{f}(p) = \arg\min_{f(p)} \psi(r, f(p))$$

The response variable here is binary, i.e., $r \in \{0,1\}$ in which, "0" indicates the failure of the pipe route in the stress analysis test and "1" illustrates the approval of the route. Because the response variable is binomial, a binomial loss function ψ can be used for creating the predictive model.

Here the optimization problem is changed to parameter estimation, by:

$$\hat{f}(p) = f(p, \hat{\theta}),$$

$$\hat{\theta} = \arg\min_{\theta} E_p \left[E_r \left(\psi \left[y, f(p, \theta) \right] \right) | p \right]$$

With N iterations, the parameter estimation can be illustrated as below:

$$\hat{\theta} = \sum_{i=1}^{N} \hat{\theta}_i$$

Here, the "steepest gradient descent" is used for the parameter estimation. With K data points in $(p, r)^K{}_{i=1}$, the empirical loss function $J(\theta)$ is required to be reduced:

$$J(\theta) = \sum_{i=1}^{K} \psi \left(r_i, f\left(p_i, \hat{\theta} \right) \right)$$

$\hat{\theta}_0$ is then estimated for each iteration t and a compiled parameter estimate $\hat{\theta}^t$ is obtained:

$$\hat{\theta}^t = \sum_{i=0}^{t-1} \hat{\theta}_i$$

The gradient of the loss function $\nabla J(\theta)$ is calculated:

$$\nabla J(\theta) = \{\nabla J(\theta_i)\} = \left[\frac{\partial J(\theta)}{\partial J(\theta_i)}\right]_{\theta=\hat{\theta}^t}$$

A new incremental parameter estimate is then calculated and added to the ensemble:

$$-\nabla J(\theta) \rightarrow \hat{\theta}_t$$

It should be noted that a boosting method has been used here instead of conventional ML techniques for optimization. The main difference is that the function estimate $\hat{f}$ is parameterized in the additive functional form.

A new function is required to be the most parallel to $\{g_t(p_i)\}^K{}_i = 1$:

$$g_t(p) = E_r\left[\frac{\partial\psi(r, f(p))}{\partial f(p)}|p\right]_{f(p)=\hat{f}^{t-1}(p)}$$

Using the "least-squares minimization" method for optimization purposes:

$$(\rho_t, \theta_t) = \arg\min_{\rho,\theta}\sum_{i=1}^{K}\left[-g_t(p_i) + \rho h(p_i, \theta)\right]^2$$

The result depends on $\psi(r, f)$ and $h(p, \theta)$. Therefore, the next step is to choose the right "loss function" and "base-learner."

Classifying the loss function depends on the response variable. As the response variable is categorical here (i.e., $r \in \{0,1\}$), either a Binomial or Adaboost loss function can be used. If $\bar{r} = 2r - 1$ and $\bar{r} \in \{-1,1\}$ are assumed, the probability of the response can be calculated by (also called the Bernoulli loss):

$$\psi(p, f) = \log(1 + \exp(-2\bar{p}f))$$

or the Adaboost loss:

$$\psi(p, f) = \exp(-\bar{p}f)$$

The base-learner can be chosen from either "decision trees," "linear models," or "smooth models."

Although many other models can be used in gradient boosting, "decision trees" are one of the most common base models. Every decision tree can be used to reduce some loss function. We add a root node for the tree and all nodes receive a list of rows as input and the root receives the entire training set. Each node asks a true/false question about one of the features and in response to this question, we split the data into two subsets. These subsets then become the input to two child-nodes we add to the tree. The goal of the question is to un-mix the labels as we proceed down. In other words, we are trying to create the purest possible distribution of the labels in each node. Creating effective trees is achieved through using information gain, to quantify the effectiveness of a question to reduce the uncertainty, and "Gini impurity," to quantify the amount of uncertainty in a single node. The process of asking questions continues until we obtain the final result and no further question could be asked.

Figure 5-10 below is an illustration of boosting for decision trees:

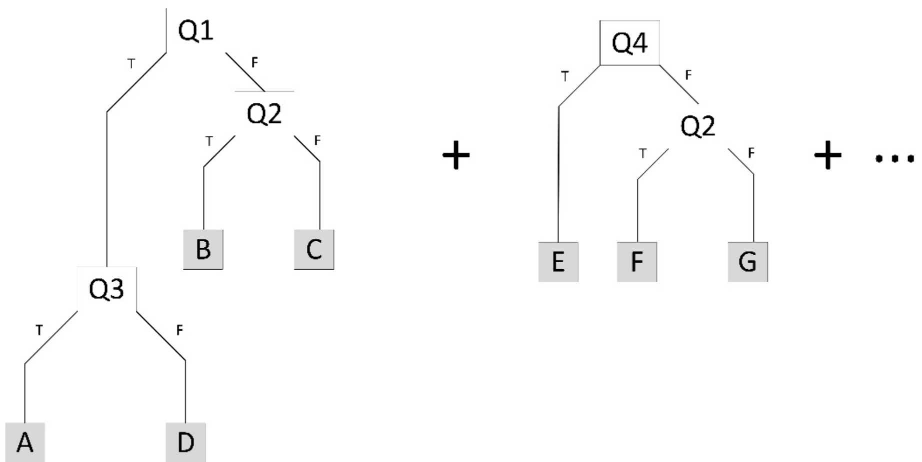


Figure 5-10: Boosting for decision trees

One of the major problems in ML is "overfitting." This is when the ML model predicts the training set instead of the new data. In this case, overfitting means that the model can predict the failure/non-failure of a pipe route from the training data, but it fails when it comes to the new pipe routes and new support positions. There are some general approaches in ML to prevent the model from overfitting, which can be used in the GBM method.

One of the best methods of preventing a model from overfitting is "cross-validation," which is used in developing the model here. In this method, all the data are used and different models are tested by different portions of the data.

5.3 Case study

In this case study, base data were adopted through the application of the Caesar II stress analysis software package. One hundred pipe routes were analyzed and the results (failure or non-failure) of the routes were recorded. Table 5-1 shows part of this dataset. The dataset is first analyzed via explanatory data analysis and a graphical representation of its content. GBM is then used to create the prediction model; 75% of the dataset is used as a training dataset and 25% is used to check the accuracy of the prediction model. Finally, 10 new pipe routes are introduced to the prediction model and the prediction results are compared to the stress analysis result using the analysis software (Caesar II).

5.3.1 Data generation

In order to increase the size of the training dataset, all the pipe routes, along with their supports were rotated around the gravity axis (i.e., the Y-axis in in this case). This is done with the knowledge that rotating pipes around the gravity axis does not affect the final result. This way, every data point from the analysis is extended to 36 data points, with different elbow and support locations. It improves the size of the dataset, in its training process toward developing a prediction model. Figure 5-11 shows the graphical model of this process.

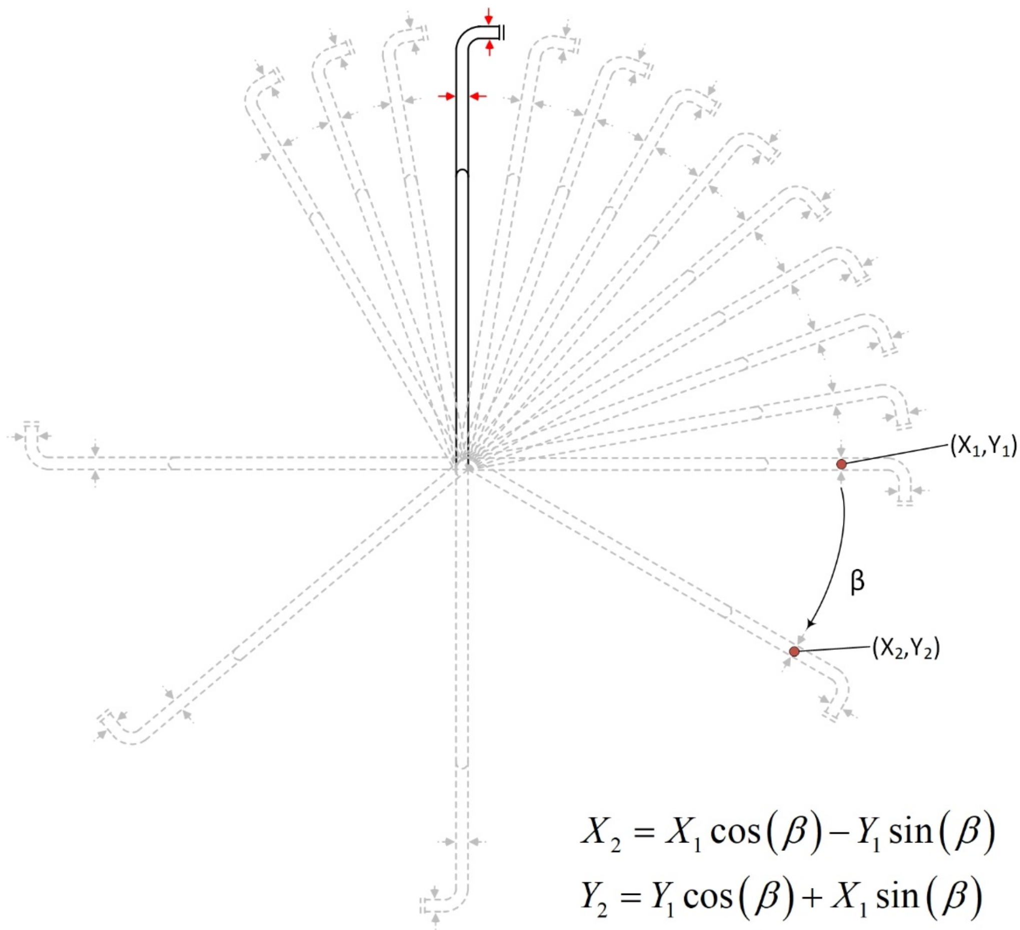


Figure 5-11: Extending the training dataset by rotating the pipes around the gravity axis

Table 5-1: Piping stress analysis dataset

Line Number	POS-H-X	POS-H-Y	POS-H-Z	POS-T-X	POS-T-Y	POS-T-Z	POS-EL-1-X	POS-EL-1-Y	POS-EL-1-Z	DI-EL-1	...	POS-SUPP-1-X	POS-SUPP-1-Y	POS-SUPP-1-Z	TY-SUPP-1	NU-ELL	NU_SUPP	SUSFail
Line 1	100000	100000	100000	130000	100000	100000	100000	100000	100000	NO	...	106000	100000	100000	SHOE	0	4	0
Line 2	100000	100000	100000	130000	100000	100000	100000	100000	100000	NO	...	106000	100000	100000	SHOE	0	6	0
Line 3	100000	100000	100000	130000	100000	100000	100000	100000	100000	NO	...	106000	100000	100000	SHOE	0	6	0
Line 4	100000	100000	100000	127000	101000	100000	127000	100000	100000	YES	...	106000	100000	100000	SHOE	1	6	0
Line 5	100000	100000	100000	125000	101000	102000	118000	100000	100000	YES	...	106000	100000	100000	SHOE	3	6	0
Line 6	100000	100000	100000	125000	106000	100000	118000	100000	100000	YES	...	106000	100000	100000	SHOE	3	6	0
Line 7	100000	100000	100000	122000	106000	103000	118000	100000	100000	YES	...	106000	100000	100000	SHOE	4	3	1
Line 8	100000	100000	100000	122000	105000	103000	118000	100000	100000	YES	...	106000	100000	100000	SHOE	4	5	0
Line 9	100000	100000	100000	122000	105000	104000	118000	100000	100000	YES	...	112000	100000	100000	SHOE	3	5	0
Line 10	100000	100000	100000	119000	105000	101000	100000	100000	97000	YES	...	103000	100000	97000	SHOE	4	5	0
Line 11	100000	100000	100000	119000	108000	104000	100000	103000	100000	YES	...	109000	103000	100000	SHOE	4	5	0
Line 12	100000	100000	100000	119000	108000	104000	100000	103000	100000	YES	...	103000	103000	100000	STOP	4	3	1
Line 13	100000	100000	100000	119000	108000	104000	100000	103000	100000	YES	...	103000	103000	100000	SHOE	4	3	1
Line 14	100000	100000	100000	119000	108000	102000	100000	103000	100000	YES	...	103000	103000	100000	SHOE	4	5	0
Line 15	100000	100000	100000	119000	108000	102000	100000	103000	100000	YES	...	103000	103000	100000	SHOE	4	3	1
Line 16	100000	100000	100000	119000	103000	100000	100000	103000	100000	YES	...	103000	103000	100000	SHOE	4	3	1
Line 17	100000	100000	100000	119000	103000	93000	100000	103000	100000	YES	...	103000	103000	100000	SHOE	4	4	0
Line 18	100000	100000	100000	119000	97000	105000	100000	97000	100000	YES	...	103000	97000	100000	SHOE	4	4	0
Line 19	100000	100000	100000	119000	97000	96000	100000	97000	100000	YES	...	103000	97000	100000	SHOE	4	5	0
Line 20	100000	100000	100000	119500	100000	105000	115500	100000	100000	YES	...	103000	100000	100000	SHOE	3	5	0
Line 21	100000	100000	100000	119500	103000	103000	115500	100000	100000	YES	...	103000	100000	100000	SHOE	3	6	0
Line 22	100000	100000	100000	111500	106000	103000	109500	100000	100000	YES	...	103500	100000	100000	SHOE	4	4	0
Line 23	100000	100000	100000	111000	106000	104000	100000	100000	101000	YES	...	103000	100000	101000	SHOE	5	5	0
Line 24	100000	100000	100000	111000	100000	99000	100000	100000	96000	YES	...	103000	100000	96000	GUIDE	5	3	0
Line 25	100000	100000	100000	109000	106000	104000	100000	100000	101000	YES	...	103000	100000	101000	STOP	4	3	1
Line 26	100000	100000	100000	107000	106000	100000	100000	100000	97000	YES	...	103000	100000	97000	GUIDE	5	3	1
Line 27	100000	100000	100000	111000	111000	100000	100000	105000	100000	YES	...	100000	100000	100000	NOSUPP	4	0	0
Line 28	100000	100000	100000	111000	111000	100000	100000	105000	100000	YES	...	103000	105000	100000	GUIDE	4	2	0
Line 29	100000	100000	100000	111000	111000	100000	100000	105000	100000	YES	...	103000	105000	100000	GUIDE	4	4	0
Line 30	100000	100000	100000	109000	107000	105000	105000	100000	100000	YES	...	100000	100000	100000	NOSUPP	5	0	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

The variables in the dataset are defined as shown in Table 5-2 .

Table 5-2: Variables in the dataset

Var. number	Variable name	Variable description
1	POS.H.X	X coordination of the head of the pipe (Constant)
2	POS.H.Y	Y coordination of the head of the pipe (Constant)
3	POS.H.Z	Z coordination of the head of the pipe (Constant)
4	POS.T.X	X coordination of the tail of the pipe
5	POS.T.Y	Y coordination of the tail of the pipe
6	POS.T.Z	Z coordination of the tail of the pipe
7	POS.EL.n.X	X coordination of the nth elbow in the pipe (1<=n<=6)
8	POS.EL.n.Y	Y coordination of the nth elbow in the pipe (1<=n<=6)
9	POS.EL.n.Z	Z coordination of the nth elbow in the pipe (1<=n<=6)
10	DI.EL.n.NO	No direction change for the nth elbow in the pipe (1<=n<=6)
11	DI.EL.n.YES	Direction change for the nth elbow in the pipe (1<=n<=6)
12	POS.SUPP.n.X	X coordination of the nth support in the pipe (1<=n<=6)
13	POS.SUPP.n.Y	Y coordination of the nth support in the pipe (1<=n<=6)
14	POS.SUPP.n.Z	Z coordination of the nth support in the pipe (1<=n<=6)
15	TY.SUPP.n.GUIDE	Guide support type for the nth support in the pipe (1<=n<=6)
16	TY.SUPP.n.NOSUPP	No support for the nth support in the pipe (1<=n<=6)
17	TY.SUPP.n.SHOE	Shoe support type for the nth support in the pipe (1<=n<=6)
18	TY.SUPP.n.STOP	Stop support type for the nth support in the pipe (1<=n<=6)
19	NU.ELL	Number of elbows in the pipe
20	NU_SUPP	Number of supports in the pipe
21	SUSFail	Failure or non-failure of pipe

The constants and constraints under consideration include:

- Design, test, and operation temperature
- Design, test, and operation pressure
- Pipe schedule/thickness
- Pipe head coordination
- Equipment nozzle allowable loads
- Maximum number of elbows: 6
- Maximum number of pipe supports: 6

5.3.2 Explanatory data analysis

In the section below, the correlation between the failure of a pipe route and the explanatory variables of the models is visualized and interpreted for 3600 data points in the training dataset. It is important to consider that the failure/non-failure of every data point in the dataset depends on a variety of variables (i.e., explanatory variables) and cannot be relied/predicted by individual parameters. To help with the understanding, Figure 5-12 to Figure 5-16 are used to illustrate the pipe failure in relation to the number of elbows, supports, and head-to-tail distance.

Elbow and failure:

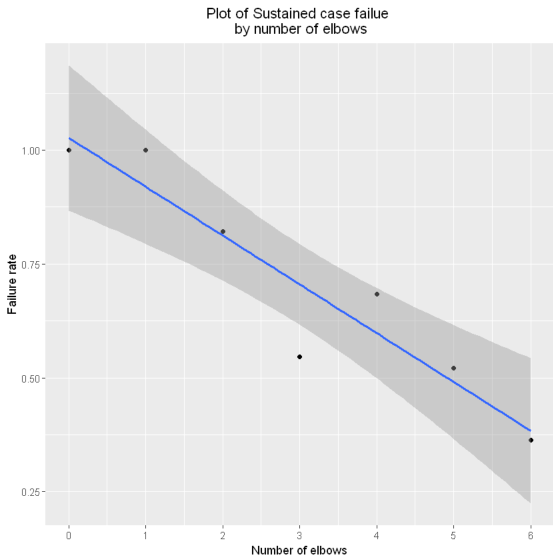


Figure 5-12: Effect of number of elbows on pipe failure rate

Figure 5-12 above shows an obvious relation between the number of elbows and the failure rate in the dataset; with the increasing number of elbows, the failure rate decreases.

Support and failure:

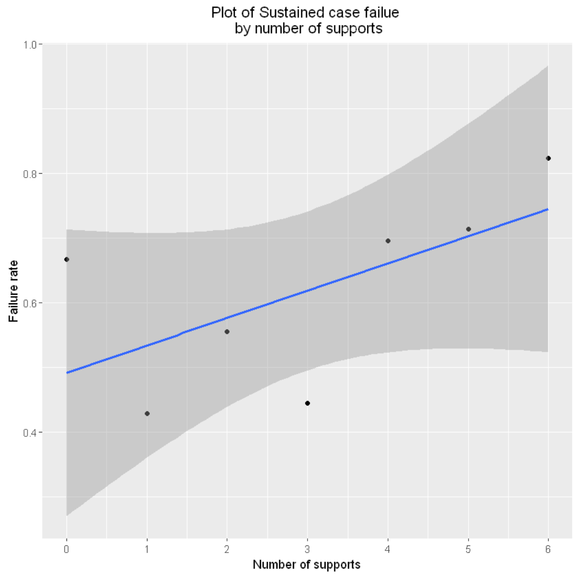


Figure 5-13: Effect of number of pipe supports on failure rate

From Figure 5-13, except for when the number of supports increased from 2 to 3, the general trend depicts that increasing support number causes an increased failure rate. It should be noted that the type of pipe support (i.e., shoes and guides) has different effects on the analysis with respect to their force axes. This graph only shows a total number and does not consider the type of support. This is the primary focus on the explanatory data analysis in the next two graphs.

Failure and number of shoe supports:

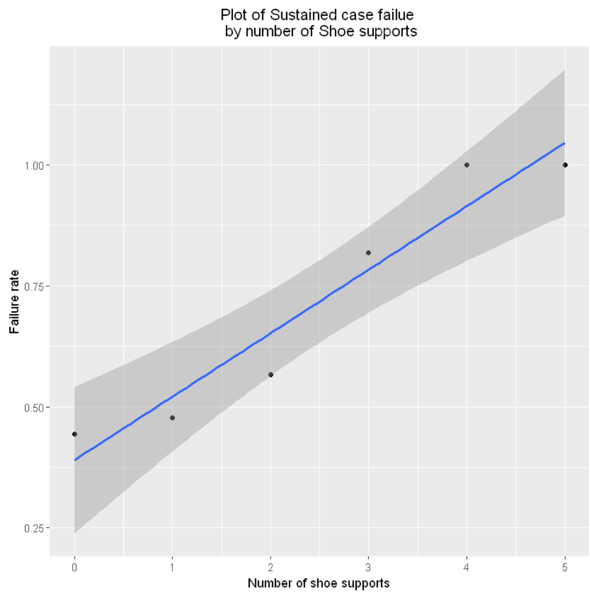


Figure 5-14: Effect of number of "Shoe" supports on failure rate

As discussed above, the number of supports, by itself, cannot be considered as the only support parameter related to the failure rate. It is also necessary to consider the type of support. The graph above (Figure 5-14) shows the relationship between the number of shoe supports and the failure rate in the whole dataset. There is obviously an increase in the failure rate with the increase in shoe supports and the slope is higher than the gradient of the supports–failure rate graph in Figure 5-13.

Failure and number of guide supports:

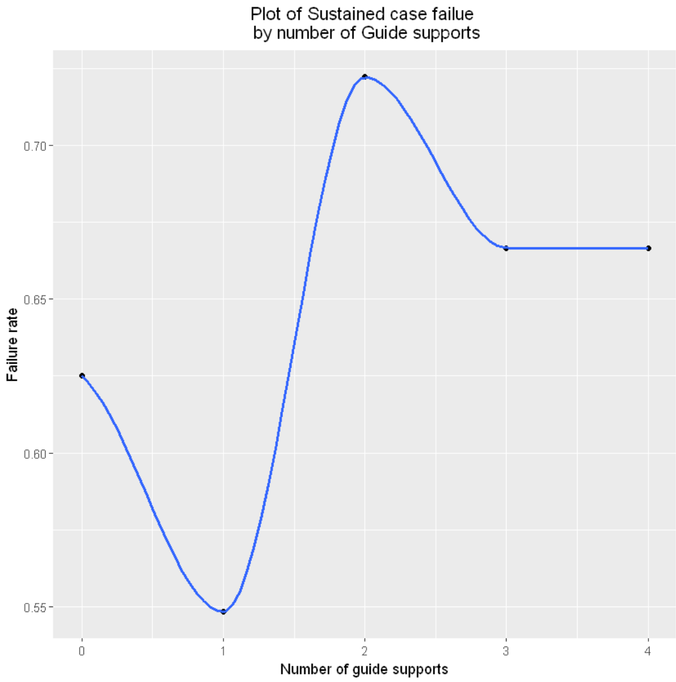


Figure 5-15: Effect of number of "Guide" supports on failure rate

The relationship between the number of guide supports and the failure rate (Figure 5-15) shows a very different trend from the shoe supports. Introducing one guide can reduce the failure from 0.63 to 0.55; however, two guide shoes brings the risk of higher failure (maximum of 0.72). The different impact from these two types of supports is due to the force axes; the shoe support is mostly used as a weight support, whereas the guide support stops the movement of the pipe along the perpendicular line on the axis of the pipe.

Head-to-tail distance:

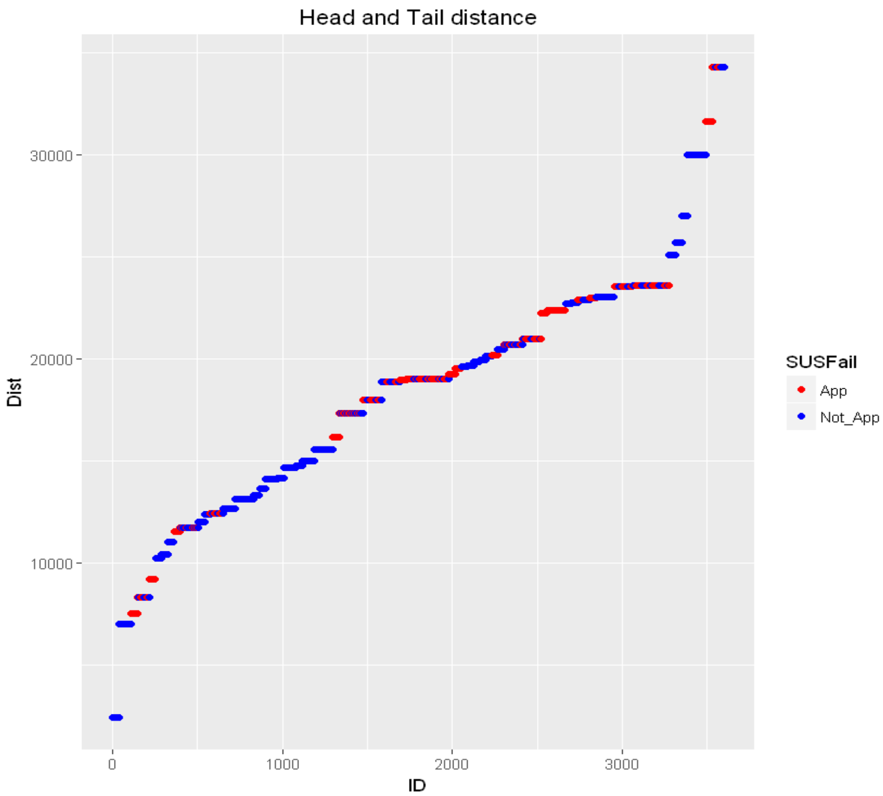


Figure 5-16: Effect of head-to-tail distance on failure rate

Figure 5-16 shows the head-to-tail distance in each route for all 3600 data points in the dataset. It is clear that the failed/non-failed routes are distributed around this graph and they are not separable. This shows a low correlation between the head-to-tail distance and the analysis result.

As discussed, GBM is an ensemble of classification trees, which takes individual decision trees and aggregates them to form a better predictor than a single decision tree would have been.

5.3.3 Accuracy verification

The dataset is split into two groups, 75% for training and 25% for testing, and GBM is used to create the model.

The variable importance is one of the outputs of the prediction model. It shows the importance level of each model input variable. Table 5-3 shows the variables in order of importance.

Table 5-3: Variable importance level: result of GBM model

Variable	Importance
POS.EL.2.Y	12.9553693
TY.SUPP.4.NOSUPP	7.8768705
POS.SUPP.2.Y	6.9308737
POS.EL.5.Y	6.1576681
POS.T.Y	5.2387948
TY.SUPP.2.SHOE	4.8641372
DI.EL.3.NO	3.5644723
NU_SUPP	3.5346972
POS.EL.6.Y	3.4808724
TY.SUPP.3.GUIDE	3.2831595
TY.SUPP.6.SHOE	3.2454378
DI.EL.5.NO	3.2082149
POS.SUPP.3.Y	2.8952452
NU.ELL	2.8773052
TY.SUPP.5.NOSUPP	2.6422876
POS.EL.1.Y	2.1370942
TY.SUPP.4.SHOE	2.0606916
TY.SUPP.6.NOSUPP	1.9041312
TY.SUPP.2.STOP	1.7380178
TY.SUPP.1.STOP	1.3891927
POS.SUPP.4.Y	1.368184
TY.SUPP.1.GUIDE	1.3667232
POS.SUPP.2.X	1.2471682
POS.EL.4.Y	1.2333643
POS.EL.3.Y	1.1414419
POS.SUPP.1.Y	1.126258
POS.SUPP.5.Y	0.9804106
POS.SUPP.6.Y	0.870888
POS.SUPP.2.Z	0.8139176
TY.SUPP.5.SHOE	0.6561795
⋮	⋮
POS.EL.2.Z	0.14409755
POS.T.Z	0.12409378
POS.SUPP.6.X	0.11163119
POS.EL.3.X	0.08204836
POS.SUPP.3.X	0.06787305
POS.EL.3.Z	0.0667646
POS.EL.5.Z	0.02979592
POS.H.X	0
POS.H.Y	0
POS.H.Z	0
DI.EL.1.NO	0
DI.EL.1.YES	0
DI.EL.2.NO	0
DI.EL.2.YES	0
POS.EL.4.X	0
POS.EL.4.Z	0
DI.EL.4.NO	0
DI.EL.4.YES	0
POS.EL.6.X	0
POS.EL.6.Z	0
DI.EL.6.NO	0
POS.SUPP.1.Z	0
TY.SUPP.1.NOSUPP	0
POS.SUPP.3.Z	0
TY.SUPP.3.STOP	0
POS.SUPP.4.Z	0
TY.SUPP.4.GUIDE	0

The 10 most important (i.e., most influential on the prediction model) variables are graphically shown in Figure 5-17. In a manual modification of the pipe route and pipe support design, these most important variables could be used to change the stress result. Increasing the training dataset would change the importance level of the variables.

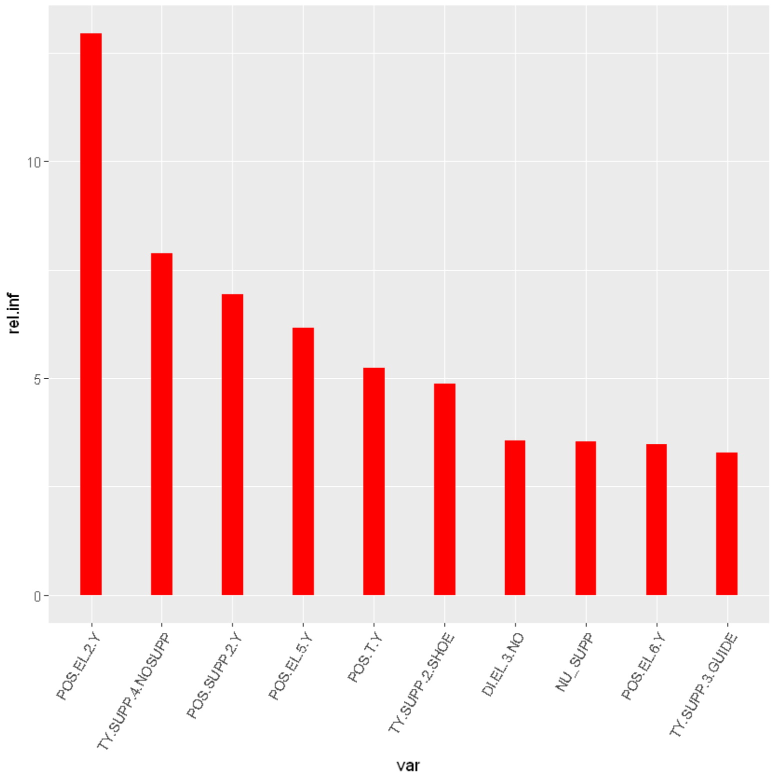


Figure 5-17: Ten most important variables in predicting stress analysis result

The relationship between the tuning parameters and the estimates of performance is shown in Figure 5-18. The GBM model tunes the parameters to gain the best accuracy by trading off between complexity and the training dataset size (Figure 5-18).

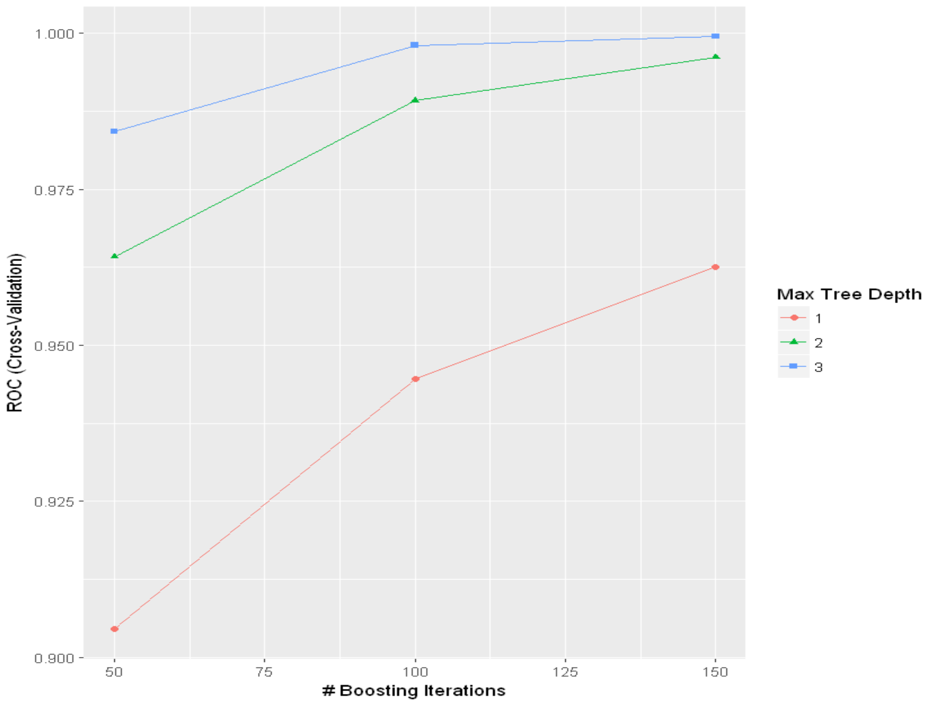


Figure 5-18: GBM tuning parameter results

Upon running the prediction on 25% test data, over 99% accuracy is achieved, as shown in Table 5-4.

Table 5-4: Results of running GBM prediction model on test dataset

Pipe No.	Prediction	Ceasar II result
1	Not_App	Not_App
2	Not_App	Not_App
3	Not_App	Not_App
4	App	App
5	App	App
6	Not_App	Not_App
7	Not_App	Not_App
8	Not_App	Not_App
9	Not_App	Not_App
10	Not_App	Not_App
⋮	⋮	⋮
273	Not_App	App
⋮	⋮	⋮
832	Not_App	App
⋮	⋮	⋮
894	App	App
895	App	App
896	App	App
897	App	App
898	Not_App	Not_App
899	App	App
900	Not_App	Not_App
901	Not_App	Not_App
902	Not_App	Not_App
903	Not_App	Not_App
904	Not_App	Not_App

Accuracy: 0.992256637168142

The accuracy of 99.2%, achieved from the GBM method, demonstrates the possibility of using ML methods in automating piping stress analysis. The required training data in this case were provided through the application of the Caesar II stress analysis software package. It should be noted that there are existing plants of which the design data can be collected and used as the training dataset to increase the accuracy of the GBM prediction model.

5.3.4 Stress analysis prediction result

Ten new pipe routes are now analyzed using stress analysis software, and then introduced to the GBM prediction model. Table 5-5 shows a part of the dataset and the stress analysis report, from the software (Caesar II). This dataset is then introduced to the GBM prediction model; Table 5-6 illustrates the prediction results. This shows that the prediction model accurately predicted the stress result.

Table 5-5: Final test dataset

POS-H-X	POS-H-Y	POS-H-Z	POS-T-X	POS-T-Y	POS-T-Z	POS-EL-1-X	POS-EL-1-Y	POS-EL-1-Z	DI-EL-1	…	POS-SUPP-1-X	POS-SUPP-1-Y	POS-SUPP-1-Z	TY-SUPP-1	POS-SUPP-2-X	POS-SUPP-2-Y
100000	100000	100000	93000	100000	100000	100000	103000	100000	YES	…	95000	103000	100000	GUIDE	100000	100000
100000	100000	100000	92000	100000	100000	100000	103000	100000	YES	…	97000	103000	100000	GUIDE	100000	100000
100000	100000	100000	92000	100000	100000	100000	103000	100000	YES	…	95000	103000	100000	GUIDE	100000	100000
100000	100000	100000	87000	101000	104000	100000	100000	104000	YES	…	97000	100000	104000	GUIDE	90000	100000
100000	100000	100000	87000	101000	104000	100000	100000	104000	YES	…	97000	100000	104000	GUIDE	91000	100000
100000	100000	100000	87000	101000	104000	100000	100000	104000	YES	…	98500	100000	104000	GUIDE	89500	100000
100000	100000	100000	87000	101000	104500	100000	100000	104500	YES	…	98500	100000	104500	GUIDE	89500	100000
100000	100000	100000	87000	101000	103500	100000	100000	103500	YES	…	98500	100000	103500	GUIDE	89500	100000
100000	100000	100000	117000	98000	92000	112000	100000	100000	YES	…	106000	100000	100000	SHOE	114000	98000
100000	100000	100000	102000	79000	93000	100000	101000	100000	YES	…	98000	98000	100000	GUIDE	98000	89000

Table 5-6: Prediction of test dataset

Test Line	Caesar II result	Prediction
TestLine-1	Not_App	Not_App
TestLine-2	Not_App	Not_App
TestLine-3	Not_App	Not_App
TestLine-4	Not_App	Not_App
TestLine-5	Not_App	Not_App
TestLine-6	Not_App	Not_App
TestLine-7	App	App
TestLine-8	Not_App	Not_App
TestLine-9	App	App
TestLine-10	App	App

5.4 Conclusions

The failure of piping routes is still considered a major hazard for all types of process plants. Ideally, the engineering design team ensures sufficient safety provisions during the detailed design stage. Such a provision method is considered time/budget-consuming and prone to human error. It also creates a bottleneck in checking different design options (i.e., equipment arrangement, pipe routing, and supporting) and PHA activities in a time/budget-constrained project schedule.

This work discussed the application of automation algorithms in piping/piping support design, and an ML algorithm in the stress analysis of piping routes. The aim of this study is to develop a predictive model to accurately predict the result of stress analysis (i.e., failure or non-failure) of pipe routes and pipe supporting, without using stress analysis software or manual calculations.

Applying a gradient boosting model on the developed dataset, and testing the prediction model on the testing dataset revealed that the prediction model is capable of predicting the stress analysis result with 99% accuracy. The existing results of stress analysis reports of different process plants can be used as a training dataset for extending the capabilities of such a prediction model.

This chapter illustrated a simplified approach in predicting stress analysis reports. A complete model/platform at the industrial stage would require a comprehensive database of previous analysis results and a major effort by a team of engineers and AI experts.

This algorithm is an assistant for the design team to cover all the possible piping routes, without missing the vital stress analysis step. This method can be easily integrated into the traditional methods of process plant detail design and ensures a safe and economic design. It can save time and resources without ignoring the safety of the plant in the operation and maintenance stages.

Chapter 6 Process Information Modelling for safe piping installation for process plants

The unique nature of each construction project, multidisciplinary activities, and usage of different plant and equipment are some of the reasons for accidents in construction industry. Process plants are considered as mega industrial projects. Construction of these projects is considered as one of the most sophisticated construction activities. One of the major sources of hazard in the lifecycle of the process plant is the lack of quality in piping joint welds. Lack of quality in weld joints poses a threat as the hazardous material can leak from these joints during the operation phase. Studies are showing the correlation between quality of weld with the environment and safety of the location for fit-up and welding activity.

This chapter proposes a method in which Field Fit-up Weld (FFW) points can be chosen at the design phase of the project, using 3D BIM models of the process plant. In this method, all the information from the 3D model are extracted and analyzed in order to find the best combination of FFW points to create a faster and safer construction method to complete a higher quality piping installation. An algorithm developed for this method has been tested on a case study which shows a clear difference between the numbers of hours required to work at height in the traditional and the new method. It also demonstrates the difference in productivity and cost of project using these two different methods.

6.1 Piping installation and field fit-up welds

Piping installation is one of the most complex activities in completing the construction of process plants. It includes the installation of scaffolding, shop and field stress relieve installation, shop and field welding, transportation to site, using cranes to hold the pipes before complete installation, sand blast and painting, hydro-test, and radiographic test. In order to install pipes, scaffolding is required to be set up as a temporary support for pipes and also as a working deck for all the activities around piping installation. A usual practice in installation of pipes is to prepare spools in a shop, transfer them to the construction site, and weld them together to complete the route. This process is like putting different pieces of a 3D puzzle together.

Although it is much faster and more convenient for the team to prepare and weld spools in a controlled environment like fabrication shop, some activities are required to be done at the construction site. There are two major reasons for that. First is the transportation of spools to the site which should consider the limitation of shipping box. For example in the case of using a flat-bed truck or a shipping container, maximum dimension of spools to be transported can be 12 × 3 × 3 meters. The second reason is the possibility of the equipment footings or the equipment not being in the right position or any mistake in the manufacturing of the equipment. For this reason, some field fit-up welds (FFW) should be considered (at least one for each X, Y, and Z axis in an imaginary Cartesian system). Normally 150 mm of extra length of pipe is considered for each FFW point for required adjustments by the fitter and welder. Figure 6-1 shows an example in which the pump has been installed in a wrong place. Adjustments are required to be made in the piping in order to rectify the problem and connect the pipe to the pump.

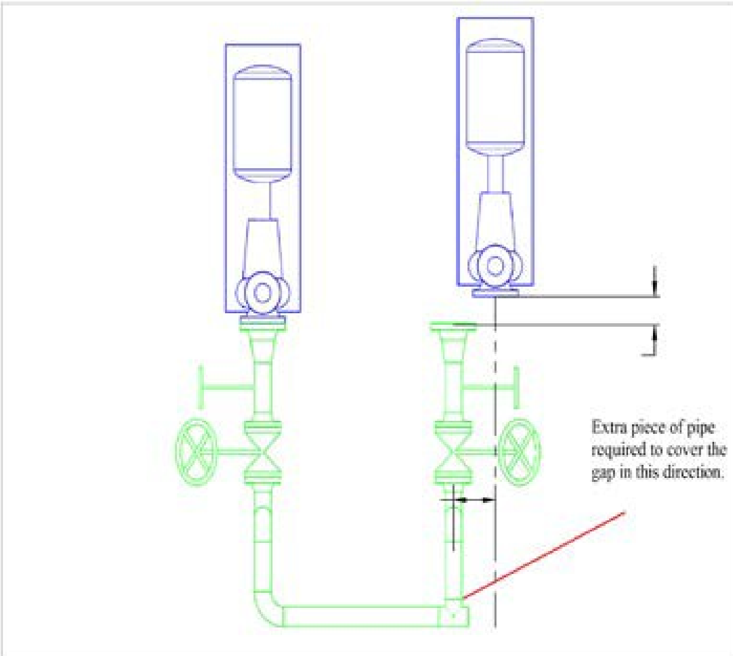


Figure 6-1: Wrong position of pipe and adjustment required in piping

In order to complete the piping installation, and, depending on the position of FFW points, a team of fitters, welders, and testers may be required to climb up the scaffolding (mostly through provided ladders). It means that finishing this activity not only requires work at height, but also requires the team to climb up and down the scaffolding. Both activities are working at height activities and are considered high-risk. Fall from height is considered as one of the major reasons for fatalities in construction industry (Haslam et al., 2005). Therefore, any effort in reducing the number of points higher than 2 meters can reduce the risk of injury.

Normally, FFW points are chosen from piping isometric drawings at the site during the construction. Construction is at fast pace and decision makings in that phase are normally bound by mistakes. Besides, in normal practices and facilities at construction site, it is not possible for the team to put all the parameters together and choose the safest combination of FFW points.

Pipe failure may result in secondary accidents, including pool formation, a cloud or a jet (Delvosalle, Fievez, Pipart, & Debray, 2006). A comprehensive database about pipe failures is introduced in reference (Lydell & Riznic, 2008). Kletz has listed major leaks of hazardous material and showed that pipe failure accounted for half of these incidents (Kletz, 2009). It also emphasis the need for focus on the design and construction to prevent these accidents from happening.

6.2 Methodology Development

The proposed method will be applied in a project schedule. Part of the activity in construction (i.e. field weld specification) is removed and shifted to design phase of the project. Besides, it shifts 2 other super ceding activities (piping pre-fabrication and piping installation) to an earlier stage of the project (Figure 6-2).

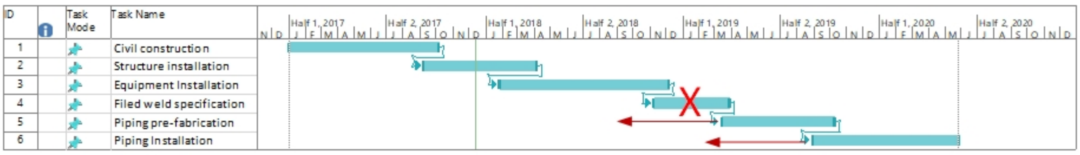


Figure 6-2: Alternative schedule

6.2.1 Information gathering from 3D model

Process plants BIM (data enriched 3D models) are capable of providing the required data for each pipe. After data pre-processing, the algorithm could be applied in developing the best combination. Figure 6-3 illustrates the algorithm.

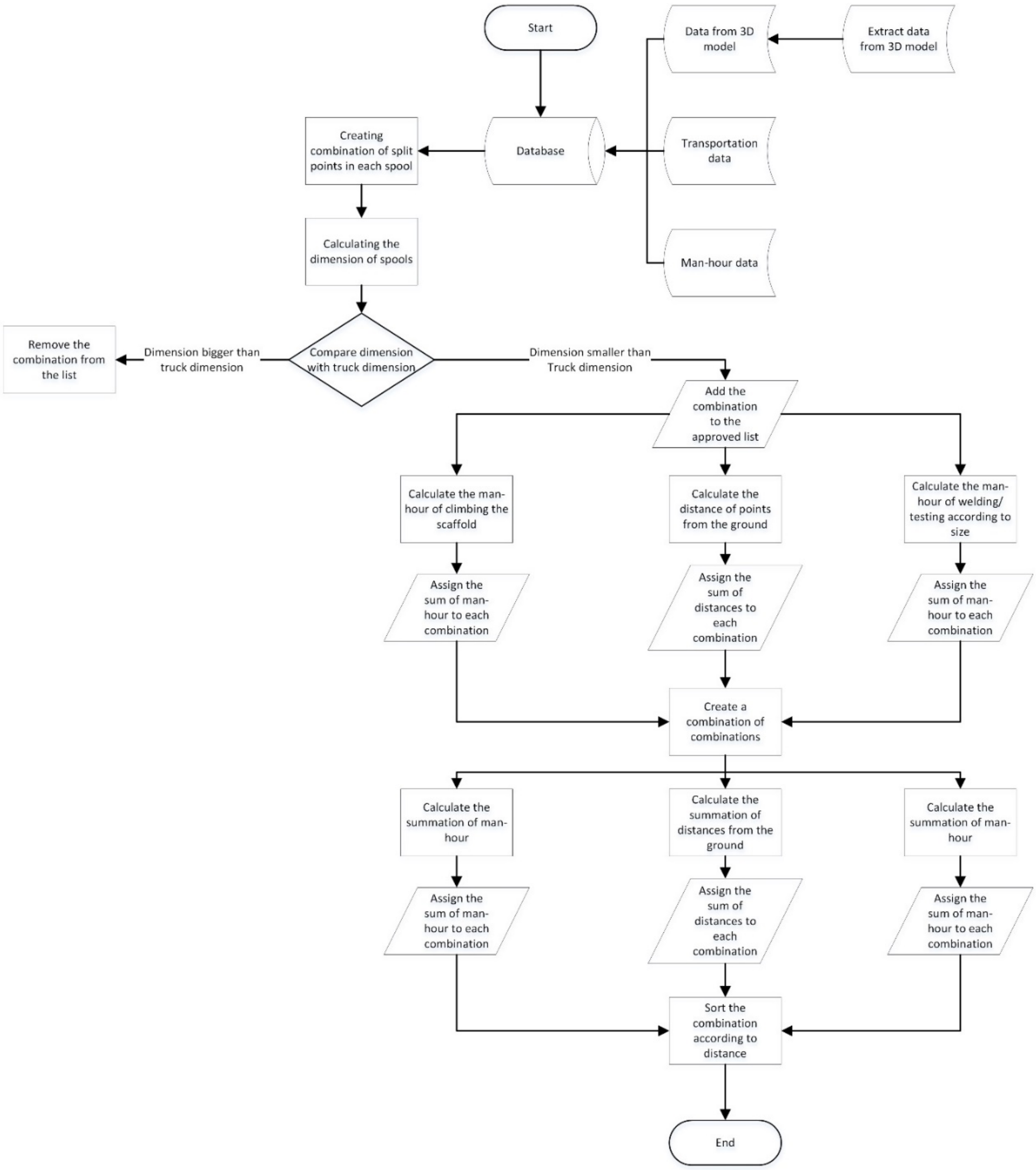


Figure 6-3: Algorithm to choose the best combination of welding points

Number of welding points (NOP) in each pipe is gathered here:

$$NOP = \begin{bmatrix} 1 & N_1 \\ 2 & N_2 \\ 3 & N_3 \\ \vdots & \vdots \\ m & N_m \end{bmatrix}$$

Also, all the information about pipes can be gathered in one place. These information includes the name of the pipe (P_k), number of welding points (NOP_k), and size of the pipe (S_k):

$$P = \begin{bmatrix} P_1 & NOP_1 & S_1 \\ P_2 & NOP_2 & S_2 \\ P_3 & NOP_3 & S_3 \\ \vdots & \vdots & \vdots \\ P_m & NOP_m & S_m \end{bmatrix}$$

Figure 6-4 shows part of the plant in which all the required information from each pipe is gathered in different matrices.

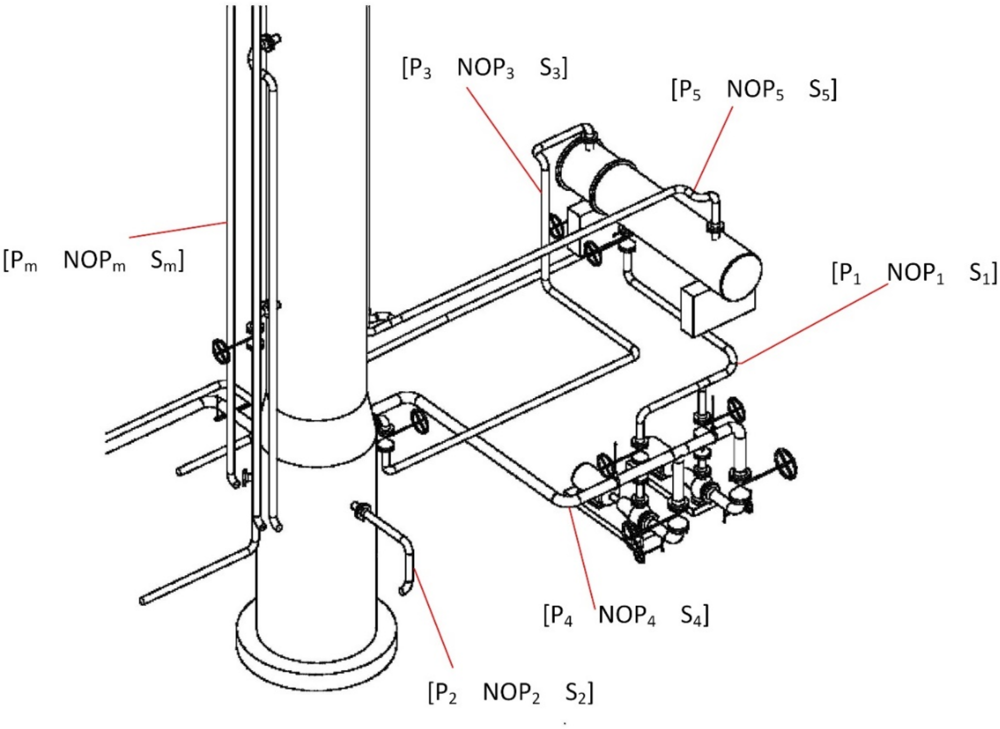


Figure 6-4: Creating matrices for each pipe

For each pipe, the information about every weld point is also gathered from the model. Figure 6-5 shows different matrices for each pipe and for every single welding point. All these matrices will eventually be combined in one matrix for each pipe.

$$P_k = \begin{bmatrix} X_1 & Y_1 & Z_1 & Dir_1 \\ X_2 & Y_2 & Z_2 & Dir_2 \\ \vdots & \vdots & \vdots & \vdots \\ X_n & Y_n & Z_n & Dir_n \end{bmatrix}$$

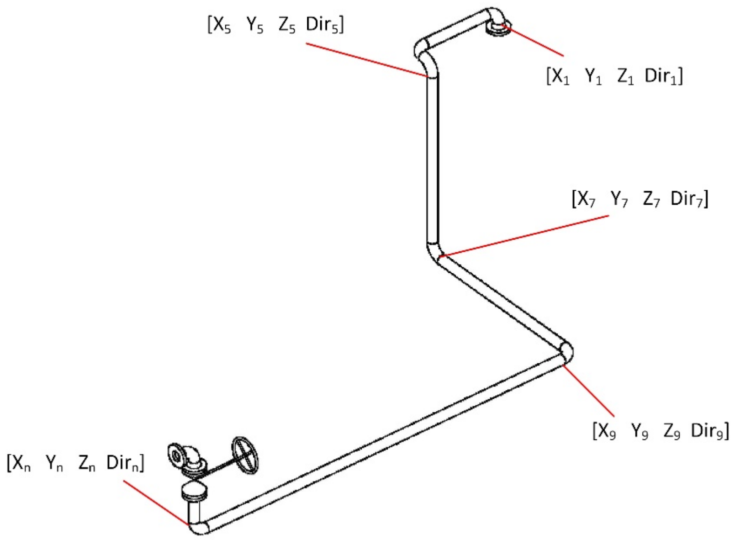


Figure 6-5: Developing matrices for each spool

6.2.2 Creating Field Weld Points

Choosing the field weld points creates different combinations for each pipe.

From here, points for spool number "n" will be split according to their directions into groups. So for pipe 'k', and for j number of points in East-West axis (EW), t number of points in North-South axis, and i number of points in Up-Down (UD) axis; we will have the arrangements as shown below:

$$NOP\_NS_k = \begin{bmatrix} NS_1 = \begin{bmatrix} X_{NS1} \\ Y_{NS1} \\ Z_{NS1} \end{bmatrix} \\ NS_2 = \begin{bmatrix} X_{NS2} \\ Y_{NS2} \\ Z_{NS2} \end{bmatrix} \\ NS_3 = \begin{bmatrix} X_{NS3} \\ Y_{NS3} \\ Z_{NS3} \end{bmatrix} \\ \vdots \\ NS_t = \begin{bmatrix} X_{NSt} \\ Y_{NSt} \\ Z_{NSt} \end{bmatrix} \end{bmatrix} \quad NOP\_UD_k = \begin{bmatrix} UD_1 = \begin{bmatrix} X_{UD1} \\ Y_{UD1} \\ Z_{UD1} \end{bmatrix} \\ UD_2 = \begin{bmatrix} X_{UD2} \\ Y_{UD2} \\ Z_{UD2} \end{bmatrix} \\ UD_3 = \begin{bmatrix} X_{UD3} \\ Y_{UD3} \\ Z_{UD3} \end{bmatrix} \\ \vdots \\ UD_i = \begin{bmatrix} X_{UDi} \\ Y_{UDi} \\ Z_{UDi} \end{bmatrix} \end{bmatrix} \quad NOP\_EW_k = \begin{bmatrix} EW_1 = \begin{bmatrix} X_{EW1} \\ Y_{EW1} \\ Z_{EW1} \end{bmatrix} \\ EW_2 = \begin{bmatrix} X_{EW2} \\ Y_{EW2} \\ Z_{EW2} \end{bmatrix} \\ EW_3 = \begin{bmatrix} X_{EW3} \\ Y_{EW3} \\ Z_{EW3} \end{bmatrix} \\ \vdots \\ EW_j = \begin{bmatrix} X_{EWj} \\ Y_{EWj} \\ Z_{EWj} \end{bmatrix} \end{bmatrix}$$

And the number of combinations for pipe 'k' is as shown below:

$$\text{Number of Combinations}_{\,k} = \binom{(n_{NOP\_EW})_k}{1} X \binom{(n_{NOP\_NS})_k}{1} X \binom{(n_{NOP\_UD})_k}{1}$$

The combinations for pipe ‘k’ to include all three axis are as follows:

$$Combinations_k = \begin{bmatrix} [EW_1 & NS_1 & UD_1] \\ [EW_1 & NS_1 & UD_2] \\ [EW_1 & NS_1 & UD_3] \\ & \vdots & \\ [EW_j & NS_t & UD_i] \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} X_{EW1} & X_{NS1} & X_{UD1} \\ Y_{EW1} & Y_{NS1} & Y_{UD1} \\ Z_{EW1} & Z_{NS1} & Z_{UD1} \end{bmatrix} \\ \begin{bmatrix} X_{EW1} & X_{NS1} & X_{UD2} \\ Y_{EW1} & Y_{NS1} & Y_{UD2} \\ Z_{EW1} & Z_{NS1} & Z_{UD2} \end{bmatrix} \\ \begin{bmatrix} X_{EW1} & X_{NS1} & X_{UD3} \\ Y_{EW1} & Y_{NS1} & Y_{UD3} \\ Z_{EW1} & Z_{NS1} & Z_{UD3} \end{bmatrix} \\ \vdots \\ \begin{bmatrix} X_{EWj} & X_{NSt} & X_{UDi} \\ Y_{EWj} & Y_{NSt} & Y_{UDi} \\ Z_{EWj} & Z_{NSt} & Z_{UDi} \end{bmatrix} \end{bmatrix}$$

Figure 6-6 illustrate an example in which 2 combinations have been developed for one pipe with different welding points.

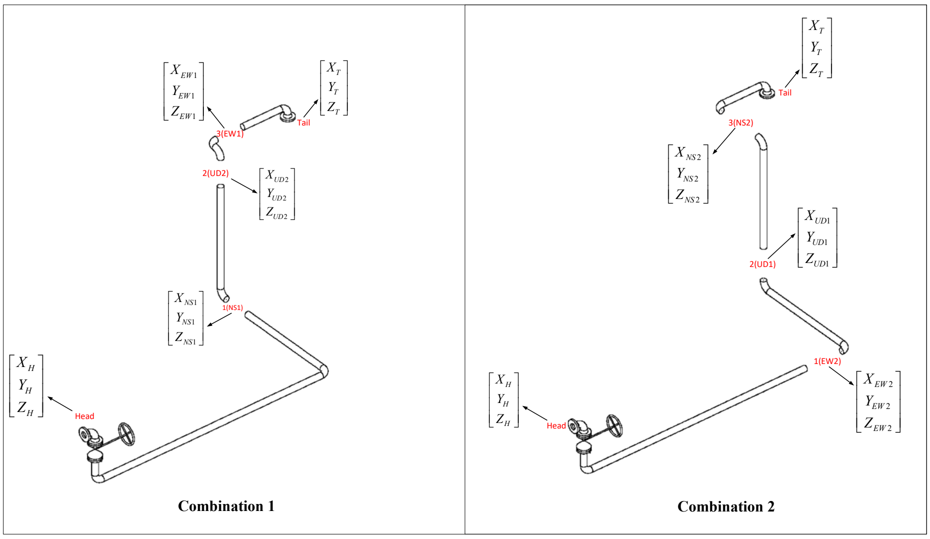


Figure 6-6: Two different welding combinations for one pipe

6.2.3 Spool dimension check for transportation

Each combination creates a number of field fit-up weld points and it means that the pipe itself will be split into spools. These spools need to be transported to site. One important thing that should be considered here is the dimension of each spool. Due to the size limitation of the shipping box. If a combination creates even one spool that has bigger dimensions than the shipping box, that spool, and also the combination, will be rejected as it is not possible to transport it to site.

For each combination, as discussed, there are:

$$L_{n1} = \sqrt{(X_{EWj} - X_{kH})^2} \qquad W_{n1} = \sqrt{(Y_{EWj} - Y_{kH})^2} \qquad H_{n1} = \sqrt{(Z_{EWj} - Z_{kH})^2}$$

$$L_{n2} = \sqrt{(X_{NSj} - X_{EWj})^2} \qquad W_{n2} = \sqrt{(Y_{NSj} - Y_{EWj})^2} \qquad H_{n2} = \sqrt{(Z_{NSj} - Z_{EWj})^2}$$

$$L_{n3} = \sqrt{(X_{UDj} - X_{NSj})^2} \qquad W_{n3} = \sqrt{(Y_{UDj} - Y_{NSj})^2} \qquad H_{n3} = \sqrt{(Z_{UDj} - Z_{NSj})^2}$$

$$L_{n4} = \sqrt{(X_{kT} - X_{UDj})^2} \qquad W_{n4} = \sqrt{(Y_{kT} - Y_{UDj})^2} \qquad H_{n4} = \sqrt{(Z_{kT} - Z_{UDj})^2}$$

Figure 6-7 shows the spool dimensions for combinations 1 and 2 in the pipe, shown in Figure 6-6.

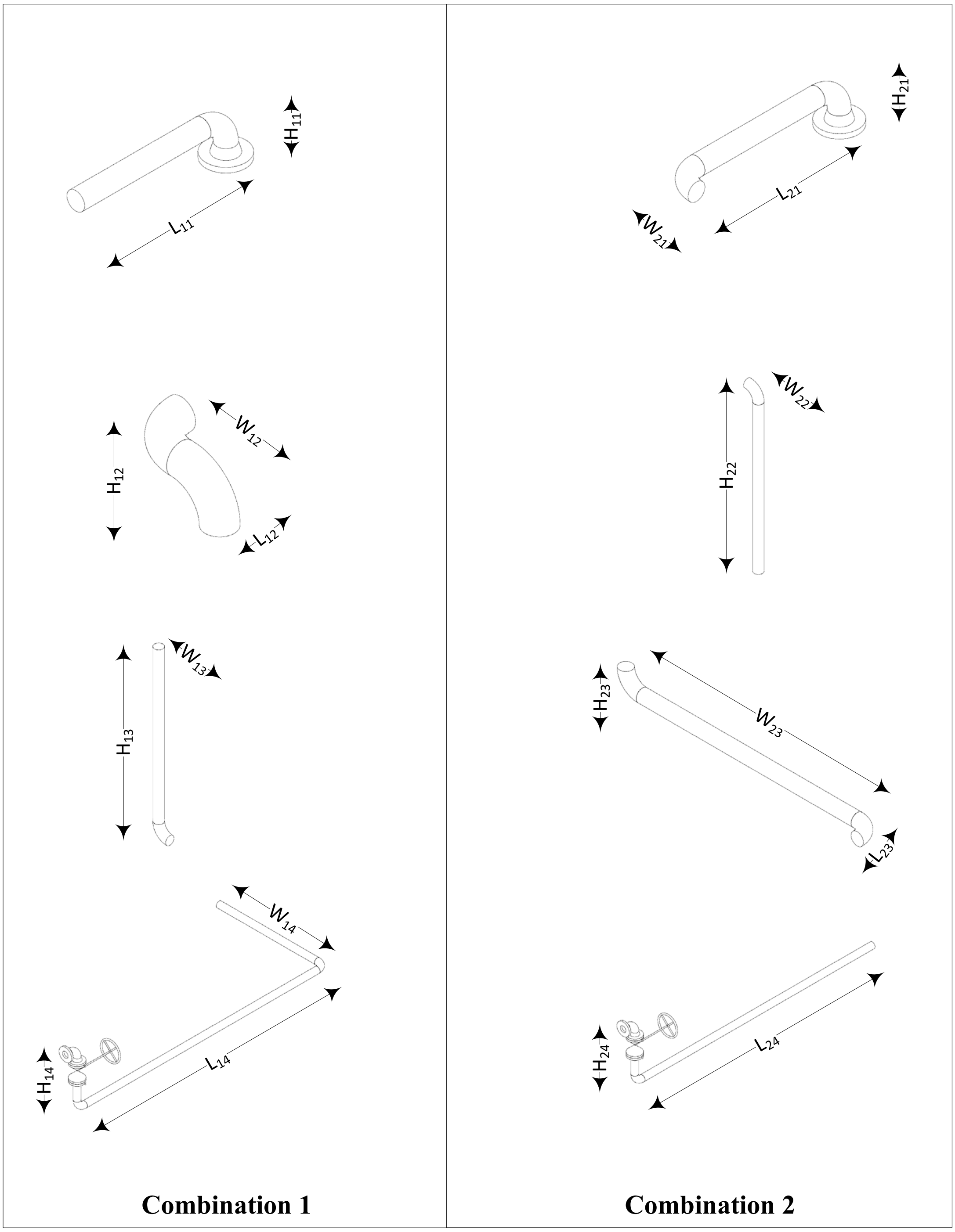


Figure 6-7: Spool length-to be checked with shipping box dimension

$$(Combinations - Dimensions)_k = \begin{bmatrix} \left[[L_{11} \quad W_{11} \quad H_{11}] \quad [L_{12} \quad W_{12} \quad H_{12}] \quad [L_{13} \quad W_{13} \quad H_{13}] \quad [L_{14} \quad W_{14} \quad H_{14}] \right] \\ \left[[L_{21} \quad W_{21} \quad H_{21}] \quad [L_{22} \quad W_{22} \quad H_{22}] \quad [L_{23} \quad W_{23} \quad H_{23}] \quad [L_{24} \quad W_{24} \quad H_{24}] \right] \\ \left[[L_{31} \quad W_{31} \quad H_{31}] \quad [L_{32} \quad W_{32} \quad H_{32}] \quad [L_{33} \quad W_{33} \quad H_{33}] \quad [L_{34} \quad W_{34} \quad H_{34}] \right] \\ \vdots \\ \left[[L_{n1} \quad W_{n1} \quad H_{n1}] \quad [L_{n2} \quad W_{n2} \quad H_{n2}] \quad [L_{n3} \quad W_{n3} \quad H_{n3}] \quad [L_{n4} \quad W_{n4} \quad H_{n4}] \right] \end{bmatrix}$$

$$Truck\_Dimensions = \begin{bmatrix} L_t \\ W_t \\ H_t \end{bmatrix}$$

From here we check the dimension of truck and compare it with combination-dimensions to prepare a list of approved combinations (Figure 6-7). Figure 6-8 shows the important dimensions on a flat-bed truck. Dimensions here are considered as the 'shipping box' dimension for the transportation of spools, from the manufacturing yard to the construction site.

Logical expression to choose the approved combinations for transportation purposes is as below:

$$NOC_k = \{1,2,3,\ldots,n\}$$

$$NOS_k = \{1,2,3,4\}$$

$$i \in NOC_k$$

$$j \in NOS_k$$

$$L_t \rangle W_t \equiv H_t$$

$$\forall i,j : \left((L_{ij} \rangle L_t) \vee (W_{ij} \rangle L_t) \vee (H_{ij} \rangle L_t) \right) \rightarrow \mathrm{Re}_k \cup \{i\}$$

$$\forall i,j : \left(\left((L_{ij} \rangle W_t) \vee (W_{ij} \rangle W_t) \vee (H_{ij} \rangle W_t) \right) \wedge \left((L_{ij} \rangle H_t) \vee (W_{ij} \rangle H_t) \vee (H_{ij} \rangle H_t) \right) \right) \rightarrow \mathrm{Re}_k \cup \{i\}$$

$$\forall i,j : \neg\left((L_{ij} \rangle L_t) \vee (W_{ij} \rangle L_t) \vee (H_{ij} \rangle L_t) \right) \wedge \neg\left(\left((L_{ij} \rangle W_t) \vee (W_{ij} \rangle W_t) \vee (H_{ij} \rangle W_t) \right) \wedge \left((L_{ij} \rangle H_t) \vee (W_{ij} \rangle H_t) \vee (H_{ij} \rangle H_t) \right) \right) \rightarrow Ap_k \cup \{i\}$$

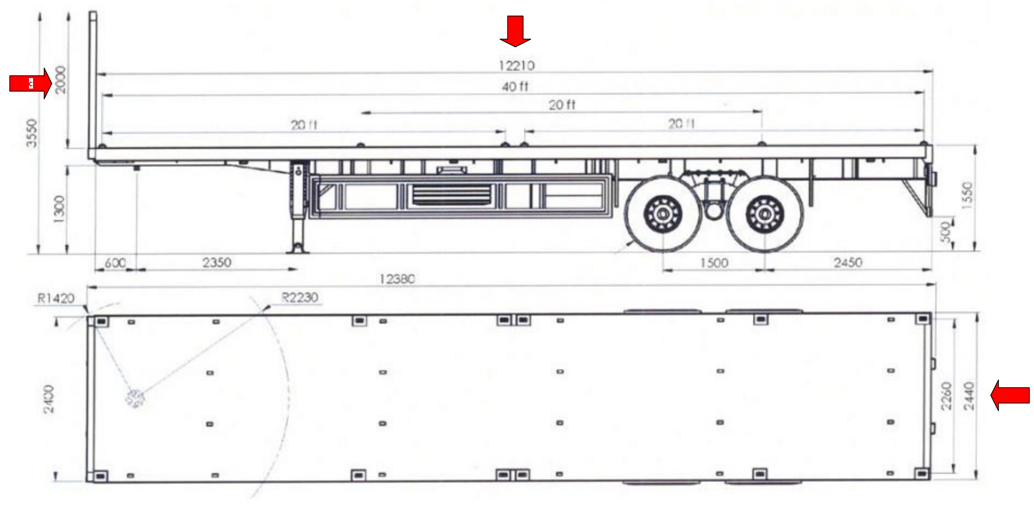


Figure 6-8: Important dimensions on a flat-bed truck

Approved combinations for spool ‘k’ is defined as:

$$Approved\_Combinations_k = \begin{bmatrix} P_{EW1} & P_{NS1} & P_{UD1} \\ P_{EW2} & P_{NS2} & P_{UD2} \\ P_{EW3} & P_{NS3} & P_{UD3} \\ \vdots & \vdots & \vdots \\ P_{EWf} & P_{NSf} & P_{UDf} \end{bmatrix}$$

6.2.4 Weld point distance from ground

For each of the approved combinations in each spool, summation of point distances from the ground is recorded (Ground level = G.L.):

$$Approved\_Combinations_k\_DistFromGround = \begin{bmatrix} \left[H_{P_{EW1}} - H_{/GL} \quad H_{P_{NS1}} - H_{/GL} \quad H_{P_{UD1}} - H_{/GL}\right] \\ \left[H_{P_{EW2}} - H_{/GL} \quad H_{P_{NS2}} - H_{/GL} \quad H_{P_{UD2}} - H_{/GL}\right] \\ \left[H_{P_{EW3}} - H_{/GL} \quad H_{P_{NS3}} - H_{/GL} \quad H_{P_{UD3}} - H_{/GL}\right] \\ \vdots \\ \left[H_{P_{EWf}} - H_{/GL} \quad H_{P_{NSf}} - H_{/GL} \quad H_{P_{UDf}} - H_{/GL}\right] \end{bmatrix} = \begin{bmatrix} \sum_1^3 Z_{k1} \\ \sum_1^3 Z_{k2} \\ \sum_1^3 Z_{k3} \\ \vdots \\ \sum_1^3 Z_{kf} \end{bmatrix}$$

This loop will be repeated for all the spools, from 1 to n, and approved combinations for all the spools will be recorded.

Number of approved combinations for each spool:

$$No\_Approved\_Combinations = \begin{bmatrix} NAC_1 \\ NAC_2 \\ NAC_3 \\ \vdots \\ NAC_n \end{bmatrix}$$

Number of total possible combinations:

$NAC_T = NAC_1 \times NAC_2 \times NAC_3 \times \ldots \times NAC_n$

6.2.5 Choosing the best combination

This final matrix lists all the combinations for the plant:

$$Total\_Combinations = \begin{bmatrix} [AC_{11} & AC_{21} & \cdots & AC_{n1}] \\ [AC_{11} & AC_{21} & \cdots & AC_{n2}] \\ [AC_{11} & AC_{21} & \cdots & AC_{n3}] \\ & \vdots & & \\ [AC_{1NAC_T} & AC_{2NAC_T} & \cdots & AC_{nNAC_T}] \end{bmatrix} = \begin{bmatrix} \left[\sum_1^3 Z_{11} \quad \sum_1^3 Z_{21} \quad \cdots \quad \sum_1^3 Z_{n1}\right] \\ \left[\sum_1^3 Z_{11} \quad \sum_1^3 Z_{21} \quad \cdots \quad \sum_1^3 Z_{n2}\right] \\ \left[\sum_1^3 Z_{11} \quad \sum_1^3 Z_{21} \quad \cdots \quad \sum_1^3 Z_{n3}\right] \\ \vdots \\ \left[\sum_1^3 Z_{1NAC_T} \quad \sum_1^3 Z_{2NAC_T} \quad \cdots \quad \sum_1^3 Z_{nNAC_T}\right] \end{bmatrix}$$

$$Total\_Combinations = \begin{bmatrix} \sum_{i=1}^{i=NoS} \sum_1^3 Z_{i1} \\ \sum_{i=1}^{i=NoS} \sum_1^3 Z_{i2} \\ \sum_{i=1}^{i=NoS} \sum_1^3 Z_{i3} \\ \vdots \\ \sum_{i=1}^{i=NoS} \sum_1^3 Z_{iNAC_T} \end{bmatrix}$$

As discussed, the best combination is the one that has the lowest summation of distances from the ground which will reduce the number of hours working at height, the number of hours climbing the scaffolding. In turn the job efficiency is increased as well as the safety.

The best combination is a combination 'r' which is $\min \sum_{i=1}^{i=NoS} \sum_1^3 Z_{iNAC_r}$ in $\begin{bmatrix} \sum_{i=1}^{i=NoS} \sum_1^3 Z_{i1} \\ \sum_{i=1}^{i=NoS} \sum_1^3 Z_{i2} \\ \sum_{i=1}^{i=NoS} \sum_1^3 Z_{i3} \\ \vdots \\ \sum_{i=1}^{i=NoS} \sum_1^3 Z_{iNAC_T} \end{bmatrix}$.

This algorithm will be demonstrated next using the case study below to show the difference between cost, efficiency, and safety risk of the job in different combinations, in a quantified manner.

6.3 Case study

A Naphtha hydro treater unit (Bausbacher & Hunt, 1993) has been modelled and the geometry data (including the coordination of all welding points, pipe numbers, pipe size, and weld point direction) has been collected from the 3D model (Figure 6-9).

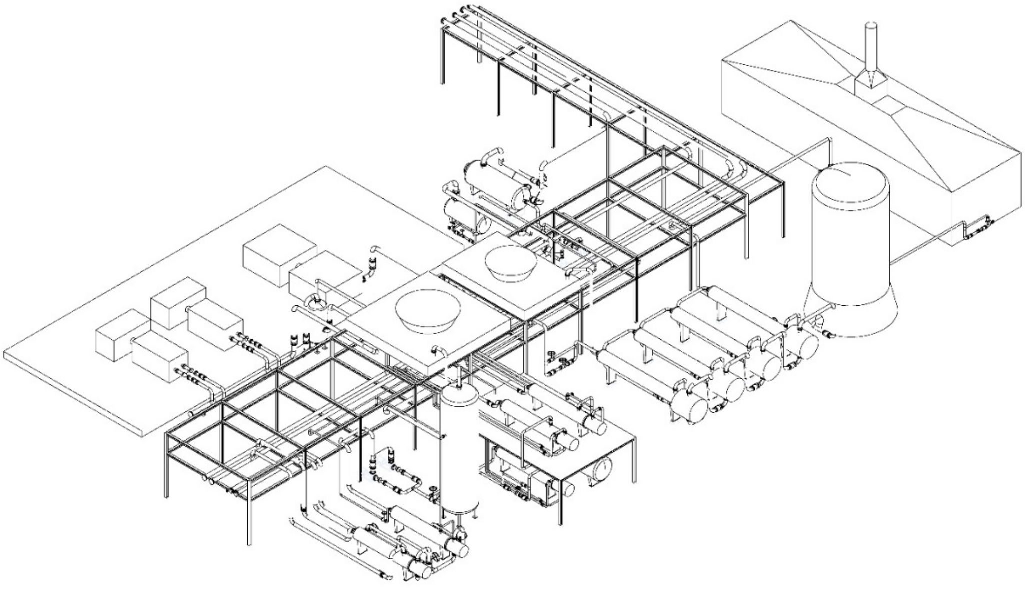


Figure 6-9: Naphtha hydro treater unit

15 pipes were randomly chosen to see the effect of different combination of points (Figure 6-10).

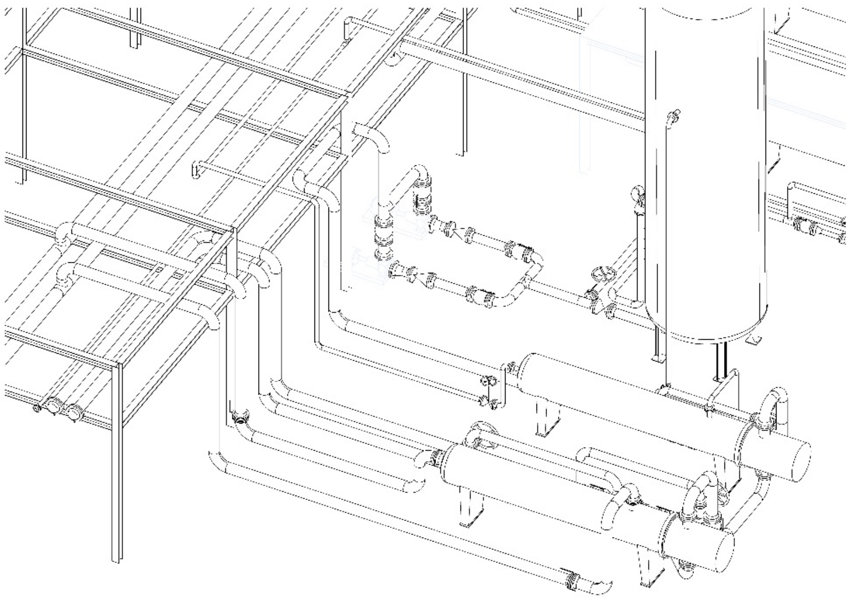


Figure 6-10: Part of the process plant-15 pipes chosen for the analysis

Table 6-1: Welding points information for 15 chosen pipes

Number of points	9				
Pipe size (Inch)	10				
Coordination and direction	Point No.	X	Y	Z	Dir.
	Point 1	11000	10000	100	E
	Point 2	12000	10000	100	E
	Point 3	12150	9850	100	N
	Point 4	12150	9000	100	N
	Point 5	12150	8850	250	U
	Point 6	12150	8850	2250	U
	Point 7	12150	8750	2400	N
	Point 8	12150	10000	2400	N
	Point 9	12300	10150	2400	E
Number of points	10				
Pipe size (Inch)	12				
Coordination and direction	Point No.	X	Y	Z	Dir.
	Point 1	12300	10000	100	E
	Point 2	12150	9850	100	N
	Point 3	12150	9000	100	N
	Point 4	12150	8850	250	U
	Point 5	12150	8850	2250	U
	Point 6	12150	8750	2400	N
	Point 7	12150	10000	2400	N
	Point 8	12300	10150	2400	E
	Point 9	13000	10150	2400	E
	Point 10	13150	10150	2250	U
⋮	⋮	⋮	⋮	⋮	⋮
Number of points	10				
Pipe size (Inch)	12				
Coordination and direction	Point No.	X	Y	Z	Dir.
	Point 1	10000	8550	100	E
	Point 2	11000	8550	100	E
	Point 3	11150	8700	100	N
	Point 4	11150	8850	250	U
	Point 5	11150	8850	2250	U
	Point 6	11150	8750	2400	N
	Point 7	11300	9000	2400	N
	Point 8	12000	9000	2400	E
	Point 9	14000	9000	2400	E
	Point 10	14150	9150	2400	N

At least 3 field weld points had to be chosen to leave enough room for required adjustments at the construction site. Information has been exported from the 3D model and formatted to show the required data for the analysis (Table 6-1). These information includes the number of pipes, size, number of welding points, direction/axis of welding points, and location of each point.

The algorithm was applied on the dataset and the best combination (with the lowest summation of distances from the ground) was chosen along with other combination, for comparison purposes. In this case, the best set of field fit-up welding joints is as below:

Pipe 1: {1: [10000, 10000, 100], 2: [11150, 9850, 100], 3: [11150, 8850, 250]},

Pipe 2: {1: [11000, 10000, 100], 2: [12150, 9850, 100], 3: [12150, 8850, 250]},

Pipe 3: {1: [12300, 10000, 100], 2: [12150, 9850, 100], 3: [12150, 8850, 250]},

Pipe 4: {1: [13300, 10000, 100], 2: [13150, 9850, 100], 3: [13150, 8850, 250]},

Pipe 5: {1: [14000, 10000, 100], 2: [15150, 9850, 100], 3: [15150, 8850, 250]},

Pipe 6: {1: [15000, 10000, 100], 2: [16150, 9850, 100], 3: [16150, 8850, 250]},

Pipe 7: {1: [17150, 10000, 1000], 2: [17150, 9850, 100], 3: [17300, 9000, 2400]},

Pipe 8: {1: [18150, 10000, 1000], 2: [18150, 9850, 100], 3: [18300, 9000, 2400]},

Pipe 9: {1: [19000, 8550, 100], 2: [20150, 8700, 100], 3: [20150, 8850, 250]},

Pipe 10: {1: [21000, 8550, 100], 2: [22150, 8700, 100], 3: [22150, 8850, 250]},

Pipe 11: {1: [22000, 10000, 100], 2: [23150, 9850, 100], 3: [23150, 8850, 250]},

Pipe 12: {1: [25300, 10000, 100], 2: [25150, 9850, 100], 3: [25150, 8850, 250]},

Pipe 13: {1: [27000, 10000, 100], 2: [28150, 9850, 100], 3: [28150, 8850, 250]},

Pipe 14: {1: [11150, 15000, 1000], 2: [11150, 14850, 100], 3: [11300, 14000, 2400]},

Pipe 15: {1: [10000, 8550, 100], 2: [11150, 8700, 100], 3: [11150, 8850, 250]}

The results from the analysis of 15 pipes in the plant are discussed below.

1) Increased number of hours required to work above 2 meters (working at height):
Figure 6-11 shows that the number of hours for working at height in this case (including welding, sand blasting, painting, and radiographic test). This number increases from 0 hours to around 350 hours which dramatically increases the risk of falling from height by choosing the wrong combination.

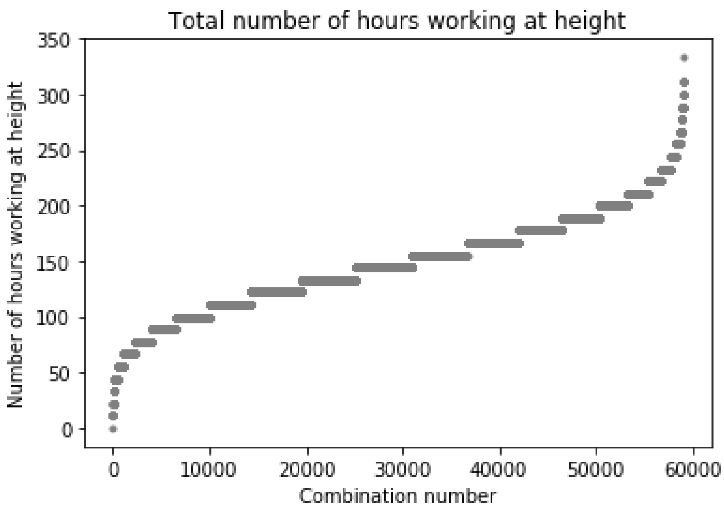


Figure 6-11: Sorted number of hours working at height

2) Increase in the number of hours climbing above 2 meters

Figure 6-12 shows that the number of meters required to climb the stairs of scaffolding. This number increases from 0 to 2 meters which not only increases the risk of falling from height, but also reduces the efficiency of work by increasing the number of hours required to finish the same amount of job.

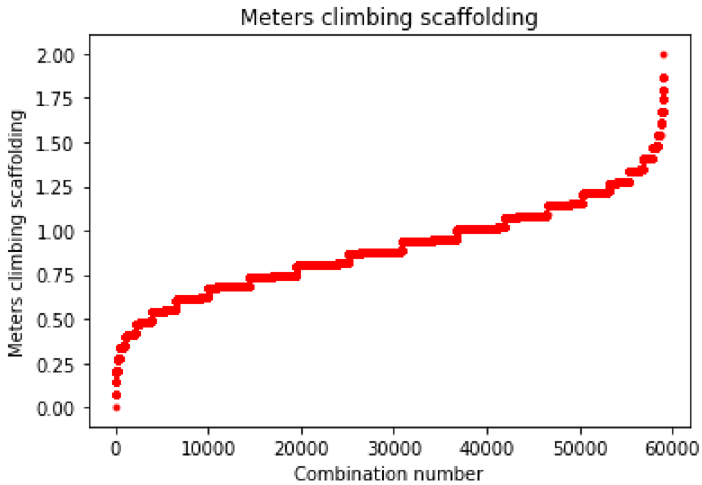


Figure 6-12: Sorted number of meters climbing of the scaffolding

3) Decrease in productivity

Here, productivity (welding per hour) is defined as "total output/total input". In this case, the output, which is the total number of field fit-up welds, is constant. On the other hand, the input, which is the total amount of time required to finish the FFW welding, changes with the chosen combination:

$$(NumberOfWeldings) \Big/ \left(\sum WeldingHoursAbove2M + \sum WeldingHoursBelow2M \right)$$

Figure 6-13 shows that the productivity decreases from 0.25 to 0.05 (20 % decrease) by choosing the wrong combination of field-weld points.

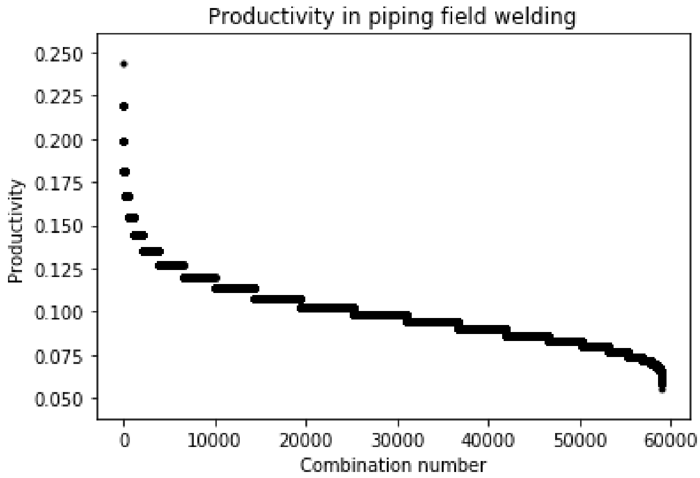


Figure 6-13: Decrease in productivity

4) Increase in cost

Figure 6-14 shows that the price of welding (with an average of 100 AUD/hour rate of payment for pipe welding in construction site) increases from around 12000 AUD to around 54000 AUD.

The cost is calculated by:

$$\left(\sum WeldingAbove2M + \sum WeldingBelow2M + \sum C\lim bScaffolding\right) \times WeldingCost/Hour$$

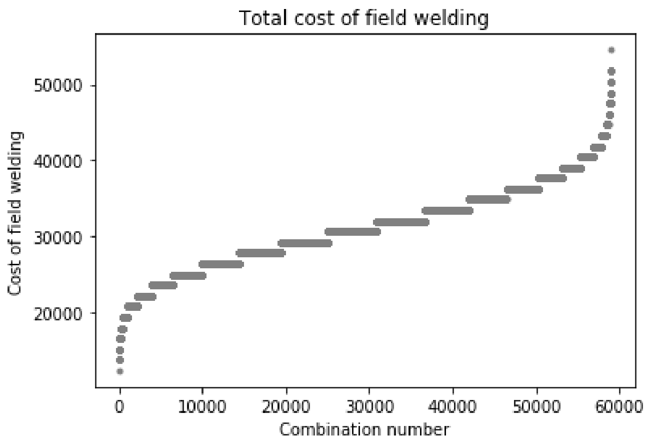


Figure 6-14: Increase in the cost of the project

6.4 Complexity analysis of the algorithm

In order to develop the complexity analysis of the algorithm, it was run on a supercomputer platform with access to 48 GB RAM and parallel computing. Figure 6-15 shows the complexity analysis.

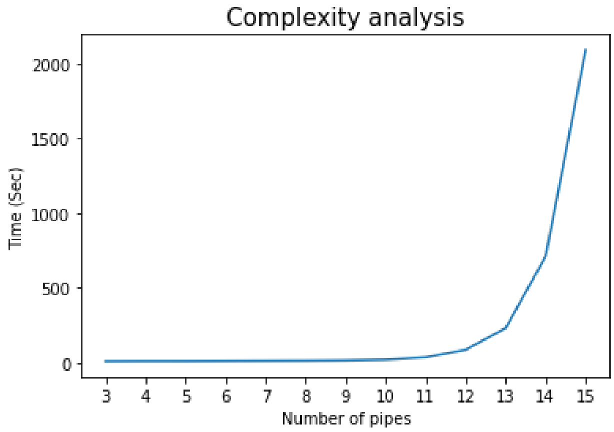


Figure 6-15: Complexity analysis

6.5 Conclusions

The traditional methods of choosing field fit-up welds, scheduling the activity for construction phase, and using hard copy piping isometric drawings are all creating a high-risk environment for fitters, welders, sandblast and painting, and radiographic test team members. Besides, with millions of combinations to choose from, it is almost impossible for the team at construction site to choose the safest and most-economic option. Construction of complex mega projects, such as process plants, requires the engagement of data from 3D models, shifting the activities to the design phase, and developing domain algorithms that can increase safety and reduce the potential for hazard.

An algorithm was developed (using 3D models) to find the best combination for this activity (with minimum working hours at height). Application of the algorithm to a 15-pipe case study suggested that this method could help in reducing the number of hours working/climbing at heights, therefore, improving efficiency of the project.

Chapter 7 Conclusions and Recommendations

Hazardous nature of process plant industry and its potential to create a catastrophic disaster for the human being and nature is still not under control. Throughout the years, different techniques have been introduced to reduce the risk in design, construction, operation, and maintenance of these mega projects. With the rise of Artificial Intelligence and capabilities of computer and data science in the past decade, it is time to propose methods that integrate AI's best practices into the process industry to reduce the risk in different phases of such projects.

The review on the literature and previous studies revealed the lack of practical proposals that can be applied into the real world practices. These methods should reach for a union with existing methodologies in industry and go beyond academic theories to deal with current problems. The aim of this research was to assess the opportunities in using information, Artificial Intelligence, and Semantic knowledge in risk analysis, risk deduction, and automation of design in process plant industry. This study successfully:

- Developed ontology-based information models from Piping and Instrument diagrams;
- Created machine-readable knowledge bases from engineering specification and lesson learned in process industry without Natural Language Processing;
- Combined human knowledge and engineering drawings, and used Description Logic for design analysis;
- Developed an algorithm to integrate engineering knowledge and extract data from P&ID to automate equipment arrangement design;
- Developed an algorithm to automate pipe routing and pipe supporting;
- Used Logistic regression methods in Machine learning to automate piping stress analysis;
- Developed an algorithm to optimise the selection of 'field fit-up weld' points, reduce risk in construction and increase speed and efficiency in construction of process plants.

Conclusions and recommendations, achieved from applying these methods, are discussed below.

7.1 Conclusions

- In this study, knowledge engineering and semantic technology were used for risk analysis in process industry. Its application on two case studies were successfully illustrated. This study shows that creating a comprehensive knowledge base and accompanying a logical query platform can minimize the time for safety analysis and minimizes human error. Furthermore, in this part of the study, flexibility of ontology knowledge base in integrating data from different sources, including data from engineering drawings, engineering specifications, and human knowledge were also presented. Also, using Controlled Natural Language to convert human natural language to ontology language were discussed and presented. Using a built-in logical reasoner to accurately gain response from the knowledge base was illustrated.

- A new algorithm to automate the equipment arrangement was proposed. This algorithm was successfully applied on two case studies and the results illustrated its power and accuracy in automating a time consuming task. The first part of the algorithm is about converting equipment objects into point matrices. In the second part, engineering specifications and practices for equipment arrangement are encoded to be a part of the code. Using this algorithm, it is now possible to use extracted data from P&ID drawings to integrate them with engineering specifications, in the programming language format, to create multiple scenarios and filter the approved ones.
- An algorithm was developed to create all possible pipe routes and pipe supports. Also a machine-learning algorithm was used to automate the process of piping stress analysis. Both algorithms were successfully used in 2 case studies. The pipe route and support algorithm created all possible design scenarios for pipe route and support between 2 points in a 3D model area. Applying the machine-learning algorithm and using the prediction model revealed its potential to reach 99% accuracy in predicting the stress analysis result of new pipe routes, with new supporting system.
- The study also proposed the use of data in process plant 3D models to choose the best (i.e. safest) set of FFW points during the design stage. Testing the developed algorithm in a case study showed its potential in decreasing the amount of hour required to work at height and climbing the scaffolding and also decrease in project cost and increase in productivity.

7.2 Recommendations

1) In order to create ontologies from process drawings (e.g. Piping and Instrument Diagrams), data-enriched CAD drawings need to be developed and meta-data should be added to different components. Currently used drawings in the industry are limited in their data and are not providing opportunities to apply semantic knowledge systems on them.
2) Creating a knowledge base to combine data from drawings and knowledge specifications requires the human language to be converted to a machine-readable

format and compatible with other part of the knowledge base (i.e. engineering drawing data). Since Natural Language Processing (NLP) is not developing semantic language format of knowledge (i.e. in the form OWL language), it is recommended that the human knowledge and engineering specifications to be converted to OWL language. Controlled Natural Language (CNL) and FE ontology editor can be used in this case. It is recommended that ISO 15926 standard to be used in converting natural language to CNL, and to OWL.

3) It is recommended that the equipment arrangement algorithm to run along with the development of the P&ID for a better collaboration between process and mechanical design teams. Future study in the section focuses on developing 3D models of the equipment arrangement to reach the capabilities beyond 2D models. Along with development of the 3D equipment arrangement models, it is recommended that the pipe routing and pipe support design algorithm to run to provide opportunities for design review in the early stages of the project. Future study in this field links this information model to a cost estimation platform to compare the cost of material in different design scenarios.
4) In order to gain more accurate results in the industrial usage of machine learning for piping stress analysis, it is recommended that the information from piping models (e.g. geometrical location of elbows, supports, etc.) and their stress analysis results in the existing process plants to be recorded in a data base and used as the 'training' data base for the machine learning algorithm. Future study in this area focuses on linking the piping design algorithm to the analysis platform, so that the automatic design and analysis could be performed simultaneously.
5) It is recommended that the Field Fit-Up weld selection activity to be shifted, from construction phase to the design phase of the project. It can reduce the error in the selection process and ultimately increase the efficiency and safety. Future study in this area can be extended to scaffolding and machineries (e.g. cranes).

Safety analysis in the basic phases of a process plant project is a significant industrial problem. By application of the modern techniques in Artificial Intelligence, semantic web, knowledge engineering, machine learning, Information Modelling, and Automation of design, a safer design for the lifecycle of a process plant could be achieved. The results could be beneficial to all process industries. We're looking forward to making contributions to further improvement and advances in this area.

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