2017

Feasibility analysis of using special purpose machines for drilling-related operations

Ana Vafadarshamasbi
Edith Cowan University

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This thesis is presented for the degree of

Doctor of Philosophy

Ana Vafadarshamasbi

Edith Cowan University

School of Engineering

2017

I would like to dedicate this thesis to the loving memory of my father, a kind teacher whom I miss every day, to my mother with love and eternal appreciation, and last but not least to my husband for his patience, and for supporting and standing by me.

Declaration

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Abstract

This work focuses on special purpose machine tools (SPMs), providing a modular platform for performing drilling-related operations. One of the main challenges in using SPMs is selecting the most appropriate machine tool among many alternatives. This thesis introduces a feasibility analysis procedure developed to support decision-making through the assessment of the strengths and limitations of SPMs. To achieve this, technical and economic feasibility analyses, a sensitivity analysis, and an optimisation model were developed and a case study was provided for each analysis. The results indicated that although technical feasibility analysis leads decision-makers to select a feasible machine tool, complementary analyses are required for making an informed decision and improving profitability. Accordingly, a mathematical cost model was developed to perform economic and sensitivity analyses and investigate the profitability of any selected SPM configuration. In addition, an optimisation procedure was applied to the cost model in order to investigate the effect of process parameters and the SPM configuration on the decision-making. Finally, the developed analyses were then integrated into a model in a proper sequence that can evaluate whether the SPM is appropriate for producing the given part and achieving higher productivity. To validate this integrated model three different case studies were presented and results were discussed. The results showed that the developed model is a very useful tool in assisting manufacturers to evaluate the performance of SPMs in comparison with other alternatives considered from different perspectives.

List of publications

On the basis of this thesis, the following papers were published/submitted (See Appendix F).

1. A. Vafadar, M. Tolouei-Rad, K. Hayward, and K. Abhary, "Technical feasibility analysis of utilizing special purpose machine tools," *Jounal of Manufacturing Systems 39*, pp. 53-62, 2016.
2. A. Vafadar, M. Tolouei-Rad, and K. Hayward, "New cost model for feasibility analysis of utilising special purpose machine tools," *International Journal of Production Research*, vol. 54, pp. 7330-7344, 2016.
3. A. Vafadar, K. Hayward, and M. Tolouei-Rad, "Sensitivity analysis for justification of utilising special purpose machine tools in the presence of uncertain parameters," *International Journal of Production Research*, pp. 1-20, 2017.
4. A. Vafadar, M. Tolouei-Rad, and K. Hayward, "Evaluation of the effect of product demand uncertainty on manufacturing system selection," *Procedia Manufacturing, 27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017*, Italy, 11, pp. 1735-1743, 2017.
5. A. Vafadar, K. Hayward, and M. Tolouei-Rad, "Drilling reconfigurable machine tool selection and process parameters optimisation as a function of product demand" *Journal of manufacturing systems*, 45, pp. 58-69, 2017.
6. A. Vafadar, M. Tolouei-Rad, and K. Hayward, "An integrated model to aid decision making of modular drilling machine tool selection," [redacted] under review.

Acknowledgements

The completion of this thesis would not have been possible without the support of a number of people. Hence, I would like to take this opportunity to offer my most sincere appreciation and thanks to them. I would first like to express the deepest appreciation to my supervisors Dr Majid Tolouei-Rad and Dr Kevin Hayward for supporting me during these past three and a half years. Without their great advice and guidance this thesis would not have been completed. Dr Tolouei-Rad freely shared his experience and knowledge throughout my PhD. I appreciate all his contributions of time and ideas to make my research experience productive. Dr Hayward's valuable suggestions and constant support kept me on the right path. His encouragement and patience helped me to overcome difficult problems in my research.

I would also like to thank Professor Daryoush Habibi, the Dean of the School of Engineering, for providing a friendly research environment. I am grateful to Associate Research Dean of School of Engineering Dr Mehdi Khiadani for his consistent support and advice. His office door has been open and he has been available for all the times when I needed his help.

I want to acknowledge Dr Greg Maguire and Dr Helen Renwick who reviewed my research manuscripts and provided me valuable grammatical and writing comments. I express my sincere appreciation to Dr Helen Renwick for reviewing my thesis and offering insightful comments.

I am sincerely thankful to Dr Douglas Chai for his guidance and support throughout my PhD candidature. My thanks also go to Dr Ferdinando Guzzomi for being very supportive and encouraging.

I must express my gratitude to Reza Esmaeili, my husband, for his continued support and encouragement. He constantly surprised me by his understanding as I experienced all of the ups and downs of my research. I am forever grateful to my family, and in particular my mother, my sisters, and my brother for their constant encouragement to accomplish my research and for the sacrifices that they have made on my behalf.

I am also thankful to postgraduate researchers and my lab colleagues in the school and all of the friends who encouraged and supported me to strive towards my goal during my PhD candidature. Special thanks to my friends in Australia, Maryam Yousefi Mitchel, Warren Mitchel, Mahtab Moradi, Sara Hashemi, Kaveh Shahbazi, and Ramsina Farmanian Eishoo and her family who supported me at the beginning of my PhD candidature and when I arrived in Australia. They helped me to deal with studying far away from home and my family. And although the pain of my father's passing remains, they gave me the strength to cope.

Last but not least, I would like to thank Edith Cowan University (ECU) and the School of Engineering for awarding me a research scholarship. I would like to express my full appreciation to the staff of the School of Engineering, ECU Library, and the Graduate Research School (GRS). My thanks go to everyone, named and unnamed, who has helped me over the last three and a half years.

Contents

List of figures

Nomenclature

A	Approach allowance (*mm*)
a	Availability of machine tool (*%*)
B	Budget (*$*)
C	Taylor tool life constant value
C_{ac}	All costs related to accessories such as rotary indexing table and control unit (*$*)
$C_{downtime}$	Cost of annual production losses (*$/year*)
C_{fix}	Fixturing costs (*$*)
C_{ic}	Installation and commissioning costs (*$*)
C_{it}	All costs related to indexing table and accessories (*$*)
C_{l}	labour cost (*$/hour*)
C_{m}	Annual machining operation cost (*$/year*)
$C_{machining}$	Annual machining cost (*$/year*)
$C_{maintenance}$	Annual maintenance cost (*$/year*)
C_{mat}	Cost of material unit before processing (*$*)
$C_{material}$	Annual material cost (*$/year*)
C_{mt}	Machine tool investment cost (*$*)
C_{mu}	Cost of required machining units (*$*)
C_{o}	Hour overhead cost (*$/hour*)
$C_{overhead}$	Annual overhead cost (*$/year*)
C_{su}	Cost of the required sliding units (*$*)
C_{t}	Annual tool cost (*$/year*)
C_{total}	Total life cycle production cost (*$*)
C_{1}	Cost of material unit (constant value) ($)
C_{2}	Working hours per year (constant value)
C_{3}	Cost of machine tool unit (constant value) ($)
C_{4}	Number of drilling heads (constant value)
C_{5}	Number of spindles per head (constant value)
C_{6}	Tool cost (constant value) ($)
C_{7}	Salvage coefficient (constant value)
C_{8}	Constant value (constant value)
C_{9}	Number of production years (constant value)
c_{t}	Cost of each tool of the spindle head (*$*)

D	Annual production volume
D_h	Hole diameter (mm)
d	length of cut (mm)
FV	Future value
$F(x)$	Unit profit ($/pc)
$f_1(x)$	Function of total material cost ($/year)
$f_2(x)$	Function of annual start demand
$f_3(x)$	Function of number of produced parts per hour
$f_4(x)$	Function of number of required machine tools
$f_5(x)$	Function of total machine tool cost ($)
$f_6(x)$	Function of total machining operation cost ($/year)
$f_7(x)$	Function of total tooling cost ($/year)
$f_8(x)$	Function of tool life of cutting tools (min)
$f_9(x)$	Function of total machining cost ($/year)
$f_{10}(x)$	Function of total maintenance cost ($/year)
$f_{11}(x)$	Function of total overhead cost ($/year)
$f_{12}(x)$	Salvage value ($)
$f_{13}(x)$	Total production cost ($)
$f_{st}(x)$	Saw-tooth frequency function
$f_{upr}(x)$	Unit profit range function
f	Feed (mm)
H	Average working hours per year (h/year)
i	Annual interest rate
j	Year of operation or production
K_1 to K_{14}	Constant values
k	Index of utilised drilling heads
l	Index of machining unit
M	Number of available machine tools
M_p	Part material
m	Number of work-stations
N_d	Number of drilling heads/operation groups
N_m	Number of required machine tools
N_{nso}	Number of sequential operation groups of single-station SPM
N'_{nso}	Number of sequential operation groups of multi-station SPM
N_p	Number of produced parts per hour
N_s	Number of spindles per drilling head
N_{so}	Number of cutting tools that perform a single operation or multiple

	operations in each sequential group of single-station SPM
N'_{so}	Number of cutting tools that perform a single operation or simultaneous operations in each group per station of multi-station SPM
N_t	Tool consumption per part
n	Taylor's tool life exponent
n'	Number of setups of single-station
o	Index of cutting tool performing a single operation or multiple operations in each sequential group
PV	Present value
p	Index of the sequential operation groups of single-station SPM
p'	Index of the sequential operation groups of multi-station SPM
P_m	Required power to drill the operation group (kW)
q	Scarp rate (%)
S	Salvage value ($\$$)
S_p	Sale price of the product ($\$$)
s_1 to s_{13}	Working stations of the optimisation model
T	Tool life for cutting tools of each drilling head (min)
T_c	Longest cutting time of all work-stations (min)
$T_c(w)$	Longest cutting time of each work-station (min)
$T_c(u)$	Cutting time of each setup (min)
T_f	Free tool travelling time (min)
T_i	Indexing time (min)
T_L	Loading time (min)
$T_{L/U}$	Loading and unloading time (min)
T_U	Unloading time (min)
T_m	Machining/Cycle time (min)
T_{mo}	Maintenance time (min)
T_s	Setup time (min)
T_{tc}	Total tool changing time per part (min)
t	Number of production years
t_c	Cutting time for each drilling head (min)
t	Number of production years
t_c	Cutting time for each drilling head per part (min)
$t_{c_p}(o)$	Cutting time for each of sequential operation groups of single-station SPM (min)
$t_{c_{p'}}(o)$	Cutting time for sequential operation groups of multi-station SPM

	(*min*)
t_{tc}	Tool changing time for each cutting tool of the spindle head
u	Index of setup of single-station ($u = 1, \ldots, n'$)
v	Cutting speed (*mm/min*)
w	Index of work-station
$X(1)$ to $X(y)$	Decision variables of the optimisation model
x_1	Required demand
x_2	Scrap rate
x_3	Availability of machine tool (%)
x_4	Machining time (min)
x_5	Labour rate ($/hour)
x_6	Operator fault rate (%)
x_7	Cutting time (min)
x_8	Cutting speed (mm/min)
x_9	Maintenance coefficient (%)
x_{10}	Overhead rate ($/hour)
x_{11}	Sale price ($)
y	Number of decision variables
α	Operator fault rate
β	Maintenance coefficient (%)
φ	Salvage coefficient (%)

Chapter 1: Introduction

About the thesis

This research focuses on the preliminary stages in the design and manufacture of special purpose machine tools (SPMs), with particular emphasis on the development of a feasibility analysis strategy to support the selection of appropriate SPMs in order to improve profitability in competitive markets.

1. Introduction

This thesis explores the development of a comprehensive feasibility analysis procedure which helps decision-makers to decide whether an SPM is an appropriate choice for machining a given part in order to achieve the highest productivity. This process should be performed before any investment is made on the preparation of detailed SPM design or purchase of an appropriate machine. To achieve this, the factors which have a key influence on the decision-making of using SPMs were identified and the relevant analyses were developed. These analyses were categorised into four main groups: technical, economic, sensitivity, and optimisation analyses. To clearly observe how these analyses work and how their results influence the final decisions, the developed analyses were applied to the same automotive part. The developed methods were then integrated into a model in a proper sequence for evaluating SPM utilisation for a given production. To examine the integrated proposed model, three more case studies were applied and the results of these case studies were evaluated and discussed. The results showed that the proposed model provided insightful information about strengths and limitations of a machine tool which could assist manufacturers in evaluating the performance of an SPM in comparison with other alternatives. Section 1.1 begins by explaining what SPMs are and why they are important in the manufacturing industry.

1.1. SPMs

SPMs can be designed and manufactured for performing drilling-related operations. These machines are modular manufacturing systems and a relatively new technology. Such machines do not have a rigid bulky configuration and may comprise a set of machining and slide units and their accessories, such as single or multiple spindles, indexing tables, and unit support columns. A typical SPM is shown in Figure 1-1. Their modular character allows SPMs to manufacture a number of similar products by rearranging the positions of units and accessories without applying major changes to the process and structure. In addition, operations can be performed from different directions simultaneously.

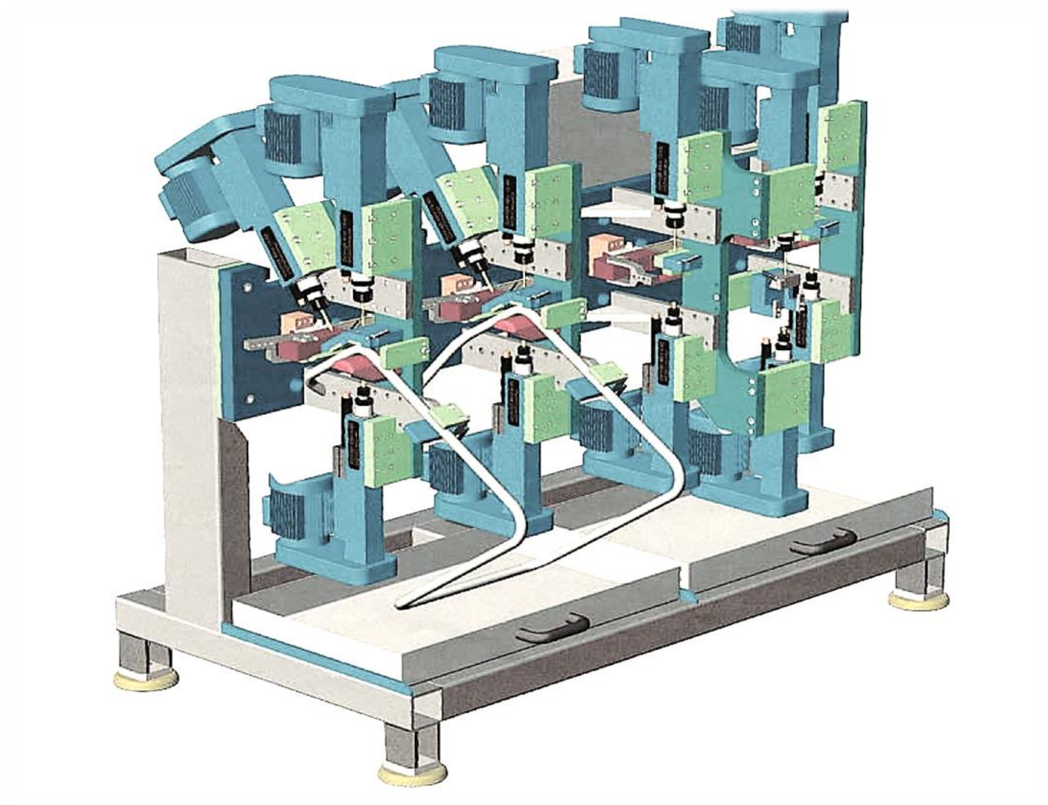

Figure 1-1 A typical SPM performing drilling-related operations [1, 2].

In the last few decades manufacturing industries have been strengthening their positions in a competitive market by using advanced technologies like SPMs, which have the ability to respond to new market requirements rapidly and effectively, produce new parts, and integrate new functions and processes into existing systems. The selection of SPMs as an appropriate machine tool among different alternatives is an important decision-making process when investing in and improving the facilities and this process requires a feasibility analysis procedure. A proper utilisation of SPMs may effectively enhance the productivity and probability of production systems by decreasing production time, and consequently reducing production costs. The next section of this thesis looks at feasibility analysis in the context of machine tool selection.

1.2. Feasibility analysis

In the context of machine tool selection, feasibility analysis is a decision-making process to evaluate the strengths and limitations of a machine tool for a given production. The initial stage of designing and manufacturing or purchasing a machine tool at the tactical level involves a feasibility analysis that considers different perspectives, such as technical and economic. Because of the risks and uncertainties in a competitive manufacturing environment, this important task should be carefully conducted before investment in purchasing or designing a machine tool. A number of different methods have been used by different researchers in order to perform feasibility analyses at the early stage of the decision-making process. These methods are discussed in Section 2.4 with a discussion of the application of feasibility analyses for selection problems in the manufacturing area.

1.3. Statement of the research problem

A review of the literature relating to advanced manufacturing systems highlights the fact that the evaluation of SPMs has not yet been addressed adequately. Although there are a few publications about modular machine tools, these studies mainly focused on milling, not on SPMs, which are used for drilling operations [3, 5, 6]. Although SPMs play an important role in a competitive market and have many benefits, the applications of these technologies are not proportional to their potential benefits [7]. Furthermore, the design and manufacturing of SPMs involves considerable expense and a proper justification of utilising an SPM should be made before attempting to design and manufacture one [7, 8]. Clearly, this process requires appropriate and effective evaluation which necessitates substantial data analysis and identification of the important factors influencing the outcome. To achieve this, an appropriate feasibility analysis is needed to help manufacturers decide whether or not an SPM should be used for a required production compared with other available alternatives.

In a competitive environment, one of the key decisions a manufacturing industry has to make is choosing the most appropriate manufacturing system from a wide range of alternatives. Maximum benefit is achieved if there is a fit between the machine tools' capabilities and the manufacturing market priorities and requirements. Indeed, improper selection of a manufacturing system has an effect on the productivity and capability of a manufacturer and may cause different problems, such as decreasing profitability and productivity [9, 10]. In addition, selecting a new manufacturing system is a difficult decision-making task requiring engineering knowledge and expertise [11, 12]. To make a well-considered decision, many factors and a large amount of information need to be evaluated [7]. Besides, manufacturers face uncertain product demand in situations where there are no forecast patterns [4, 13]. Accordingly, the process of selecting a new manufacturing system becomes more difficult as demand variation influences many factors simultaneously. Samvedi, et al. [14] found that the selection of the appropriate manufacturing system is an important initial investment decision for industries and influences the profitability of the facility. Accordingly, a reliable decision should be made before making an investment in a particular production method.

Conducting a feasibility analysis is one of the important steps in finding solutions for many engineering problems, and it plays an important role in a competitive manufacturing market. While researchers have explored feasibility analyses in different areas of manufacturing [11, 15, 16], few have addressed SPMs. Tolouei-Rad and Zolfaghari [7] presented a cost model for a feasibility analysis relating to the use of SPMs; however, improvements can be made to the feasibility analysis method proposed, particularly from strategic and economic perspectives. For selecting and using appropriate SPM components, strategic evaluation, which is not quantitative in nature and economic analysis should be considered for developing any feasibility analysis method. Feasibility analysis is a complex task as the evaluation involves an uncertain environment and inadequate data at the early stages of selecting machine tools.

1.4. Research objectives

This research investigates the following objectives:

1. **To develop a model to analyse the feasibility of using SPM(s) from a technical perspective for a given part (or family of parts).**

   Within this objective, the following points were considered:

   1.1. To identify the type of SPM required and related components required to produce a given part(s).

   1.2. To identify and characterise effective technical factors of the given part and the SPMs for performing the feasibility analysis.

   1.3. To develop a framework for the technical feasibility analysis in regard to utilising SPM(s).

2. **To develop a model to analyse the feasibility of using SPMs from an economic perspective for a given part (or parts).**

   If utilisation of SPMs is technically feasible, then an economic feasibility analysis would be required to make a reliable decision. The following processes were required for the development of the economic feasibility method of utilising SPM(s) for a given part (or parts).

   2.1. To identify and characterise effective time and cost factors in the utilisation of SPM(s).

   2.2. To develop a mathematical model for estimating the time and cost factors one of the main effective economic factors at an early stage.

   2.3. To develop financial indicators for performing a feasibility analysis.

3. **To investigate the effect of sensitivity analysis on the decision-making process informing the utilisation of SPMs.**

   To evaluate the effect of sensitivity analysis on the economic feasibility results, the following objectives were considered:

   3.1. To identify independent uncertain input and dependent output variables.

   3.2. To develop a mathematical model based on the dependent and independent variables to be used in order to perform sensitivity analysis on selecting SPMs.

3.3. To identify the most sensitive uncertain parameters.

3.4. To investigate the effect of uncertain parameters on the feasibility analysis outputs.

4. To investigate the effect of the optimisation process on the decision-making process.

To investigate the effect of optimal decision variables – process parameters and SPM configuration – on the machine tool selection problem, the following objectives were studied:

4.1. To define decision variables, objective function, and required options.

4.2. To develop an optimisation mathematical model.

4.3. To identify required boundaries and constraints for the developed model.

4.4. To simulate the cost model by using MATLAB/Simulink and connecting it to the GA toolbox.

4.5. To compare the results of feasibility analyses before and after performing optimisation to observe the effect of the optimal solution.

5. To develop an integrated model for decision-making in the early stages of the utilisation of SPM(s) to improve productivity and minimise cost and time over the life cycle of production.

The objectives were:

5.1. To identify the sequence of feasibility analyses as part of the development of an integrated model an integrated model.

5.2. The performance of a feasibility analysis by using the developed model for more case studies.

5.3. Comparing the results to check how the developed feasibility analysis works in regard to different components.

1.5. Outline of thesis chapters

On the basis of the content of the following chapters several papers were published/submitted and they are presented in Appendix F. The chapters within this thesis are organised as follows.

Chapter 2: Literature review

This chapter covers a literature review of manufacturing systems and the significance of SPMs in advanced manufacturing systems. It also addresses the feasibility analysis methods and highlights the effectiveness of proper feasibility analysis in regard to the use of SPMs.

Chapter 3: Technical feasibility analysis

This chapter provides a review of technical feasibility analyses for manufacturing system selection. It also presents a technical feasibility analysis methodology for evaluating SPM utilisation and selecting efficient SPM components for a given production. To verify the proposed model, a case study taken from industry is presented, and then results are discussed.

Chapter 4: Economic feasibility analysis

This chapter presents a review of cost analysis in the manufacturing field and also proposes an economic feasibility analysis strategy to support companies when deciding whether to use SPM for special production purposes. Important issues addressed in this chapter include determining critical effective time and cost factors and developing relevant mathematical models. The case study which is studied in Chapter 2 is used to examine the cost model developed.

Chapter 5: Sensitivity analysis

This chapter involves a literature review of sensitivity and uncertainty analyses and the effect of these analyses on the manufacturing selection problem. Moreover, in this chapter sensitivity analysis (SA) is applied to investigate the sources of uncertainties and errors which may reveal new insights for evaluating a machine tool. To achieve this, the developed cost model is subjected to a SA technique. Then critical independent variables which are uncertain are identified. This model is applied to the case study presented in the previous chapters.

Chapter 6: The effect of an optimisation process on feasibility analysis outcomes

This chapter focuses on the investigation of the effect of optimal process parameters and SPM configuration on the machine tool selection problem versus product demand changes. In this chapter, a simulated model using genetic algorithm is proposed to find the optimal process parameters and machine tool configuration. To achieve this, an optimisation model is presented and objective function, constraints, and relevant settings are explained in detail. The production of this case study is subjected to the optimisation model and the results post optimisation are compared to the results before optimisation.

Chapter 7: An integrated feasibility analysis model

The aim of this chapter is to integrate the above analyses into a whole decision-making process model that would support decision-makers in using SPMs for a given production. This model deals with evaluating the performance of SPMs from different points of view. Moreover, three more case studies are presented to clarify how the proposed model facilitates the decision-making process involved in choosing an SPM.

Chapter 8: Conclusion

This chapter covers conclusions and the main achievements of this research. Research scope are also discussed in this section. In addition, several lines of research arising from this work are recommended which may be pursued for future work.

Chapter 2: Background and literature review

2. Background and literature review

This literature review establishes the significance of SPMs in advanced manufacturing systems and highlights the effectiveness of an appropriate feasibility analysis for deciding whether to use SPMs to manufacture a part (or parts) versus other machine tools.

2.1. Manufacturing systems

Increasing manufacturing competition and rapidly changing consumer demands have led many industries to use advanced manufacturing systems. To meet these requirements a good understanding of manufacturing systems is necessary. As shown in Figure 2-1 ElMaraghy [3] classified manufacturing systems into three major groups: Dedicated Machining Systems (DMSs), Flexible Manufacturing Systems (FMSs) and Reconfigurable Manufacturing Systems (RMSs) which have different characteristics. The former paradigms of manufacturing methods are dedicated (DMS) and flexible manufacturing system (FMS) [17].

DMSs are designed to produce a single part at a constant volume over the production life of the machine and involve dedicated machine tools (DMT) which cannot be changed cost effectively to accommodate new requirements. An example of these machines is unit head machine which is dedicated to machine unique product or similar parts for the mass production [18]. Aguilar, et al. [5] argued that considerable engineering effort should be dedicated to add configurability to the machine tool design. This would facilitate the production of a great variety of tooling and manufacturing machines for different volumes [5]. Accordingly, FMSs are designed to machine a variety of undefined parts in changeable volumes and often involve general purpose machines (GPMs) which are not typically designed for a defined set of machining operations. Therefore,

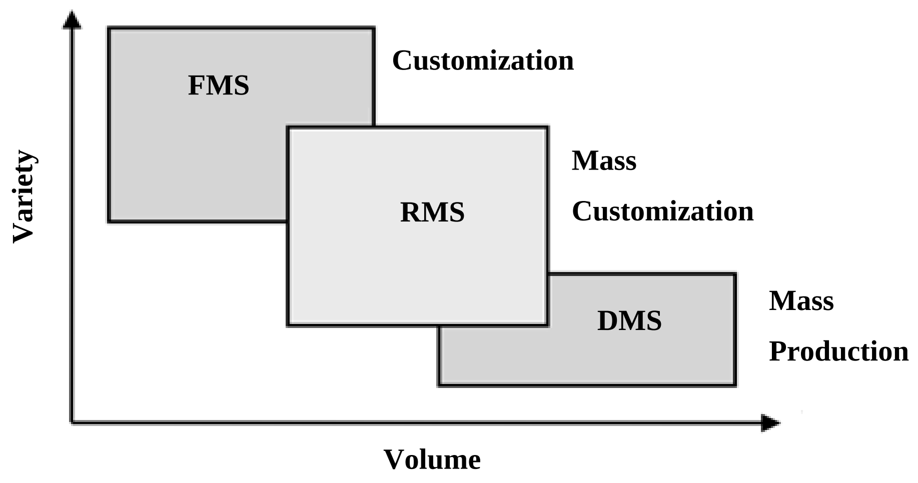

Figure 2-1 Manufacturing systems paradigms [3].

the manufacturer has to pay for unrequired capabilities and the cost of extensive efforts for meeting machine requirements. However, the current market is forcing manufacturers to be flexible enough to produce various specific parts in different quantities on the same system without the need for a large investment. RMSs are designed to meet a specific range of machining production requirements. The capacity and functionality of RMSs, unlike DMSs and FMSs, are not fixed and may lie between DMS and FMS (Table 2-1). Furthermore, these systems have customised flexibility making them less expensive than GPMs and FMS. Indeed, SPMs a main part of RMSs are enable to be reconfigured rapidly and cost-effectively when rapid changes are required due to unpredictable market demands.

Koren, et al. [19] proposed reconfigurable manufacturing systems (RMSs) with technology advances that are designed with adjustable components. These systems respond effectively to the market variations. Moreover, RMSs as a relatively a new class of manufacturing systems include the advantages of the high throughput of DMSs with the flexibility of FMSs, and also response to changes rapidly and efficiently [20]. Their modular structure allows them to quickly react to changes [3]. Indeed, these systems can be reconfigured from one configuration to another based on market requirements [21]. RMS configurations are designed and manufactured by using hardware and software modular components that can be changed over time in response to market requirements. The configuration of this manufacturing system may be similar to DMS or FMS, or a combination of both [3]. Therefore, as Table 2-1 shows, it is sometimes not possible to distinguish the features of RMSs from DMSs and FMSs from the perspective of capacity and functionality. The main factors highlighting the difference between RMS, DMS, and FMS are provided in Table 2-1.

The main components of RMSs are Reconfigurable Machine Tools (RMTs) which their changeable structure allows them to adjust to other resources. The modular design of RMTs enables them to be reconfigured rapidly and cost-effectively by removing, adding, changing, or rearranging components. RMTs may perform machining operations such as milling, drilling, turning, and tapping, or a combination of these operations. The broader perspective of these machine tools is performing different processes such as heat treatment, assembly, machining, and combinations of these processes which can be considered. The main components of these systems

Table 2-1 A comparison of manufacturing systems.

	RMS/RMT/SPM	**DMS**	**FMS**
Production Volume	Changeable	Fixed	Changeable
Functionality	Changeable	Fixed	Fixed
Cost	Intermediate	Intermediate	High
Structure	Adjustable	Fixed	Fixed
Part mix	Family	Single	Various
Flexibility	Customised	No	Yes
Simultaneous operating machine tools	Yes	Yes	No

are reconfigurable machine tools (RMTs) which may be designed to be cost effective tools for specific operations [22].

Recently, manufacturing industries have come up with modular machine tools. These machines are modular and can be reconfigured at after design and purchase [23]. Indeed, the modular characteristics of these machines allow users to rearrange a machine in different configurations in order to respond to production requirements [24]. Tolouei-Rad and Zolfaghari [7] introduced modular drilling machine tools that are designed for performing drilling-related operations. These machines are leading economic production solutions by considering current and future market demands. Indeed, this technology is designed to perform a particular machining operation or process to produce family of parts and manufacturer pays for the required capability. The structure of these machines is compact and modular including different components such as machining and sliding units, tables and chassis, rotary or sliding add-ons for tables, spindle heads, supporting components, and other accessories. Because of modular properties, similar products can be produced by rearranging their modular components [25, 26].

According to Youssef, et al. [27] machine tools can be categorised into special purpose machine tools SPMs and GPMs. SPMs are specially designed and manufactured for particular machining operations, whereas GPMs are typically not designed for a set defined of machining operations. GPMs may involve additional unrequired capabilities and greater uncertainty about whether machine requirements will be met. Since the machine tools introduced by Tolouei-Rad and Zolfaghari [7] are designed for performing specific machining operations, they are called SPMs. Some SPMs may have modularity: such machines consist of a set of machining and sliding units and accessories. The modular character allows these machines to manufacture a number of similar products by rearranging the positions of units and accessories. Hence SPMs are useful however they entail high investment costs.

2.2. SPMs

SPMs are specially designed and manufactured for the particular machining operations and the manufacturer only pays for the required capability. Their modularity allows the structure and functions of the machine tool to be rearranged to produce similar products. Manufacturing industries are strengthening their positions in a competitive market by using advanced technologies in the manufacturing process. Advanced manufacturing technologies (AMTs) facilitate quick responding to market demands and enable manufacturers to stay competitive in terms of cost, quality, and responsiveness to customers. SPMs are modular manufacturing systems which are a relatively new technology whose design is based on current and future market requirements.

These machines can be considered as the leading economic production solutions for performing drilling-related operations [7]. SPM design is based on the current and future requirements of manufacturing systems and market demands. These machines are modular making them possible to apply minor changes to the configuration of the machine by repositioning the units and other accessories [28]. This characteristic allows manufacturers to produce different products by changing the configurations of components in a product type without applying major changes to the process [29, 30]. Furthermore, an appropriate utilisation of SPMs can effectively enhance the productivity of production systems. This can be achieved by increasing the quality of production and decreasing production time, and consequently reducing production cost [12, 20]. SPMs, as economical and productive machines, and as such are often used for drilling-related operations. These types of operations are typical hole-making operations that carry out a large portion of machining operations to produce industrial parts [31]. While several studies of modular machine tools have primarily focused on milling machines [5, 6, 32-35], modular machines which perform drilling operations have received less attention from researchers.

The general structure of SPMs has limited configurability and consists of several components such as machining and sliding units, an indexing table, and accessories. These components can be put together to assemble a machining station for a particular application [36]. The re-configurability character allows these machines to manufacture a number of similar parts by

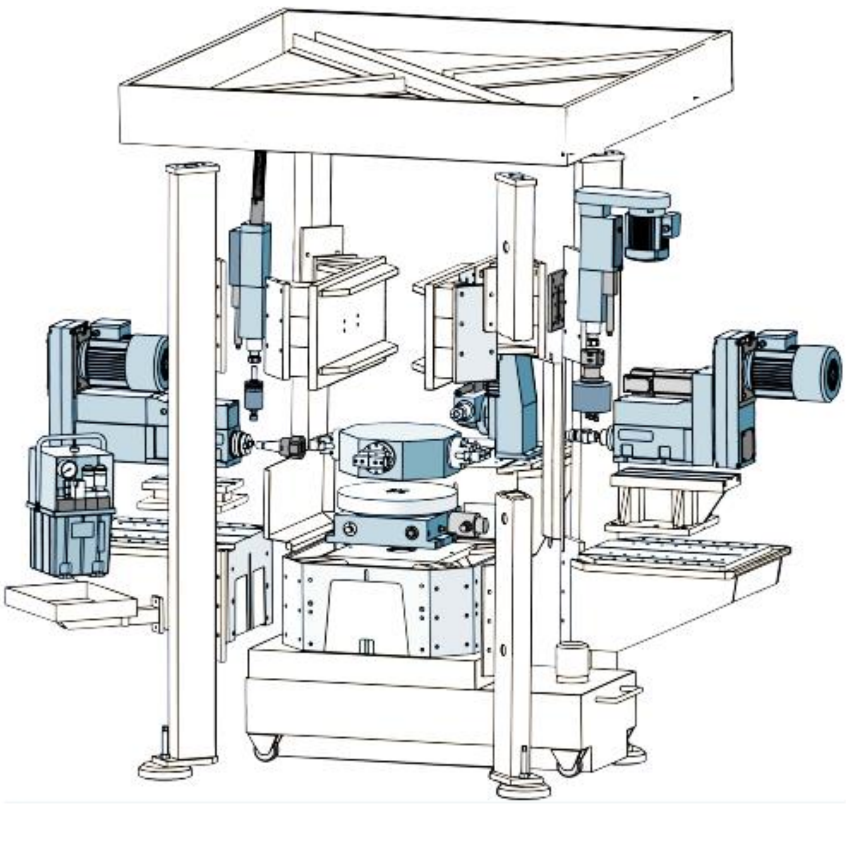

Figure 2-2 An SPM for producing parts with drilling-related operations [1].

rearranging the positions of components. Figure 2-2 shows an SPM configuration which is used for performing drilling related operations consisting of several machining stations to perform drilling-related operations.

2.2.1. SPM components

SPM units are divided into two main categories: machining and sliding. Machining units are equipped with a motor which rotates the spindle by means of a pulley and belt system. Standard tool holders are used to connect cutting tools to various machining units as shown in Figure 2-3 including: MONO, MULTI, POWER, CNC and TAP machining units [1], as shown in Figure 2-3. MONO machining units are used for single-purpose applications and featured variable spindle speed combinations operated through interchangeable pulleys. These machining units also provide the spindle with the required linear movements to allow a cutting tool to penetrate the work piece. MULTI machining units are used for multi operations and featured variable spindle speeds operated through interchangeable pulleys. These units may be appropriate when a degree of automation, ease of operation, resetting, and linking with other manufacturing stages are required. Power transmition is provided with flexible drive shafts between the motor and the drilling spindle. POWER machining units are used for high-precision drilling as well as normal drilling and for milling operations where high cutting forces are encountered. These units cannot perform linear movements because of the existence of high cutting forces which may cause deflections in spindle. Therefore, sliding units are designed to provide necessary linear movements to penetrate into the work piece. CNC machining units are used for performing different types of machining operations such as drilling, tapping and reaming. These programmable units are used in high speed and high feedrate operations and are designed to provide variable spindle speeds through the use of a frequency inventor that facilitates different working cycles with a digital AC-servomotor. CNC units may require sliding units to increase the range of linear movement. TAP machining units are used for tapping operations which require a variable spindle speed combination operated through interchangeable timing belts and pulleys. These machining units are designed to provide a spindle with the required linear movements to support penetration of the cutting tool into the work piece. Table 2-2 provides the list of different types of SPM machining units which some of them are utilised in the present work. The technical specifications of these machining units are provided in Appendix A.

a) An example of MONO machining unit (BEM 3)

b) An example of MULTI machining unit (BEW 3)

c) An example of POWER machining unit mounted on a sliding unit (BEX 15/UA 15)

d) An example of CNC machining unit with a servomotor for providing a linear motion of the Spindle (BEA 16)

e) An example of TAP machining unit (GEM 6)

Figure 2-3 Examples of different machining units [1].

Machining units mounted on the sliding units (as shown in Figure 2-3 (c)) provide necessary feed motions, fast advances and return strokes for cutting tools by means of pneumatic cylinders, hydraulic cylinders and AC-servomotors. Generally, different types of limit switches are used to adjust the unit’s movements. The adjustment of movements is provided by mechanical systems or micro switches [8]. Depending on the machining operations and required cutting tool motions, the machining units can perform necessary motions with or without sliding units. It is noteworthy that machining units can be installed on sliding units so that the cutting tool axis is either perpendicular or along with the sliding motions.

Multi-spindle heads are used for precision drilling and tapping operations. They provide a high degree of automation with a low cost investment [1]. These heads produce many holes on the same plane simultaneously [1]. The spindle heads are divided into fixed and adjustable types [1]. In fixed multi-spindle heads, positions of tools are fixed while the tool position can be adjusted in adjustable multi-spindle heads. Multi-drill heads can be used with different types of machining units mentioned above. An Adjustable 3-spindle head is shown in Figure 2-4.

Assembly components such as special stands, base plates, different types of supports and slide blocks are designed to be used for placing and supporting machining units at any angle in different positions. These components should be rigid enough to minimise vibrations caused by machining operations. They are also designed to reduce or eliminate vibrations during machining operations [8]. Figure 2-5 shows a vertical support which is designed with multiple positions to allow different height positions for machining units.

An indexing table is often used in SPMs to provide precise positions of a work piece in different machining stations. Once operations and working stations are established, then fixtures can be placed on the indexing table [1]. Indexing tables can be divided into two main categories: rotary and sliding tables. Figure 2-6 shows an example of rotary indexing table providing a full 360^0 rotation.

Figure 2-4 Examples of multiple spindle head [1].

Figure 2-5 A machining unit is attached to a vertical assembly component [1].

Figure 2-6 An example of rotary indexing table [1].

Table 2-2 list of different types of SPM machining units [1].

	MONO [1]	MULTI [2]	POWER [3]	CNC [4]	TAP [5]
1	BEM 3	BEW 3	BEX 15	BEA 16	GEM 6
2	BEM 6	BEW 6	BEX 35	BEA 25	GEM 8
3	BEM 6D	BEW 12	BEX 15/ UA 15	BEA 16/ UA 15	GEM 12
4	BEM 12	BEWI 4	BEX 35/ UA 35	BEA 35/ UA 35	GEM 20
5	BEM 12D	BEWI 6	-	-	GSX30-90
6	BEM 12VC	BEWI 12	-	-	-
7	BEM 20	-	-	-	-
8	BEM 28	-	-	-	-
9	BEM 25H	-	-	-	-

1: MONO units are used for single-purpose applications and featured variable spindle speed combinations operated through interchangeable pulleys.

2: MULTI units are used for multi operations and featured variable spindle speeds operated through interchangeable pulleys.

3: POWER units are used for high-precision drilling as well as drilling related and milling operations where high cutting forces are encountered.

4: CNC units are used for performing different types of machining operations such as drilling, tapping and reaming. These programmable units are used in high speed and high federate operations and are designed to provide variable spindle speeds through the use of a frequency inventor which facilitates different working cycles with a digital AC-servomotor.

5: TAP units are used for tapping operations which require a variable spindle speed combination operated through interchangeable timing belts and pulleys.

2.2.2. SPM utilisations

The productivity and profitability of industries may considerably increase by using SPMs [7]. While SPMs are often superior to GPMs in the case of high volume production, the extent of the utilisation of these machines is not proportional to the potential benefits [12]. The reason is the lack of a proper methodology for selection of these manufacturing systems. Maximum profit will be achieved if there is a fit between the production requirements and the capabilities of an SPM. Few research publications have focused on the using SPMs in manufacturing. Tolouei-Rad [12] proposed a Knowledge-based (KB) system for analysing using SPMs when dealing with qualitative and quantitative information. Tolouei-Rad and Zolfaghari [7] introduced SPMs and the relevant components and proposed a method for improving productivity with SPMs. However, a comprehensive feasibility analysis for using SPMs have not yet been adequately addressed.

Feasibility analysis is one of the necessary steps for any engineering problem which evaluates the viability of a proposed system. This analysis facilitates enterprise decisions relating to a detailed system design and then its manufacture [9]. While researchers have explored feasibility analyses in different areas of manufacturing [20-22], few addressed SPMs. Tolouei-Rad and Zolfaghari [7] presented an economic method for a feasibility analysis of using SPMs. There is a need to improve the methodology associated with feasibility analyses for SPM utilisation particularly from technical and economic points of view.

2.3. Feasibility analysis

A feasibility analysis, which is also called feasibility study, is one of the major steps in solving any engineering problem and assessing a project's potential to be successful [11]. Feasibility analysis finds the strengths and weaknesses of a proposed project, and provides recommendations to enable managers to make well-informed decisions and improve their results. In general, feasibility analyses includes four main steps as follows (Figure 2-7).

Step 1: Input data

At this stage, all the required information for performing the relevant feasibility analysis is identified and applied to the model.

Step 2: Evaluation of a project from different aspects

In the first step, a project is evaluated by establishing different factors such as technological, operational, and economic capabilities. Chan, et al. [37] concluded that evaluation methodologies for feasibility analyses relating to the use of manufacturing systems can be grouped into three main categorises: analytic, strategic and economic.

Step 3: Summary of results

In this step, the strengths and weaknesses of the available solutions are evaluated. The potential advantages and disadvantages of using different machine tools can be summarised.

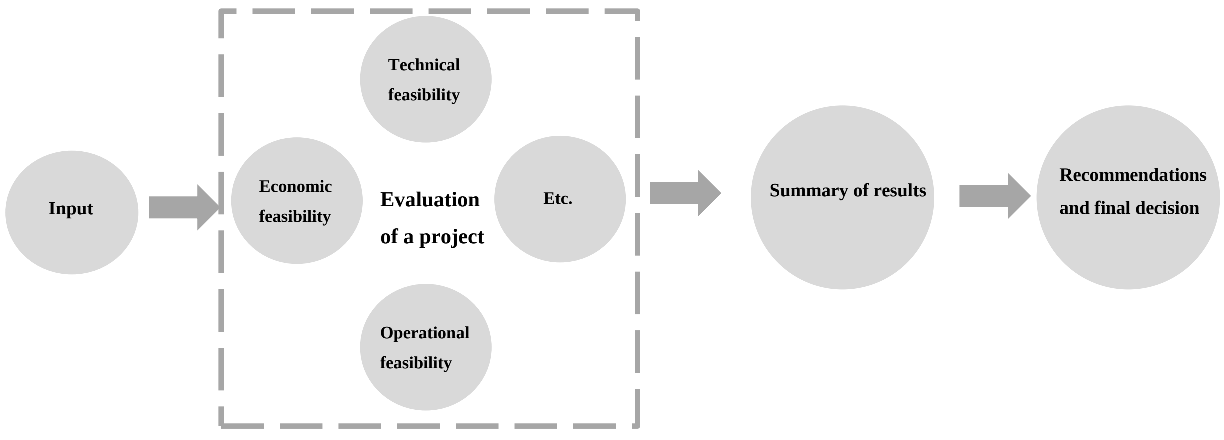

Figure 2-7 Feasibility analysis steps.

Step 4: Recommendations and final decision

The last part of feasibility analysis is recommendations containing some new insights for making a reliable decision or providing guidance in regard to improvements to facilitate better implementation. In addition, an appropriate choice is selected before a considerable amount of money is spent on it.

2.4. Feasibility analysis methods

Today's competitive environment has led many industries to utilise advanced machine tools and manufacturing systems to meet market demands. Selecting the most appropriate machine tool from among available machine tools is a critical process which helps achieve high productivity, quality, efficiency, safety and profit [38]. Furthermore, decision making at the early design stages greatly influences the success of the final product [39]. Some researchers have also stated that nearly 70 percent of the production cost is committed during the early design phase [40, 41]. Therefore, machine tool selection at the early stage is an important step of designing or purchasing a machine tool. However, this is a difficult decision making process for companies [42], because many factors should be considered and improper machine tool selection may reduce productivity and cause a range of problems [43]. Furthermore, a key challenge in initial decision making is the lack of reliable information about SPM and other machine tool alternatives and access to an expert with considerable knowledge of SPM properties. Furthermore, manufacturers face uncertainties which do not have forecast patterns [13, 44]. Rönnberg Sjödin, et al. [45] asserted that uncertainty is one of the key challenges at the early stages of projects that can have devastating consequences of in overall project performance. Accordingly, the process of selection a new manufacturing system becomes more difficult as uncertain parameters variation influences different factors simultaneously. Samvedi, et al. [14] found that the selection of an appropriate manufacturing system is an important initial investment decision for industries which influences the profitability of the facility. Accordingly, an informed decision should be made before making an investment on the production method.

The selection of manufacturing systems and machine tools has been investigated from different points of view. Chan, et al. [37] categorised methodologies justifying manufacturing selection into three main groups: analytic, strategic and economic. Table 2-3 summarises justification methods which are used for selection problems. This table also provides advantages and disadvantages of theses method in justifying of advanced manufacturing systems. A majority of researchers rely on the application of analytical methods such as the analytical hierarchy process (AHP) [11], technique for order of preference by similarity to ideal solution (TOPSIS) [46], integrated linguistic multi decision making method [47], fuzzy ranking method [48, 49] and a hybrid of the ranking methods [14]. Several strategic methods have been applied in manufacturing research. Some of them applied expert systems (ES) for a machine tool evaluation problem to

Table 2-3 Justification methods for selection of advanced manufacturing systems.

	Methods	Advantages	Disadvantages	References
Economic	Net Present Value (NPV) Payback period, Return on investment (ROI) Internal rate of return (IRR)	Data collection is easy. Uncertainty can be considered in this method.	This method does not take into account technical point of view. This method ignores the criteria which are qualitative.	Banakar and Tahriri [10] Santander-Mercado and Jubiz-Diaz [50] Dai and Lee [51] Qian and Ben-Arieh [52] Méndez-Piñero and Colón-Vázquez [53] Wiesemann, et al. [54] Amidpour, et al. [55] Vila, et al. [56] Baird and Rother [57] Nasr, et al. [58]
Strategic	Technical analysis Market and business analysis Research and development	Performing these methods is easy. Less technical information is required for users.	It is recommended to use these methods with economic or analytic to provide reliable data. Expertise and engineering knowledge is required to develop this method.	Banakar and Tahriri [10] Baird and Rother [57] Klocke, et al. [59] Vila, et al. [56] Baird and Rother [57] Nasr, et al. [58] Battaïa, et al. [60] Guldogan [61]
Analytic	Scoring methods (such as Analytic Hierarchy Process (AHP) and technique for order of preference by similarity to ideal solution (TOPSIS)) Fuzzy set method Programming	Uncertainty can be considered in this method. Qualitative and quantitative parameters can be considered by using these methods.	More data is required. This method is usually more complex than economic analysis.	Banakar and Tahriri [10] Yurdakul [62] Abdi and Labib * [11] Abdi and Labib [63] Xue, et al. [47] Samvedi, et al. [14] Taha and Rostam [64] Hsu, et al. [65] Chang, et al. [66] Yurdakul [62]

consider qualitative factors (Battaïa, et al. [9]; Guldogan [61]). Several studies focused on economic feasibility analysis as an effective and accepted assessment tool for selecting suitable machine tools [51, 67].

Since the design and manufacturing of an SPM has relatively high cost, a proper justification method for using an SPM and related components should be established before any decision to design and manufacture an SPM machine [7]. Clearly, this process requires appropriate and effective evaluation which necessitates substantial data analysis and identification of the major factors affecting at the accuracy of the analysis. To do this an appropriate feasibility analysis is needed to decide whether a SPM should be used for the required production process.

From the above it can be concluded that although there are some publications on the feasibility analysis of manufacturing system selection, SPM has not been adequately addressed in publications. The literature of important feasibility analysis methods used in justifying the application of SPMs are presented in the following sections.

2.4.1. Technical feasibility analysis

Technical feasibility is one of the analyses that must be performed after defining a project is defined. This analysis assesses the details of how a proposed project works. Indeed, the technical feasibility study is a logistical plan that shows how a given product can be produced, and this informs the process of machine tool selection. This analysis can serve as a flowchart of how products and machine tools evolve and move through a reliable decision making process to cope with the market demands.

To perform this analysis for machine tool selection, an understanding of an expertise and experience with in depth understanding of machine tools is required. Thus, this process can be difficult and time consuming as many critical technical qualitative and quantitative factors have to be determined and analysed prior to design and implementation. Kou, et al. [68] concluded that without intelligent systems, collecting the expert knowledge needed to make final decisions would be time-consuming and protracted. Clearly, an intelligent system is required for manufacturing industries to successfully perform feasibility analysis and to inform the decision-making surrounding the use of machine tools by considering part(s) specifications and machine tool characteristics.

Several intelligent systems have been applied in manufacturing research. Tan, et al. [69] proposed fuzzy ARTMAP (FAM) neural network model and a hybrid intelligent case-based reasoning (CBR) to assist users in manufacturing investment decision making. Their system included a database library comprising of the details of past manufacturing technology projects. A set of features defined by engineers and experts were employed to characterise each project. Following this, a FAM network was used to match the features of a new proposal with previous cases of the database. Similar projects were retrieved, and the data from these projects were used as inputs to prioritisation of new proposed manufacturing technologies. Culler and Burd [70] demonstrated a framework in which computer-aided process planning (CAPP) and activity based costing (ABC) were incorporated into a decision making system for documentation and cost control. Some studies applied decision support systems (DSS) which majority of existing DSSs were limited to selecting machine tools and manufacturing systems by applying optimisation tools [60, 71]. Several publications reported the use of expert systems to consider qualitative information in relation to machine tool assessment. Chowdary and Muthineni [72] developed a knowledge-based system for flexible manufacturing system selection. The proposed system included three main modules: a database for storing machining system characteristics; a knowledge base to store rules that assist selection problem; and an inference engine to select a proper machining system. Chakraborty and Dey [73] proposed a quality function deployment (QFD) method for selection of non-traditional machining processes. They designed an expert system to automate the decision making process. This system employed a quality matrix for comparing products and processes characteristics. The authors show that by estimating the weight of different processes the optimal choice can be selected. Guldogan [61] proposed a hybrid model applying the knowledge-based system to machine tool selection problem. This system consists of a two-step approach. The first step determines the potential feasibility of machine tools by using the knowledge-based expert system. The second step uses the genetic algorithm technique to find the optimum machine tool.

From the above it can be concluded that there are some research about machine tools evaluation for decision making of applying them by using intelligent systems; yet performing technical feasibility analysis of using SPMs by using intelligent system based on the expert and experience knowledge has not been adequately addressed.

2.4.2. Economic feasibility analysis

Economic feasibility analysis evaluates costs and revenues of a project to determine whether it is potentially feasible to be completed. This analysis indicates whether the proposed project is cost effect and can make any profit. Banakar and Tahriri [10] concluded that economic evaluations play a key role in a competitive manufacturing market. Economic feasibility requires cost estimations which are fundamental criteria for performing analysis in engineering fields [43]. On the whole, economic analysis has received scant attention in the literature. The studies have been published in different engineering disciplines such as the moulds and dies industries [74], automotive field [75, 76], power systems [77], product packaging [78, 79], aerospace , and manufacturing [53, 80].

To perform economic feasibility analysis different financial metrics can be used. Meredith and Suresh [81] applied the net present value (NPV), the payback period, the return on investment (ROI), and the internal rate of return (IRR) as financial indicators to perform feasibility analysis of using advanced manufacturing systems. Dai and Lee [51] performed economic feasibility analysis for adopting flexible material handling systems. To do this, they estimated the internal rate of return (IIR) and payback periods in order to evaluate the economic performance of alternatives. Klocke, et al. [59] compared face milling versus surface grinding by considering the cost of machine depreciation, labour and consumable items such as cutting tools. Quintana and Ciurana [43] developed a cost estimation method, for utilising vertical high speed machining centres which is based on multiple regression analyses. Klocke, et al. [82] performed a cost analysis for utilising unconventional manufacturing systems such as electro discharge machining (EDM) and electrochemical machining (ECM) technologies based on material removal rate for rough milling of titanium- and nickel-based alloys. Vila, et al. [56] used an economic analysis to select face milling operations in comparison with surface grinding operations for manufacturing of hardened steel surfaces dies and moulds. The applications of these financial indicators have not been limited to the manufacturing field and have been used in different engineering disciplines [55, 76, 83]. For instance, Méndez-Piñero and Colón-Vázquez [53] applied the payback and the internal rate of return methods to identify feasible economic alternatives to minimise energy use. Santander-Mercado and Jubiz-Diaz [50] presented a literature survey for economic analyses which have been investigated in the field of economic lot scheduling. It can be seen that the application of economic feasibility analysis has been investigated by many researchers. However, the majority of publications considered the economic performance of alternatives whereas sensitivity analysis has not been adequately addressed. Moreover, there are only limited research found in the literature which explore feasibility analysis in relation to the selection of machine tools, especially SPMs versus different alternatives.

2.4.3. Sensitivity analysis

Hazir, et al. [84] believed that the number of publications which applied cost- or profit- methods in the manufacturing field is increasing. Economic analysis provides important information about a manufacturing system selection process and avoids costly and timely studies; a key challenge is the lack of sufficient and reliable data at the preliminary stage of designing or purchasing a machine tool. In addition, uncertainties may influence the manufacturing system performance and consequently the final decision on selecting a manufacturing system. It is also important to note that the estimation of input parameters and assumptions of any economic mathematical model are made under uncertainty which complicates the evaluation of investment decisions [85]. Rönnberg Sjödin, et al. [45] believed that uncertainty was one of the key challenges at the early stages of projects which can have huge consequences in project performance. Furthermore, they asserted that when the behaviour of a system is described by a mathematical model a poor decision may be made due to uncertainty in the parameters of the model [86]. Accordingly, the economic model may not be sufficiently robust for the decision making process, thus a supplementary technique is needed with the cost model for investigating the inputs of the model under uncertainty. A literature review reveals that several papers applied SA in order to make accurate decision; however, adequate studies have not yet been focused on manufacturing system selection under conditions of product demand uncertainty.

For studies concerning the evaluation of future or unpredicted situations, an analysis is required to determine the range of possible outputs which are the result of imprecise input parameters [4]. Essentially, sensitivity analysis (SA) is applied to analyse the contribution of estimated uncertainty ranges in the output results of a model [4, 87]. As shown in Figure 2-8 this analysis provides a better understanding of the relationships between input and output variables in a model. This figure indicates that how SA studies the output of a system or a mathematical model by

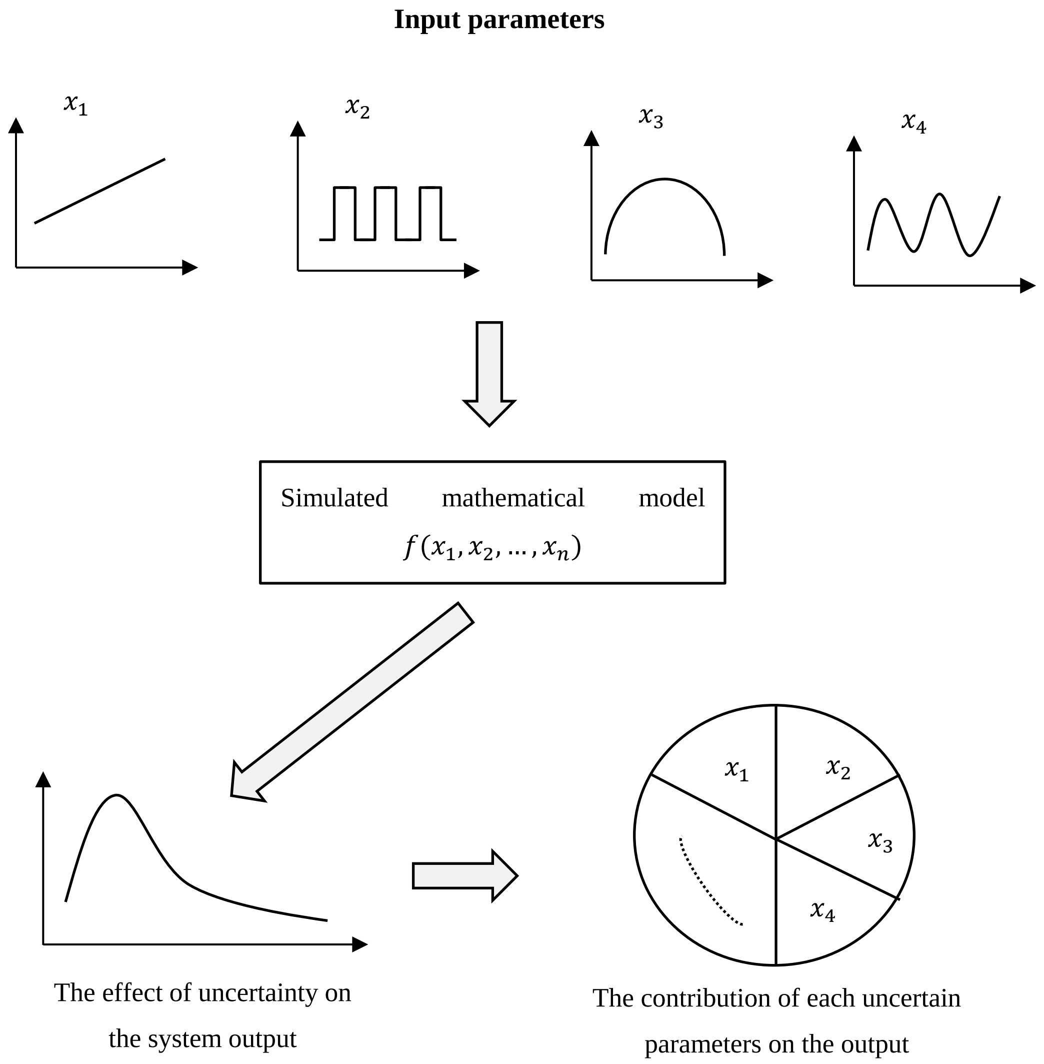

Figure 2-8 The schematic presentation of sensitivity analysis process (The figure is a summary of the De Moel, et al. [4] work).

determining how different distributions of independent variables influence the output of a simulated model. Furthermore, SA enables users to distinguish which uncertainty parameters or sources have the most effect on the output [4]. In addition, SA may provide additional information and robust measures for the decision-making process in the presence of uncertainty [88]. Over the last few years, increasing attention has been paid to the application of these analyses in different engineering decision-making processes, such as the selection of the configuration of MRRC for low-temperature refrigeration systems in petrochemical industries [55], the optimal design of the biofuels [85], and slicing system selection [66].

Sensitivity analysis (SA) investigates the inputs of the model and tests the robustness of the results in the presence of uncertainty. Generally, SA methods may be categorised into two main groups: local and global sensitivity analyses. Local sensitivity analysis studies the sensitivity of one input variable, while keeping the values of other input variables constant. Global sensitivity analysis operates in a random or systematic way to explore the global input space of variables [89]. There is a large literature about SA. Wainwright, et al. [88] compared the local and global sensitivity analyses. They demonstrated that both methods gave similar results and concluded that a local sensitivity analysis should be performed first, because it may provide sufficient information to identify influential variables. Furthermore, they concluded that global sensitivity analysis provides additional information to provide robust measures in the presence of nonlinearity among variables. Foglia, et al. [90] explored different types of SA and found that local SA provides sufficient information to justify the results and global SA methods do not provide additional information.

Pannell [91] divided the objectives of SA into four main groups: decision making purposes or development of justifications and information for decision makers; communication; quantification of the system; and model development. Considerable studies applied SA methods in different areas of engineering [55, 87, 92, 93]. Amidpour, et al. [55] applied economic and sensitivity analyses to a systematic model including mathematical methods and thermodynamic model to optimise design configurations. Chang, et al. [66] developed an AHP model sensitivity analysis for selecting an appropriate slicing machine. Then, a sensitivity analysis was applied to the developed model to test the stability of the priority results. Chen, et al. [94] performed a sensitivity analysis technique for a multi-criteria decision making problem to test the effect of weight sensitivity on the results, which is usually difficult to be quantitatively evaluated. Karaoğlu and Secgin [92] developed an empirical mathematical model for optimising process parameters. They also carried out a sensitivity analysis is carried out to optimise process parameters and fine tuning requirements for the optimised weld bead geometry. In addition, the effect of relations between input parameters and output results are investigated. A review of literature indicates that performing SA on machine tool selection and manufacturing area has received less attention from researchers. It can be concluded although there are some publications on economic analysis of manufacturing processes; sensitivity analysis for justifying machine tool selection has not yet been adequately addressed in these publications.

2.4.4. Optimisation methods for selecting machine tool

The literature about selection problems shows that optimisation techniques have been published in different engineering problems. Decision making results may be improved by applying an optimisation process to the feasibility analysis model. Amidpour, et al. [55] developed an economic optimisation by combining multi-stream exchanger design and optimised operation parameters. The aim of this research was minimising the consumed power by an enumerative method to find a proper design configuration of mixed refrigerant refrigeration cycles (MRRCs). Ardjmand, et al. [13] proposed a robust optimisation model to maximise profit, which leads to selecting the most appropriate production plan. To perform this process, a modified unconscious search (US) algorithm is applied. Bouaziz and Zghal [95] developed an algorithm to find a set of optimal cutters for machining complex geometries with a CNC machine. Liu and Liang [96] used an optimisation technique to select a proper design configuration of a reconfigurable machine tool. The aim of this research was developing a model to generate and assess alternative design configurations. Méndez-Piñero and Colón-Vázquez [53] developed an optimisation model to evaluate feasible economic alternatives in order to reduce energy use. The objective of this optimisation problem was maximising the net economic benefits to identify the optimum feasible alternative that could cope with the constraints. The economic analysis methods used were the payback and the internal rate of return. Gontarz, et al. [97] developed a methodology for evaluating reasonable investments; then an optimisation technique is applied to find optimum potentials with the economic evaluation of selected solutions.

In recent decades, many researchers have explored computer aided process planning (CAPP). Xu, et al. [138] comprehensively reviewed recent developments and future perspectives for CAPP. Li, et al. [106] asserted that process planning optimisation includes optimal machining parameters and machining sequence generation. Yusup, et al. [98] published an overview and a comparison of the recent year researches – from 2007 to 2011 – that used evolutionary optimisation methods to optimise machining process parameters of machining processes. Majority of process planning studies focused on generating optimum machining parameters [11, 12]. Pawar and Rao [99] presented an optimisation algorithm for finding optimum process parameters. The model was applied to three machining processes including two conventional machining operations – grinding and milling – and an advanced machining process namely the abrasive water jet machining process. Yildiz [100] developed an optimisation model based on artificial bee colony algorithm to find optimal cutting parameters of turning operations. Zain, et al. [101] applied genetic algorithm (GA) to find optimum cutting parameters – the radial rake angle of a tool integrated with cutting speed and feed rate – to observe the optimal effect on the surface roughness results. Yildiz [102] applied an optimisation technique – cuckoo search algorithm – for selecting optimal machining parameters in milling operations. Salehi and Bahreininejad [103] presented an intelligent search strategy to generate optimum sequences based on the order constraints for job shop machining. Zhang, et al. [104] presented an integrated multi-objectives model to find optimum sequence planning.

From the above it can be concluded that some studies focused on process planning and operation sequencing. But today CAPP has faced new challenges which have drawn researchers' attention to the dynamic and ever-changing competitive market. Since production requirements and demand may change in this competitive market, appropriate utilising of machine tools and process parameters are becoming of more importance to manufacturers. Some researchers defined process planning as the process of deciding on the selection of machines and the machining processes needed to produce a part [69]. Determination of optimal process parameters may affect productivity, operation time, and production cost. Therefore, when manufacturers desire to use

SPMs, appropriate selection of SPM configuration and process parameters may significantly influence the decision to use SPMs instead of other machine tools at the feasibility analysis stage.

In a highly competitive market manufacturers must respond quickly to demands. Evolutionary or meta-heuristic optimisation techniques meet the requirement for fast optimisation of multi-variable problems [96]. A review of the optimisation techniques showed that evolutionary techniques are useful tools which are utilised broadly for different manufacturing problems [96-98]. These techniques are genetic algorithm (GA), simulated annealing (SA), particle swarm optimisation (PSO), artificial bee colony (ABC), and Tabu search (TS), which are inspired by the nature behaviours. Some research studies of evolutionary algorithms in the manufacturing fields have been published by Ardjmand, et al. [13]; Méndez-Piñero and Colón-Vázquez [53]; D'Addona and Teti [105]; Yildiz [100]; Li, et al. [106]; Zain, et al. [107]; Cus and Balic [108].

2.4.5. Genetic algorithm

Genetic algorithms (GAs) are based on the principles of natural selection process and genetics to

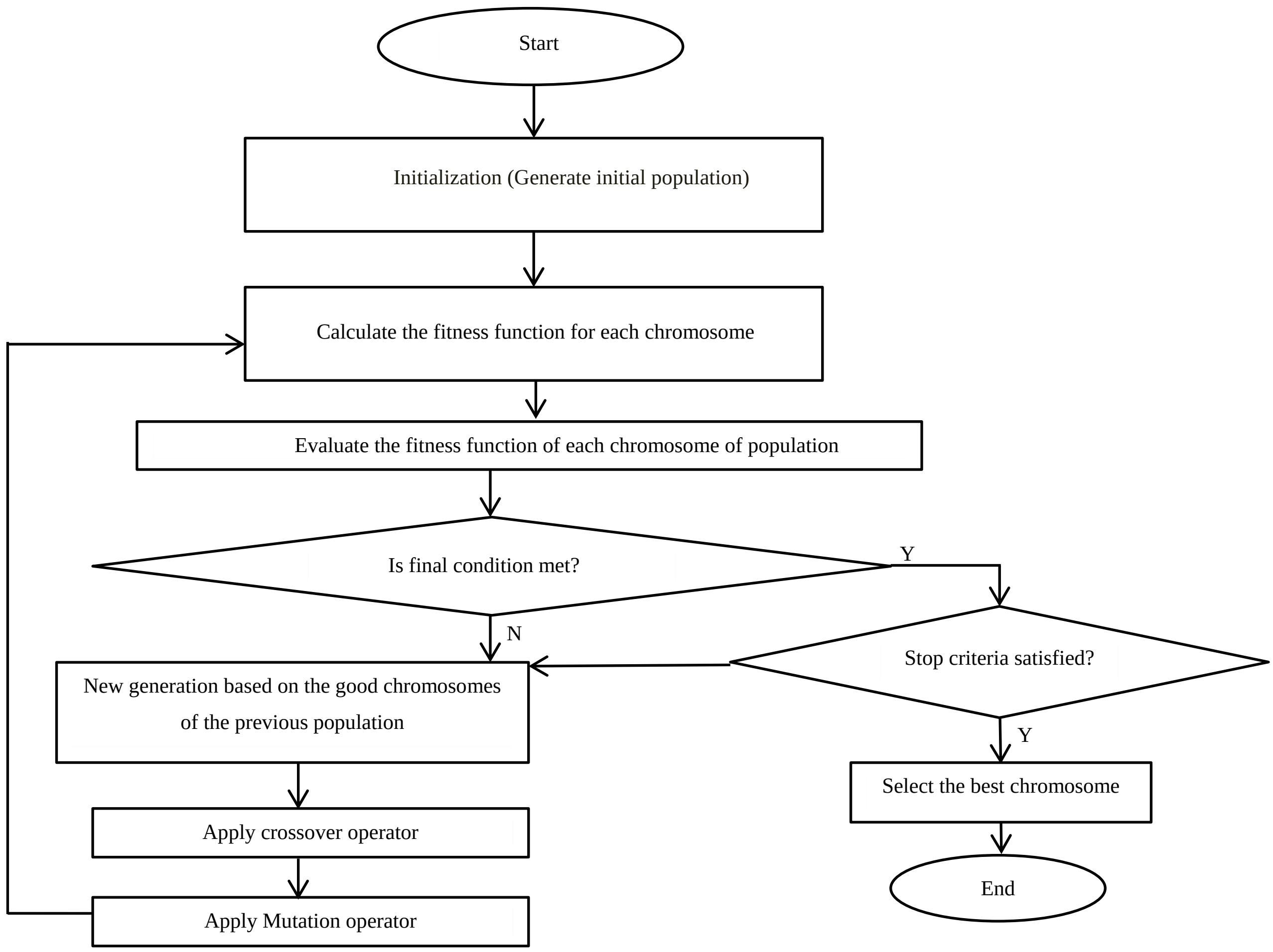

Figure 2-9 A flowchart of GA process steps.

solve constrained and unconstrained complex optimisation problems (Hassani and Treijs [109]; Holland [110]). In a GA optimisation problem, a population of candidate solutions namely individuals is evolved toward optimal solutions. Indeed, in this technique a population of individual solutions is repeatedly modified. At each phase, individuals are randomly selected from the current population and these individuals are used as parents to create new children for the next generation. In each generation, the fitness of all individuals is calculated and evaluated; the fitness is usually the value of the objective function in the optimisation problem being solved. Normally, the GA process completes when either the fitness value has been satisfied for the population or the number of generations has been reached to the maximum value [110] .

Figure 2-9 shows a schematic flowchart of the GA process which includes the following steps [111-114]:

Initialisation: First of all, the algorithm generates an initial population randomly allowing the entire search space including all possible solutions. The size of population depends on the problem. Traditionally, candidate solutions in the generated populations are shown by strings which include binary codes 0s and 1s. However, different encoding can be used [115].

Selection: To create a new generation namely children, individual solutions called parents are selected from a population for later breeding. There are some selection methods rating the fitness of each individual solution and consequently choosing the best solutions. Since these methods

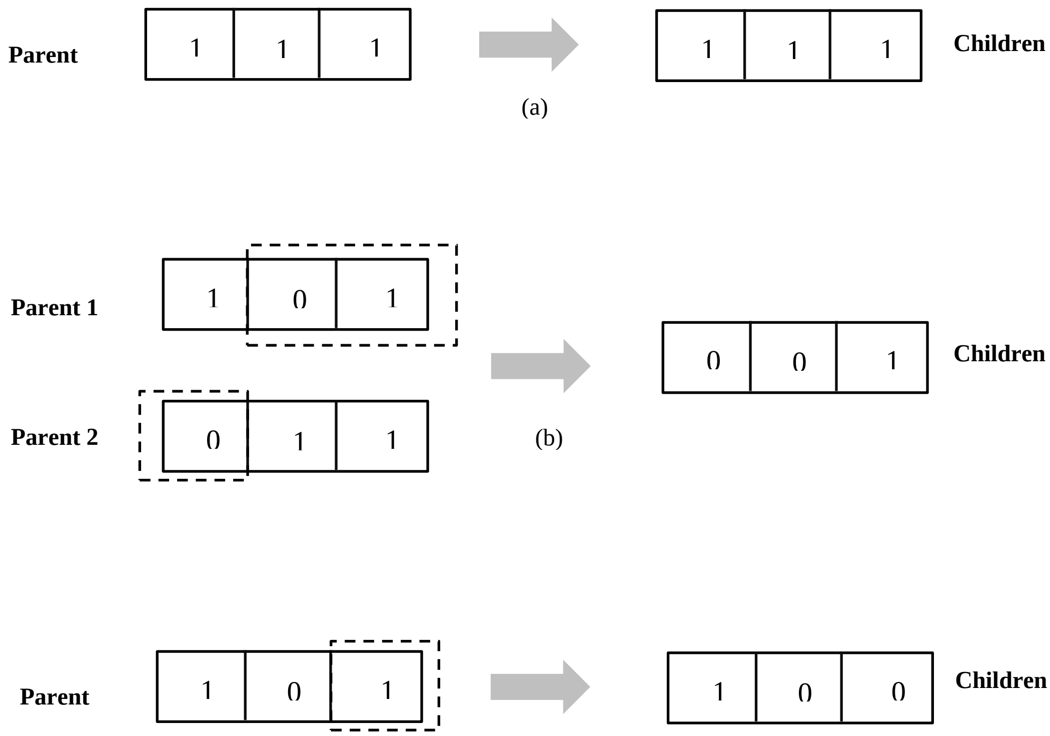

Figure 2-10 GA operators for creating next generation; (a) Elite, (b) Crossover, (c) Mutation.

may be time-consuming processes, other methods exist which rate only random individuals of a population. In the selection process, the fitness function value is calculated for all individuals. Then, these values are normalised. Normalisation means that the fitness value of each individual is divided by the sum of the fitness values of all individuals so that the sum of all achieved fitness function values is equal to 1. After that, the selection method sorts the population by descending fitness values. Next, normalised fitness values are accumulated, where the accumulated fitness of the last individual should be 1 (otherwise there is something wrong in the normalisation phase). In the next step, a random number is selected between 0 and 1 so that this number is greater than the accumulated normalised value of the selected individual. In general, to generate children GA chooses individuals which have higher fitness values as parents.

Genetic operators: For creating a new generation, the following operators are used [116]. Figure 2-10 shows a schematic diagram of these operators.

- Elite generates new children by using the individuals of the current generation having the best fitness values. Indeed, these individuals are automatically survived for the next generation.
- Crossover creates new children by combining the vectors of parents’ chromosomes or from the current generation.
- Mutation generates new children by randomly changing the genes of the chromosomes of individual parents.

Termination: The algorithm terminates as soon as any one of the following items is met [116].

- Generations: When the number of generations reaches to the defined value of generations.
- Time limit: When running time in seconds is equal to the defined time limit.
- Fitness limit: When the fitness function value for the best individual solution of the current population is less than or equal to the defined fitness limit.
- Stall generations: When the average relative variation of the fitness function value is less than the defined function tolerance.
- Stall time limit: When there is not any improvement in the fitness function value during the defined stall time limit in seconds.
- Function tolerance: When the average relative variation of the fitness function value over generations is less than the defined function tolerance.

It is noteworthy that the stall time limit and time limit options prevent excessive running time. If the algorithm terminates due to one of these conditions, the results might be improved by increasing the values of these options.

2.4.6. Application of GA in machine tool selection problem

According to D'Addona and Teti [105] and Yusup, et al. [98], GA is one of the best and popular optimisation techniques which has been used in different engineering areas. Li, et al. [117] applied the genetic algorithm (GA) technique to minimise processing time for finding the optimal process plan for single manufacturing and distributed manufacturing systems. The results show that applying GA to CAPP provides better solutions than the conventional CAPP. Huang, et al. [118] presented a new approach by applying GA and constraints to increase the productivity of assembly sequence planning. To do this, the assembly capability was considered as a fitness function and assembly constraints were developed based on the concept of future market. The application of GA in optimising turning, facing, and operating parameters was studied by Saravanan and Janakiraman [119]. In the developed model, minimising the machining time was considered as the objective function. Moreover, different constraints such as cutting power, cutting force, tool life, surface finish, and the range of cutting parameters was applied. published articles concerning the application of GA in the process planning [120]. Zain, et al. [107] studied the application of GA in finding the optimum cutting parameters to minimise the surface roughness (Ra) of parts in the milling process. Altiparmak, et al. [121] proposed a novel solution based on genetic algorithms to determine optimal solutions for optimising multi-objective supply chain network (SCN) design problems. Ozcelik and Erzurumlu [122] presented an integrated model including Artificial neural network (ANN) and GA techniques to minimise warpage of plastic part. To achieve this, process parameters such as mold and melt temperatures, packing and cooling times, packing pressure, runner type, and gate location were considered as decision variables. Xie, et al. [123] used a GA technique to search, combine, and optimise a plate–fin type Compact Heat Exchanger (CHE). The fitness function of this optimisation model was total annual cost of the CHE. Li, et al. [106] reported a new two phase GA to minimise operation time in determining optimal process parameters and machining sequences for drilling parallel holes in different faces. In this model, different constraints such as feed, drilling speed, thrust force, torque, power, tool life, hole positions were considered. From the above, it can be concluded that GA has been successfully applied to complex optimisation problems.

Since machine tool selection problem is a difficult and time-consuming task that has to consider different parameters, a GA technique may be suited to solve this problem. A review shows that GA has been applied by different researchers for selection of feasible machine tool or configuration design problem. Youssef and ElMaraghy [24] developed a GA optimisation model to find a feasible configuration of reconfigurable manufacturing systems. The model minimised the capital investment of RMS configurations to find the optimum number of parallel machines per stage and operation assignments. Guldogan [25] proposed a model integrating a knowledge-based expert system and GA to consider qualitative and quantitative parameters for machine selection and operation selection. Cus and Balic [12] proposed an optimisation method based on genetic algorithms (GA) for generating cutting parameters in flexible manufacturing systems (FMS). Chaube, Benyoucef and Tiwari [26] proposed a new algorithm to generate a dynamic process planning considering time and cost of production for reconfigurable machine tools. The considered variables in the model presented by Chaube, Benyoucef and Tiwari [26] are part, operation, machine, configuration, tool and tool approach direction. Wu, et al. [115] proposed a hierarchical genetic algorithm to simultaneously determine manufacturing cells and the group layout of a cellular manufacturing system. To perform this, a two-layer chromosome structure is developed to handle concurrent decision variables. The application of GA in the selection of a reconfigurable manufacturing system configuration is investigated by Youssef and ElMaraghy [124]. This optimisation problem was performed in two phases to determine optimal configuration including arrangement of machines, equipment selection, and assignment of operations. The results showed this approach can provide a support for users in selecting appropriate configurations in the early stage of each configuration period. While there has been some research about application of GA in selection of machine tools and manufacturing systems; yet that integrated optimisation of machining parameters and the configuration layout for SPMs have not been adequately addressed.

Chapter 3: Technical feasibility analysis

Chapter 4: Economic feasibility analysis

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Chapter 5: Sensitivity analysis

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AND

The second article is open access and available through Research

Online: https://ro.ecu.edu.au/ecuworkspost2013/3681/

Chapter 6: The effect of optimisation process on the feasibility analysis outcomes

Chapter 7: An integrated feasibility analysis model

Chapter 8: Conclusion

8. Conclusion

This thesis detailed a novel feasibility analysis model for evaluating SPMs versus other alternative machine tools in order to make a profitable machine tool selection. Selecting an appropriate machine tool among different alternative is an important and complex problem for manufacturing companies. Thus an appropriate feasibility analysis methodology is needed to decide whether an SPM should be used for the required production process. Generally, these methods are categorised into three main groups: analytic, strategic, and economic. The literature review demonstrated that there is the lack of a reliable procedure for the feasibility analysis of using SPMs versus other alternatives.

Chapter 3 outlined the development of a model for performing a technical feasibility analysis – research objective 1 – in deciding whether SPM is applicable for machining a given part. To do this, part and SPM characteristics influencing the feasibility analysis were identified. Next, relations between the desired part properties and the characteristics of the SPM components were identified and a relevant framework was created based on the experience and engineering knowledge and facts. To examine this model, a case study – a throttle body – was presented and the results were discussed. Results showed that technical analysis facilitates the selection of appropriate SPM components, taking into consideration the part and SPM characteristics, numerous factors, rules and constraints. In addition, this analysis offers industries the possibility of decreasing decision-making time and costs.

Chapter 4 explored an economic feasibility analysis strategy – research objective 2 – which aimed to facilitate logical decision-making by assessing the strengths and limitations of an SPM in comparison with other machine tools. This analysis evaluated an SPM’s economic performance for the required production tasks. To do this, the effective factors – cost and time – were identified and the relevant mathematical equations were developed based on the part properties, SPM characteristics and production requirements. Next, financial indicators – total production cost, profit, unit profit, and return on investment – were developed to evaluate the SPM’s economic performance. The proposed economic feasibility model was successfully applied to the throttle body case study used in Chapter 3. Results demonstrated that applying the proposed cost model helps companies to assess SPM performance and other machine tools in the preliminary stages of designing and manufacturing an SPM. The analysis also found that an SPM can outperform other machine tools, but production requirements must be taken into account. In addition, this method is lead to different conclusions on a case-by-case basis.

Since contemporary manufacturers face uncertainties in a competitive market and the analysis conducted in Chapter 4 indicated that the developed cost model might not support reliable decision-making, work reported in Chapter 5 applied a sensitivity analysis model to the developed mathematical cost model – research objective 3 – in order to investigate the sources of uncertainties which may influence the performance of SPMs and other alternatives. To achieve this, all the independent input and dependent output variables were identified in the developed model. The model was subjected to one-at-a-time (OAT) to analyse the effect of all the individual independent variables on the developed economic functions one at a time while holding the other variables constant. Some of the uncertain variables naturally may change over time and some may be estimated incorrectly. Accordingly, based on the engineering knowledge and production life cycle requirements, appropriate thresholds for each identified uncertain variable were defined. Then, by estimating the sensitivity index, effective variables were identified which were required for further evaluation. The analysis was successfully performed for the throttle body studied in the analyses reported in Chapters 3 and 4. Results showed that sensitivity analysis improved the economic analysis results by considering uncertainties such as underestimation or overestimation within manufacturing. Moreover, this analysis provided a comprehensive understanding of the relationship between input variables and the performance of machine tools.

The work reported in Chapter 6 used the mathematical cost model described in Chapter 4 for developing an optimisation model – research objective 4 – in order to investigate the effect of optimal process parameters and SPM configuration on the machine tool selection problem during the decision-making phase. To achieve this, the objective function was developed and the decision variables were identified along with boundaries and constraints. This analysis targeted the highest possible unit profit and was given by the value of the following decision variables: SPM configuration selection, machining unit assignment to each operation group, and the feed and cutting speeds of all operations. The production part was simulated by Simulink/MATLAB and was integrated into the GA technique to perform the optimisation. Having shown how the problem was formulated, Chapter 6 presented the same case study (i.e. the throttle body) to exemplify the operation of the proposed model. The results were evaluated and discussed with respect to two main areas. The first of these related to the comparison between the results of optimisation and the initial feasibility analysis, before performing the optimisation process. The results showed that selecting an appropriate SPM configuration and process parameters can significantly influence machine tool performance, and this has an influence on the decisions taken during the early stages of investment in a machine tool. The second item related to investigating the results of the optimisation output and identifying the critical factors which influence the performance of SPMs. The analysis found that the bottleneck operation group, tooling costs, and machining time were critical factors which were influenced by decision variable values.

Finally, Chapter 7 reported the development of an integrated feasibility analysis model – research objective 5 – in order to provide a comprehensive feasibility analysis procedure. This was developed through integrating the above analysis methods into a whole decision-making process model. The model was successfully applied to three more case studies taken from automotive components. Results showed that using integrated feasibility analysis at the early decision-making phase of machine tool selection provides insightful information which helps in the assessment of other designing and manufacturing processes or purchasing an appropriate SPM.

In conclusion, the model detailed here is a useful tool for making a reliable and informed decision at a preliminary or investment stage and eliminating a costly and time-consuming process.

8.1. Research scope and recommendations

This research focused on the development of a feasibility analysis approach to the use of SPMs. The following areas were outside the scope of this research, but the mathematical model developed in the present work can be extended in a number of ways for future work.

First of all, this research used some assumptions and engineering and expert's knowledge for performing case studies. Research could be developed with further industry-based experiments examining the proposed methodology. In addition, industrial limitations and relevant constraints based on the production and organisation limitations could be taken into consideration.

Second, the feasibility analysis model could also be improved considering uncertainty when applying a GA-based methods in the context of the dynamic optimisation problem. Another consideration could be comparing a GA approach with other emerging optimisation methods. Applying the proposed objectives in this research will help companies to make relatively quick and accurate decisions by selecting the near optimal SPM and process parameters that will facilitate choosing the right machine tool in the preliminary stages of the investment phase.

Third, the sensitivity analysis of the model can be improved by fully exploring the input space of variables and considering the input changes of different variables simultaneously. Furthermore, potential interactions between input variables may be another source of uncertainty which can be studied. Since sufficient data and literature is not available on future market requirements and manufacturing selection at the initial stages of utilising SPMs, a uniform distribution is used in this study. Future work could usefully consider the identification and forecasting of potential distribution patterns in terms of type and range. The proposed model can also form the basis for future work to investigate other uncertain parameters which may significantly influence the final decision.

Other points that could be considered in further studies could include structural analysis results for technical feasibility analysis, effective use of retooling existing machines and use of unused machine time.

Another research area where the feasibility analysis model can be extended is designing and developing a simulation tool to evaluate the feasibility of SPMs producing a given part. Since by using SPMs drilling-related operations are performed from different directions simultaneously, the finite element method could be added to the proposed technical feasibility analysis model in order to compute the part's deformations.

The primary recommendation emerging from this work is that there should be continued examination of the model in the context of new products involving different levels of complexity and comparing SPMs to other types of machine tools under different production circumstances. Thus the strengths and limitations of the proposed model will be revealed. These results will contribute to the further improvement of the model.

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Appendices

Appendix A: SPM MONO machining unit

This appendix provides some information about technical specifications of the MONO machining units used in this research work (see Table 10-1).

Table 10-1 Technical properties of machining units [1]

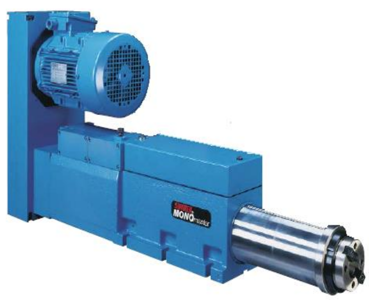
BEM 3		
Total stroke (mm)	40	
Maximum drilling capacity (mm)	3	
Thrust at 85 psi (N)	380	
Speed range at 50 Hz (min^{-1})	940-10,270	
Maximum allowable speed (min^{-1})	Up to 18,000	
Adjustable working stroke (mm)	25	
Concentricity (mm)	0.02	
Weight (kg)	9	
BEM 6		
Total stroke (mm)	80	
Maximum drilling capacity (mm)	6	
Thrust at 85 psi (N)	700	
Speed range at 50 Hz (min^{-1})	550-7,730	
Speed range at 60 Hz (min^{-1})	660-9,276	
Maximum allowable speed (min^{-1})	10,000	
Braking stroke variable (mm)	50	
Concentricity (mm)	0.02	
Weight (kg)	16	
BEM 6D		
Total stroke (mm)	80	
Maximum drilling capacity (mm)	6	
Speed range at 50 Hz (min^{-1})	1,450-11,600	
Speed range at 60 Hz (min^{-1})	1,750-14,000	
Maximum allowable speed (min^{-1})	14,000	
Concentricity (mm)	0.02	
Weight (kg)	12	
BEM 12		
Total stroke (mm)	80	
Maximum drilling capacity (mm)	12	
Thrust at 6 bar (N)	1,470	
Speed range at 50 Hz (min^{-1})	35-7,730	
Speed range at 60 Hz (min^{-1})	40-9,280	
Maximum allowable speed (min^{-1})	10,000	
Braking stroke variable (mm)	50	

Concentricity (mm)	0.02
Weight (kg)	26
BEM 12D	
Total stroke (mm)	80
Maximum drilling capacity (mm)	12
Speed range at 50 Hz (min^{-1})	90-2,900
Speed range at 60 Hz (min^{-1})	110-3,500
Maximum allowable speed (min^{-1})	10,000
Braking stroke variable (mm)	50
Concentricity (mm)	0.02
Weight (kg)	20

BEM 12VC	
Total stroke (mm)	80
Maximum drilling capacity (mm)	12
Thrust at 5.5 bar (N)	1,350
Speed range at 50 Hz (min^{-1})	35-7,760
Speed range at 60 Hz (min^{-1})	40-9,280
Maximum allowable speed (min^{-1})	10,000
Adjustable total stroke (mm)	80
Concentricity (mm)	0.02
Weight (kg)	26

BEM 20	
Total stroke (mm)	125
Maximum drilling capacity (mm)	20
Working stroke (mm)	125
Feed force at 6 bar (N)	4,130
Speed range at 50 Hz (min^{-1})	360-5,800
Speed range at 60 Hz (min^{-1})	432-6,960
Maximum allowable speed (min^{-1})	8,000
Concentricity (mm)	0.01
Weight (kg)	73

BEM 28	
Total stroke (mm)	200
Maximum drilling capacity (mm)	28
Thrust at 6 bar (N)	8,200
Speed range at 50 Hz (min^{-1})	400-2,580
Speed range at 60 Hz (min^{-1})	480-3,100
Maximum allowable speed (min^{-1})	3,480
Concentricity (mm)	0.01
Weight (kg)	150



BEM 25H		
Total stroke (mm)	125	
Maximum drilling capacity (mm)	25	
Feed force at 30 bar (N)	15,000	
Speed range at 50 Hz (min^{-1})	360-5,800	
Speed range at 60 Hz (min^{-1})	432-6,960	
Maximum allowable speed (min^{-1})	8,000	
Working stroke (mm)	125	
Concentricity (mm)	0.01	
Weight (kg)	68	

Appendix B: SPM multiple spindle head

This appendix provides some information about technical properties of the multiple spindle heads used in this research work (see Table 10-1 and Table 10-2).

Table 10-2 Technical properties of multipe spindle heads [1]

MH 20		
Drilling capacity (mm)	2.5-16	
Number of spindles	2	
Adjustment range (mm)	9-157.5	
Speed range (min^{-1})	3,000-6,000	
Weight (kg)	0.8-10.5	
MH33		
Drilling capacity (mm)	2.5-16	
Number of spindles	3	
Adjustment range (mm)	9.5-97.5	
Speed range (min^{-1})	3,000-6,000	
Weight (kg)	0.8-13.3	
MH30		
Drilling capacity (mm)	2.5-16	
Number of spindles	3	
Adjustment range (mm)	14.5-172.5	
Speed range (min^{-1})	3,000-6,000	
Weight (kg)	0.9-13.6	
MH40		
Drilling capacity (mm)	2.5-16	
Number of spindles	4	
Adjustment range (mm)	22-195	
Speed range (min^{-1})	3,000-6,000	
Weight (kg)	1.0-17.8	
MHF		
Drilling capacity (mm)	1.5-25	
Maximum number of spindles	10	
Adjustment range (mm)	7-190	
Speed range (min^{-1})	2,500-8,000	
Weight (kg)	1.1-32.5	

MHFP		
Drilling capacity (mm)	7-20	
Maximum number of spindles	10	
Adjustment range (mm)	18-190	
Speed range (min^{-1})	5,000-8,000	
Weight (kg)	5.0-19.0	
PMF		
Drilling capacity (mm)	12 in brass	
Maximum number of spindles	10	
Adjustment range (mm)	13.2-110	
Speed range (min^{-1})	6,000	
Weight (kg)	6.2-7.2	
PMFW		
Drilling capacity (mm)	22 in brass	
Maximum number of spindles	10	
Adjustment range (mm)	50-190	
Speed range (min^{-1})	2,500	
Weight (kg)	12.0-14.0	

Appendix C: Power estimation for simultaneous drilling operations

This appendix provides some information about the estimation of the required power for drilling each operation group. As shown in Figure 10-1, in order to drill an operation group, the required power can be estimated by considering number of holes/spindles, the hole diameter, and the part material [1].

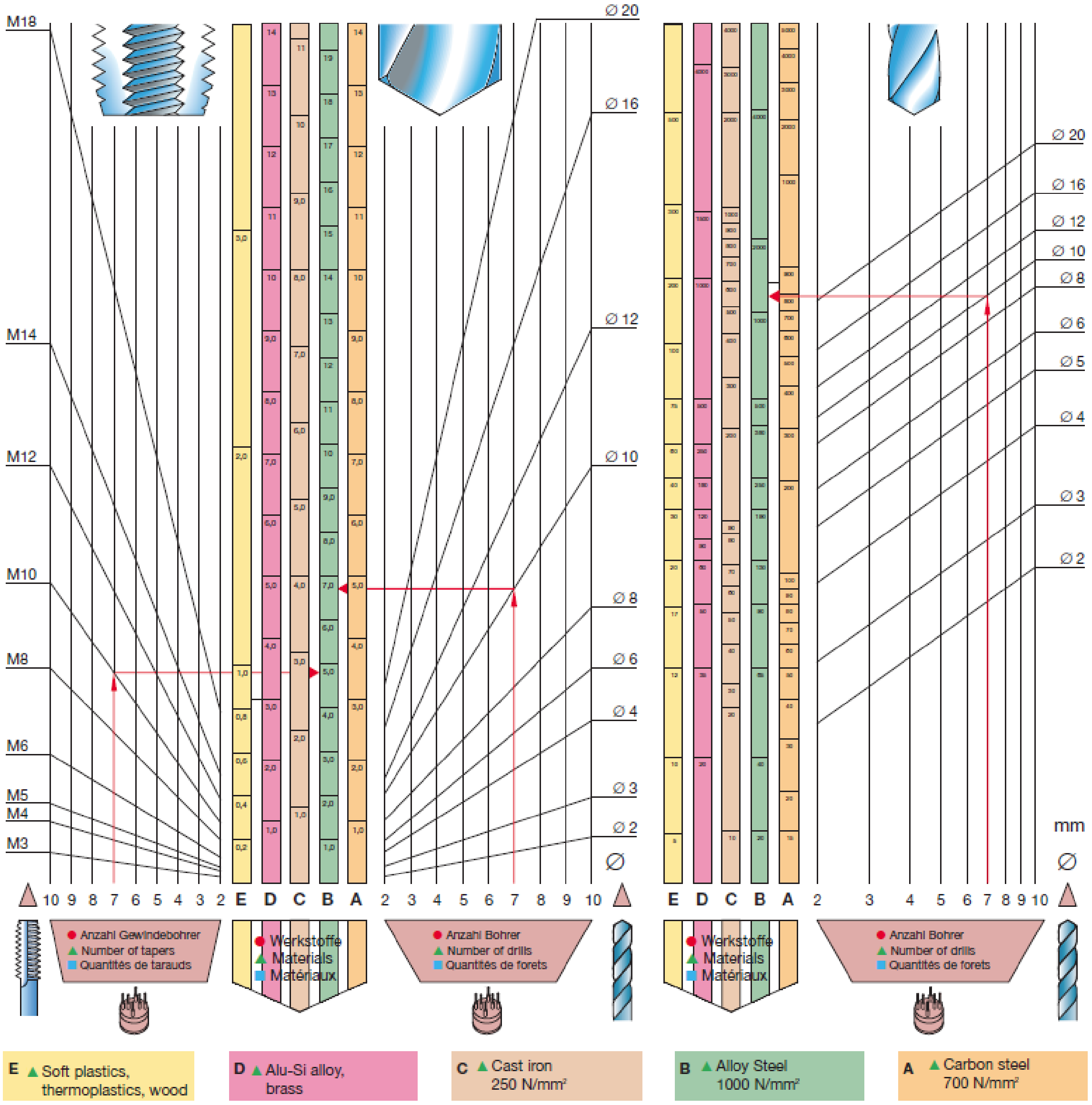


Figure 10-1 Power estimation diagram for single- or multiple-operations[1].

Appendix D: The results of economic analysis

This appendix represents the outputs of the economic feasibility analysis for the production of the brake disc and the power steering pump body. Tables 10-2 and 10-3 provide production information for the manufacturing of these parts with SPM, CNC, and conventional machine tools. The demand considered for this analysis is 100,000 units per year.

Table 10-3 Comparison of brake disc production with SPM, CNC and conventional machines

		SPM/Multi-station	CNC	Conventional
Production information	**Eq.**			
Demand per year (D)	-	100,000	100,000	100,000
Scrap rate (q)	-	0.03	0.03	0.05
Starting demand per year(D_o)	-	103,093	103,093	105,263
Cycle time (years) (t)	-	5	5	5
Interest rate (i)	-	0.06	0.06	0.06
Working hours per year (H)	-	2080 [1]	2080	2080
Overhead rate ($\$/h$) ($C_o$)	-	12	12	12
Labour rate ($\$/h$) ($C_l$)	-	22	22	22
Sale price ($) ($S_p$)	-	32	32	32
Machine tool information				
Maintenance coefficient (β)	-	10%	10%	10%
Availability (a)	-	93%	95%	90%
Produced parts per hour (N_p)	(4-19)	19	19	6
Number of required machines (N_m)	(4-18)	2.74 => 3	2.77 => 3	9.2=> 10
Time (sec): Time units are converted from minutes into seconds for convenience of the reader.				
Cutting time per unit (T_c)	(4-6)	43.2	43.4	135
Free travel time per unit (T_f)	-	7.8 [2]	18 [3]	312 [3]
Indexing time per unit (T_i)	-	10.2	-	-
Loading time per unit (T_L)	-	5 [5]	5 [5]	5 [5]
Unloading time per unit (T_U)	-	5 [5]	5 [5]	5 [5]
Tool changing time per unit (T_{tc})	(4-11)	0.4	0.4	25
Set up time for spindle heads per unit (T_s)	-	120	120 [6]	120 [6]
Total machining time per unit (T_m)	(4-12)	191.6	191.8	602
Single- and multi-station SPM, CNC and conventional machining time equations are, respectively.	(4-14) (4-15)			
Total maintenance time per unit (T_{mo})		19.1	19.1	60.2
Costs for the first year of the production ($)				
Material cost per unit (C_{mat})	-	20	20	20
Material cost [7] ($C_{materail}$)	(4-16)	2,061,856	2,061,855	2,061,855
Machine tool cost per unit	-	55,350	83,100	9,600
Total machine tool cost (C_{mt})	(4-17)	166,050	249,300	96,000
Tool cost [7] (C_t)	(4-22)	1,169	1,169	4,320 [8]
Machining cost [7] ($C_{machining}$)	(4-20)	118,135	118,135	372,326
Maintenance cost [7] ($C_{maintenance}$)	(4-25)	11,696	11,692	36,800
Overhead cost [7] ($C_{overhead}$)	(4-26)	361,747	361,747	1,138,162

Salvage value ($)				
Salvage value at the end of the production year	(4-28)	8,303	12,465	4,800
Results				
Total production cost ($)	(4-2)	12,927,017	13,007,157	18,136,928
Profit (*$*)	(4-3)	3,072,983	2,992,843	(2,138,142)
Unit profit (*$/pc*)	(4-4)	6.1	6.00	(4.28)
Return on sales (%)	(4-5)	19.2%	18.7%	(13%)

1: It is assumed that there is one shift per day, 8 working hours per day, 5 working days per week and 52 weeks per year.

2: Free travel time for SPM is the required time for all tools to reach the workpiece.

3: Free travel time is the sum of the required time for the tool to reach the workpiece and the time for which the tool travels to reach the hole diameter for all tools.

5: In this work, all the machines applied manual loading and unloading (L/U). It is not reasonable to use two operators at the same time for a single SPM and the task for L/U is t automated. However, automation of this function was not considered in this work.

6: Set up time is the sum of the spindle head changing times.

7: The given cost is for the first year of production. For subsequent years the annual interest rate is also considered as represented in Eq. (4-24).

8: Operator fault rate (α) is considered 20% for tool consumption calculation of the conventional machine tool and zero for CNC and SPM.

Table 10-4 Comparison of power steering pump body production with SPM, CNC and conventional machines

		SPM/Multi-station	CNC	Conventional
Production information	**Eq.**			
Demand per year (D)	-	100,000	100,000	100,000
Scrap rate (q)	-	0.03	0.03	0.05
Starting demand per year(D_o)	-	103,093	103,093	105,263
Cycle time (years) (t)	-	5	5	5
Interest rate (i)	-	0.06	0.06	0.06
Working hours per year (H)	-	2080 [1]	2080	2080
Overhead rate ($\$/h$) ($C_o$)	-	12	12	12
Labour rate ($\$/h$) ($C_l$)	-	22	22	22
Sale price (\$) (S_p)	-	39	39	39
Machine tool information				
Maintenance coefficient (β)	-	10%	10%	10%
Availability (a)	-	93%	95%	90%
Produced parts per hour (N_p)	(4-19)	216	17	14
Number of required machines (N_m)	(4-18)	0.24 => 1	3.1 => 4	4.12=> 5
Time (sec): Time units are converted from minutes into seconds for convenience of the reader.				
Cutting time per unit (T_c)	(4-6)	14.3 [2]	23.4	23.4
Free travel time per unit (T_f)	-	12 [3]	91.2 [4]	141 [4]
Indexing time per unit (T_i)	-	1.1 [5]		
Loading time per unit (T_L)	-	5 [6]	5 [6]	5 [6]
Unloading time per unit (T_U)	-	5 [6]	5 [6]	5 [6]
Tool changing time per unit (T_{tc})	(4-11)	1.28	89.45 [7]	89.45 [7]
Total machining time per unit (T_m) Single- and multi-station SPM, CNC and conventional machining time equations are, respectively.	(4-12) (4-14) (4-15)	16.68	214.07	263.87
Total maintenance time per unit (T_{mo})		1.67	21.4	26.38
Costs for the first year of the production [8] (\$)				
Material cost per unit (C_{mat})	-	28	28	28
Material cost [9] ($C_{materail}$)	(4-16)	2,886,597	2,886,597	2,947,368
Machine tool cost per unit	-	210,048	85,000	11,100
Total machine tool cost (C_{mt})	(4-17)	210,048	340,000	55,500
Tool cost [9] (C_t)	(4-22)	2,548	13,103	16,055 [10]
Machining cost [9] ($C_{machining}$)	(4-20)	13,056	147,970	185,797
Maintenance cost [9] ($C_{maintenance}$)	(4-25)	1,050	13,486	16,974
Overhead cost [9] ($C_{overhead}$)	(4-26)	6,304	404,600	509,224

Salvage value ($)				
Salvage value at the end of the production year	(4-28)	10,502	17,000	2,775
Results				
Total production cost ($)	(4-2)	14,737,247	17,590,579	18,350,245
Profit (*$*)	(4-3)	4,762,753	1,909,421	1,149,755
Unit profit (*$/pc*)	(4-4)	9.53	3.82	2.3
Return on sales (%)	(4-5)	24%	9.8%	6%

1: It is assumed that there is one shift per day, 8 working hours per day, 5 working days per week and 52 weeks per year.

2: This value represents the bottleneck cutting time which is the maximum calculated cutting time of all stations.

3: Free travel time for SPM is the required time for all tools to reach the workpiece.

4: Free travel time is the sum of the required time for the tool to reach the workpiece and the time for which the tool travels to reach the hole diameter for all tools.

5: There are 10 stations for this machine and each indexing/sliding time is 1.1 seconds. Since all the stations perform the required operations simultaneously, only one indexing times is considered for calculating of the machining time.

6: In this work, all the machines applied manual loading and unloading (L/U). It is not reasonable to use two operators at the same time for a single SPM and the task for L/U is t automated. However, automation of this function was not considered in this work.

7: Tool changing time is the sum of the tool changing times for changing the operation and changing the tool after it has finished its useful tool life.

8: The costs may change over the production life time which can be estimated by relevant developed equations. At the early stages of utilising SPM sufficient information on the costs is not available; and therefore, in this work all the parameters of each cost equation are assumed to remain constant over the production life time except cost parameters such as labour rate, overhead rate, and material cost which by increasing annual interest rate they raise over the time. Indeed, these parameters are multiplied by $(1+i)^j$ to estimate the value of them for the next years.

9: The given cost is for the first year of production. For subsequent years the annual interest rate is also considered as represented in Eq. (4-24).

10: Operator fault rate (α) is considered 20% for tool consumption calculation of the conventional machine tool and zero for CNC and SPM.

Appendix E: Simulation-based optimisation model

This appendix provides some information about the simulated model created by the author. The production part was simulated by Simulink/MATLAB and was integrated into the GA technique to perform the optimisation. This simulated model consists of three main subsystems: operation group, machining time and SPM configuration, and economic analysis subsystems. There are interactions between input and output signals of these subsystems. In addition, Simulink is integrated with MATLAB for performing optimisation process and data is easily transferred between the simulated model and GA.

Operation group subsystem

Operation group subsystem simulates drilling operation and calculates tool changing time, cutting time, tool life, and machining unit cost for an operation group by considering input decision variables (feed, cutting speed, and selected machining unit). As shown in Figure 10-2, the subsystem includes two functions which are used for estimating tool life and machining unit cost. These functions are programmed as below

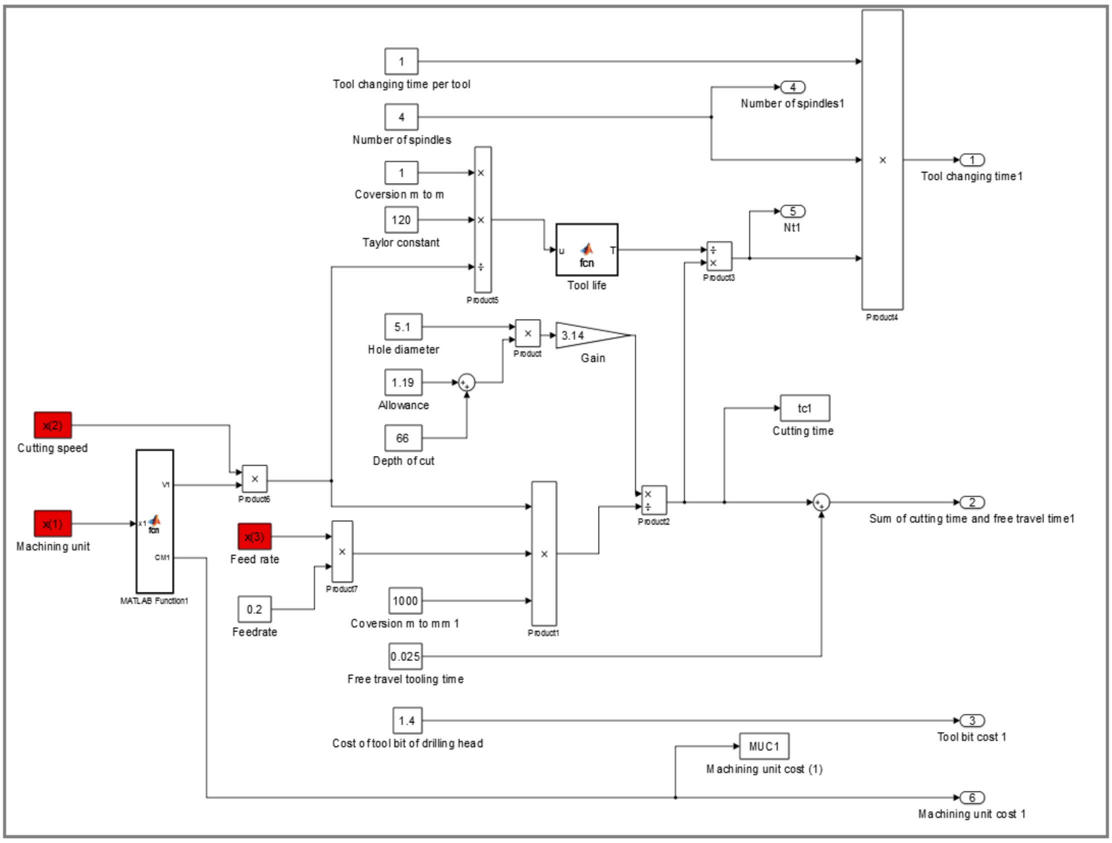


Figure 10-2 Simulated model for performing operation groups.

Function 1: Tool life calculation

Tool life is a function of the Taylor constant value and Taylor exponent which are determined by the material for the part and cutting tool [128]. Since the throttle body material – the case study illustrated in Chapters 3 to 5 – is aluminium alloy and the selected cutting tool material is high speed steel, the Taylor exponent is 0.125 [128]. The coding used for calculation of the tool life is shown below

```
function T = fcn(u)
%#codegen

Toollife= u.^8;
T= Toollife;
% Taylor tool life exponent is selected 0.125.
```

Function 2: The estimation of machining unit cost

Below an example of the coding used for the estimation of machining unit cost is presented. For performing this operation group, three machining units (BEM20, BEM 28, and BEM 25H) are feasible. CM1 and V1 indicate the cost of the selected machining unit and the maximum cutting speed that this machining unit can provide.

```
function [V1,CM1]= fcn(x1)
%#codegen
% BEM20 ($9000), BEM 28 ($37500) and BEM 25H ($12900) can drill this hole.

if  x1 < 0.33 && 0<=x1
CM1 = 9000;
V1=128.11;

elseif   x1 <0.66 && 0.33<=x1
CM1 = 37250;
V1=90;

else

CM1=12900;
V1=128.11;

end
end
```

Total machining time and SPM configuration subsystem

Total machining time subsystem simulates the calculation of required time to machine each a part. This subsystem considers tool changing, set up, cutting, loading and unloading time for calculation of machining time (see section 4.2.1). As shown in Figure 10-3, the output of this subsystem is the machining time and SPM configuration cost.

Economic analysis subsystem

This subsystem simulates the proposed economic feasibility analysis strategy (see Section 4.1). Figure 10-4 shows a part of the simulated model created for economic analysis. The simulated model includes all the part and SPM characteristics and production characteristics which are required for the analysis. The outputs of the machining time and machining operation subsystems are transferred to this subsystem in order to calculate the unit profit.

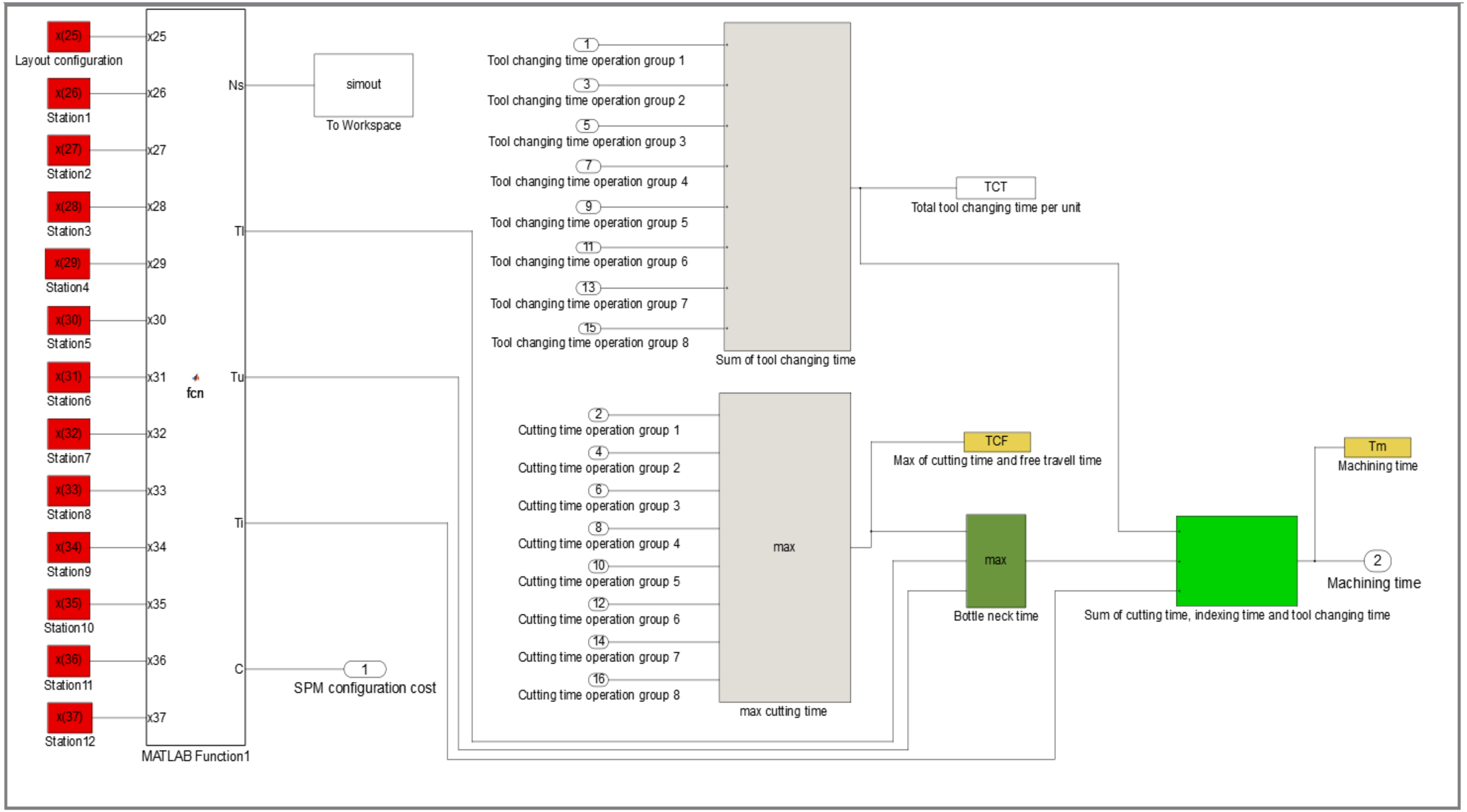


Figure 10-3 Simulated model for estimating the total machining time.

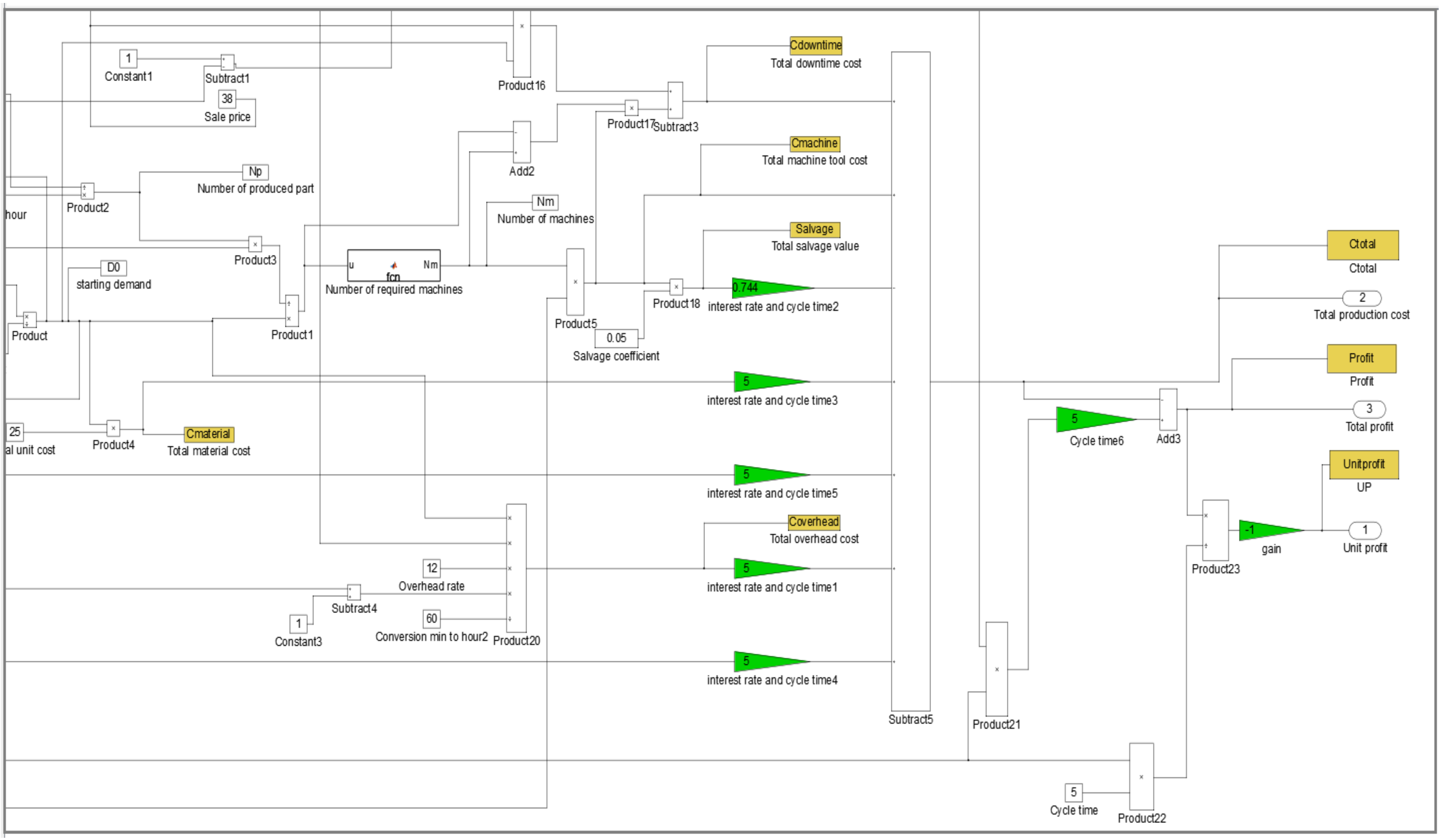


Figure 10-4 A part of simulated model for performing the economic analysis.

Appendix F: Publications

This appendix provides six papers which were published/submitted on the basis of this research work.

The publications are not included in this version of the thesis