FUZZY MULTI-CRITERIA ANALYSIS FOR MACHINE TOOL SELECTION AND OPTIMAL MACHINE LOADING IN FLEXIBLE MANUFACTURING CELL

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THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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ABSTRACT

The flexible manufacturing cell (FMC), a unit of FMS, has the potential to be adapted widely by the small and medium enterprises (SMEs) in the automotive industry due to the low investment costs and less risk levels. The implementation of FMC, however, is a challenging task requiring complete integration of numerous components coming from various vendors. In particular, production planning related to machine loading problem (MLP) should be firstly considered when starting production process. Machine selection and machine loading strongly affect the system's efficiency and flexibility, thus forms a very strategic planning decision to achieve substantial manufacturing efficiency in automotive industry.

In this research, an integrated framework is developed for the selection of appropriate machine tools and suitable combinations of machines and operations for machining. Past research have focused on only the selection of machines for processing a particular part type in manufacturing cell, thus the issues of machines and operations have been addressed individually and superficially. In addition, the allocation of operations to the selected machine is solved without real evidence of consideration of multiple objectives which are more relevant in the actual manufacturing context of the manufacturing enterprise.

This developed framework for machine tool selection and machine loading in FMC consists of three phases. In the first phase, a decision support system is developed for solving a model of preliminary machine tool evaluation based on integration of fuzzy AHP (Analytic Hierarchy Process) and fuzzy COPRAS (COmplex PRoportional Assessment) from database of potential machines in the market. Subsequently, the finalization of machine selection decisions were carried out based on the novel hybrid approach of fuzzy ANP (Analytic Network Process) and COPRAS-G (Grey COmplex

PRoportional Assessment). In addition, the sensitivity analysis is conducted to check the robustness of the alternative ranking of newly designed approach. A database of machine tools was collected from a potential set of machines from the market based on their specifications described in product catalogues of vendors, experts' experience and literature. In the second Phase, the FMC is formulated based on the selected machine from Phase 1. Several steps are implemented to select the most suitable solution for machine loading in FMC, which is presented in the form of the most appropriate combination of machine tools and operations. Problem formulation is established by constructing a mathematical model for FMC loading issue comprising of three objectives of minimizing the system unbalance, makespan and total flow time with the constraints of machines and tool magazines. Then, the combination of biogeography-based optimization (BBO) and non-dominated sorting procedure is developed to solve the proposed model. Finally, in the third Phase, a simulation of proposed FMC is implemented to evaluate and observe the performance and the applicability of the newly designed cell with respect to selected strategy of allocation. It was also used to verify the numerical results and validate the practical applicability to manufacturing cells in SMEs. The numerical results obtained showed that the proposed method has a potential alternative when compared with other research and the results of simulation based on performance indices such as system unbalance, makespan and total flow time.

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ABSTRAK

Persaingan ekonomi global telah memacu sektor pembuatan untuk melakukan penambahbaikan dan pelaburan dalam peralatan moden untuk memenuhi keperluan pasaran. Di samping itu, perkembangan dramatik pada pasaran pembuatan global telah mencipta keperluan untuk Industri Kecil dan Sederhana (IKS) supaya mengaplikasikan penggunaan Teknologi Pembuatan Yang Maju (TPM).

Perkembangan bidang teknologi bagi memenuhi permintaan dan harapan pelanggan telah menyokong kefleksibelen kejuruteraan pembuatan dalam persekitaran global. Para pengurus operasi dan jurutera mengambil perhatian terhadap isu-isu kritikal seperti produktiviti dan kualiti, dan berusaha untuk mencari pelbagai strategi untuk menambah-baik kefleksibelen tersebut, juga sebagai respon pantas terhadap keperluan pasaran.

Kefleksibelen Sel Pembuatan, sebuah unit daripada (FMS), yang boleh dianggap sebagai strategi pembuatan yang berdaya saing tinggi untuk memastikan kejayaan perusahaan-perusahaan di Negara membangun, dan mampu beradaptasi untuk digunakan secara meluas oleh semua IKS disebabkan oleh kos pelaburan dan risiko yang rendah.

Walaubagaimanapun, implementasi FMC adalah suatu tugas yang sukar dilaksanakan kerana memerlukan integrasi yang lengkap pada pelbagai komponen daripada pelbagai pengedar. Secara khusus, perancangan pengeluaran yang berkaitan dengan permasalahan kemampuan mesin (MLP) perlu menjadi kunci utama yang perlu diberi perhatian apabila ingin mengaplikasi FMC.

Pemilihan dan kemampuan mesin sangat mempengaruhi efisiensi dan fleksibiliti sesebuah sistem. Daripada perspektif ini, adalah mudah untuk mengetahui bahawa pemilihan dan kemampuan mesin adalah beberapa keputusan perancangan strategik dan

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suatu hubungan yang penting antara beberapa keputusan operasional dan taktikal untuk mencapai pencapaian sistem yang substansial.

Dalam penyelidikan ini, sebuah kerangka kerja yang terintegrasi telah dimajukan untuk pemilihan alatan-alatan mesin yang sepatutnya dan kombinasi mesin-mesin serta operasi yang terbaik dalam mengimplimentasi FMC.

Daripada penyelidikan yang lalu, isu-isu di atas diperincikan secara individu dan luaran sahaja. Kebanyakan daripada penyelidikan memfokuskan kepada pemilihan mesin yang sepatutnya untuk memproses sesuatu bahagian di dalam sel pembuatan. Tambahan pula, peruntukan daripada operasi-operasi pada mesin terpilih diselesaikan tanpa bukti yang nyata daripada pelaksanaan dan pengesahan kebolehgunaannya di dalam perusahaan pembuatan.

Di dalam tesis ini, kerangka kerja dibuat terdiri daripada 3 fasa; Dalam fasa pertama, sistem sokongan keputusan dibina untuk menyelesaikan sebuah model pemilihan alatan mesin utama berdasarkan penyepaduan daripada ketidaktentuan Proses Analisis Hirarki (AHP) dan Penilaian Keseimbangan Kompleks (COPRAS)

Kemudian, penyelesaian daripada keputusan pemilihan mesin dibuat berdasarkan pendekatan hybrid ketidaktentuan Proses Analisis Hirarki (AHP) dan Penilaian Keseimbangan Kompleks Grey (COPRAS-G).

Selain itu, tahap kepekaan analisis dijalankan untuk memeriksa kekuatan peringkat alternatif. Sebuah pusat data peralatan-peralatan mesin dikumpulkan daripada set-set mesin yang berpotensi di pasaran berdasarkan spesifikasi-spesifikasinya seperti yang ditunjukkan di katalog pengedar-pengedar, pakar-pakar, pengalaman dan penulisan.

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Dalam Fasa Kedua; FMC diformulasikan berdasarkan mesin yang dipilih daripada Fasa 1. Beberapa langkah telah dijalankan dalam fasa ini untuk memilih beberapa penyelesaian yang paling sesuai untuk kemampuan mesin dalam FMC, yang menunjukkan kombinasi peralatan mesin-mesin dan operasi-operasi yang paling berkesan.

Formulasi masalah ditegakkan dengan membina model matematik bagi isu kemampuan FMC yang terdiri daripada tiga objektif untuk mengurangkan ketidakseimbangan sistem, waktu aliran maksimum, dan perjalanan waktu keseluruhan dengan kekangan mesin-mesin serta peralatan.

Kemudian, kombinasi optimalisasi berdasarkan biogeografi (BBO) dan prosedur pengkelasan tanpa dominasi telah dikembangkan untuk menyelesaikan masalah model yang telah dicadangkan.

Pengumpulan data telah dilakukan untuk mencapai segala keperluan model. Penyelesaian kemampuan FMC yang paling berpatutan adalah berdasarkan kepada penyelesaian-penyelesaian yang sesuai yang diperolehi daripada pendekatan yang dicadangkan.

Akhir sekali, Fasa ketiga, simulasi FMC yang dicadangkan dilaksanakan untuk mengevaluasi kebolehgunaan sel yang direka. Dengan simulasi, sifat dan prestasi sel dapat dikenalpasti berdasarkan peruntukan strategi yang telah dipilih.

Tambahan lagi, eksperimen ini juga diimplimentasikan untuk mempastikan hasil-hasil angka, simulasi dan mengesahkan kebolehgunaan praktikalnya di IKS pembuatan. Eksperimen ini telah menunjukkan bahawa model FMC yang dicadangkan berpotensi untuk diaplikasikan secara meluas untuk menghasilkan jenis-jenis bahagian yang berbeza.

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For any errors or inadequacies that can remain in this thesis, the responsibility is totally my own.

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LIST OF SYMBOLS AND ABBREVIATIONS

AMT	: Advanced Manufacturing Technology
SME	: Small and Medium Enterprise
PROTON	: Perusahaan Otomobil Nasional
FMS	: Flexible Manufacturing System
FMC	: Flexible Manufacturing Cell
CNC	: Computer Numerical Control
AS/RS	: Automated Storage and Retrieval Systems
AHP	: Analytic Hierarchy Process
FAHP	: Fuzzy Analytic Hierarchy Process
ANP	: Analytic Network Process
FANP	: Fuzzy Analytic Network Process
COPRAS	: COmplex PRoportional Assessment
FCOPRAS	: Fuzzy COmplex PRoportional Assessment
COPRAS-G	: Complex Proportional Assessment of alternatives with Grey relations
BBO	: Biogeography Based optimization
NSBBO	: Non-dominated Sorting Biogeography Based optimization
SMI	: Medium and Small Industry
MCDM	: Multi-Criteria Decision Making
MADM	: Multi-Attribute Decision Making
NC	: Numerical Control
DSS	: Decision support system
PROMETHEE	: Preference Ranking Organization Method for Enrichment Evaluations
TOPSIS	: Technique for Order Preference by Similarity to Ideal Solution

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ANN	:	Technique for Order Preference by Similarity to Ideal Solution
GRA	:	Grey Relational Analysis
TOPSIS-G	:	Technique for Order Preference by Similarity to Ideal Solution with Grey relations
SAW-G	:	Simple Additive Weighting with Grey relations
ELECTRE III	:	Elimination and Choice Translating Reality
VIKOR	:	VIse Kriterijumska Optimizacija Kompromisno Resenje
MOORA	:	Multi-Objective Optimization on the basis of Ratio Analysis
DM	:	Decision-Makers
MTS	:	Machine Tool Selection
TFN	:	Triangular Fuzzy Numbers
MILP	:	Mixed Integer Linear Programming
HSI	:	Habitat Suitability Index
SIV	:	Suitability Index Variables
MPX	:	Multi-point Preservative Crossover
IH	:	Immigrating Habitat
EH	:	Emigrating Habitat
SU	:	System Unbalance
TH	:	Throughput
TFT	:	Total Flow Time
MK	:	Makespan
NSGA	:	Non-dominated Sorting GA
MIP	:	Mixed Integer Programming
CFPR	:	Consistent Fuzzy Preference Relations
PIS	:	Positive Ideal Solution
NIS	:	Negative Ideal Solution

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CHAPTER 1: INTRODUCTION

1.1 Background

Manufacturing companies have started to implement operational strategies based on agility, flexibility and opportunity to improve their competitiveness in the dynamic and uncertain environment due to the economic downturn in 2008 (Wu, Shamsuddin, Tasmin, Takala and Liu, 2012). Advanced manufacturing technologies (AMTs) have created significant impact on the manufacturing capacity of the small and medium enterprises (SMEs) in adopting modern technologies. However, this adoption will require substantial investment, re-configurability of organizational structure and changes in working cultures (Yusuff, Yee and Hashmi, 2001).

Countries in the ASEAN community have been developing their automotive industries based on the fundamentals of global automotive industry. The industrial environment in ASEAN has been received substantial investments from foreign companies for supply of components, module production and systems (Punnakitikashem, Laosirihongthong, Adebanjo and McLean, 2010). Most of these SMEs were affected by the financial tsunami in 2008, registering losses and were fighting for survival. They have been in lower profits and unable to be serious for the development of the global economy. Therefore, around 80% of the large ones have been falling into the group of SMEs in the world. Thus, the adoption of the systematic management and innovation of technology is needed for the survival of SMEs, especially for markets in developing countries such as Malaysia, Indonesia, Vietnam, Thailand and other SMEs elsewhere (Hung, Chou and Tzeng, 2011). In Malaysian context, a number of policies were developed to support the SMEs such as providing RM12bil for 157 development programs to elevate their productivity and capacities (Anis, 2014).

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SMEs play a vital role in the global economy and are the core component of the industrialization process in many developed countries. They are seen as the lifeblood of modern economies. The development and expansion of SMEs is heavily dependent on the capital market, where it is challenging for the smaller players to enter because of various requirements and high costs (Anis, 2014). In Malaysia, about 92.6 percent of SMEs are related to the field of manufacturing. To complete in the global arena, manufacturers are required to improve product life cycles and satisfy a variety of customers. In addition, the increasing labor cost and volatility will also need to be factored into the input prices. These require the manufacturers to be innovative, responsive, adaptive and flexible. These improvements can be assisted with the adoption of advanced manufacturing technology, to give SMEs considerable advantages over the large companies and ensures high productivity. Although significant investments have been made to adopt AMT in SMEs, limitations still remain in the implementation process. The failure can be attributed to inadequate detailed planning. It is said that production planning is a key factor of the innovation's potential, shows the level of integration, the functions and all other essential changes (Yusuff, Chek and Hashmi, 2005). The development of manufacturing is considered to be a competitive strategy in the global marketplace and the use of AMT has enabled the small companies to obtain the competitive performance advantage (Mechling, Pearce, and Busbin, 1995).

The increasing demand on a variety of products is essential, the reduction of the product life cycles is very important, and the values of manufacturing costs are dynamic. The flexibility and technologies based on time must be included in the manufacturing capacity of the global as well as the domestic manufacturers. Moreover, for scalable traditional economies, new strategies are needed to facilitate the flexibility, reduce the design time, delivery time and cycle time. Manufacturing technology is considered as a new competitive strategic weapon. New strategies of agile, responsive and adaptive manufacturing must be considered under level of management for the companies. The adoption of AMT is a strategy for responding to the flexibility and technologies based on time. Hence, the companies' size and AMT adoption are expected to be positively related to and affected by the capacity of manufacturing industries with AMT (Mechling et al., 1995). For example, Malaysian-owned automotive manufacturer, Proton (an abbreviation of Perusahaan Otomobil Nasional) was set up in 1983 and has greatly affected the automotive scene in Malaysia. Half of the Malaysian suppliers were sole providers to Proton with 62.7% being SMEs (Abidin et al., 2012). All policies and rules were applicable to automakers and vendors operating in Malaysia. Thus, the SMEs are under very high pressure to improve their performance and are always considering to expand their facilities to create working opportunities and contribute to the local economic development. SMEs should be able to adapt the current production in response to the dynamic conditions of the market in order to ensure the goal production are met as well as maintaining their competitive advantage. Surveys have showed that several advanced manufacturing technologies can be used in the production line such as manufacturing cell, NC (numerical control) machines, automated machines and systems with low utilization ratio. The equipment is being implemented lowly in the Malaysian SMEs, and thus hindering the development and expansion of SMEs. Until now, local SMEs are still dependent past technologies and dated production automation strategies (Anuar and Yusuff, 2011; Dawal et al., 2015).

Nowadays, the rapid development strategy of manufacturing industry has reduced the product life cycles, which comprises of dramatic changes to the product mix, customers' demands and requirements of various shapes with the shortest processing time. Simultaneously, the development of technology to meet the customer demands and expectations has encouraged the adoption of flexible manufacturing in the global arena (Candan and Yazgan, 2014). New strategies are being implemented by operation

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managers and engineers to increase productivity and quality to meet the market demands. The automation of manufacturing facilities is a key factor in improving the quality and productivity seeking new strategies to improve flexibility to meet the demands of the market. Therefore, it is necessary to implement flexible manufacturing methods which have the ability to complete and meet market demands on variety of products with short product life cycles and uncertain demands (Dawal et al., 2015). One of the factors contributing to the increase of the flexibility is the production planning problems. These are commonly considerations such as the selection of machines, operations, cutting tools and determination of the sequence of robot and scheduling of parts according to the laid out plan. Scheduling is at the heart of smart management in SMEs for implementing the production systems with the desired production goals (minimize the average lateness, minimize the make-span, maximize the utilization, minimize work-in-progress and setup time, minimize the tardiness and flow time) (Gamila and Motavalli, 2003; Slomp and Stecke, 2011). In general, the operational decision in SMEs is very important to achieve global competitiveness. So they have to be flexible to satisfy the customers' demands. Thus, the decision model for the production planning should be considered and implemented in first SMEs.

The dramatic competition in the global manufacturing market for part types have required manufacturers to improve delivery time and determine suitable competitive prices for small and medium level orders. Reduced batch size of part types and the specific customer requirements on flexibility have made FMS to be a highly competitive manufacturing strategy of the late twentieth century (Udhayakumar and Kumanan, 2010). They have become important elements in the success of manufacturing enterprises in the last decade (Candan and Yazgan, 2014). FMS is an innovative manufacturing strategy, an automated manufacturing system with job shop flexibility and flow shop efficiency which have been paid the attention to implement in SMEs. The

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benefit of FMS is the high machine utilization, fewer machine and reduction in the floor space, ability of responding to changeability, easiness for re-configurability and agility, reduced inventory requirements, lower labor force and opportunity for automated production (Groover, 2007). Moreover, according to Udhayakumar and Kumanan (2010), the integration of manufacturing methods and technologies enable FMS to have other advantages such as reduction of work-in progress and cost, minimized setup time, minimized flow time, minimized idle time of resources, minimized changeover time, minimized material handling time, shorten lead times, simplification of manufacturing, reduced floor space, improved product quality, improved market responses and etc.

In production facilities, the flexible manufacturing cell (FMC) is the key component of FMS, which consists of four to six CNC machines and robots for loading/unloading parts and automated storage and retrieval systems (AS/RS) (Costa and Garetti, 1985). It is an effective manufacturing unit although comes at a high price, and so the management of system is extremely important for achieving the desired performance of utilization and reducing the risk of investment (Abazari, Solimanpur, and Sattari, 2012). One of the factors contributing to increase flexibility and productivity of system is the production planning, which commonly considers the machine selection, part selection, and determines the sequence of robot and scheduling of parts according to the plan laid out.

Since the cost for implementing the FMS is very expensive, it is not particularly suitable for SMEs which determines the national economics. The benefits of FMC is expected to reduce the complexity, high flexibility, reduce software development costs, improve fault tolerance and high modularity, extendability and transferability (Duffie and Piper, 1987). FMC, as compared to FMS, has a lower cost, is more flexible and easier to invest or reconfigure the manufacturing system, and can adapt to the customer

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demands. Thus, FMC is meaningful for creating large benefits towards manufacturing economics. The formation of FMC is a step toward flexibility, quick response in producing the high quality parts at low cost and satisfying the customer's demand (Sujono and Lashkari, 2007). However, for effective utilization, the implementation of FMC is quite challenging. Production planning related to the machine loading problem is the first-key issue for consideration in implementing the FMC in practice. The machine selection and machine loading are extremely influential for the system's efficiency and productivity (Mahmudy, Marian and Luong, 2013). Due to the high investment required, a high level of resources utilization must be achieved and this issue can be handled by establishing a good production planning which increases productivity and flexibility (Mahmudy et al., 2013). The decisions on the issues of production planning must be implemented before the start of the actual production (Chen and Ho, 2005). In production planning, the machine selection and machine loading are the strategic planning decisions and important connection link between the operational level and tactical level decisions in production to achieve large system performance (Biswas and Mahapatra, 2008; Prakash, Shankar, Shukla and Tiwari, 2007). In addition, machine loading is one of the most crucial aspects to obtain the desired effective utilization of resources with the aim at reducing the manufacturing costs by at least 10-30% and material handling cost by at least 10-70% (Abazari et al., 2012).

1.2 Problem statement

The manufacturing SMEs are under great pressure to improve productivity and expand their market to provide more job opportunities and growth for the local economic development. SMEs have the ability to adapt and respond quickly to the conditions of market volatility in order to achieve the competitive goals in production. In countries of developed economies such as the USA, Japan, UK, Australia and Europe, FMS had been used, showing significant improvements in production and productivity (Raj, Shankar and Suhaib, 2007). FMS/FMC can respond to the requirements of flexible manufacturing and achieve flexibility and high efficiency, up to 90% (Nguyen, Dawal, Nukman and Aoyama, 2014). However, FMS is very expensive to implement. Thus, FMC, a unit of FMS, is a suitable alternative. In developing countries, the deployment and applications of FMC are still in the early stages at the level of backwardness (Raj et al., 2007). However, there is no framework to support the decision-makers in implementing FMC for manufacturing SMEs of automotive industry in developing country. Therefore, there is an urgent need for the design and development of FMC to meet competitiveness and development of SMEs, where a small production model based on private economy is strongly encouraged. During the design phase of FMC, the integrated model of machine tool selection and machine loading is critical to establish the cell and implement in the process plan in a more flexible manner. In machine tool selection problem in uncertain environments, there are some existing methods but is difficult to implement in practice due to the large number of judgment and large computational efforts. Production planning with multiple objectives is extremely important to decide the success of enterprises because it produces inputs for the scheduling decisions of resources, operation and control. Therefore, it is very necessary to develop a framework and a methodology for machine tool selection and machine loading problems to support the implementation of FMC in manufacturing SMEs of automotive industry.

In conclusion, machine selection and machine loading are considered as the two main topics of production planning for FMC (Abazari et al., 2012). A good production plan will make the system work optimally and efficiently. Therefore, the proper planning of FMC is critical in the development and design phase to evaluate the performance and will assist production managers in decision-making for machine selection and operation allocation.

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1.3 Research Aim and Objectives

1.3.1 Research Aim

The overall aim of this research is to develop a model for machine tool selection and machine loading in FMC which is suitable for deployment in SMEs of the automotive industry. In particular, a framework will be proposed for machine selection in uncertain environment. In addition, a framework will also be developed for determining the most appropriate combination of machines and operations for production in FMC that satisfies the manufacturing goals.

1.3.2 Research objectives

The research objectives are listed as follows:

1. To identify the criteria and potential alternatives of machine tools.
2. To determine the most suitable machine based on the ranking of alternatives using the multi-criteria decision making (MCDM) model of Fuzzy AHP and Fuzzy COPRAS; Fuzzy ANP and COPRAS-G with consideration of attributes.
3. To develop a mathematical model for machine loading problem in FMC to select the most appropriate combination of machines and operations.
4. To provide a solution on the machine loading problem in FMC using the newly designed non-dominated sorting Biogeography Based Optimization approach.
5. To validate the proposed model using FlexSim simulation.

1.4 Scope of the Research

This research develops a model for machine selection and machine loading problem in FMC, a model suitable for development of local economics, particularly in the context of Malaysia. The scope of the research is limited to list of machines and manufacturing equipment available in Malaysian automotive industry market. The

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appropriate process plan is chosen for implementing FMC and is validated at small SMEs in Malaysia.

1.5 Significance of study

Machine tool selection and machine loading are two critical steps to establish the FMC. This implementation of FMC will enable the SME to become the main players in the automotive industries. To ensure the success of FMC in the industrial effort on the flexibility and productivity, the issue of machine selection and machine loading are essential to be considered and support the production managers in effective decision-making.

The results of this study are for those manufacturing SMEs in the automotive industry who wishes to evaluate and select appropriate machine tools and to make the necessary process plan for producing numerous different part types with respect to their customers' demand. The model helps the production managers to make a decision in machine tool selection to establish the manufacturing cells with quantitative and qualitative factors. Two proposed hybrid methodologies are developed for evaluating machine tools based on fuzzy logic to decrease the number of judgment from experts and consider the interaction of the attributes. This model is practical to be applied and brings economic benefits for manufacturing SMEs of automotive industry. Moreover, the machine loading model is another significant result which can assist decision-makers in selecting the most suitable combination of machines and operations for processing various part types. The combination of machines and operations in FMC will be optimized based on the performance’s indices such as system unbalance, makespan and total flow time to ensure the delivery time and other benefits are experienced by both customers and manufacturers.

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1.6 Contributions

The main contribution of this research is to develop a model for machine selection and machine loading in FMC. Two novel hybrid approaches were developed based on Fuzzy AHP-Fuzzy COPRAS and Fuzzy ANP-COPRAS-G for evaluating and finalizing the decisions in machine tool selection. Then, a mathematical model of machine loading for FMC is presented with multiple objectives. The non-dominated sorting BBO is developed to determine the optimal solution of machine loading problem in FMC. Finally, the model is verified and validated by using virtual FlexSim simulation.

1.7 Thesis Layout

This thesis is a research work on fuzzy multi-criteria analysis for machine tool selection and machine loading problem in FMC. The content of this thesis is organized into the following six chapters.

Chapter 1 introduces the background, problem statement, objectives, scope and importance of the research.

Chapter 2 presents the relevant literature review on the methodologies of multi-criteria analysis for decision-making in machine tool selection. Then, the relevant literature is also reviewed on machine loading problems in FMS/FMC using mathematical programming model, meta-heuristic methods, and fuzzy logic.

Chapter 3 divides to two parts:

- In the first part, the main developments of two integrated approaches are described for multi-criteria decision-making in machine tool evaluation and selection in uncertain environment. These are (1) the integration of fuzzy AHP and fuzzy COPRAS; (2) the hybrid method of fuzzy ANP and COPRAS-G for selecting machines to establish FMC.

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- In the second part, the FMC is established based on selected CNC machines. In addition, the main mathematical programming model formulation of the machine loading problem (MLP) in FMC is presented with three objective functions of minimizing system unbalance, makespan and total flow time. Lastly, the Biogeography based Optimization (BBO) combined with non-dominated sorting procedure, adaptable for the MLP, is described.

In chapter 4, the analytical results of FAHP-FCOPRAS, FANP and COPRAS-G are presented to assist decision-makers in machine tool selection. In addition, the full computational results of the non-dominated sorting BBO for mathematical programming model of MLP are also presented. The result was used to aid the decision-makers in selecting the most suitable combination of machines and operations for producing part types in FMC. The results have been verified based on LINGO software and the literature.

Chapter 5 details and shows the results of the simulation experiments of FMC model to validate the results obtained and highlight their applicability in manufacturing SMEs.

Lastly, Chapter 6 contains the conclusion of this research and gives recommendations for future work.

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CHAPTER 2: LITERATURE REVIEW

2.1 Flexible manufacturing cell in developing countries

Today, with economic restructuring, the developing countries are investing heavily in the manufacturing sector. Many companies and factories have been set up to meet production needs for society, especially small and medium enterprises (SME) - a business form which is consistent with the private economies. However, competition with other companies in the market and varieties of products to produce according to customer needs always require the SMEs to restructure the production system to respond and adapt to that changeability.

Small and medium enterprises (SMEs) have the reputation of promoting employment, dynamic economic development. Hence, in the developed and developing countries or economic regions, much efforts are being made throughout the past decades to promote SMEs to recognize and implement innovation efforts to adapt to the advanced manufacturing technology (AMT) (Keizer, Dijkstra and Halman, 2002; Radas and Božić, 2009).

The current understanding of innovation efforts in SMEs is relatively poor (Edwards, Delbridge and Munday, 2005). In developing countries, SMEs are facing many problems, with the most important issue of inadequate infrastructure. Thus, SMEs would start with low-level skills, and expertise including management and organization. Nowadays, developing countries have been investing heavily in manufacturing sector with economic restructuring. Many companies and factories are competing to achieve the demands of social production, especially SMEs with business forms suitable for the private economy (Dawal et al., 2015).

The medium and small industries (SMIs) have played an extremely important role in the process of industrialization in the developing as well as the developed countries.

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They are under high pressure of innovation in the global competitive environment to adopt applications of AMT. The Malaysian government has considered SMIs as the engine for economic growth, moving from an economic model of agriculture to economic development based on AMT. The SMIs/SMEs of Malaysia (representing 84% of the manufacturing sector) must play a similar role as the SMEs of Japan, Korea and Taiwan in supporting activities for large companies and promoting the success of these countries towards industrialization (Rosnah, Ahmad and Osman, 2004). For SMEs in Malaysia, implementing AMTs is needed to face the challenges of globalization and to ensure survival in the future. The demands on cost and production efficiency improvements have forced a large number of companies to apply AMT in their operations. AMT plays a major role in improving the flexibility and quality for SMEs. SMEs cover a wide class of industries and play an important role in the developed as well as the developing countries (Dangayach and Deshmukh, 2005).

A survey in Malaysia showed that the implementation of AMT had not obtained the full potential strength of the SMI in Malaysia because of the lack of expertise, training and practice, and the lack of team work with the technical skills. CNC machine tools are mainly the application of AMT in the SMEs. For example, in Japan, 2/3 of CNC machine was put into use in SMEs. The effectiveness of labor is part of the reason that small companies in Japan can use FMS technology effectively (Rosnah et al., 2004).

One of the systems that is able to respond flexibly is FMS. However, the implementation of FMS is extremely difficult, it involves many different components such as CNC machines, transportation systems or robot, and the central computer system. In contrast, the FMC is considered as the basic component in accordance with development strategies in SMEs, and it is the survival of the modern manufacturing industry. Even in the machine shop of SME, nowadays, FMC becomes a main player; as a result, the intended operation becomes widespread (Ito, 2014). In Malaysia, there are 50% of SME having implemented AMT for improving flexibility and reducing cost in the past five years. The implementation of flexible manufacturing cells (FMC) is the primary focus of developing countries due to its flexibility and high efficiency of up to 90%. However, the implementation and planning of FMC in SMEs play an important role as the key issues that need to be addressed in order to increase the utilization of CNC machines and cutting tools (Dawal et al., 2015).

In developed countries, suppliers/vendors are capable of providing the equipment component in building the complete systems as FMS. Therefore, the integrated system of various elements can work perfectly in the operational process. However, the developing countries lack many devices from different vendors. The equipment is imported from multiple vendors from numerous countries using different specifications and standards. Decisions in machine selection from various vendors are important problem in implementing FMC. For perfect operation, a robust production plan of machine loading is thus needed. In conclusion, the integration and construction of a manufacturing cell or system that can operate well are big challenges for manufacturing SMEs in developing countries.

To make a better understanding in implementing the manufacturing cell for SMEs, this chapter reviews the problems of machine selection and machine loading for FMS. Then, the suitable approaches are proposed for solving the potential solutions and applying for FMC.

2.2 Previous works on machine tool selection problem

2.2.1 Introduction

Globalization of business, the worldwide competitive economy and the dramatic development in product life have forced companies to invest and improve production

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facilities, especially in the introduction of new equipment into the market. Therefore, the machine tool selection to invest and improving the facilities are an important decision and plays a critical role to the development of the manufacturing enterprises. Bad selection of machines could negatively impact the performance of the whole system such as the productivity, precision, flexibility, adaption and responsiveness. So, this is a time-consuming and intractable problem and is the largest drawback for engineers and managers due to the lack of in-depth knowledge, experience and technological understanding.

Ensuring customer needs is an important goal of manufacturers that can increase flexibility, timely delivery and product quality as well as for customer service. Therefore, the development of a strategy takes into account within the flexibility, efficiency, quality, reduced production time, increased profits, reduced production costs, increased productivity and regular maintenance services.

One of the priority issues to be resolved in the first stage of production planning is the appropriate selection of CNC machines. This is a critical issue that has been causing difficulties for the operation managers and manufacturing engineers. A survey given by Gerrard (1988) discovered that the engineers and technical experts contributed only 6% to the final selection and the remainder of 94% belongs to the decision of the middle and upper management. Therefore, a simple and comprehensive approach for the machine selection based on expert judgments is thus needed.

2.2.2 Previous approaches in solving the machine tool selection problem

2.2.2.1 Analytic Hierarchy Process and Analytic Network Process

The AHP approach, developed by Saaty, described how to determine the weights of a pool of alternatives and relative importance of criteria in MCDM problems (Wei, Chien and Wang, 2005). The robust applications of AHP/ANP in manufacturing have been

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implemented in many situations and have brought success for numerous companies. For instance, Lin and Yang (1996) presented a model of the machine selection using the AHP, from a spectrum of machine available for producing numerous part types. The hierarchy of AHP method consisted of three layers; the first layer was the objective of machine evaluation, the second layer was the criteria involving lead time, cost, machine procedures and operation shift; and the third layer was the alternatives such as classical machine, NC machine and FMC. The results showed that FMC was the most suitable candidate of machines tool and the second choice was NC machine.

Yurdakul (2004) presented a strategic justification tool for machine tool based on AHP/ANP. The hierarchical decision structures were formed to evaluate machine tool alternatives for investment. In particular, ANP was used to enable the interdependences among the elements of hierarchy. The ranking of alternatives was obtained through AHP/ANP as an outcome of application.

Tsai, Cheng, Wang and Kao (2010) described an MCDM approach to evaluate the criteria of selected machine tool from a set of specifications along with experts' judgment in the field of mold manufacturing technology. AHP was used to predict the priorities of criteria and ranking of alternatives through Expert Choice software. Numerical example was implemented for 4-axis CNC machine centers with the main criteria comprising of capacity, space of dimensions, maintenance and service, environment and safety, and sub-criteria consisting of productivity, flexibility, adaptability, precision, floor space, machine height, training, repair service, regular maintenance, mist collector, safety door, fire extinguisher, bearing failure rate, initial cost, running cost and reliability of drive systems. The results showed that the MCDM model satisfied the demands of an organization.

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Paramasivam, Senthil and Rajam Ramasamy (2011) described three MCDM approaches of digraph and matrix approach, AHP and ANP for the equipment evaluation process. The result was applied for the milling machine selection in manufacturing environment. They also showed that the results of AHP were different from ANP and digraph and matrix approach because AHP does not consider the interdependency and the impact of criteria.

2.2.2.2 Fuzzy AHP/Fuzzy ANP approach

Ayağ and Özdemir (2006) proposed a fuzzy AHP to rank the multi-attribute machine tool alternatives. In AHP method, the pair-wise comparison is imprecise and inadequate to handle the expert's judgments. So, the fuzzy set is integrated into AHP for solving the uncertain problems. First, the fuzzy AHP is employed to identify the weights of the attributes and the ranking of alternatives; second, the Benefit/Cost (B/C) analysis is employed to choose the ultimate machine tools based on the highest ratio. The numerical example contains eight main attributes, 19 attributes and three machine alternatives such as Maho, Hass and Seiki. The result showed that Hass was the most suitable selection.

Similarly, the fuzzy AHP was presented by Durán and Aguilo (2008) for evaluating and modifying the advanced manufacturing system. They also developed fuzzy AHP software for applications of machine tool selection through weights of criteria and alternatives' ranking. In addition, Abdi (2009) constructed a fuzzy MCDM model for evaluating reconfigurable machines using fuzzy AHP. Their model was developed to integrate the uncertain decisive factors for selecting the equipment with operational characteristics along with criteria of economic, quality and performance. However, AHP has some disadvantages. Thus, they suggested that development of ANP algorithm is the future research direction for MCDM in exploring the properties of reconfigurable layout and the formation of main components such as material handling systems, machines, floor space, tools and operators.

Ayağ and Özdemir (2011) proposed an intelligent technique for selecting machine tool using fuzzy ANP. ANP is more advanced than AHP since it accommodates the dependences, interactions and feedbacks between higher and lower level components. The fuzzy set is included in ANP to solve the vagueness, uncertainty on the judgments of decision-makers. Thus, fuzzy ANP was proposed to improve the imprecise ranking results from AHP/ANP. The preference analysis is used to reach the final solution through fuzzy ANP and costs of potential alternatives.

2.2.2.3 Hybrid of (Fuzzy) AHP/ANP approach

(Fuzzy) AHP/ANP requires a large amount of questions to collect experts' judgments to make a decision. Thus, numerous studies have developed the hybrid method of (fuzzy) AHP/ANP combined with other approaches to reduce the need for judgments. For example, Myint and Tabucanon (1994) described a decision support system (DSS) framework for decision-making process in the most appropriate machine selection for FMS. Their framework consisted of two stages of AHP and GP (goal programming). The AHP was utilized to dramatically decrease all candidates of machine and GP was used to find out the satisfactory alternatives, and finally the sensitivity analysis was conducted to optimize the proposed model. In addition, Tabucanon, Batanov and Verma (1994) proposed the MCDM method for machine selection in FMS using the AHP and the rule-based technique of Expert System. Their result was applied for selecting a CNC turning center to produce a family of rotational parts.

Dağdeviren (2008) integrated AHP and PROMETHEE for multi-attribute equipment selection. The AHP was employed to analyze the hierarchy of the equipment selection issue and to calculate the priorities of criteria. Then, PROMETHEE (Preference

Ranking Organization Method for Enrichment Evaluations) method was used to determine the final ranking. The robustness of ranking was validated by sensitivity analysis based on the changes of weights. They applied the developed model in an international company for the selection process of milling machines.

Bo, Hua, Laihong and Yadong (2008) presented a model based on grey relation theory and AHP methods for machine tool selection in a networked manufacturing set up. Firstly, potential machine tool ranking system was presented based on the factors of quality, time and cost. Secondly, a multi-hierarchy grey evaluation model of machine tools was developed for decision-making process. Finally, the AHP was utilized for ranking alternatives and finalized the decision.

Ayağ (2007) has integrated the AHP approach and simulation method for machine tool selection. AHP was utilized to limit all potential machine candidates in the market by evaluating the weights of alternatives. Then, simulation was employed to model the manufacturing organization in which the most appropriate machine is used. The ranking of alternatives was determined according to the investment cost ratio.

Önüt, Soner Kara and Efendigil (2008) described the hybrid fuzzy MCDM approach to select vertical computer numerical control (CNC) machining centers at a manufacturing enterprise in Istanbul based on the integrated approach of fuzzy AHP and fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). The priorities of criteria are determined through fuzzy AHP to handle the qualitative criteria, and the result from the alternative's ranking is obtained by fuzzy TOPSIS.

İç and Yurdakul (2009) developed a decision support system for machining center selection using the integration of fuzzy AHP and fuzzy TOPSIS. In particular, fuzzy AHP was used to determine the weights of criteria and fuzzy TOPSIS is utilized to rank

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the most appropriate machining centers. They introduce the triangular and trapezoidal fuzzy number to model the criteria of machine in fuzzy AHP and TOPSIS methods.

The decision support system (DSS) for machine tool selection in FMC using the fuzzy AHP and artificial neural network (ANN) was also proposed by Taha and Rostam (2011a). ANN with the feedback propagation was utilized to verify fuzzy AHP and to determine the ranking of alternatives. A numerical example was carried out with ten criteria and four alternatives of CNC turning machines (Doosan, Mazak, Nakamura and Romi). The judgments of the questionnaire design were collected from five experts for pair-wise comparison. The result shows that Mazak was the best choice for machine tool.

Taha and Rostam (2011b) also presented a DSS based on a hybrid approach of fuzzy AHP and PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluation) for evaluating the machine tool of FMC. The survey was implemented for seven criteria and four alternatives (Nakamura, Dossan, Romi and Mazak). The fuzzy AHP was used to calculate the weights of criteria and the PROMETHEE was employed to determine the ranking of alternatives through the Decision-Lab software. The numerical example was carried out, and the results have shown that Mazak was the best machine alternatives in the implementation of FMC.

Samvedi, Jain and Chan (2011) presented an integrated approach of fuzzy AHP and GRA (Grey Relational Analysis) for MCDM process to select machine tools. Fuzzy AHP was used to determine the weights of criteria, and GRA was utilized to predict the ranking of alternatives. They built the proposed model with eight criteria and four alternatives of CNC machining centers as a case study. Finally, sensitivity analysis was used to further support their claim, and integration of fuzzy ANP and GRA was suggested for future research work due to interdependences of factors.

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Ozgen, Tuzkaya, Tuzkaya and Ozgen (2011) proposed a fuzzy MCDM approach for machine tool selection using a combination of modified DELPHI method, AHP and PROMETHEE approaches with fuzzy sets theory. Their results were verified by the results from other methods such as fuzzy AHP and fuzzy TOPSIS. In addition, sensitivity analysis was carried out to predict the changes with respect to changes in the weights of criteria.

Ic, Yurdakul and Eraslan (2012) proposed a fuzzy MCDM models using technical specifications provided by machining-center manufacturers. The AHP method was used to evaluate the machining center components and determine the ranking of alternatives. The results of AHP based on the components were compared to other MCDM models (AHP, TOPSIS) using only technical specification values. Moreover, the addition of other components and the relationships among the criteria were suggested for future research directions.

A recent study by Ayağ and Gürcan Özdemir (2012) has presented a fuzzy MCDM model relying on fuzzy ANP and modified version of TOPSIS for evaluating the machine alternatives. ANP was used to model the feedback and interactions, dependences between elements at various levels. Fuzzy ANP is the integration of fuzzy logic into ANP which can be used to solve vague human preference as information resource of input for decision-making procedure. In their study, the weights or priorities of criteria involving flexibility, productivity, adaptability, space, precision, reliability, environment and safety, maintenance and service were calculated through fuzzy ANP, and the modified TOPSIS was employed to determine the alternative's rankings.

2.2.2.4 Other approaches

Lin and Liu (1997) presented a method for the selection of coordinate measuring machines using neural network. Wang, Shaw and Chen (2000) developed a MCDM

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approach for machine selection in implementing an FMC including machine center, milling machine and robot. The membership functions of weights for those attributes were determined according to their robustness and distinguishability when the ranking was identified. The results showed that the proposed model provided efficient decision for the most suitable machine selection.

Arslan et al. (2004) stated that the standard format in the catalogues of machines is important for machine tool selection process in order to significantly classify and compare the machines. The model of machining process was built to realize the process requirements, and is integrated into the decision support system for the multiple criteria machine tool selection. In particular, a multiple criteria weighted average method was proposed to rank the alternatives of machine through nine criteria. Then, the Cost/Benefit (C/B) analysis was also conducted to modify the purchase and its optional features of machines.

Chtourou, Masmoudi and Maalej (2005) developed an expert system to select machines in a manufacturing system based on simulations. The purpose was to modify the resource relying on due date through measuring the performance in simulation process.

Ertuğrul and Güneş (2007) proposed a fuzzy MCDM for the most appropriate machine selection. The trapezoidal fuzzy numbers were introduced to integrate into the fuzzy TOPSIS method for evaluating the criteria and three alternatives. Rao (2007) reviewed some methodology for machine selection in FMC. The GTMA, SAW, WPM, AHP, TOPSIS and modified TOPSIS were mentioned for evaluating machine tool alternatives.

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Balaji, Gurumurthy and Kodali (2009) presented a MCDM model using ELECTRE III (Elimination and Choice Translating Reality) for selecting the most suitable machine tool. Twenty attributes based on technical specifications were chosen for decision-making process. A numerical example was implemented for selecting the best alternative of CNC lathe.

Yurdakul and İç (2009) developed the fuzzy MCDM method in machine tool selection for a manufacturing company. In particular, fuzzy logic was used to solve the vagueness and imprecision in machine tool selection issue. TOPSIS was used as MCDM approach to rank the machine tools. The obtained result was compared with the ranking obtained with crisp value.

Qi (2010) presented a fuzzy MCDM approach including both qualitative and quantitative factors to make a decision in machine tool selection. The logarithmic least squares technique using fuzzy pair-wise comparison matrix was used to predict the uncertain weights of selected criteria. Then, the performance values of the alternative were interpreted respectively, and fuzzy integral was utilized to aggregate the performance scores of the alternative in terms of desired criteria. The case study was carried out with three CNC wire-cut EDM and the relevant specifications to validate the proposed method. Alberti, Ciurana, Rodríguez and Özel (2011) designed a DSS for high-speed milling machine selection using characteristics of machines and performance tests. Artificial neural network (ANN) was employed to predict the most suitable machine tool.

Chakraborty (2011) proposed the MOORA (multi-objective optimization on the basis of ratio analysis) for decision-making process in manufacturing environment. The applications of the most suitable selection of the industrial robot, FMS and CNC

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machine, and machining process were implemented to prove the effectiveness, flexibility, applicability and potentiality of the proposed method.

2.2.2.5 Remarks and assessment of approaches for machine tool selection problem

Previous findings have shown that the applications of the AHP/ANP algorithms are very heartening and widely used in the decision-making processes. AHP/ANP archived the reasonable results in evaluating and ranking the alternatives and has been applied successfully in the manufacturing environment because it simultaneously evaluates qualitative and quantitative factors. Moreover, one of the important advantages of using the AHP/ANP is that it is capable of generating weighted priorities of criteria and the priorities of alternatives from the pair-wise comparison matrices of expert judgments. However, ANP, which is the extension of AHP, is better than AHP because it accounts for the interdependence, feedback relationships, and interaction between the higher-level and lower-level elements. ANP is a MCDM that converts qualitative values to quantitative values and performs analysis on these values. It uses the pair-wise comparison matrices from experts' judgments, which contains imprecise, uncertain information, to calculate the relative priorities of the attributes. As ANP is insufficient to handle the uncertain information, fuzzy logic is integrated into the ANP to describe the experts' judgments. However, fuzzy ANP has a weak point which is the high demands of complex computation. During the implementation of the fuzzy ANP, the experts or decision makers need to provide answers to a large number of pair-wise comparisons; which is impossible to obtain in some cases.

Fuzzy sets and grey theory have the capacity of solving the potential problems that of uncertainty, incompleteness, imprecise, tangible and intangible information. In most cases, fuzzy logic is integrated into AHP/ANP to handle uncertain information. The advantage of hybrid approaches of (Fuzzy) AHP/ANP with other methods such as

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TOPSIS, PROMETHEE, ELECTRE and COPRAS are not only to reduce a number of judgments collected from experts but also enable a large number of alternatives for decision-making process. Figure 2.1 presents the widely used methods for solving the machine tool selection problem based on the multi-criteria decision making. The previous works related to machine tool selection are listed in Appendix A, and the selected criteria for decision making found in the literature are presented in Appendix B.

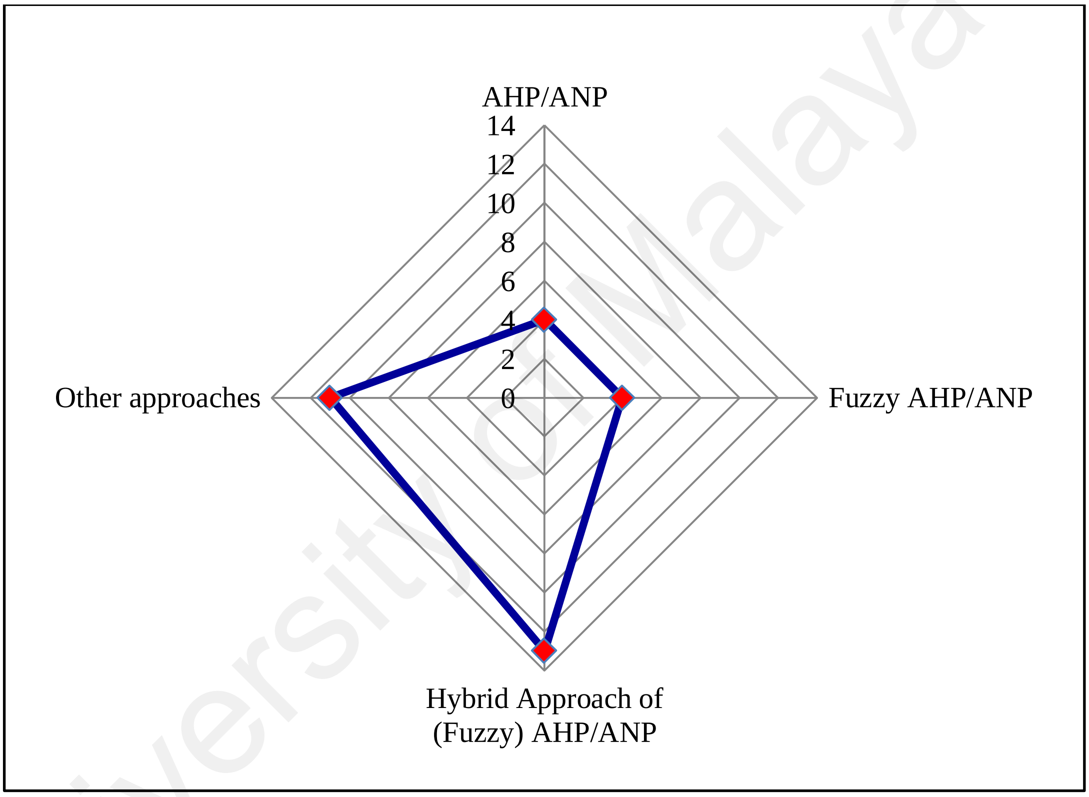

Figure 2.1: The number of approach used for machine tool selection

As seen from past findings, the best approaches have considered reducing a number of judgments but still maintained the accuracy of methods. Moreover, the consideration of interactions of the attributes which characterizes the property of machines is included in the method. Therefore, the integrated and hybrid methods (fuzzy AHP and fuzzy COPRAS, Fuzzy ANP and COPRAS-G) are identified as potential alternatives for solving the machine tool evaluation and selection problems.

2.3 Machine Loading Problem

2.3.1 Flexible manufacturing cell/system in automotive industry

Many manufacturing facilities are facing problem in configurability of production systems to adapt to the changeability of the internal and external factors. The only main reason for modern equipment investment is to respond to the dynamic and uncertainty of the manufacturing environment under the impact from the customer demands or requirements. The production performance is no longer determined by manufacturing cost alone. Other factors of quality, flexibility, delivery and customer services also play a significant role for the success of enterprises. The growing trend of production enterprises is to satisfy the customer's needs by reducing the batch quantities and increasing the variety of product and shrinking the product life cycle. In particular, the characteristics of flexibility, efficiency and quality are considered as vital criteria in improving the manufacturing systems with the aim of reducing the production lead time to meet the customer requirements. Moreover, the flexibility enables it to adapt to the dynamic manufacturing environment and improve the productivity as well as the cost and service to maintain market share (Atmani and Lashkari, 1998; Chan and Swarnkar, 2006).

FMS is an automated manufacturing system that has the flexibility of job shop together with the efficiency of the flow shop to produce many part types with different small-to-medium size batches. The duality of efficiency and flexibility causes the management of FMS to become more difficult, which is reflected in planning as well as scheduling (Kumar and Shanker, 2000). In other words, this system is an attempt to preserve the efficiency of mass production while maintaining the flexibility of traditional production process (Tiwari, Rika, Rthi, Jaggi and Mukhopadhyay, 1997). The structure of the system comprises at least four programmed and multifunctional machines, or a group of processing workstations interconnected together mechanically by an automatic material handling devices (Robots, Automated Guide Vehicle, conveyor, etc.) and controlled electronically by a communication network. The benefit of FMS is high machine utilization, fewer machine and reduction in the floor space requirements, ability to respond to changeability, easiness for re-configurability and agility, reduced inventory requirements, lower labor productivity and opportunity for automated production (Groover, 2010).

One of the factors contributing to the increase in the flexibility of production systems is in the planning and production. The problems commonly considered include machine selection, part selection, machine tools selection and determination of the sequence of robot and scheduling of parts according to the plan laid out. Scheduling is the heart of smart management for the FMS with the goal to minimize the average lateness, minimize the make-span, maximize the utilization, minimize work-in-progress (WIP) and setup time, minimize the tardiness and flow time.

Use of FMSs leads to (Gamila and Motavalli, 2003):

- Increase the variety of products to satisfy customer demands.
- Shorten the product development cycle.
- Be flexible to adapt the changes in the market.
- Improve the utilization of resources.
- Increase productivity and decrease goods and services' costs to preserve the market share.
- Reduce the setup time and WIP (work-in-progress).

Create the rapid cell for the family of new product by simply reprogramming FMS.

FMS is one of the systems that can respond flexibly and is a powerful innovation for production environment (Kumar and Shanker, 2000). As FMSs are expensive, it is extremely important that high efficiency can be obtained at minimal investment risks (Kumar, Tiwari, Shankar and Baveja, 2006; Yang and Wu, 2002). However, the

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implementation of FMS is a challenging task, involving many different components such as CNC machines, transportation systems or robot, and the central computer system. In comparison, FMC is considered as the basic component in accordance with development strategies in SMEs and is the survival of the modern manufacturing industry. In recent years, FMC has become an attractive option for implementation in developing countries due to its flexibility and high efficiency of up to 90%. The implementation and re-planning of FMC in SMEs play an important role and should be addressed in order to increase the utilization of CNC machines and cutting tools. Furthermore, the operational management of FMS is more complicated than classical manufacturing systems because it requires more decisions to achieve its effective flexibility and productivity (Rai, Kameshwaran and Tiwari, 2002).

For production facilities, an FMS compromises of 5 to 25 Numerical Control (NC) machines, material handling system and a central storage system (Prakash, Khilwani, Tiwari and Cohen, 2008). In particular, FMC with small number of machines (less than 4) is the key component to the implementation of FMS. The structure of FMC consists of the CNC machine tools (computer numerically controlled milling and lathe machine with the automatic tool magazines), robots for loading/unloading parts and automated storage and retrieval systems (AS/RS). The loop layout controls the parts to flow smoothly to the robot position. The robots pick the parts up and would move to the machine tools for loading, then unload the parts from the first machine after finishing operation and will continue moving the next machine for loading. After completion of the machining process and becoming the finished product, it is unloaded from the machine by robots and moved to the drop-off position by conveyor loop layout or AGV.

2.3.2 Machine loading problem in flexible manufacturing cell environment

Machine loading problem defines the allocation of operations and essential cutting tools into suitable machines to produce many different part types with the satisfied technological and capacity constraints. The techniques and methods for solving the conventional job shop loading problem can be utilized for the loading problem of FMC. However, these methods will not take advantage of the flexibility in FMC, thus the performance will be decreased significantly.

In general, operational decisions in FMS/FMC are classified into two types, which are the pre-decision and post-decisions. The pre-release decisions will relate to the planning issues, such as considering the re-arrangement of machining parts and cutting tools before starting the machining process. Post-release decision is known as the scheduling problem of FMS, which involves solving the sequencing of part types when operating the system. The pre-decisions include the grouping of machines, part type selection, calculation of the production rate, allocation of resources and loading issues. Among the pre-decisions, the machine loading issue is one of the most crucial production planning issues because of its strong influences on the productivity of the system (Abazari et al., 2012).

Loading problem of FMS/FMC is more challenging than of job shops. This is because: (1) the machines are more flexible and capable of processing numerous operations, (2) several part types can be processed simultaneously, and (3) each part type can be processed by more than one production route. In particular, job sequence, allocation, and reallocation are the three critical contents (Vidyarthi and Tiwari, 2001). Five sub-problems of FMS/FMC loading were defined by Stecke (1983a).

1. *Machine grouping*
2. *Part type selection*
3. *Production rate determination*
4. *Resource allocation*
5. *Loading*

Solution for MLP may affect the optimal operation of FMS. Under the manager viewpoint, Stecke (1983a, 1983b) presented six objectives in machine loading.

1. *Balancing the machine processing time.*
2. *Minimizing the number of movements*
3. *Balancing the workload per machine for a system of groups of pooled machines of equal sizes.*
4. *Balancing the workload per machine for a system of groups of pooled machines of unequal sizes.*
5. *Filling the tool magazines as densely as possible.*
6. *Maximizing the sum of operational priorities.*

The developing countries have realized that FMS investment is an important and responsive to the requirement of manufacturing development. However, the cost for implementation of FMS is very expensive. Thus, it is not suitable for small and medium enterprises (SME). Flexible manufacturing cell (FMC) has a reduced cost, more flexibility to respond to the customer demands. Therefore, FMC can be useful for creating large benefit of manufacturing economics. However, for effective utilization, the implementation of FMC is a challenging because of the complexity of the system. Production planning related to the machining loading problem is the first-key issue to be considered for implementation of FMC in practice. Finally, machine loading in FMC is considered in two sub-issues: (1) machine tools selection for investment; (2) machine loading problem inclusive of the optimal machine tools selection and tools assignment and operation allocation in FMC.

Machine loading involves the decision-making process for selection of parts, operation assignment and tool allocation to the various machine tools in the manufacturing process, a critical link between operational and strategic level decisions

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in production (Vidyarthi and Tiwari, 2001). It is stated as *"... given a set of parts to be produced, set of tools that are needed for processing the parts on a set of machines, and using a set of resources such as material handling system, pallets and fixtures, how should the parts be assigned and tools allocated so that some measure of productivity is optimized...*"(Kumar et al., 2006). CNC machine is more flexible and accurate in performing the various operations than conventional machine tools (Raj et al., 2007). Thus, the machine tool types give the negative impact on the machine loading issue. FMC is used in the unmanned environments. Each CNC machine can perform several different operations. Therefore, it is necessary to understand the characteristics and capacity of machine tools before formulating the loading problem (Raj et al., 2007). The first work for FMS loading has been published by (Berrada and Stecke, 1986; Stecke, 1983a, 1983b) and until now, this problem is still attracting the attention of researchers.

Flexible machines are able to produce a various range of operations, equipped with the automated tool changers and have s short setup time. The pool of operations can be produced on a machine that has been restricted by a number of tools mounted on tool magazine at a given time. When a part is loaded on the machine, the next operation can be produced on the same machine with a sufficient technological capacity such as the corresponding tools and available materials as well as waiting and setup time. Let a pool of part requirements to be simultaneously produced, the constraints of technology and resources, how to assign tools to machines in a short-term planning problem in FMS is defined as the 'FMS loading problem' (Stecke and Solberg, 1981). In most industrial cases, the loading problem plays an important role in production planning with the aims of looking for reasonable solution with the suitable time, and should be considered and handled at the beginning of each shift or day (Koşucuoğlu and Bilge, 2012).

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Given an FMC with the number of CNC machine and the number of part type with different batch sizes for performing several operations, robot for loading and unloading parts at each CNC machine and other workstations, where several part types arrive for other processing requirements. The batch size is determined with the number of part for each type which is chosen for producing in the planning horizon. The basic problem is how the parts are to be assigned into the various CNC machines so that the system unbalance, makespan and total flow time are minimized with the technological constraints and capacity of resources of machines and tool magazines. The machine loading problem involves "*the allocation of part operations and required tools amongst the CNC machines for a given product mix*" (Nagarjuna, Mahesh and Rajagopal, 2006).

2.3.3 Importance of manufacturing objectives of machine loading problem

The objective of loading is problem dependent. Balancing workload was the most commonly used objective in research, and was the least practiced in developed industry. The balancing of workload or system unbalance has been popular in conventional systems and FMS/FMC, which attempts to allocate the total processing times to each CNC machine as equal as possible. The reason is that if the workload is uniform, the congestion will be reduced and the performance will be improved. So this objective makes all machines in system complete the desired operations more or less at the same time. Therefore, minimization of system unbalance (balancing the workload) is very important in reconfiguring the system to produce new batch of part types (Stecke and Solberg, 1981).

Minimization of transportation time as well as minimization of the number of part type movements will make the workload unbalanced with the larger queue closed to the most heavily used machines. If the transportation time in the system is considerably larger than the processing time of operations, this objective is worth considering. The

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managers always look for ways to assign several consecutive operations on a machine with the aim at balancing. Related to the factors of time such as processing time and transportation time, the makespan, total flow time and manufacturing cost are considered as the indices for measuring the performance of system. For more detail information, Section 2.3.4 reviews the contributions in field of loading problem. It mentions about the studies of models and analytical solutions as well as intelligent techniques. In particular, the objectives are described and techniques for determining the solution are introduced.

2.3.4 Different approaches in solving the machine loading problem

Grieco, Semeraro and Tolio (2001) provided the survey on the different techniques to solve the MLP in FMS, which is classified based on the kind of FMS, the objective function and constraints. The components of FMS and relative issues were introduced such as machines, control system, cutting tools and tool handling system (tool life, tool copies and tool magazine), pallets and fixtures (part loading, fixture cycle time, part requiring more than one fixture) and the characteristics related to the plant such as the shifts, tool room management, preventive maintenance, downstream assembly operations and production planning hierarchy. Besides, some issues of due dates, priorities and unforeseen events were also mentioned and explained in detail.

For solving the MLP, many approaches have been suggested in the literature. Especially application of intelligent techniques is an interesting direction. With overall view of FMS loading, Prakash, Shukla, Shankar and Tiwari (2007) provided a survey of intelligent methods of artificial intelligence (AI) for finding the solutions of MLP in FMS. Those techniques are genetic algorithm (GA), simulated annealing (SA), tabu search (TS), ant colony optimization (ACO) and artificial immune systems (AIS) were used to explore the suitable solutions. The performance of algorithms was evaluated

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based on the data set from previous literature. Then, the future direction for MLP is also identified and strongly encouraged for future.

In the context of manufacturing shift at company, Slomp and Stecke (2011) examined and improved the production control of a company which wants to operate its FMC during an untended shift. Their mentioned FMC includes a machining center, the pallet storage, a rail-guide AGV and clamping/unclamping station. The changes in the hierarchy of the current production control were proposed, and some new approaches to handle major production control issues were presented as a reference for future research on FMC planning, sequencing and scheduling.

To understand and approach the MLP, the summarization of related works on proposed methods in the literature are essential. The methods widely used include Mathematical programing (Section 2.3.4.1), heuristics (Section 2.3.4.2), metaheuristics (Section 2.3.4.3) and simulation based methods (2.3.4.4).

2.3.4.1 Mathematical programing approach

Atmani and Lashkari (1998) developed a 0-1 linear integer model of machine selection and allocation of operations for FMS to minimize the total costs of operations, material handling and system setups. The constraints considered involved the tool life, tool magazine and capacity of machine. The result of the proposed model was carried out by Hyper LINDO optimization modeling tool. However, the optimization tool can obtain the desired solutions from small data set but the computational run time is large. Therefore, it becomes more difficult for operation managers who need to make decision quickly. Besides, the cost is always dramatically changed and unstable according to competitive manufacturing market. Gamila and Motavalli (2003) improved the model of production planning in FMS with consideration of the part-tool loading and scheduling. A 0-1 MIP (mixed integer programming) model was established to describe an integration of loading and routing to minimize the total processing time, transportation time and summation of maximum completion time. The LINGO optimization modeling tool used to explore the solution of mathematical model based on the B&B (Branch-and-Bound) exact algorithm.

Das, Baki and Li (2009) continued solving the FMS planning involving the allocation of cutting tools, part type grouping and machine loading. In their work, a sequencing of operation was extended and developed to gain the optimal operation time, orientation change times and non-productive tool change times. The mathematical model of integer programming was formulated for grouping the parts and handling the operation sequencing, and the optimal solutions obtained were based on LINGO 9.0 optimization modeling tool.

Jahromi and Tavakkoli-Moghddam (2012) developed a novel and dynamic model of FMS for selecting the machines and operation with considering the movement policies of part and cutting tool. This is a good model which included both transporting part and tools but it is complicated and difficult to implement in practice. A mathematical model of 0-1 linear programming is formulated during manufacturing stage to minimize the production costs. To achieve the solutions, a novel heuristic approach based on five simple procedures (FSP) is proposed and compared with Branch-and-Bound algorithm by LINGO 8.0 optimization modeling tool. The application of other metaheuristics such as ACO, GA, SS (Scatter Search) and AIS is encouraged, and the consideration of multi-objectives issue, stochastic, and fuzzy environment for their proposed model should be direction for future research.

The latest work of using mathematical programming is presented by Soolaki and Zarrinpoor (2014). They proposed a novel integer linear model of assignment in FMS. The machine selection and allocation were considered to simultaneously satisfy

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objectives of the minimum costs of processing, material traveling, setup and maximizing the machine workload time and tool life. Due to the complexity of nondeterministic polynomial (NP)-hard nature, the GA was developed to determine the most suitable solution for selecting the combination of machines and operations. However, this model is very complicated, and its validation is difficult when it is being implemented in practice for an experimental design.

2.3.4.2 Heuristics approach

Heuristics is a potential approach to handle many problems of optimization. For example, Tiwari at al. (1997) solve the FMS loading based on heuristics to obtain the optimal system unbalance and maximal throughput. Their heuristics is based on the SPT (shortest processing time) sequencing rule and Petri Nets theory. The important assumptions were included to reduce the problem complexity such as non-splitting of job, unique job routing, non-considering the sharing and duplication of tool slots, sufficiency of pallets, fixtures and parts are ready available on machines, transportation time is negligible. However, the transportation time is a critical factor which has a strong impact to cost of the manufacturing and delivery time. For the evidence of this statement, the transportation that costs are significant in manufacturing around 15-70% of the total the manufacturing cost (Tompkins, White, Bozer and Tanchoco, 2010). Several studies stated that transportation operation generally accounts for 30-40% of production costs (Anand, Kodali and Kumar, 2011; Onut, Kara and Mert, 2009) or 30-75% of total cost, and it is mainly in charge of decreasing a company's operating cost by 15-30% (Kulak, 2005).

Vidyarthi and Tiwari (2001) presented a heuristic solution based on fuzzy logic for MLP to minimize the system unbalance (SU) and maximize the throughput (TH). The membership function is used to evaluate the job sequence based on some specifications of batch size, essential and optional machining time. The decision for selecting the optimal combination of operation-machine is made based on the membership function of the allocation vector of operation-machine. However, the determination of membership function is difficult when the real data is insufficient and experts' opinion is not considered. To continue this work, Kumar et al. (2004) also proposed a fuzzy-based method to determine job sequencing, allocation of operation and reallocation of jobs to satisfy the minimum system unbalance and maximum throughput. Additionally, an extension of neuro-fuzzy petri net is also studied to handle MLP in a more detailed which have been further developed to learn the experience and perform inferences in order that the properties of the intelligent system could be realized.

Tiwari, Saha and Mukhopadhyay (2007) combined the job sequencing and FMS loading using two heuristics of standard and non-standard sequencing rules (LPT, SPT, FIFO, LILO, MENOF, MENPT and HREPTF) and GA. Nagarjuna et al. (2006) developed the heuristic method based on multi-stage programming for MLP in random FMS. The purpose is to minimize the SU and satisfy the constraints on processing time and tool slots. The verification of algorithm is implemented by comparing the obtained results of proposed heuristic with existing method of GA, SA and SPT rule.

Goswami and Tiwari (2006) presented a reallocation-based heuristic method to handle the MLP, including three segments such as determination of part type sequence, allocation of operation in the machines, and reallocation of part types. The two objective functions of minimizing SU and maximizing TH are used with the constraints of machine time, tool slots and AGVs' availability. However, when the system unbalance is minimized, of course the throughput is maximized due to the correlation of these objectives. So the consideration of throughput as an objective is not essential. The part type sequence has been conducted based on the contribution of part type to

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properties which comprised the batch size, AGV movement and the total processing time. Then allocation of operation was implemented relied on the priority index, and reallocation process was to obtain the desired goals.

A recent study by Goswami, Tiwari and Mukhopadhyay (2008) suggested the integrated method to address the grouping of tool-part, allocation and scheduling of jobs in FMS to gain the maximum production rate, minimum makespan and the minimum system unbalance. In particular, tool-part grouping is realized using ‘principle component analysis’ and tool allocation was conducted based on the priority-based technique by developing a potency index. However, since the priority-based technique is derived from a non-optimal potency index, the solution for optimization problem is difficult in practice.

2.3.4.3 Metaheuristics approach

Soft computing and intelligent decision techniques have been developed to analyze and generate helpful methods that enable the manufacturing systems to handle the work flow, material and information flow (Chien, Kim, Liu and Gen, 2012). Evolutionary techniques have turned out to be potent methods to solve the process planning problems. The adaption of evolutionary method to the problems of manufacturing system is very challenging but frustrating. The success of evolutionary algorithms in manufacturing and logistics was identified and reported by (Gen and Lin, 2014; Gen, Lin and Zhang, 2009). In machine loading of FMS, metaheuristics is an intelligent technique in lieu of classical methods used to find the optimal solutions when the problem size is large, and have been proven to be an effective method through numerous studies. For instance, Kumar and Shanker (2000) have developed the GA to select part types and solve MLP in FMS. An MIP (mixed integer programming) model was established with constraints including operation assignment, requisite tooling, tool magazine capacity, tool type

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availability, workload definitions, machine capacities and unique job routing. Their results were compared with the results obtained in CPLEX optimization modeling tool to validate the proposed model. The non-dominated sorting GA (NSGA) is suggested to further extend for multi-objective machine loading with multiple objectives of maximization of throughput, flexibility, resources utilization, minimization of production cost, balance workload and satisfaction of due date.

Mukhopadhyay et al. (1998) have used the simulated annealing algorithm (SA) to minimize the system imbalance for machine loading. In addition, Rai et al. (2002) presented the model of machine selection and allocation to achieve the minimum total cost of machining, material conveying and setup. The constraints include the capacity of machines, tool life and tool magazine. A fuzzy goal programming is formulated based on the membership function, and GA was used to determine the optimal solutions. Then, the proposed fuzzy goal programming model is solved with ant colony optimization (ACO) by Chan and Swarnkar (2006), a quick converging simulated annealing-based solution by Mishra et al. (2006), and an artificial immune system (AIS) by Chan, Swarnkar and Tiwari (2005).

Yang and Wu (2002) proposed the MIP model to integrate the selection of part types and MLP. The objective function was used as minimization of difference between maximum and minimum machine workloads of each batch. To handle MIP model, GA was employed to find the near-optimal solution and compared with the obtained results from Branch and Bound (B&B) algorithm. At the same time, Sarma et al. (2002) developed the modeling framework based on a generic 0-1 MIP formulation to minimize the system unbalance (SU) and maximize the throughput (TH). The tool slots' availability and time on the machines are the constraints of the model. The proposed solutions used such heuristic relied on the fixed sequencing rules of part and tabu search

(TS) algorithm for finding the near-optimal solution. On the other hand, with the same objectives and additional and modified constraints, Swarnkar and Tiwari (2004) developed a hybrid approach of TS and SA for handling generic 0-1 integer programming model, and the results obtained are compared with other previous findings.

With the same objectives of minimizing SU and maximizing TH, Kumar et al. (2006) presented a constraint-based GA to solve a complexity of variables and constraints in MLP. Many operators of different crossover and mutation are employed to avoid getting trapped at the local minima in finding the near-optimal solutions. The results obtained were compared with other standard rules such as SPT, LPT, LIFO, FIFO and others from previous works. With the same idea, Tiwari et al. (2006) made use of the model and extended using a novel approach based on constraint-based fast simulated annealing algorithm. The combination of GA and SA was designed to overcome their drawbacks and to escape from the local minima.

Arikan and Erol (2006) developed meta-heuristic based on SA and TS for solving part selection and tool allocation to determine the minimization of part numbers in a batch. The results of MIP model were verified with OSL solver of GAMS (general algebraic modeling system). Moreover, their work was also extended further (Arıkan and Erol, 2012) with consideration of the SU minimization and resolving using a hybrid of SA-TS, and then the results were validated by CPLEX optimization modeling tool of GAMS.

Prakash et al. (2008) developed a more effective immune algorithm (IA) with decreased memory requirements and reduced computational complexity for selecting the job and allocating the operation in FMS. The objective function is to minimize SU and maximize TH. Prakash, Tiwari and Shankar (2008) also proposed an adaptive

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hierarchical ant colony algorithm for resolving the traditional MLP in FMS with the same objectives. Their research considered the job sequence, optional machines, and technological constraints. The results achieved have been compared with other algorithms viz. GA, SA, AIS, simple ACO, TS and 4 standard rules such as SPT, LPT, LIFO and FIFO. Yogeswaran, Ponnambalam and Tiwari (2010) discussed the MLP in FMS with two objectives of obtaining minimum SU and maximum TH with the technological constraints using GA and SA. In addition, Kumar, Murthy and Chandrashekara (2012) also addressed the MLP with the same objectives while satisfying the system constraints using a meta-hybrid heuristic method based on GA and PSO. The results were validated through four standard rules such as SPT, LPT, LIFO, FIFO and Branch-and-Bound (B&B) technique using LINDO optimization software. Besides, Biswas and Mahapatra (2008) presented the modified PSO to minimize SU while satisfying similar technological constraints.

Mandal, Pandey and Tiwari (2010) solved the traditional machine loading with consideration of machine breakdown in predetermined and stochastic cases of dynamic manufacturing environment. The status of machine in operating process is an important factor to ensure the continuation of system. The objectives were the makespan, system unbalance and throughput. The algorithms such as GA, SA and AIS were developed to determine the near-optimal solutions.

Koşucuoğlu and Bilge (2012) solved the FMS loading with consideration of material handling system. The operation and tool loading were included in the model to minimize the total traveling distance of part types. The flexibility of machines and process plans required the flexibility of the part routing using candidate sequences of operations on potential machines. A mixed-integer non-linear programming (MINLP) model and two MIP models, which require different representations for flexible process plans, were established. The GA algorithm was employed to be integrated with linear programming (LP) for evaluating the fitness and incorporating several adaptive strategies for diversification. The result of MIP and LP formulation used in GA were solved using CPLEX 11.0.

Guldogan (2011) proposed an integrated model of expert system based on knowledge engineering and GA for MCDM in machine selection and operation allocation. In particular, the knowledge-based expert system was used to evaluate the potential machine types for each operation. Then, the GA was employed to search the solution space to find the optimal machine set.

Basnet (2012) proposed a hybrid GA for making decisions to allocate machines and cutting tools to different jobs in FMS where the jobs are chosen to process during a planning horizon. The operation of each job was assigned to alternative machine and potential cutting tools to minimize the system unbalance from the larger data set. At the same time, Abazari, Solimanpur and Sattari (2012) presented a linear programming model of continuous and 0-1 variables for selecting job and allocating operations to obtain the maximum utilization and profitability. Their model has considered the capacity of tool magazine and machine, processing time, tool requirements, batch sizes and machining costs. The GA was presented to handle the proposed model and validated when compared with the results from previous literature. The special point in their work was to formulate a new objective function of minimizing the SU in the novel view. This means that the under-utilized and over-utilized times were allowed on each machine.

The most significant task in FMS loading is to apply the multi-objective optimization in balancing the benefits between the objectives. For example, Chen and Ho (2005) developed a novel technique to production planning in FMS based on efficient multi-

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objective GA (EMOGA). They have formulated a mathematical model of multiple objectives including the minimum total flow time, total tool cost, machine workload unbalance, and the greatest machine workload. Then, EMOGA has used the Pareto frontier to determine the most suitable solutions without using relative preferences among the objectives.

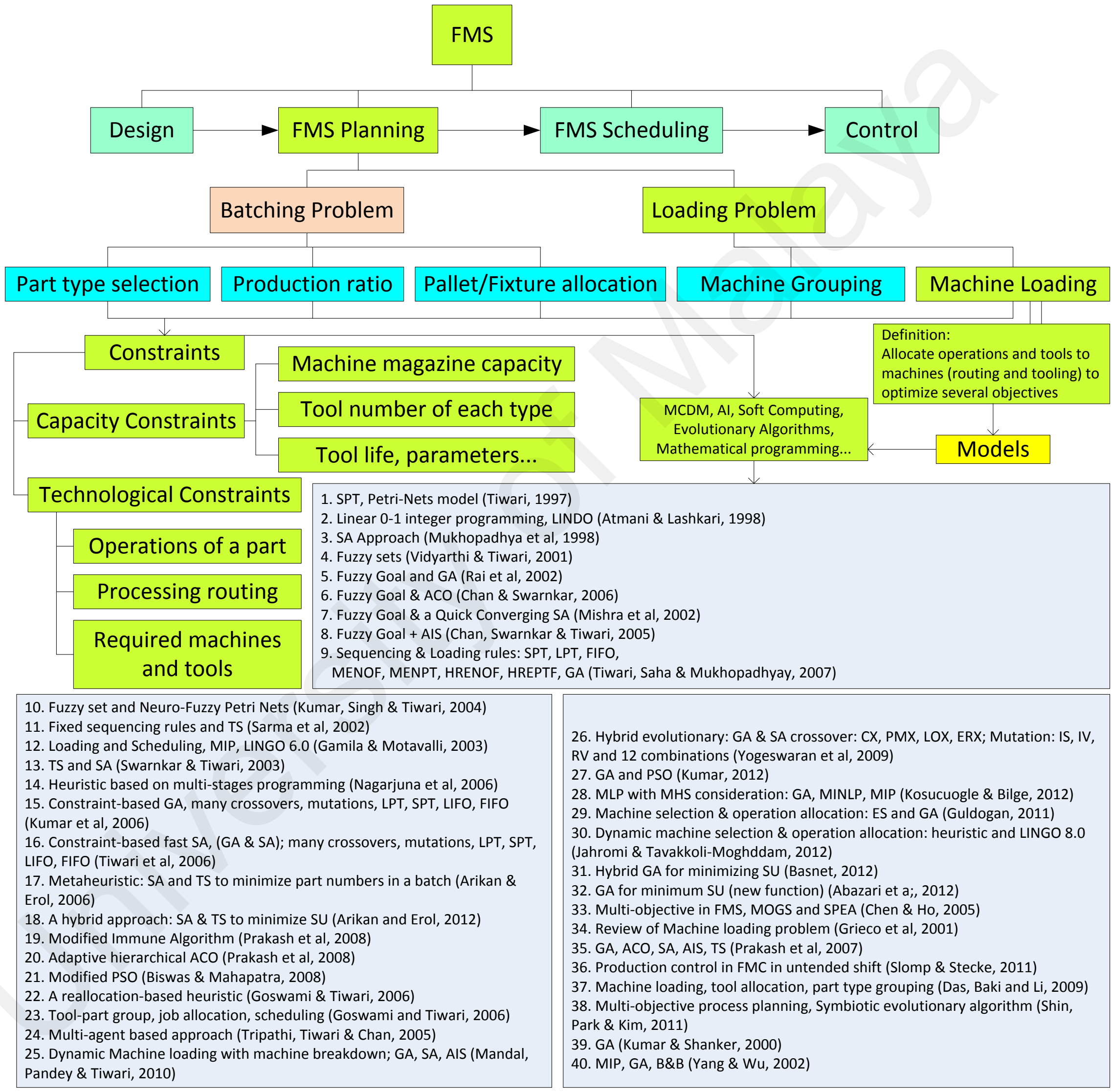

Figure 2.2: Previous findings on MLP

The improved study of Shin, Park and Kim (2011) presented a multi-objective symbiotic evolutionary algorithm for solving the multi-objective process planning in FMS. They considered the flexibilities of machine, tools, sequencing and process with three objectives of machine workload balance, minimization of the movements of parts and tool changes. The potential solutions were selected based on Pareto Frontier of MOSEA and compare with other existing standard algorithms of NSGA-II and SPEA 2. However, their model was very complicated, and sometimes it becomes intractable to implement in practice. Moreover, the validation of their model was verified and investigated from real experiments.

On average, metaheuristics method is an advanced method and potential to bring more success in finding the optimal plan for FMS. The structure of FMS problem and many relevant studies of loading issues are shown in Figure 2.2, and description of its research objectives and methodology are listed in Appendix C.

2.3.4.4 Simulation based methods

Simulation is a potential tool to analyze the general systems as well as the complex stochastic systems. It is widely used to design and evaluate operation of manufacturing system. The successful application of simulation in solving numerous real world problems in practice has proven to be an extremely useful analysis tool to handle various issues in the manufacturing field (Negahban and Smith, 2014; Smith, 2003). Simulation involves the development of computer models to describe a system and to observe the behavior and predict the operational performance of underlying system (Smith, 2003). Simulation is used to verify the mathematical model using a computer model to predict the unknown outcomes, and the validation of the model is that the simulation can be conducted for some cases and to obtain solutions which can be compared with real data. The accuracy of the prediction in the simulation will validate the mathematical model of FMS. Simulation has been successful with an adoption in numerous studies related to manufacturing system design and operation which has led to increasing interest in this research topic.

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Simulation is the imitation of the system through experimental work with a model describing the real system. Simulation involves performing activities such as the definition, design and modeling, experimental definition, collect and analyze data, interpret results from experiments (Lavery, Beaverstock, Greenwood, Nordgren and Warr, 2011). Thus, simulation of manufacturing systems is an imitation of system based on knowledge or assumptions about behavior of the parts of production system with the aim of achieving insight in the behavior of the total system (Chan, 2014). In general, it means that simulation can help in observing the behavior of the predicted system, the flow of information about the system, and to be able to train personnel to operate without disrupting the real system because the real system experiments are uneconomic and impossible (Carrie, 1988).

The simulation model is a collection of the objects representing an actual system with full detail information to show the system behavior. The objects in the models consist of fixed and mobile resources connected together in the systems. In particular, the objects of fixed resources are the backbone of the simulation models because they are used to define the product flow (Chan, 2014). The simulation models have been often used to evaluate the systems as it is being designed or investigate the operation of system, evaluate the performance, avoid the stochastic events such as machine breakdown, tool or lack of supplied materials and electricity. Moreover, it is used to train personnel because experimenting in the real-system is impossible and uneconomic.

Application of simulation models is important to develop the manufacturing systems. For instance, numerous studies applied the simulation for scheduling problems (Huang, Sung, Huang and Li, 2012; Selvaraj, 2011; Song, Luo, Qu, Lv and Huang, 2010; Yao and Zhu, 2010), storage location problems (Guiliang and Weihong, 2010; Zhou and Mao, 2010), allocation (Chen, Hu and Xu, 2013; Peng, 2010a, 2010b), sequence (Cheng

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and Chan, 2011; Pawlewski, Rejmicz, Stasiak and Pieprz, 2012), and determination of buffer sizes (Srinivas, Satyanarayana, Ramji and Ravela, 2011). Besides, for FMS loading problem, Tripathi, Tiwari and Chan (2005) developed the multi-agent-based method for selecting the parts and allocating the task in FMS. Four agents used are part, communicator, handling system and machine. Multi-agent system uses the strategy of call-for-bid in communicating to other agents, and task allocation must be based on objective function of processing costs, transporting costs and time.

In general, most of the studies have utilized the simulation methods to find the solutions quickly and to validate the mathematical model of FMS through the performance index.

2.3.5 Remarks and assessment of previous approaches in solving on machine loading problem

It is realized from the literature that most of the mathematical models of machine loading were solved based on the analytical methods and mathematical programming which representative are integer programming (linear and non-linear), dynamic programming, branch and bound (B&B) algorithms and some of their extensions. These methods are proven to be robust in applications but they have some limitations of computational time and are impossible to use for large-sized problems.

To find the suitable solutions, many researchers have developed the heuristic methods which are based on the rules of operations in engineering systems. However, the heuristics have become impractical to evaluate the status as well as the results in dynamic manufacturing environment where much of information is not known in advance and imprecise. Meanwhile, simulation techniques have been proven to be very effective in solving dynamic problems and required a large number of running

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simulation iterations to evaluate the operating state of the system. These methods have the disadvantage that they cannot determine the optimal solution of the system.

Optimization of MLP has a strong influence on productivity and spatial structure of the system. Many optimization techniques have also been developed as single-objective optimization and multi-objective optimization. In the manufacturing environment, the multiple production goals is more of concerned, they are shown in the objective functions. The objective functions can be aggregated into a total single function based on the weights of objectives, which can be calculated based on the reference of the production management. To solve the single objective issue, numerous meta-heuristic algorithms have been applied and developed such as GA, PSO, ACO, AIS and etc. Multi-objective optimization issues are different from single objective optimization issues. The best solution is absolutely superior to all other alternatives in single objective optimization. In contrast, this is not necessary for multiple objective optimization problems. However, multiple objectives goals may come into conflict with the other objective. It means that the solution can satisfy one objective but do not satisfy the other objectives. Therefore, the multi-objective optimization is a technique to balance the benefits of the objectives and allows managers to choose the most appropriate solution (Gen, Cheng and Lin, 2008). Many meta-heuristics methods had been presented for this purpose. The multi-objective optimization is complex and difficult to implement. Moreover, the production and operation managers have little math skills to understand and solve problems quickly in a very competitive environment; a multi-criteria analysis can be proven to be simple, easy to understand in identifying potential solutions with limited alternatives. Thus, the combined search technique of multi-objective approach can be conventional to identify the suitable solutions for operating the system. The proposed framework of multi-criteria model is shown in Figure 2.3.

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Most of the studies on the MLP to seek an optimal solution for the allocation of part types to machines and satisfy the constraints related to the capacity of the machine and cutting tools such as tool magazine, tool life, duplicated tools, and machining time. The constraint is one of the main factors that makes the issue increased in complexity, especially the nonlinear constraints. The goal is often to obtain the smallest system unbalance of machine workload and the largest throughput. In addition, very few researchers pay attention to the allocation, assignment as well as the constraints on pallets, jig/fixtures, and AGV and the movement of the work-piece and the cutting tool through the transport system. Hence, other loading problems can be incorporated with the above mentioned devices into the objective function. Some objectives such as minimization of part type movement and cutting tool changeover time have been received as an attention, and it can be extended by considering the dynamicity in manufacturing environment such as machine breakdown, cutting tool breakdown and stochastic processing time. Therefore, the stochastic machine loading problem can be considered based on the explorations on machine, tool, and part type disruptions. Besides, the choice of machines is a key element that dramatically effects on performance of systems, it had received little attention scrutinized in real production environments, where the information is frequently uncertain and imprecise. Therefore, the selection of the machine should be focused by the experts.

Another aspect of the MLP is that can also be combined with the machine selection or selection of the type of work-piece suitable for the cutting tool. Moreover, determining the machining parameters which are suitable for the combination of machine-cutting tool-workpiece has become extremely difficult and impractical. Most of the research has not been confirmed and verified through practical applications, and the collected data for the model were not derived from empirical data in the real industry.

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There are many methods for solving MLP but most of the research focuses on mathematical modeling and optimizing the system performance without a deep understanding the characteristics and the interaction among the components of the system during operation. The proposed methods have the limitations on computation time in finding the optimal solutions, so it has become more difficult to adapt to the real-life situations where it is to require the rapid solutions of production planning. Moreover, the development of programming code for a mixed integer linear/non-linear models is not easy for production managers to do and comprehend.

Many objectives are used in solving the MLP such as production cost (comprises cost of machining, traveling, setup, loading/unloading time and storage time), system unbalance, throughput, makespan, movement of cutting tools, part types and AGV, etc. The system unbalance is correlated with the throughput. Maximization of system unbalance will enable the throughput to obtain a maximum value. However, few other objectives have got very little attention to the following: makespan and total flow time when to consider the MLP. These factors have a strong impact on the system's performance and to satisfy the customers' demand on delivery time, especially in which the travelling time of part types is included, the industrial managers complained that the theoretical models of MLP is difficult to apply in the practice because of the large number of variables and constraints need to be considered. Therefore, from the discussion above, it is easy to realize that more attention should be made to MLP for it to be able to be applied in the real world.

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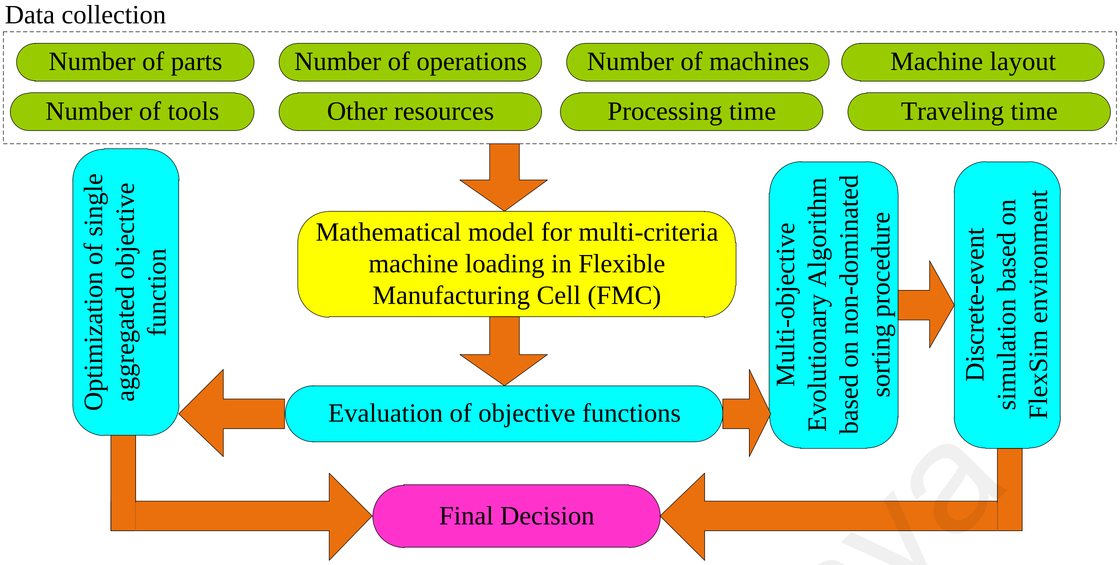

Figure 2.3: Decision aiding framework for MLP

2.4 Conclusion

In general, this chapter presented the numerous approaches in solving machine tool selection and machine loading problems in FMC. Moreover, the remarks and assessments of previous approaches for machine tool selection and machine loading problems were discussed to identify the advantages and disadvantages. Simulation was mentioned as a tool to validate the designed FMC.

For machine tool selection problem, we analyzed the multi-criteria decision making methods and have found that:

- The AHP method combined with the fuzzy linguistic preference relation will reduce the number of judgment.

- The integration of fuzzy AHP and fuzzy COPRAS will be a good choice to evaluate the preliminary machine tools.

- Fuzzy ANP has more advantages in consideration of the interaction of the attributes to make a decision more accurate. In addition, the hybridization of fuzzy ANP with COPRAS-G will decrease the judgments need to be collected and make a decision more flexible.

For machine loading problem in FMC, the previous approaches had their strengths but there still remain some notable weakness which limit the constraints of system and sometimes become difficult in the implementation in practical applications. To the best of our knowledge, almost all existing methods for determining the most suitable combination of machine tool and operation in problem of machine loading for FMC were based on two dependent objectives of system unbalance and throughput. Therefore, their results of solution cannot be used to evaluate the performance indices because sometimes all the batch sizes of product are not completed. So the delivery time is difficult to determine and strongly impact the customers. As the traveling time is a factor that influences on FMC's capacity of completion for desired jobs. The makespan, and total flow time should be considered along with system unbalance to ensure the better utilization rate in FMC. Establishing a new approach for multi-criteria machine loading model of FMC has a significant meaning to further the research and practical applicability of implementation. Finally, standard discrete-event simulation of manufacturing system is reviewed showing it is a helpful tool to validate the applicability of proposed model.

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CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the models and methods are introduced for the problems of machine tool selection and machine loading. The methodology starts with the research design to explain the sequence of the whole procedure of research. The research contains two main parts: (1) machine tool selection and (2) machine loading problem. First, a new model and method is developed to support the decision makers in machine tool evaluation and selection with uncertain information. The purpose of this part is to determine the most suitable machine tools from a potential set of machines in the marketplace based on the experts' judgments. Then, the flexible manufacturing cell (FMC) is proposed based on the most appropriate machine tools. In order to operate FMC effectively, the second part of exploring the good process plans is required. In this part, a novel model of machine loading which is a representative of machine assignment is introduced based on multiple objectives of manufacturing. In addition, a biogeography-based optimization (BBO) combined with non-dominated sorting procedure is developed to explore the most suitable solutions for machine loading of FMC. The final decision is verified based on the literature, LINGO software and validated relied on FlexSim simulation. The remainder of the chapter introduces the procedure of constructing a model for discrete event simulation.

3.2 Research design

This research aims to develop a model and method of fuzzy multi-criteria decision making for machine tool evaluation and selection based on fuzzy AHP/fuzzy COPRAS and fuzzy ANP/COPRAS-G. Furthermore, a model for machine loading in FMC is developed based on non-dominated sorting BBO. Multiple objective functions are used to minimize the system unbalance, makespan and total flow time. Because of the

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constraints of the model, the problem formulated is established to achieve the requirements of FMC system. The flowchart of research methodology is presented in Figure 3.1.

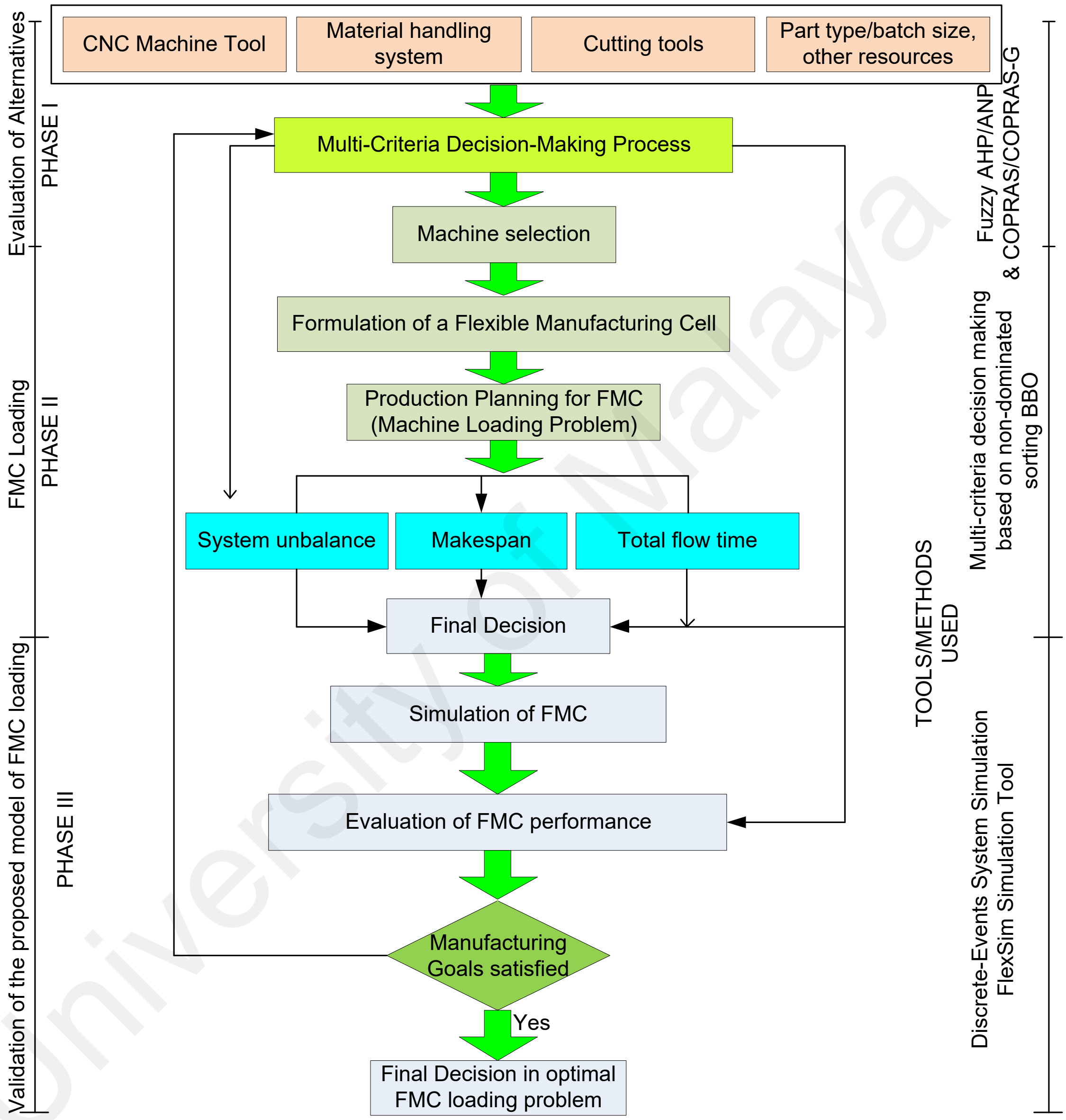

Figure 3.1: Flowchart of research methodology

The process for conducting this study is based on three phases which consist of the models and methods' development for this research, shown in Figure 3.1. The detail procedures to conduct this research along with the proposed methods are described in Figure 3.2. The objectives and scope of this research are established according to the literature review of machine tool selection and machine loading problems. Figure 3.2 also describes the detailed information of the three phases in this research.

• Phase 1: A decision support system is developed for solving a model of preliminary machine tool selection based on integration of fuzzy AHP and fuzzy COPRAS. Then, final decision is determined using hybrid approach of fuzzy ANP and COPRAS-G. In addition, the sensitivity analysis is carried out to check the robustness of the alternative ranking.

• Phase 2: The FMC is formulated based on the selected machine from Phase 1. Several steps are conducted in this phase for selecting the most suitable solutions for machine loading in FMC. Problem formulation is established by constructing a mathematical model for FMC loading issue. After the problem is formulated, the loading model is developed using combination of biogeography-based optimization (BBO) and non-dominated sorting procedure. Data collection is carried out to achieve the requirements of proposed model. The most appropriate solution of FMC loading is conducted based on the feasible solutions which are obtained from the proposed approach.

• Phase 3: Simulation experiment of FMC in FlexSim is used to validate the proposed model and observe the behavior of the whole system. Moreover, benchmark of numerical and simulation method is compared with other research to evaluate the applicability of proposed model.

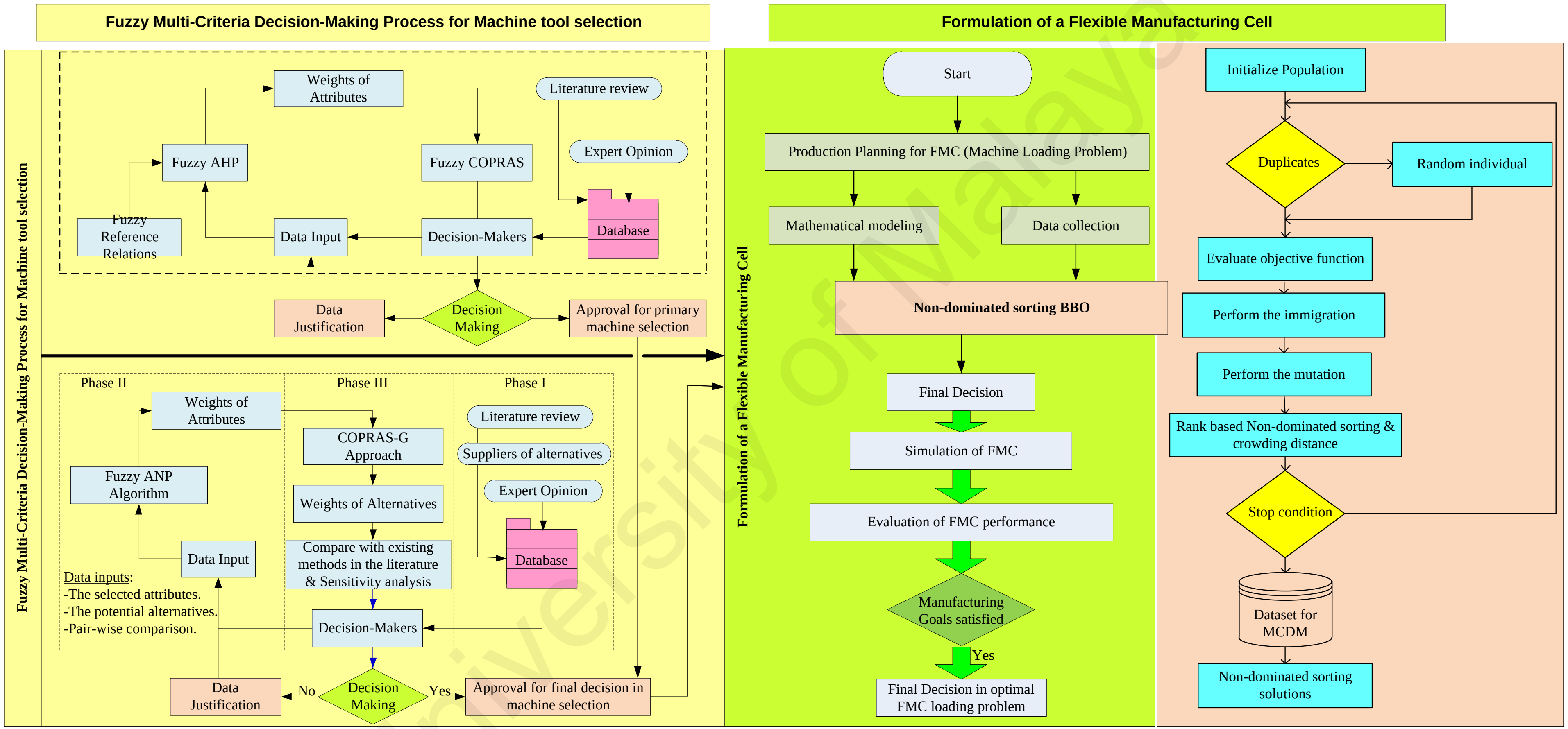

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Figure 3.2: The detailed procedure of research methodology

3.3 Preliminary machine tool selection

3.3.1 Hierarchy of preliminary machine tool selection (MTS)

The structure of machine tool selection problem is developed based on the multiple attributes defining the machine's characteristics. The attributes in the decision support model are extracted from the literature (see Appendix B), catalogues and interviews from the experts in the field of manufacturing. The hierarchical structure of model is depicted in Figure 3.3. It contains three top-down levels: At the first level (level 1), the manufacturing goal is determined for machine tool selection; the middle level (level 2) consists of attributes for decision-making process such as Cost (A1), Power (A2) , Maximum Spindle Speed (A3), Maximum Tool Diameter (A4), Number of Tools (A5), Cutting Feed (A6), Traverse Speed (A7), Positioning Precision/Accuracy (A8), Machine Dimension (A9), Table Area (A10) and the machine tool's candidates (MC1, MC2, MC3, MC4, and MC5) are listed in the bottom level (level 3) for ranking process.

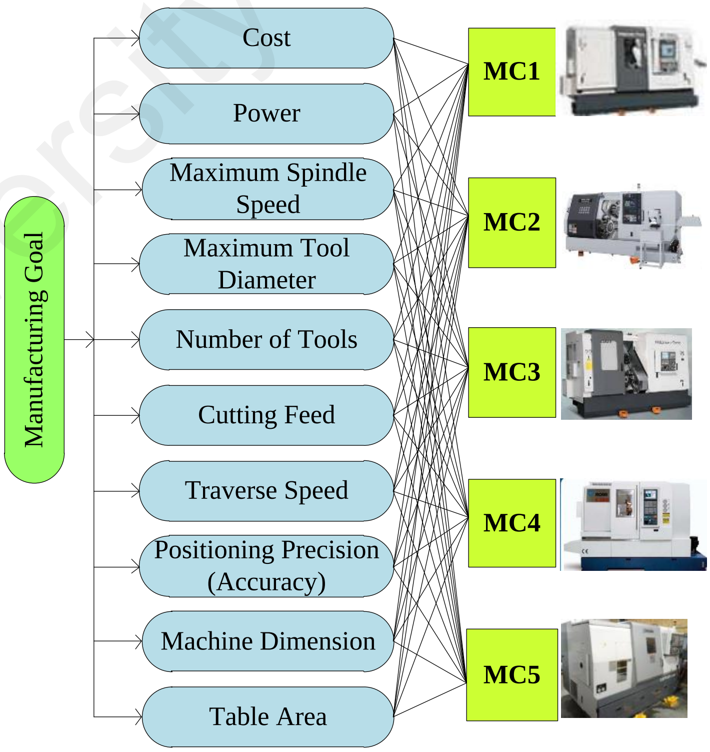

Figure 3.3: The hierarchical structure for preliminary machine tool selection

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3.3.2 Proposed method for preliminary MTS

3.3.2.1 Fuzzy linguistic preference based AHP (FAHP)

The AHP presented by Saaty in 1980 is become the most popular choice in multi-criteria decision making method (Chen and Chao, 2012). In manufacturing environment, many problems cannot be solved with vague and imprecise information. Thus, fuzzy logic is integrated within the model to solve these uncertain problems, and fuzzy AHP combines the pair-wise comparison matrix of expert judgments and theory of fuzzy sets to handle these uncertain problems in manufacturing environment. Thus, this method has become very famous for multi-attribute decision-making (MADM) process.

The existing fuzzy AHP uses a pair-wise comparison matrix with the collection of n(n-1)/2 comparisons. A table of questionnaire design is implemented to obtain feedback from expert's judgments. The larger number of attributes, the more pair-wise comparison questions and the questionnaire design table is required making it more complicated. Too many questions in the questionnaire will increase the probability of the expert giving incorrect replies. This will lead to inconsistent result as the consistent ratio is not less than 0.1, thus requiring the experts will be recheck and re-answer the questions again. Thus, it leads to wastage of time and inefficiency (Chen and Chao, 2012).

To overcome this problem, Wang and Chen (2008) and Rezaei and Ortt (2012) proposed the integration of consistent fuzzy preference relations (CFPR) in the AHP approach to improve the consistency of fuzzy AHP. When using CFPR, the number of pair-wise comparisons are dramatically reduced from n(n-1) to (n-1) comparisons and the rest of other comparisons can be computed through the fuzzy preference relations. Thus, experts or decision-makers will spend less resource and can focus more effort to make the pair-wise comparisons of attributes (Chen and Chao, 2012). For example, if we have 10 attributes and five alternatives, the number of the pair-wise comparison matrices will be eleven matrices. In particular, one 10x10 pair-wise comparison matrix for attributes contains 10(10-1)/2=45 judgments and ten 5x5 pairwise comparison matrices contain 10*5(5-1)/2=100 judgments. Thus, the minimum number of judgments collected from experts must be 145 judgments. Besides, one more thing needs to be remembered for evaluating the alternative is the consistent ratio (CR) must be less than 0.1. If the CR is not less than 0.1, we must ask the expert to re-evaluate the judgments among the criteria and alternatives. However, the number of pair-wise comparisons is only (10-1) = 9 if the integration of the improved consistent fuzzy AHP and fuzzy COPRAS is used for decision-making. According to our knowledge, although there are also other similar hybrid approaches with AHP like VIKOR (VIse Kriterijumska Optimizacija Kompromisno Resenje), SAW (Simple Additive Weighting), PROMETHEE (Preference Ranking Organization METHod for Enrich Evaluation), ELECTRE III (Elimination and Et Choice Translating Reality) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) but the integrated approach which is proposed in this study, is more practical and accurate in decision-making process involving the conflicting attributes which includes the imprecision, uncertain information. The procedure for implementing the fuzzy AHP with the linguistic reference relation is shown in section 3. The fuzzy linguistic preference relations are described to be integrated into AHP as follows (Buckley, 1985; Ekel, Silva, Schuffner Neto and Palhares, 2006; Wang and Chen, 2008; Chen and Chao, 2012; Chen, Wang and Wu, 2011; Rezaei and Ortt, 2012).

Definition 1: A fuzzy positive matrix $\tilde{A} = (\tilde{a}_{ij})$ is reciprocal $\Leftrightarrow$ $\tilde{a}_{ji} = \tilde{a}_{ij}^{-1}$. (3.1)

Definition 2: A fuzzy positive matrix $\tilde{A} = (\tilde{a}_{ij})$ is consistent $\Leftrightarrow$ $\tilde{a}_{ij} \otimes \tilde{a}_{jk} \approx \tilde{a}_{ik}$(3.2)

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Proposition 1: Consider a set of alternatives, $X = \{x_1, x_2, \dots, x_n\}$ associated with a fuzzy reciprocal preference matrix $\tilde{A} = (\tilde{a}_{ij})$ with $\tilde{a}_{ij} \in [1/9, 9]$ and the corresponding fuzzy reciprocal linguistic preference relation $\tilde{P} = (\tilde{p}_{ij})$ with $\tilde{p}_{ij} \in [0,1]$.

a) $p_{ij}^L + p_{ji}^R = 1, \forall i, j \in \{1,2,\dots,n\}$ (3.3)

b) $p_{ij}^M + p_{ji}^M = 1, \forall i, j \in \{1,2,\dots,n\}$ (3.4)

c) $p_{ij}^R + p_{ji}^L = 1, \forall i, j \in \{1,2,\dots,n\}$ (3.5)

Proposition 2: For a reciprocal fuzzy reference relation $\tilde{P} = (\tilde{p}_{ij}) = (p_{ij}^L, p_{ij}^M, p_{ij}^R)$ to be consistent, the following statement must be equivalent:

a) $p_{ij}^L + p_{jk}^L + p_{ki}^R = \frac{3}{2}, \forall i < j < k.$ (3.6)

b) $p_{ij}^M + p_{jk}^M + p_{ki}^M = \frac{3}{2}, \forall i < j < k.$ (3.7)

c) $p_{ij}^R + p_{jk}^R + p_{ki}^L = \frac{3}{2}, \forall i < j < k.$ (3.8)

d) $p_{i(i+1)}^L + p_{(i+1)(i+2)}^L + \cdots + p_{(j-1)j}^L + p_{ji}^R = \frac{j-i+1}{2}, \forall i < j.$ (3.9)

e) $p_{i(i+1)}^M + p_{(i+1)(i+2)}^M + \cdots + p_{(j-1)j}^M + p_{ji}^M = \frac{j-i+1}{2}, \forall i < j.$ (3.10)

f) $p_{i(i+1)}^R + p_{(i+1)(i+2)}^R + \cdots + p_{(j-1)j}^R + p_{ji}^L = \frac{j-i+1}{2}, \forall i < j.$ (3.11)

If the entries of the design matrix or the values of the matrix $\tilde{P} = (\tilde{p}_{ij}) = (p_{ij}^L, p_{ij}^M, p_{ij}^R)$ are not in the interval [0, 1] but fall in a interval [-c, 1+c], (c>0), the obtained fuzzy numbers would need to be transformed by using transform function to preserve the reciprocity and addictive consistency; namely $f: [-c, 1+c] \longrightarrow [0,1]$.

$$f(x^{L,M,R}) = \frac{x^{L,M,R} + c}{1+2c} \quad (3.12)$$

3.3.2.2 Fuzzy COPRAS (FCOPRAS) approach

COPRAS (COmplex PRoportional Assessment) method, introduced by Zavadskas and Kaklauskas in 1996 (Zavadskas, Kaklauskas, Langford and Retik, 1996), is one of the well-known MADM approaches for selecting the most suitable alternative among a set of available potential alternatives by determining a solution with direct and proportional ratio to the best solution to ratio with the ideal-worst solution. It is constructed based on the attributes of alternatives to handle complex real-world problems where the properties of attributes are conflicting (Chatterjee and Bose, 2012). However, the properties of the attributes and the expert's judgments contain uncertain, imprecise information. Thus, the classical MADM approaches are insufficient to model the complex real-world problems. Thus, the fuzzy sets theory is the most suitable to be employed to handle the problems in the uncertain environment. The fuzzy sets are integrated into the COPRAS method to be called the fuzzy COPRAS, which is a fuzzy MADM technique (Fouladgar, Yazdani-Chamzini, Zavadskas and Moini, 2012). The method is very practical and has been used by various researchers in solving their research problems. For examples, Chatterjee and Bose (2012) used fuzzy COPRAS for site selection of wind farm, Fouladgar et al. (2012) evaluated the working strategies at the construction company based on fuzzy COPRAS, and Yazdani, Alidoosti and Kazimieras Zavadskas, (2011) used fuzzy COPRAS for risk analysis of critical infrastructures.

The machine tool selection is a complicated multi-attribute problem due to conflicting properties of the attributes for each machine. These factors contain uncertain, imperfect and imprecise information. Therefore, the fuzzy sets are used to handle the decision-making process more accurately and the fuzzy COPRAS is applicable if the priorities of the attributes and the ranking of the machine alternatives

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are given by fuzzy linguistic variables, that are addressed using the fuzzy numbers with the help of expert's judgments.

The procedure of the fuzzy COPRAS includes the steps as follows:

Step 1: Define the linguistic terms, used by decision-makers are shown in Table 3.3.

Step 2: Construction of the fuzzy decision support matrix. The preference ratios of alternatives are expressed by fuzzy linguistic variables in triangular fuzzy numbers.

Step 3: Determine the priority weights of the attributes using the improved fuzzy AHP with preference relation.

Step 4: Calculate the aggregated fuzzy ratio $\tilde{x}_{ij}$ of alternative A_i with respect to the attributes C_j, where i = 1, 2, …,m and j = 1, 2, …,n.

$$D = \begin{array}{cc} & \begin{matrix} C_1 & C_2 & \cdots & C_n \end{matrix} \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array}, \text{ i = 1, 2, …, m; and j = 1, 2, …, n.} \quad (3.13)$$

$\tilde{x}_{ij} = (x_{ij1}, x_{ij2}, x_{ij3}),$

$$x_{ij1} = min\{x_{ijk1}\};\ x_{ij2} = \frac{1}{K}\sum_{k=1}^{K} x_{ijk2};\ x_{ij1} = max\{x_{ijk3}\} \quad (3.14)$$

where $\tilde{x}_{ijk}$ is the ratio of alternative A_i with respect to the attribute C_j evaluated by k-th expert, $\tilde{x}_{ijk} = (x_{ijk1}, x_{ijk2}, x_{ijk3})$.

Step 5: Defuzzification of the aggregated fuzzy decision support matrix:

After aggregating the fuzzy scale in the fuzzy decision support matrix is completed, the matrix D is converted into the aggregated fuzzy decision support matrix and then the defuzzification of this matrix is implemented to obtain the crisp values by applying the center of area method by the following equation (Chang and Wang, 2009; Fouladgar et al., 2012; Wu, Tzeng and Chen, 2009).

$$x_{ij} = \frac{[(Ux_{ij} - Lx_{ij}) + (Mx_{ij} - Lx_{ij})]}{3} + Lx_{ij} \quad (3.15)$$

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Step 6: Normalize the data in the decision support matrix (f_{ij}). The normalization of the decision-making process is implemented by determining the ratio of the value of each attribute and the largest value in each column to transform the values of the attributes into value boundary [0, 1] and all the attributes are dimensionless.

Step 7: Determine the weighted normalized decision support matrix $(\hat{x}_{ij})$ through each element/cell in the matrix. It is determined by multiplying the weights of the selected attributes (w_j) with the respecting normalized value in the decision support matrix:

$$\hat{x}_{ij} = f_{ij} \times w_j \tag{3.16}$$

Step 8: Calculate the total summarization P_i of the values of the attributes with the desire to achieve the greatest value in the maximal optimization direction for each alternative (line/row of the decision support matrix):

$$P_i = \sum_{j=1}^{k} \hat{x}_{ij}. \tag{3.17}$$

Step 9: Calculate the total summarization R_i of the values of the attributes with the desire to achieve the smallest value in the minimal optimization direction for each alternative (line/row of the decision support matrix):

$$R_i = \sum_{j=k+1}^{m} \hat{x}_{ij}. \tag{3.18}$$

In the above formula, there are (m-k) attributes needed to be minimized.

Step 10: Determine the minimal value of R_i:

$$R_{min} = \min R_i;\ \mathrm{i} = 1, 2, \ldots, \mathrm{n}. \tag{3.19}$$

Step 11: Determine the priority weight of each alternative Q_i:

$$Q_i = P_i + \frac{R_{min} \sum_{i=1}^{n} R_i}{R_i \sum_{i=1}^{n} \frac{R_{min}}{R_i}} \tag{3.20}$$

The above formula can be written as follows:

$$Q_i = P_i + \frac{\sum_{i=1}^{n} R_i}{R_i \sum_{i=1}^{n} \frac{1}{R_i}} \tag{3.21}$$

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Step 12: Calculate the optimality criterion K:

$$K = maxQ_i, \text{ i} = 1, 2, \ldots, \text{n} \tag{3.22}$$

Step 13: Assignment of the weights of the alternatives. The greater is priority weight of alternative Q_i, the higher is the rank of the alternative. Therefore, the alternative with Q_{max} value is the most suitable selection in the decision-making process, which obtains the highest satisfaction degree.

Step 14: Determine the utility degree of each alternative:

$$N_i = \frac{Q_i}{Q_{max}} \times 100\% \tag{3.23}$$

where Q_i and Q_{max} are the weight of alternatives obtained from the above equation.

3.3.2.3 Integrated approach of FAHP and FCOPRAS

(a) ***The proposed model for preliminary MTS***

The structural hierarchy of the developed model is depicted in Figure 3.4. The required data is initially prepared for decision-making process. The database is collected from several sources such as literature, expert's judgments and the catalogues of many manufacturers by questionnaires design. Meetings were frequently organized to get the feedback from the expert for the alternatives and attributes, and determination of data inputs for the fuzzy AHP with the preference relations. The priorities or weights of attributes are calculated by the improved fuzzy AHP with the pair-wise comparison matrix based on the expert's judgments and fuzzy preference relations.

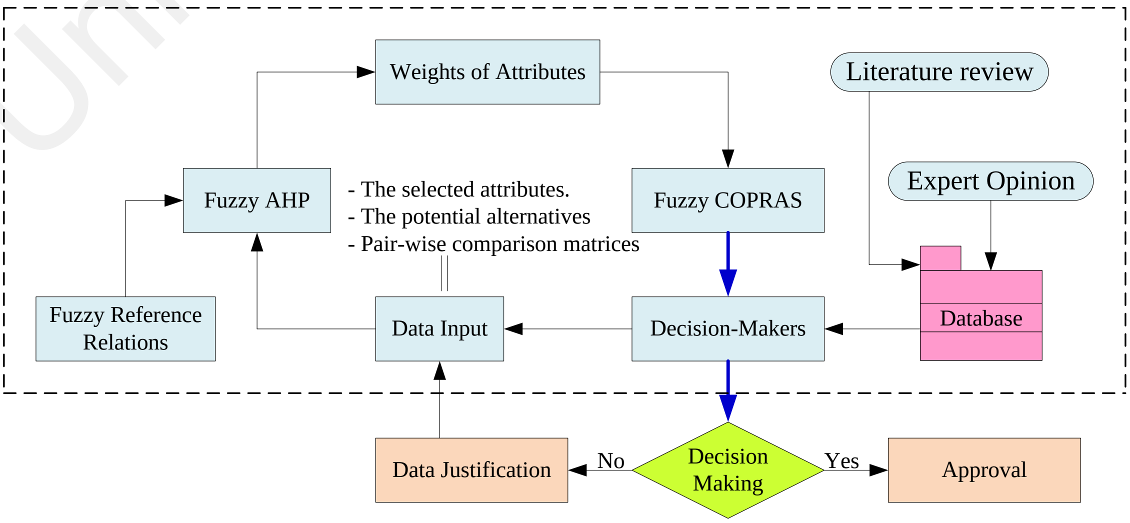

Figure 3.4: Scheme of the proposed model for preliminary MTS

The outputs of improved fuzzy AHP are imported into the fuzzy COPRAS for determining the ranking of alternatives. The decision-makers can use this result for decision-making process. If the result is not satisfactory, the data justification can be implemented for inputs of improved fuzzy AHP, and the final decision is made by decision-makers.

(b) ***The integration of FAHP and FCOPRAS for preliminary MTS***

This method, based on the integration of fuzzy AHP and fuzzy COPRAS, is developed for decision-making process in machine tool selection. It makes use of the advantages of fuzzy AHP in determination of weights of attributes and the simplicity of fuzzy COPRAS for ranking alternatives.

The integrated approach consists of three phases. Phase 1 is the stage to conceive with team working and formulate the idea for decision-making. In this stage, decision-makers define the attributes and alternatives from the market of machines or current manufacturing facilities. The handbook, literature and suppliers need to support the knowledge and information for decision-makers to make accurate decision in machine tool selection.

Finally, the pair-wise comparison matrices are formulated from the attributes to prepare for the computation in phase 2 and phase 3. In phase 2, fuzzy AHP with linguistic preference relation is applied to determine the weights of attributes and phase 3 inherits the result form phase 2 which are the weights of attributes in order to predict the weights of alternatives. The steps in phase 2 and phase 3 are shown in the flowchart of method in Figure 3.5 and depicted in detail as follows:

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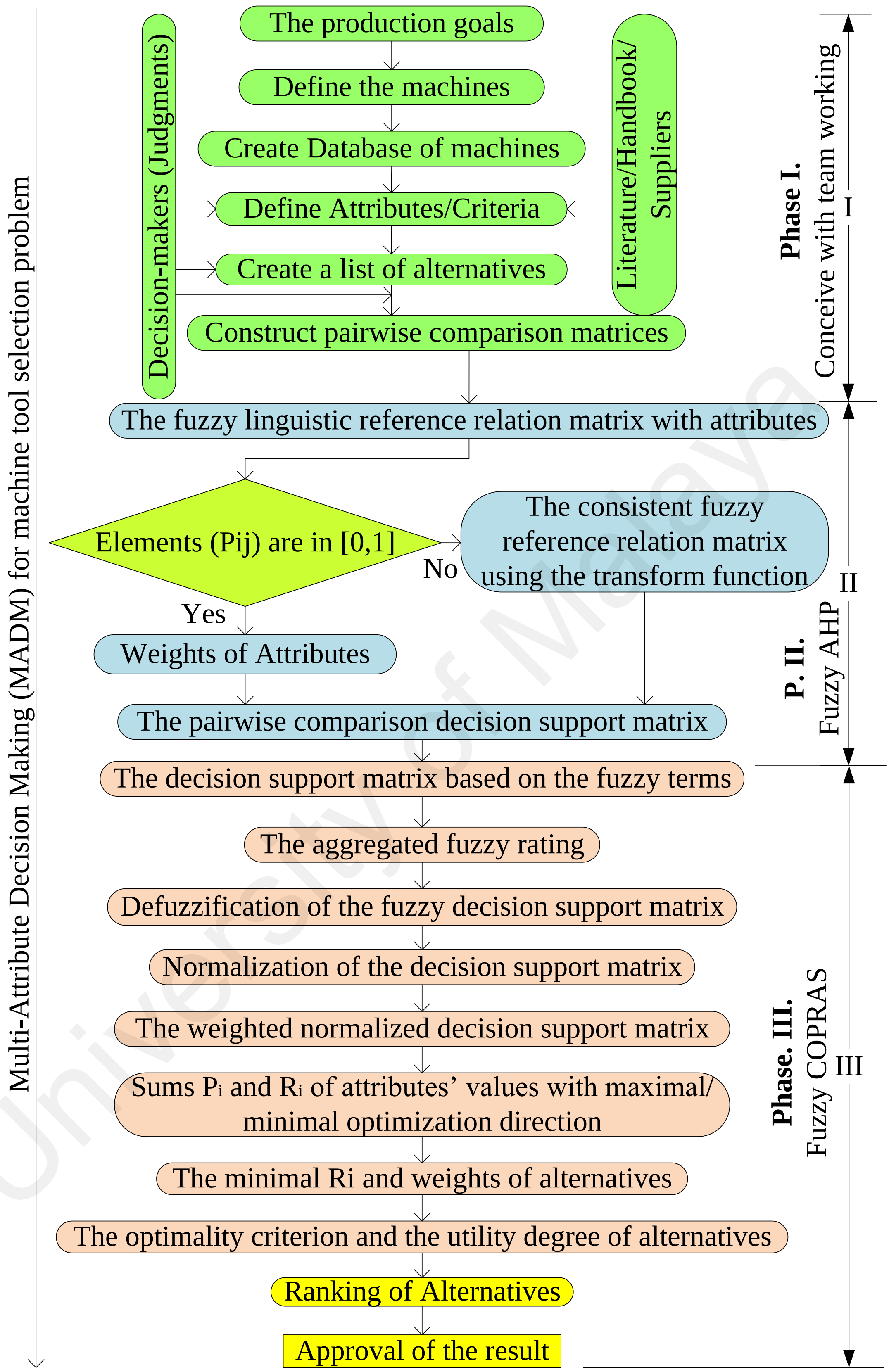

Figure 3.5: Flowchart of the proposal model for preliminary MTS

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• **Fuzzy number** (Klir and Yuan, 1995; Wang and Chen, 2008)

Let $\tilde{A}$ be a fuzzy triangular number on $\mathbb{R}$, $\tilde{A}$ is defined as follows: $\tilde{A} = (l, m, u)$ if the membership function $\mu_{\tilde{A}}(x)$ satisfies the following rules (see Table 3.1 and Figure 3.6):

$\mu_{\tilde{A}}(x)$: $\mathbb{R} \longrightarrow [0,1]$ and expressed as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-l}{m-l}, l \leq x \leq m \\ \frac{u-x}{u-m}, m \leq x \leq u \\ 0, \text{ otherwise} \end{cases} \tag{3.24}$$

Table 3.1: Fuzzy linguistic assessment variables (Ertuğrul and Güneş, 2007; Wang and Chen, 2008)

Linguistic variables	Triangular fuzzy numbers (TFN)
Very poor (VP)	(0,0,0.1)
Poor (P)	(0,0.1,0.3)
Medium poor (MP)	(0.1,0.3,0.5)
Medium (M)	(0.3,0.5,0.7)
Medium good (MG)	(0.5,0.7,0.9)
Good (G)	(0.7,0.9,1)
Very Good (VG)	(0.9,1,1)

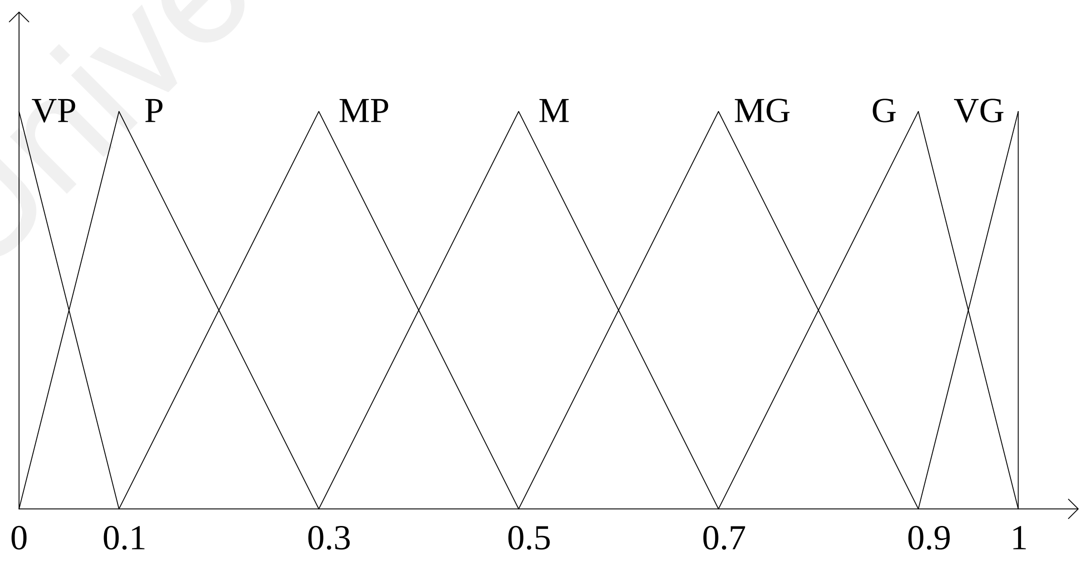

Figure 3.6: Fuzzy linguistic assessment variables (Rezaei and Ortt, 2012)

- **Phase I: Conceive with tem working**

Step 1: Define the manufacturing goal for producing some desired types of part according to the customer's demand.

Step 2: Define the machine tools which is necessary for formulating the manufacturing system in the manufacturing factory.

Step 3: Create the database of the machine tool from manufacturing supplier and the existing machine tool in factory.

Step 4: Determine the desirable attributes implemented by decision-makers (DMs) for evaluating the machine tools.

Step 5: Choose the machine tool alternatives for decision-making process.

Step 6: Build the hierarchical structure for decision-making process which presents the relationship of manufacturing goal, the attributes and alternatives in machine tool selection.

Step 7: Questionnaire design for data collection from expert's judgments.

- **Phase II: The AHP with consistent fuzzy reference relation** (Chen and Chao, 2012; Rezaei and Ortt, 2012)

Step 8: Establish pair-wise comparison decision matrix A based on the expert's judgments for the attributes. Let A_i (i = 1,2,…,n) be a set of attributes (a_{ij}), and the relative importance between two attributes is evaluated using the TFNs:

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{12}^{-1} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{1n}^{-1} & \tilde{a}_{2n}^{-1} & \cdots & 1 \end{bmatrix} \qquad (3.25)$$

where $\tilde{a}_{ij}$ is a TFN or fuzzy linguistic variables, a_{ij} = (0.5, 0.5, 0.5) shows that no difference between i-th attribute and j-th attribute (Rezaei and Ortt, 2012), which are presented in Table 3.1. Because the pair-wise comparison is reciprocal, the reciprocal property is applied to determine the value of $\tilde{a}_{ij}^{-1}$ in matrix $\tilde{A}$ (see Eqs. 3.1 and 3.2). In this step, the number of expert's judgments needed to be collected is (n-1), which is different from collecting n(n-1)/2 judgments in the normal fuzzy AHP (Rezaei and Ortt, 2012; Wang and Chen, 2008). The other elements are determined based on the fuzzy preference relations from Eqs. 3.1-3.11.

Step 9: To build the fuzzy pair-wise comparison decision matrix based on the fuzzy linguistic preference relations as shown in Table 3.2. It is necessary to note the use of the transform function to obtain the consistent fuzzy reference relation matrix from the fuzzy linguistic reference relation matrix with attributes. It means that after the pair-wise comparison decision matrix is determined, the value of some elements in the matrix is not in the interval [0,1] but fall in an interval [-c, 1+c], (c>0 and c is the maximum amount of violation from the interval [0,1] among the elements of the decision matrix). The obtained triangular fuzzy numbers needs to be transformed using the transformation function (see Eq. 3.12) to preserve the reciprocity and additive consistency (Rezaei and Ortt, 2012; Wang and Chen, 2008).

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{p}_{12} & \cdots & \tilde{p}_{1n} \\ \tilde{p}_{21} & 1 & \cdots & \tilde{p}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{p}_{n1} & \tilde{p}_{n2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \tilde{p}_{12} & \cdots & \tilde{p}_{1n} \\ \tilde{p}_{12}^{-1} & 1 & \cdots & \tilde{p}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{p}_{1n}^{-1} & \tilde{p}_{2n}^{-1} & \cdots & 1 \end{bmatrix} \tag{3.26}$$

Table 3.2: The result of fuzzy linguistic reference relation matrix with the transforming function (Wang and Chen, 2008)

Goal	A_1	A_2	A_3	…	A_n	Average	Weights
A_1	1	$\tilde{p}_{12}$	$\tilde{p}_{13}$	…	$\tilde{p}_{1n}$	$\bar{A}_1$	$\widetilde{w}_{a_1}$
A_2	$\tilde{p}_{12}^{-1}$	1	$\tilde{p}_{23}$	…	$\tilde{p}_{2n}$	$\bar{A}_2$	$\widetilde{w}_{a_2}$
A_3	$\tilde{p}_{13}^{-1}$	$\tilde{p}_{23}^{-1}$	1	…	$\tilde{p}_{3n}$	$\bar{A}_3$	$\widetilde{w}_{a_3}$
…	…	…	…	…	…	$\bar{A}_i$	$\widetilde{w}_{a_i}$
A_n	$\tilde{p}_{1n}^{-1}$	$\tilde{p}_{2n}^{-1}$	$\tilde{p}_{3n}^{-1}$	…	1	$\bar{A}_n$	$\widetilde{w}_{a_n}$

where $\bar{A}_i$ is the average of the values of the pair-wise comparison elements for each i-th row or each i-th attribute and $\widetilde{w}_{a_i}$ is the weight of the i-th attribute.

$$\bar{A}_i = \frac{1}{n}\sum_{j=1}^{n} p_{ij} = \left(\frac{1}{n}\sum_{j=1}^{n} p_{ij}^{L}, \frac{1}{n}\sum_{j=1}^{n} p_{ij}^{M}, \frac{1}{n}\sum_{j=1}^{n} p_{ij}^{R}\right) \tag{3.27}$$

$$\widetilde{w}_{a_i} = (w_{a_i}^{L}, w_{a_i}^{M}, w_{a_i}^{R}) = \frac{\bar{A}_i}{\sum_{i=1}^{m} \bar{A}_i} = \frac{\left(\frac{1}{n}\sum_{j=1}^{n} p_{ij}^{L}, \frac{1}{n}\sum_{j=1}^{n} p_{ij}^{M}, \frac{1}{n}\sum_{j=1}^{n} p_{ij}^{R}\right)}{\bar{A}_1 + \bar{A}_2 + \cdots + \bar{A}_m} \tag{3.28}$$

Step 10: Determine the defuzzied priorities/weights of the attributes using the simplest fuzzy mean (Rezaei and Ortt, 2012).

$$w_{a_i} = \frac{w_{a_i}^{L} + w_{a_i}^{M} + w_{a_i}^{R}}{3} \tag{3.29}$$

- **Phase III: Fuzzy COPRAS**

Step 11: Formulate the fuzzy decision support matrix/trade-off matrix using the fuzzy linguistic variables (see Table 3.3 and Figure 3.7)

Table 3.3: Fuzzy linguistic variables

Linguistic variable	TFN
Very Low (VL)	(1,1,3)
Low (L)	(1,3,5)
Medium (M)	(3,5,7)
High	(5,7,9)
Very High (VH)	(7,9,9)

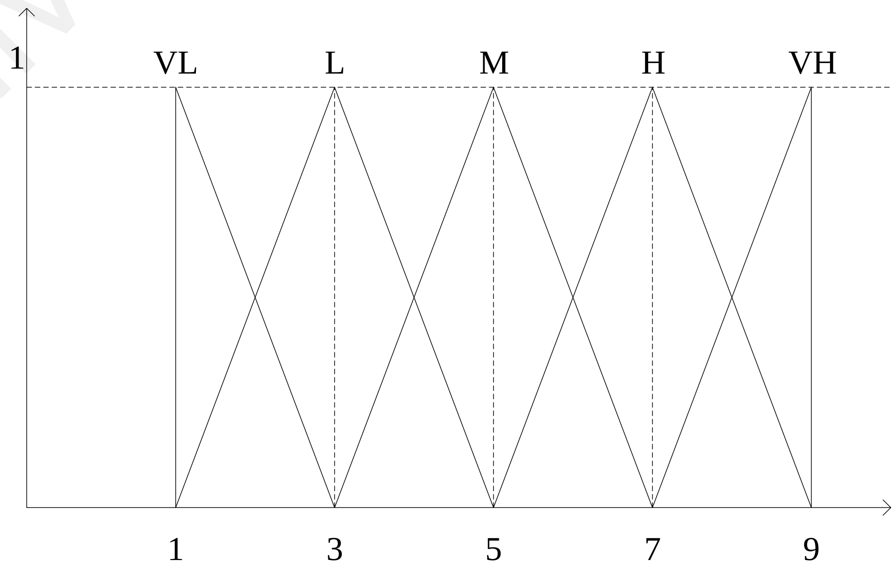

Figure 3.7: Linguistic variables for evaluating alternative

Step 12: Defuzification of the fuzzy trade-off matrix.

Step 13: Data normalization of the trade-off matrix.

Step 14: Determine the weighted normalized trade-off matrix.

Step 15: Calculate the total summarization P_i (maximum optimization direction).

Step 16: Calculate the total summarization R_i (minimum optimization direction).

Step 17: Determine the minimal of R_i value.

Step 18: Calculate the priority of each alternative.

Step 19: Determine the optimality criterion K.

Step 20: Calculate the utility degree of each alternative and determine the ranking.

3.4 Finalization of machine tool selection (MTS) decision

3.4.1 Hierarchy of MTS finalization

The basic accepted attributes (see Table 3.4) in the model is extracted from the existing literature and interviews of the machine tool experts. The attributes for decision-making are divided into two classification involving the main-attributes and sub-attributes. However, to simplify the model, a list of the attributes for machine tool selection is carried out with 12 attributes. The structural hierarchy of the decision model is depicted as in Figure 3.8, showing the diagram of attributes for decision-making process. At the first level (Level 1), the aim of the proposed model is to evaluate the most appropriate CNC machine tool for implementing a FMC from the set of the alternatives shown at the bottom level to produce suitable types of parts, satisfying the demands of customers.

To obtain the objective, the number of attribute is determined at the second/middle level (Level 2) with consideration of the feedback relationship, interactions and interdependence among the attributes in the cluster, which are accommodated or covered in the box. Each attribute has the interaction with one another and will be described by a line with the cluster. This consideration of the relationship among the attributes is a significant and different point to make the decision more accurate and flexible in the implementation of FMC. To rank alternatives, data input is collected as a number of decision-makers, number of attributes and alternatives, expert's judgment, and output of results for decision-making is the priorities of the attributes and weights of alternatives.

Table 3.4: List of the selected attributes for machine tool selection (Ayağ & Gürcan Özdemir, 2012)

No.	**Attributes**	**Symbol**	**Sub-attributes**
1	Productivity	A1	Power, spindle speed, cutting feed, and traverse speed.
2	Flexibility	A2	Number of tools, capacity of magazine, and production time/processing time, rotary table.
3	Space	A3	Machine tool dimension.
4	Adaptability	A4	CNC type, number of taper, easy to interact with other systems
5	Precision	A5	Repeatability, thermal deformation.
6	Reliability	A6	Bearing failure rate, reliability of drive system.
7	Safety	A7	Mist collector, safety door, fire extinguisher.
8	Maintenance and service	A8	Repair service, regular maintenance.
9	Cost	A9	Cost of machine, cost of the option feature.
10	Installation easiness	A10	Practical, fast and simple installation
11	User friendliness	A11	The easy use of machine tool, minimization of the training expenses and the operation errors.
12	Green standards	A12	Minimization of waste, friendly environment, use of less power or low consumption of energy.

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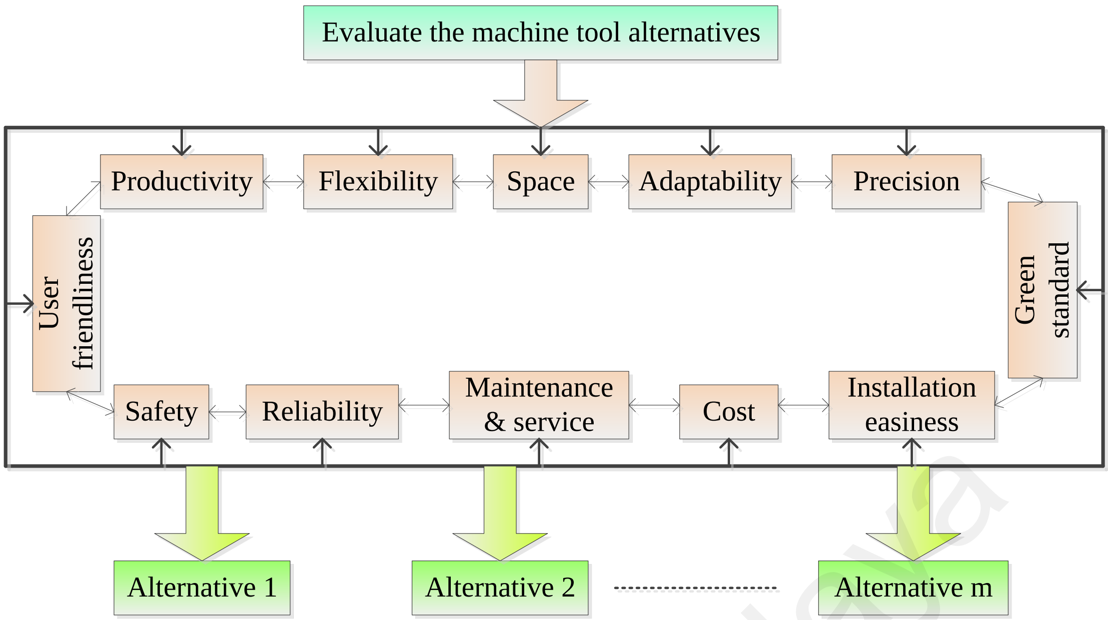

Figure 3.8: Hierarchical structure for evaluating the machine tool

Considering the interaction and feedback relationships among the attributes, the three-level evaluation system for machine tool selection is presented, as shown in Figure 3.8. It should be noted that the attribute A1 has an effect on the attribute 2, so a line with an arrow pointing from A1 to A2 is shown and whereas an arrow from A2 to A1 is added to illustrate the interaction of A2 and A1.

3.4.2 Proposed method for MTS

The types and the number of machines selected depends on several factors such as types of job, the cost of machine, expected demand and processing time (Ayağ, 2007). There are many criteria considered for decision making process in machine tool selection, comprising of both qualitative and quantitative criteria. For the qualitative criteria, it is actually a difficult task to quantify the uncertain information. That is why fuzzy MCDM method for machine tool selection is needed to handle the imprecise, vague and uncertain information of criteria, both qualitative and quantitative (Samvedi et al., 2011). This makes the theory of fuzzy sets, grey relational analysis, and AHP/ANP are becoming popular in decision-making process because of the ability in modeling uncertain information. In particular, AHP/ANP is very strong for quantifying the qualitative factors through the expert's judgments.

Recent research has proved that the application of fuzzy AHP/ANP methods in the decision-making process can be utilized. Fuzzy AHP/ANP achieved good results in evaluating and ranking the alternatives and is widely used in manufacturing environment. One of the important benefits of using the fuzzy AHP/ANP is the ability of generating the weights of criteria and the priorities of alternatives from the pair-wise comparison matrices of expert's judgments. However, fuzzy ANP, which is the extension of fuzzy AHP, is a better alternative as compared to fuzzy AHP because it considers interdependence, feedback, relationship between the higher level and lower level elements. However, fuzzy ANP has a weak point which is high demand of complex computation. Hence, ANP is difficult to be implemented for the practical problems of manufacturing. To overcome the drawback of the existing fuzzy ANP method, the integration of the consistent fuzzy ANP and COPRAS-G is introduced for machine tool selection. This proposed method of machine tool selection is very simple and can be easily implemented without any constraints and can solve large dataset of machine tools.

3.4.2.1 Fuzzy numbers

Fuzzy sets are the classes whose objectives have 'a continuum of grades of membership'. Each class is 'specified by a membership function', which assigns the grade of membership having a value in interval [0, 1] for each objective (Zhou, 2012). This theory is proposed by Zadeh (1965) with the aims at solving vague, imprecise, and uncertain information. The expert's judgments contain vagueness and uncertainty of information so using only ANP based on the pair-wise comparison matrices, which collect data from expert's judgments, is insufficient and imprecise to handle and make accurate decision. Thus, fuzzy logic is employed to be integrated into the pair-wise comparison matrices of ANP. The specification of fuzzy sets is to pose the membership function having the value in interval [0, 1] with many fuzzy number such as monotonic, triangular, and trapezoidal (Taha and Rostam, 2011a). The triangular fuzzy numbers (TFNs) are commonly used to describe the situations of decision-makers judgments in decision-making process and denoted as M(l,m,u) in the literatures, as shown in Figure 3.9. The parameters l, m, u express respectively the smallest, medium (the most promising value), and largest values for modeling the fuzzy judgments. The membership function of TFNs is determined as follows (Chang and Wang, 2009; Moalagh and Ravasan, 2012).

$$\mu(x/M) = \begin{cases} 0, x < l. \\ \frac{x-l}{m-l}, l \leq x \leq m. \\ \frac{u-x}{u-m}, m \leq x \leq u. \\ 0, x > u. \end{cases} \tag{3.30}$$

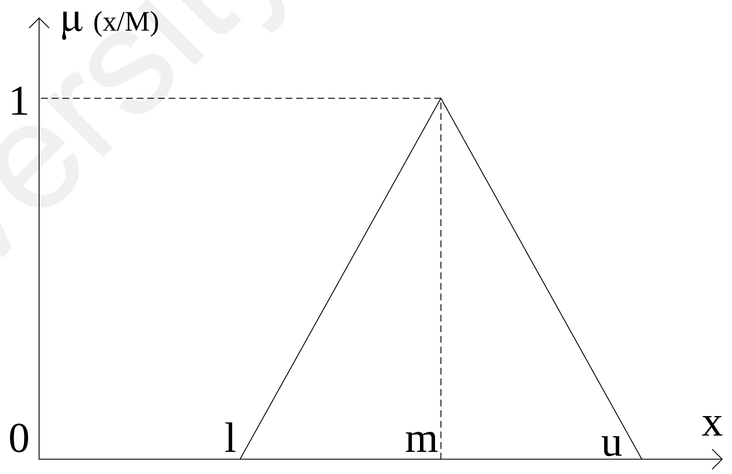

Figure 3.9: Membership function of fuzzy triangular number (TFN)

For multi-attribute decision-making process, let $X = \{x_1, x_2, \ldots, x_n\}$ be a set of attributes and $g = \{g_1, g_2, \ldots, g_n\}$ be a set of alternatives, in which each alternative is described through the set of attributes. According to the model, each attribute is chosen

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and an extent analysis is applied for each alternative, g_i, respectively. Thus, the value m of extent analysis for each attribute is determined as follows:

$$M_{gi}^1, M_{gi}^2, \dots, M_{gi}^m, \qquad i = 1, 2, \dots, n$$

where all the $M_{gi}^j (j = 1, 2, \dots, m)$ are expressed as the TFNs.

3.4.2.2 The structure of fuzzy ANP (FANP)

The ANP considers the interaction, inter-dependence, and feedback relationships with the groups of attributes (inner-dependence) and between groups (outer-dependence). The attribute may influence other attribute with respect to each of various attributes. The final purpose is to determine the overall influence of all the attributes to the desired goal. First of all, the attributes must be organized and prioritized in the hierarchical structure. Then, the pair-wise comparison is implemented and evaluated to obtain the relative weights of the attributes. Moreover, in the feedback system, the influence of attributes with respect to each of the other attributes must be considered. Therefore, the interaction of the attributions has a dramatic impact on the overall influences on the network of decision-making (Önüt, Kara and Işik, 2009; Önüt, Kara and Tekin, 2008). The super-matrix representation of a hierarchy with three levels, shown in Figure 3.10, is determined as follows.

$$W = \begin{array}{r} Goal\ (G) \\ Criteria\ (C) \\ Alternatives \end{array} \begin{bmatrix} 0 & 0 & 0 \\ W_{21} & 0 & 0 \\ 0 & W_{32} & I \end{bmatrix} \tag{3.31}$$

where the vector W_{21} represents the influence of the goal on the attribute, the vector W_{32} represents the relative influence of the attribute for each in the set of alternatives, and I is the identity matrix. W is considered as a super-matrix, which contains the matrices of its entries. If the attributes are dependent among themselves, then the cell (2, 2) is added into super-matrix W, presented as W_{22} with the nonzero entries. The inter-dependence is shown by the representative of the matrix element W_{22} in the super-

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matrix W (Önüt et al., 2009; Önüt, Kara, et al., 2008; Saaty and Vargas, 1998). Finally, synthesis of all the interactions of the attributes in the hierarchical network of decision-making is determined through the limit super-matrix. The total influence of the alternatives and the alternative with the largest total weight is carried out from the super-matrix (Önüt, Kara, et al., 2008).

$$W = \begin{bmatrix} 0 & 0 & 0 \\ W_{21} & W_{22} & 0 \\ 0 & W_{32} & I \end{bmatrix} \tag{3.32}$$

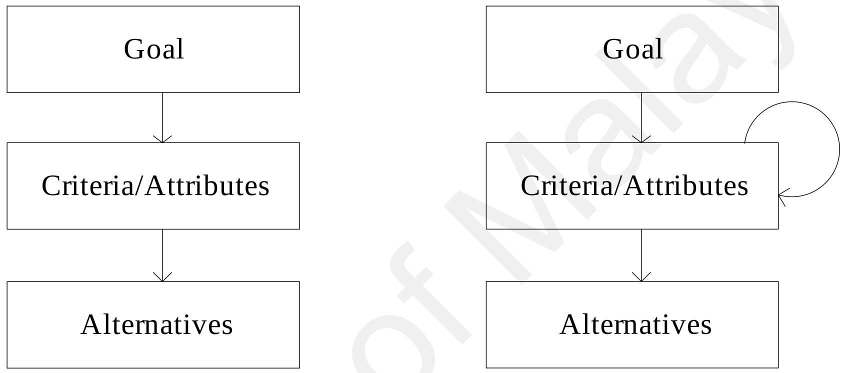

Figure 3.10: Hierarchy and network: (a) hierarchy; (b) network (Önüt et al., 2009; Yükseland Dagdeviren, 2007)

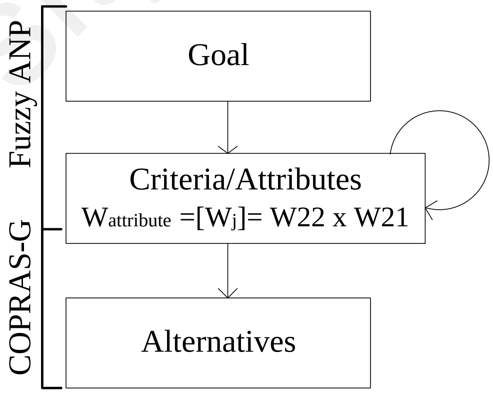

Figure 3.11: The proposed approach for finalizing decision of the machine tool selection

In this study, the weights of the attributes including the feedback relationships, and interactions of the attributes and alternatives according to the respective attributes are calculated by fuzzy ANP. Then, COPRAS-G is utilized to determine the ranking of alternatives through TFNs, shown in Figure 3.11.

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Since fuzzy ANP is only utilized to calculate the weights of attributes to decrease the number of the judgments needed to be collected. Hence, the super-matrix is defined as follows (Önüt et al., 2009; Önüt, Kara, et al., 2008):

$$W = \begin{bmatrix} 0 & 0 \\ W_{21} & W_{22} \end{bmatrix} \tag{3.33}$$

where W_{21} presents the relative importance or weights of the attributes, which are determined using the above procedure in step 4. The fuzzy inter-dependence among the attributes (feedback relationships of attributes) is subsequently specified based on fuzzy linguistic variables. These weights are evaluated as shown in step 4 and assigned to the fuzzy inter-dependence matrix W_{22}. The overall weights of the attributes are calculated by multiplying W_{22} with W_{21} as shown in Figure 3.11.

$$W_j = W_{attributes} = W_{22} \text{ x } W_{21} \tag{3.34}$$

where j is the number of the selected attributes for decision-making process

3.4.2.3 The procedure of FANP

(a) ***Build the pair-wise comparison matrix***

- Step 1: Build the hierarchical network model for decision-making problem with the consideration of the feedback relationships, interdependence, and interaction between the clusters and the attributes. In decision-making process, the qualitative factors are transformed into quantitative factors using the preference ratios, which are assigned by decision-makers. The decision-makers make decision based on natural language, which has been described by the fuzzy variables. The triangular fuzzy numbers (TFNs) are used to represent the fuzzy linguistic variables for transforming from natural to fuzzy logic language (see Table 3.5, Figure 3.13). These variables describing a human word are shown in Table 3.5 and Table 3.6. In this study, the fuzzy linguistic variables are used to represent the relative importance in the pair-wise comparison matrices (Table 3.5).

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- Step 2: Build the pair-wise comparison matrices between an attribute and other attributes for decision-making using TFNs. The question list is designed to ask the decision-makers' judgments, which presents the relative importance of this attributes when compared with each other attribute in the pair-wise comparison matrix. In this study, the question is required as follows "How important is the first attribute when it is compared with another attributes in satisfying the manufacturing goals? And if the answer is "absolutely important", the TFN (5/2, 3, 7/2) is placed in the relevant element of the pair-wise comparison matrix. Similarly, the rest of the elements in the matrix are implemented in the same manner.

(b) ***Determine the weights of the attributes***

The procedure of this algorithm is suggested by (Chang, 1992, 1996; Metin Dağdeviren, Yüksel, and Kurt, 2008; Kahraman, 2008; Moalagh and Ravasan, 2012; Pang and Bai, 2013; Yüksel and Dağdeviren, 2010) and is described as follows:

- Step 1: The fuzzy synthetic extent value for i^{th} attribute is determined as:

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} \tag{3.35}$$

where the value of $\sum_{j=1}^{m} M_{gi}^{j}$ is the fuzzy aggregation of m TFNs, which are the extent analysis values for particular matrix.

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j}^{m} l_j, \sum_{j}^{m} m_j, \sum_{j}^{m} u_j\right) \tag{3.36}$$

And to calculate the reciprocal value $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1}$, firstly the fuzzy aggregation value of $M_{gi}^{j}(j = 1,2,\dots,m)$ values is needed to be determined as follows.

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right] = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i\right) \tag{3.37}$$

And finally, the reciprocal value of the vector in the above equation is calculated as below.

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right) \tag{3.38}$$

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- Step 2: The degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, if\ m_2 \geq m_1 \\ 0, if\ l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, otherwise, \end{cases} \tag{3.39}$$

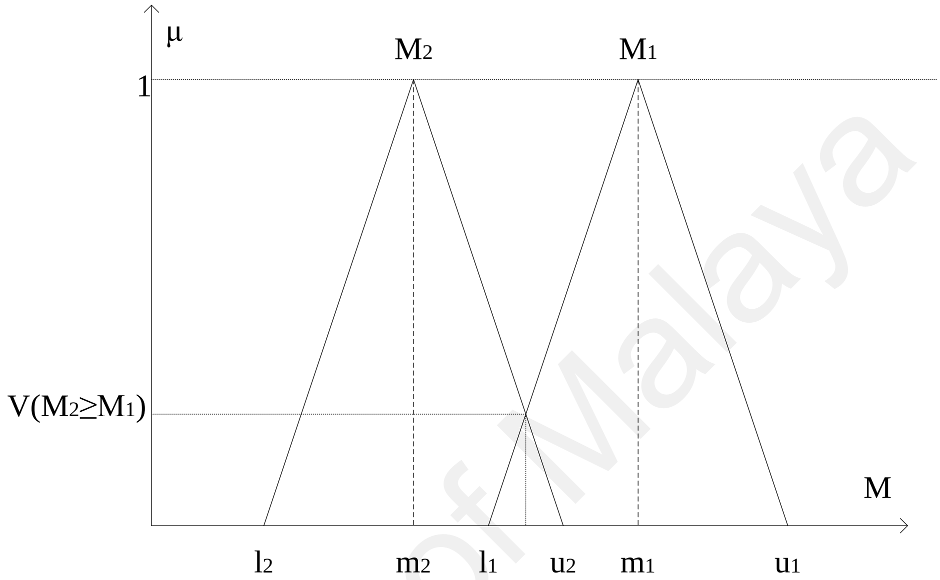

Figure 3.12: Intersection node of membership functions between the fuzzy numbers

In Figure 3.12, two membership functions $\mu_{M_1}$and μ_{M_2} intersect at the highest intersection point D, and d is considered as the ordinate of this point. Moreover, $hgt(M_1 \cap M_2)$ is a separation index for two fuzzy numbers. If the value of $hgt(M_1 \cap M_2)$ is closer to 1, the comparison between the fuzzy numbers M_2 M_1 becomes very difficult. Thus, the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ are necessary to determine when comparing the fuzzy numbers M_1 and M_2.

- Step 3: The degree possibility for a fuzzy number M to be greater than k fuzzy numbers M_i (i = 1, 2, …, k) can be determined as follows.

$$V(M \geq M_1, M_2, \dots, M_k) = V(M \geq M_1) \text{ and } (M \geq M_2) \text{ and } \dots \text{ and}$$

$$\dots (M \geq M_k) = minV(M \geq M_i), \quad i = 1,2, \dots, k \tag{3.40}$$

For k = 1, 2, …, n; $k \neq i$. Then the weighted vector is given by:

$$W' = (d'(A_1), (A_2), \dots, d'(A_n))^T, \text{ where } A_i \text{ (i= 1, 2,…, n) are n attributes} \tag{3.41}$$

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• Step 4: The normalized value of weighted vectors is calculated as follows:

$$W = (d(A_1), (A_2), \dots, d(A_n))^T, \qquad (3.42)$$

where W is a crisp number

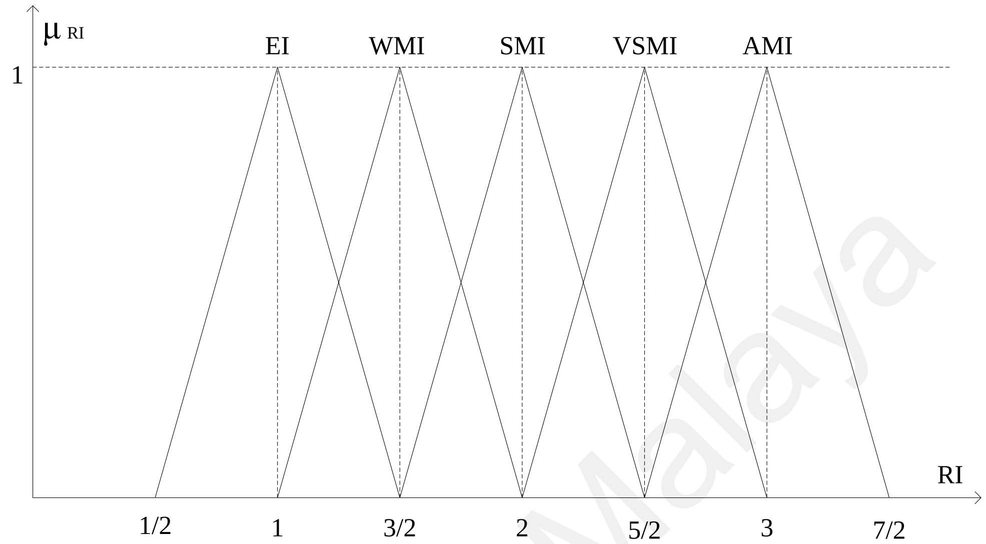

Figure 3.13: Linguistic scale for relative importance (Dagdeviren and Yuksel, 2008)

Table 3.5: Linguistic scale for importance (Dagdeviren and Yuksel, 2008)

Linguistic scale for importance	Triangular fuzzy scale
Just equal (JE)	(1,1,1)
Equally importance (EI)	(1/2,1,3/2)
Weakly more important (WMI)	(1,3/2,2)
Strongly more important (SMI)	(3/2,2,5/2)
Very strongly more important (VSMI)	(2,5/2,3)
Absolutely more important (AMI)	(5/2,3,7/2)

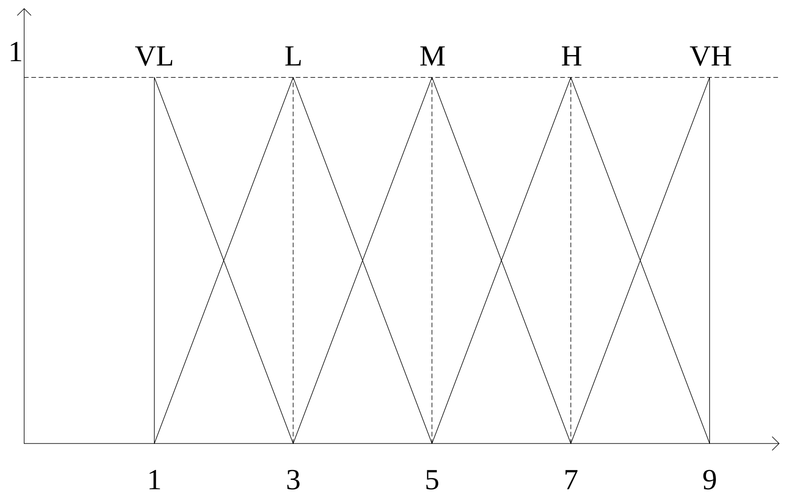

Figure 3.14: Membership function of fuzzy numbers for evaluating the alternatives

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Table 3.6: Linguistic variables, fuzzy numbers and grey numbers for evaluating the alternative

Linguistic variables	Triangular fuzzy scale	Grey numbers
Very Low (VL)	(1,1,3)	[1, 2]
Low	(1,3,5)	[2, 4]
Medium	(3,5,7)	[4, 6]
High	(5,7,9)	[6, 8]
Very High	(7,9,9)	[8, 9]

3.4.2.4 COPRAS-G method

In most cases, the MADM process involves both quantitative and qualitative attributes. Thus, to evaluate the decision exactly is a very difficult because the attributes values are expressed in terms of fuzzy number or in interval values for the uncertain information (Zavadskas, Turskis and Vilutiene, 2010). Moreover, the decision-maker's judgments contribute to the incomplete information, so the theory of grey system is applied to transfer from the crisp values (white number) to the grey numbers where it plays as an important role for the MADM process in the real-time environment (Bindu and Padmaja, 2010; Maity, Chatterjee and Chakraborty, 2011). Grey relational grade model is very effective in handling with discrete data (Bindu et al., 2010). Grey number is a basic concept in theory of grey system which is used to solve uncertain information, can be modeled as white, black and grey system. In particular, the white system is the system having internal information which is clear and completely known. Whereas, the black system is a system in which any information and characteristics/properties cannot be attained. Hence, grey system is defined as a system with uncertain information, in the position between the white and black systems (Zavadskas, Kaklauskas, Turskis, and Tamošaitiene, 2008). Therefore, the decision-maker's judgments that accommodate the uncertain level of information can be described by the grey system through the classification of white, black and grey numbers (Maity et al., 2011).

The COPRAS-G method (*Complex Proportional Assessment of alternatives with Grey relations*) is suggested by Zavadskas et al. (2008) with attributes expressed in interval values, which are suitable for the real situations of decision-makers, and the applications of grey theory. COPRAS-G is a newly developed approach for the MADM process in the evaluation of alternatives, in which values of the attributes are expressed in interval (Zavadskas, Turskis, Tamosaitiene and Marina, 2008). It is completely logic and useful mathematically for dealing with incomplete information in a system (Zavadskas, Kaklauskas, et al., 2008) and is intended to increase the efficiency and improve the accurate level of the resolution in decision-making process (Zavadskas, Turskis, et al., 2008). The COPRAS-G approach is used to analyze different alternatives, and to estimate the alternatives according to the significance and the utility degree (Maity et al., 2011). The utility degree of alternative is shown in a percentage to which one alternative is considered as better or worse when compared to other existing alternatives, and to 'estimate the market value' of alternatives, as well as to gather diverse recommendations. Other MADM approaches do not have such features and that is the reason why COPRAS-G succeeded in decision-making process, and having very high citation in recent publications. COPRAS-G supports the decision-makers in figuring out the decisions in a more accurate manner. COPRAS-G has been proven for effectively handling the problems which deal with uncertainty, subjectivity, and imprecise data (Zavadskas, Kaklauskas, Turskis and Tamosaitiene, 2010).

The procedure of COPRAS-G is presented as follows by several researchers (Bindu et al., 2010; Maity et al., 2011; Zavadskas, Kaklauskas, et al., 2008; Zavadskas, Turskis, et al., 2008; Zavadskas et al., 2010).

- Step 1: Determine the most crucial attributes to describe the alternatives for multi-attribute decision-making process.

- Step 2: Build the decision support matrix with the value of attributes expressed in the intervals using grey numbers (see Table 3.6 and Figure 3.14).

$$X = \begin{bmatrix} [x_{11}, u_{11}] & [x_{12}, u_{12}] & \dots & [x_{1n}, u_{1n}] \\ [x_{21}, u_{21}] & [x_{22}, u_{22}] & \dots & [x_{2n}, u_{2n}] \\ \dots & \dots & \dots & \dots \\ [x_{m1}, u_{m1}] & [x_{m2}, u_{m2}] & \dots & [x_{mn}, u_{mn}] \end{bmatrix}; i = 1,2, \dots, m; j = 1,2, \dots, n \quad (3.43)$$

where $[x_{ij}, u_{ij}], i = 1,2, \dots, m; j = 1,2, \dots, n$ is the interval value of ith alternative with respect to jth attribute, described by the smallest value x_{ij} and the highest value u_{ij}. In particular, m and n are the number of alternatives and attributes, respectively.

- Step 3: Determine the weight priorities of the selected attributes q_j of alternatives.
- Step 4: Normalize the data of the decision support matrix X using the below formula:

$$[\bar{x}_{ij}]_{m \times n} = \frac{2x_{ij}}{[\sum_{i=1}^{m} x_{ij} + \sum_{i=1}^{m} u_{ij}]} \quad (3.44)$$

$$[\bar{u}_{ij}]_{m \times n} = \frac{2u_{ij}}{[\sum_{i=1}^{m} x_{ij} + \sum_{i=1}^{m} u_{ij}]} \quad (3.45)$$

Thus, a decision support matrix is formulated after the normalization of data:

$$\bar{X} = \begin{bmatrix} [\bar{x}_{11}, \bar{u}_{11}] & [\bar{x}_{12}, \bar{u}_{12}] & \dots & [\bar{x}_{1n}, \bar{u}_{1n}] \\ [\bar{x}_{21}, \bar{u}_{21}] & [\bar{x}_{22}, \bar{u}_{22}] & \dots & [\bar{x}_{2n}, \bar{u}_{2n}] \\ \dots & \dots & \dots & \dots \\ [\bar{x}_{m1}, \bar{u}_{m1}] & [\bar{x}_{m2}, \bar{u}_{m2}] & \dots & [\bar{x}_{mn}, \bar{u}_{mn}] \end{bmatrix}; i = 1,2, \dots, m; j = 1,2, \dots, n \quad (3.46)$$

- Step 5: Determine the weighted normalized decision support matrix $\hat{X}$, in which the weighted normalized values are determined as follows.

$$\hat{x}_{ij} = \bar{x}_{ij} \times q_j \quad (3.47)$$

$$\hat{u}_{ij} = \bar{u}_{ij} \times q_j \quad (3.48)$$

$i = 1,2, \dots, m; j = 1,2, \dots, n$; and q_j is the weights of the jth attribute.

Thus, the result of the weighted normalized decision support matrix is written as follows:

$$\bar{X} = \begin{bmatrix} [\hat{x}_{11}, \hat{u}_{11}] & [\hat{x}_{12}, \hat{u}_{12}] & \dots & [\hat{x}_{1n}, \hat{u}_{1n}] \\ [\hat{x}_{21}, \hat{u}_{21}] & [\hat{x}_{22}, \hat{u}_{22}] & \dots & [\hat{x}_{2n}, \hat{u}_{2n}] \\ \dots & \dots & \dots & \dots \\ [\hat{x}_{m1}, \hat{u}_{m1}] & [\hat{x}_{m2}, \hat{u}_{m2}] & \dots & [\hat{x}_{mn}, \hat{u}_{mn}] \end{bmatrix}; i = 1,2, \dots, m; j = 1,2, \dots, n \quad (3.49)$$

- Step 6: Calculate the weighted mean normalized sums of both the beneficial attributes and non-beneficial attributes for all the alternatives.

$$P_i = \frac{1}{2}\sum_{j=1}^{k}(\hat{x}_{ij} + \hat{u}_{ij}) \tag{3.50}$$

$$R_i = \frac{1}{2}\sum_{j=k+1}^{k}(\hat{x}_{ij} + \hat{u}_{ij}) \tag{3.51}$$

where P_i and R_i are the weighted mean normalized sums of the beneficial and non-beneficial attributes for i^{th} alternative, k is the number of beneficial attributes, need to be maximized and (m-k) is the number of non-beneficial attributes, need to be minimized.

- Step 7: Calculate the minimum value of R_i:

$$R_{min} = \min R_i \ (i = 1,2,\dots, m) \tag{3.52}$$

- Step 8: Determine the weights of alternatives based on Q_i values. The greater the value of Q_i, the higher is the weight of alternative, which depicts the satisfied degree of the alternative. The alternative with the highest weight (Q_{max}) is the most suitable candidate among the potential alternatives, is implemented based on the decreasing order of the weights of alternatives. It means that the best alternative possess the highest weight priority (Maity et al., 2011).

The weight of i^{th} alternative is calculated as follows.

$$Q_i = P_i + \frac{R_{min}\sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m}\left(R_{min}/R_i\right)} = P_i + \frac{\sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m}\left(1/R_i\right)} \tag{3.53}$$

- Step 9: Determine the maximum weight of alternative.

$$Q_{max} = \max Q_i \ (i=1, 2, \dots , m) \tag{3.54}$$

- Step 10: To determine the quantitative utility (U_i) for i^{th} alternative based on the weight values of Q_i. The degree of an alternative's utility is defined as the rate of the priorities of all the alternatives with the best candidate. It shows the optimal ranking of the alternatives, and is expresses in the below formula (Maity et al., 2011).

$$U_i = \left[\frac{Q_i}{Q_{max}}\right] \times 100\% \tag{3.55}$$

These quantitative utility for alternatives is shown as a percentage from 0% to 100%. Therefore, COPRAS-G approach evaluates the 'direct and proportional dependence' of the weight and the utility degree of the selected alternatives in the MADM (Maity et al., 2011).

3.4.2.5 Hybridization of FANP and COPRAS-G for MTS

(a) ***The proposed model for machine tool selection***

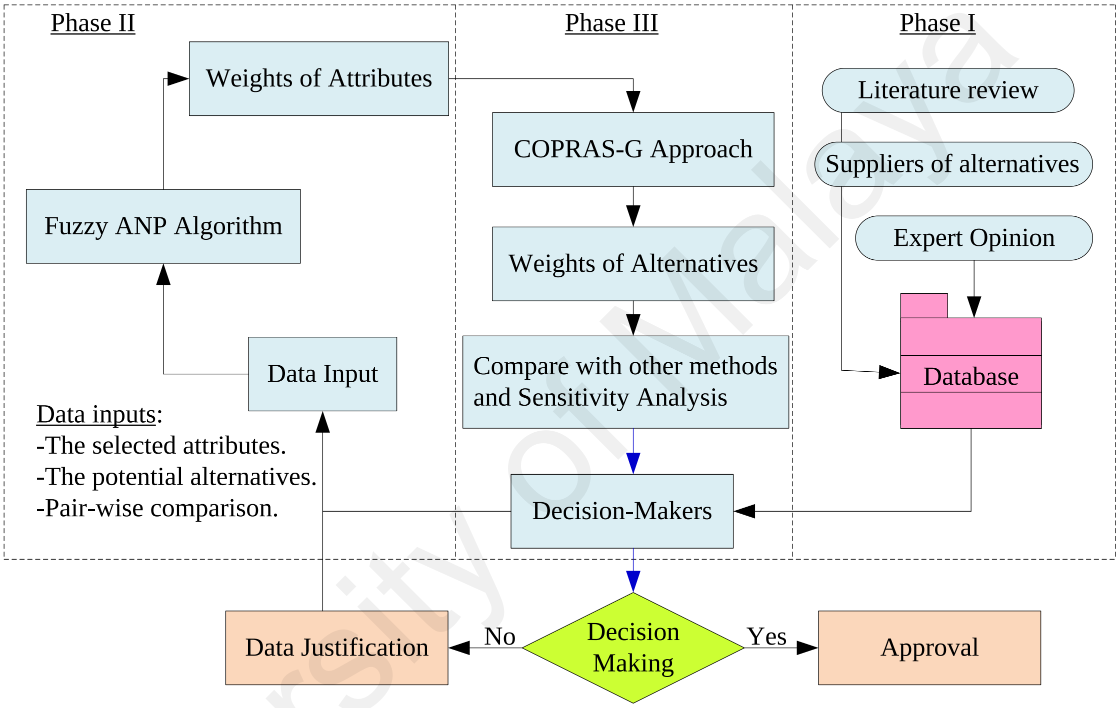

Figure 3.15: Scheme of the proposal model of machine tool selection

The structure of the model is depicted in Figure 3.15 and classified into three phases. Firstly, in the Phase 1, the required data were suggested by decision-makers through the survey from the literatures and expert opinion in order to form the database for Phase II. Secondly, the relationship, dependence and feedback between the attributes are described in the fuzzy ANP algorithm for evaluating the weights of the attributes in Phase II. Finally, in Phase III, the results of Phase II are the weights of the attributes, imported into the COPRAS-G methodology to estimate the weights of alternatives for ranking. The higher the weight of alternative, the better it is. Thus, the approval of these results satisfies the manufacturing goals and the final decision is carried out by the decision-makers. Whereas, the data are need to be justified for the re-procedure.

(b) ***The procedure of hybridization of FANP and COPRAS-G for final decision in MTS***

The flowchart of the proposed model is depicted in Figure 3.16. The method is based on the integration of fuzzy ANP and COPRAS-G. This procedure comprises of three phases for decision-making in machine tool selection. In Phase 1, conceive with team-working is implemented to define the attributes and alternatives, the production goals. In this stage, decision-makers define the machine alternatives, and determine the attributes for machines based on the suppliers, handbooks, and literature in the previous research works. The database of machine tools is prepared and collected from various sources such as manufacturing facilities, and the catalogues of the manufacturers in the market of CNC machine tools. The machine alternatives are the candidate machine tools selected from the large number of machines that are able to ensure the satisfaction of manufacturing goals or requirements of the customers. In Phase 2, the relationship, interaction, dependence and feedback among attributes are identified through the pair-wise comparison matrices among the attributes, which are derived from decision-makers or expert judgments with questionnaire design list. Fuzzy ANP uses these matrices to predict the weights of attributes. The steps for determining the weights of attributes are described in detailed in fuzzy ANP method (see Section 3.4.2.3). The determination of the relationship, interaction, and inter-dependence of the attributes helps to define priority weights to improve the precision of the results. Then, the content of phase 3 is introduced to make decision in the best alternative through the weights of alternatives which are evaluated based on the COPRAS-G approach.

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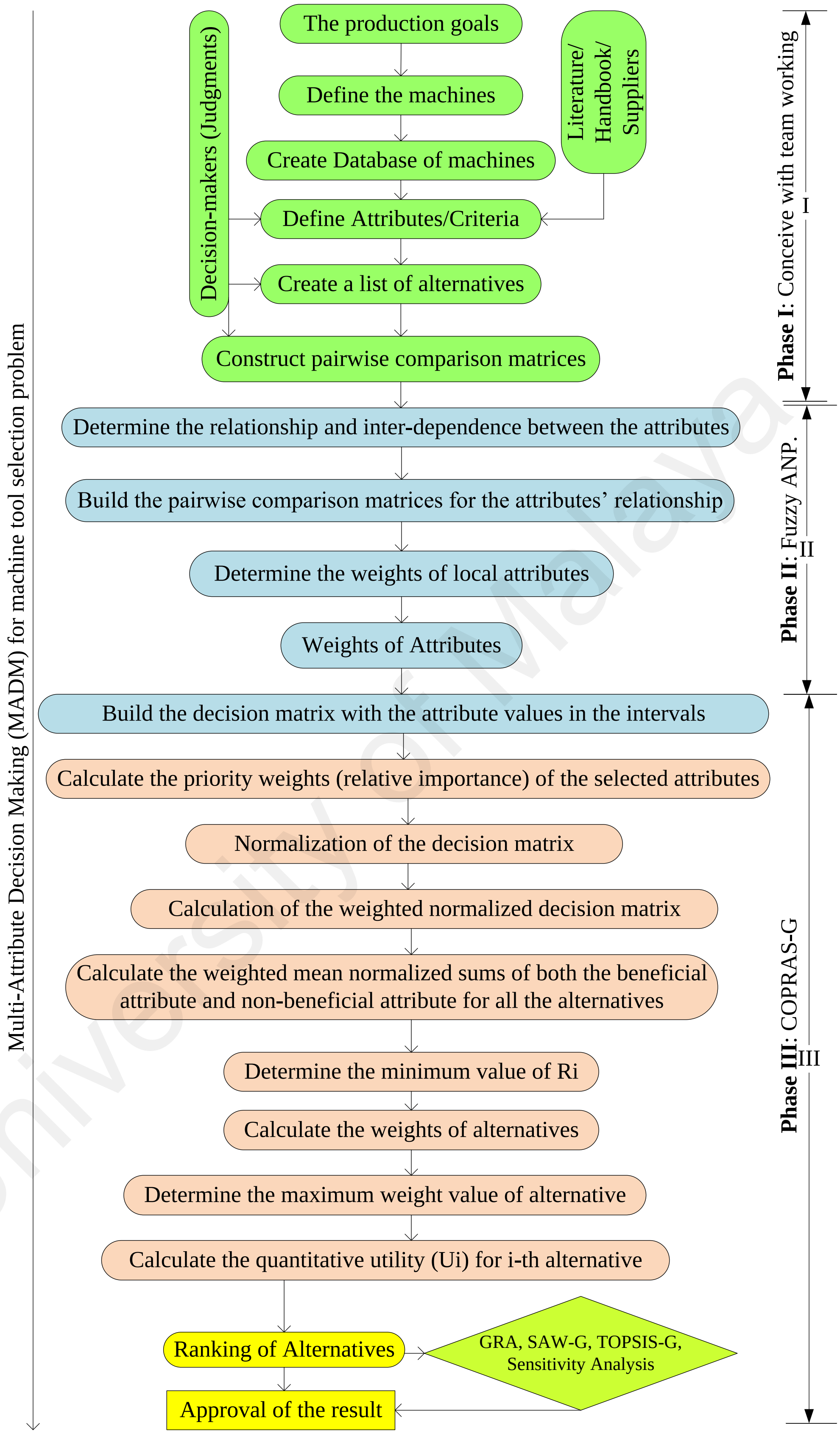

Figure 3.16: Flowchart of the proposed model to finalize decision in machine tool selection

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The procedure of COPRAS-G for ranking alternatives is described in Section 3.4.2.4, containing decision/trade-off matrix, normalization of data, weighted normalized data, mean weighted normalized sums, the minimum value R, the weights of alternatives, and the quantitative utility. Finally, the comparison of the proposed approach with acceptable recent popular existing methods such as GRA, TOPSIS-G and SAW-G is implemented to validate the model. The procedure is shown in the detail of fuzzy ANP and the steps of the COPRAS-G method are summarized in the structure as shown in Figure 3.16.

3.5 Method in solving the machine loading problem in FMC

3.5.1 Introduction

The objective of this study is to determine the most suitable best allocation of operations into machines to satisfy the manufacturing goals, which are presented as the objective functions. These objective functions are considered for this system as minimization of system unbalance, makespan and total flow time. In Figure 3.17, the FMC consists of four CNC machines connected together by the conveyor system. Each CNC machine has a buffer for part storage. The conveyor transports the parts from the loading/unloading station into the buffers of CNC machines. Besides, it can transfer the parts among CNC machines for continuous machining operations. The machines receive the parts from the buffer and conduct operations of machining process as planned and scheduled. Once the part is completed, it will be picked up and transported to the loading/unloading station for unloading by the conveyor. The finished parts can be stored in an automatic storage and retrieval system (AS/RS). All equipment in the system operate together simultaneously to produce the part types according to the customer's demand.

The procedure in solving the machine loading problem is first to define the operations in FMC system:

- Setup is an operation of setting up machine for starting the required machining operation in CNC machines.
- The loading of machining parts is the process of mounting a part on the destination from buffer storage by the material handling system.
- Part transporting is the process of conveying a part to the required destination by material handling system (conveyor).
- Part unloading is the process of removing a part from material handling system into the buffer storage.
- Loading is the process of loading a machining part into CNC machine to be produced.
- Machining is an operation of machining a part on CNC machine like milling, turning and drilling, etc.
- Unloading is an operation of removing the machined part from CNC machines into the buffer storage.

The procedure of computation to obtain the suitable solutions for machine loading in FMC contains the following steps:

- Select the four most suitable machine tools (from previous phase) to put into the place of FMC layout.
- Collect production data from the process plan (processing time and traveling time).
- Build the mathematical model of machine loading in FMC.
- Develop the method to obtain the solutions for machine loading problem.

The general assumptions for this study are that all the parts can obtain the machining operations on the CNC machines in FMC and that each part can comprise of multiple machining operations. Each operation is processed on one or many CNC machines with different processing times.

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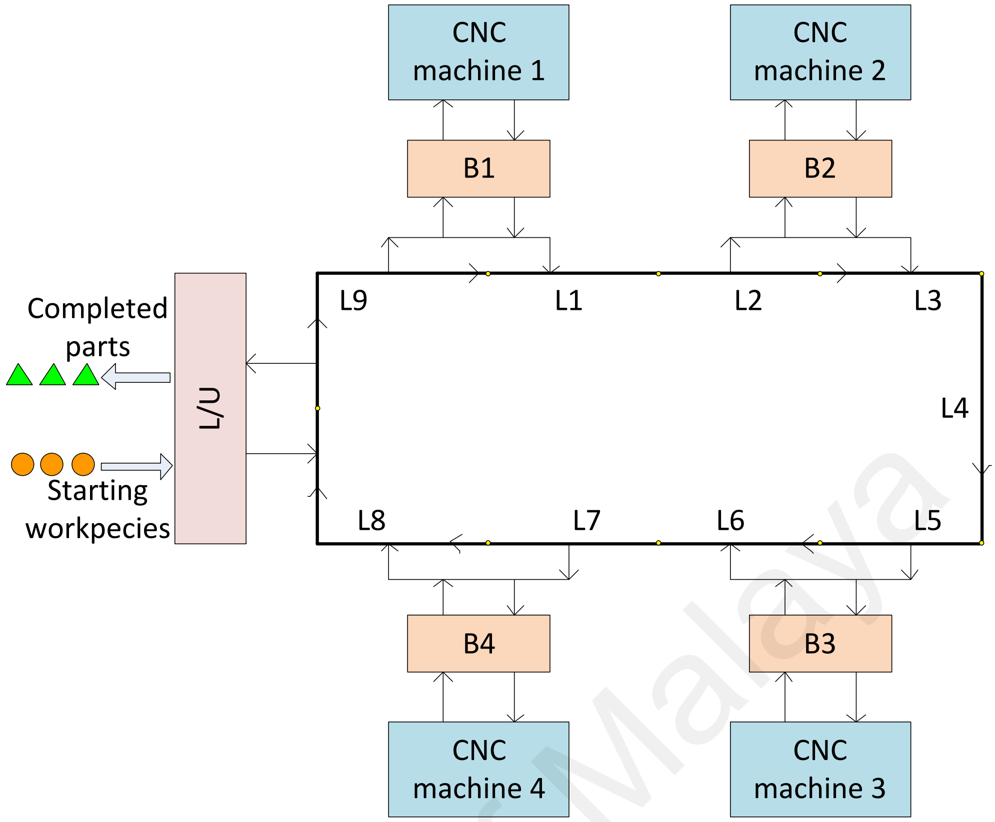

Figure 3.17: Flexible Manufacturing Cell (FMC)

3.5.2 Flexible manufacturing cell environment

In this study, the FMC comprises of four CNC (computer numerical control) machines which are evaluated and selected from Phase I. The structure of FMC is shown as in Figure 3.17. The conveyor system is served to transport the part types according to the requirements of different processing. Many part types have different desired batch sizes and chosen for machining process in FMC to complete the customers' demand. The buffers are used to store the parts at each machine. The workpieces will start at the loading station, and the completed parts are moved to unloading station for storage. The part types' selection and loading is considered as a tactical planning problem in manufacturing system.

3.5.3 Elements of process plan in FMC

A production plan includes the indices of part types, operations and machines corresponding to the operations of all parts. Therefore, each operation is processed on the corresponding machines. Production plan is adapted from the existing literature, especially from Chen and Ho (2005), Biswas and Mahapatra (2008) and Abazari, Solimanpur and Sattari (2012). A machining part consists of more operations, and each operation can be produced on a number of CNC machines. It is assumed that the requirements for production of part types, a number of operations, machining time, and tool slots prepared for each operation of each part type are pre-determined.

Table 3.7: General sample of production plan for FMC

Part type	Batch size	Operation number	Unit processing time	Tool slot needed	Machine number
P_1	B_1	O_{11} O_{12} … O_{1-p1}	pt_{o11} pt_{o12} ... pt_{o1-p1}	ts_{o11} ts_{o12} ... ts_{o1-p1}	M_{o11} M_{o12} ... M_{o1-p1}
P_2	B_2	O_{21} O_{22} … O_{2-p2}	pt_{o21} pt_{o22} ... pt_{o2-p2}	ts_{o21} ts_{o22} ... ts_{o2-p2}	M_{o21} M_{o22} ... M_{o2-p2}
P_3	B_3	O_{31} O_{32} … O_{3-p3}	pt_{o31} pt_{o32} ... pt_{o3-p3}	ts_{o31} ts_{o32} ... ts_{o3-p3}	M_{o31} M_{o32} ... M_{o3-p3}
P_4	B_4	O_{41} O_{42} … O_{4-p4}	pt_{o41} pt_{o42} ... pt_{o4-p4}	ts_{o41} ts_{o42} ... ts_{o4-p4}	Mo41 Mo42 ... M_{o4-p4}
…	…	…	…	…	…
P_p	B_p	O_{p1} O_{p2} … O_{p-pp}	pt_{op1} pt_{op2} ... pt_{op-pp}	ts_{op1} ts_{op2} ... ts_{op-pp}	M_{op1} M_{op2} ... M_{op-pp}

Essential and optional types of operation for each part type are united in each part type. Essential operations can be processed only on pre-determined machine using a certain number of tool slots while optional operations can be produced by a number of machines with various processing time and tool slots. Therefore, the flexibility demonstrated by optional operations is integrated in FMC through the selection of a suitable machine for producing the optional operations of the part types.

Table 3.7 shows part type, batch size, operations, machines and processing time and constraint of tool slots in tool magazine. To produce the finished part types, one or more operations of part type have to be passed with the machining process on one or more machines. In general, it is not easy to find a real production plan in practice because this is a business secret of enterprises. Therefore, the processing time is usually generated randomly to mimic real production planning in practical manufacturing cells.

With a given production plan, there are many solutions for suitable selection of operation and the responding machine for processing to produce the complete product. The sample of necessary data for a production plan is presented in Tables 3.7-3.9. Tables 3.8 and 3.9 describe the constraints on tool slots in tool magazine of machines and transportation time of parts among machines in the system. The structural hierarchy for understanding a production plan is shown as in Figure 3.18.

Table 3.8: Capacity of tool magazine in machine

Machine	Tool slots
M_1	Ts_1
M_2	Ts_2
…	…
M_n	Ts_n

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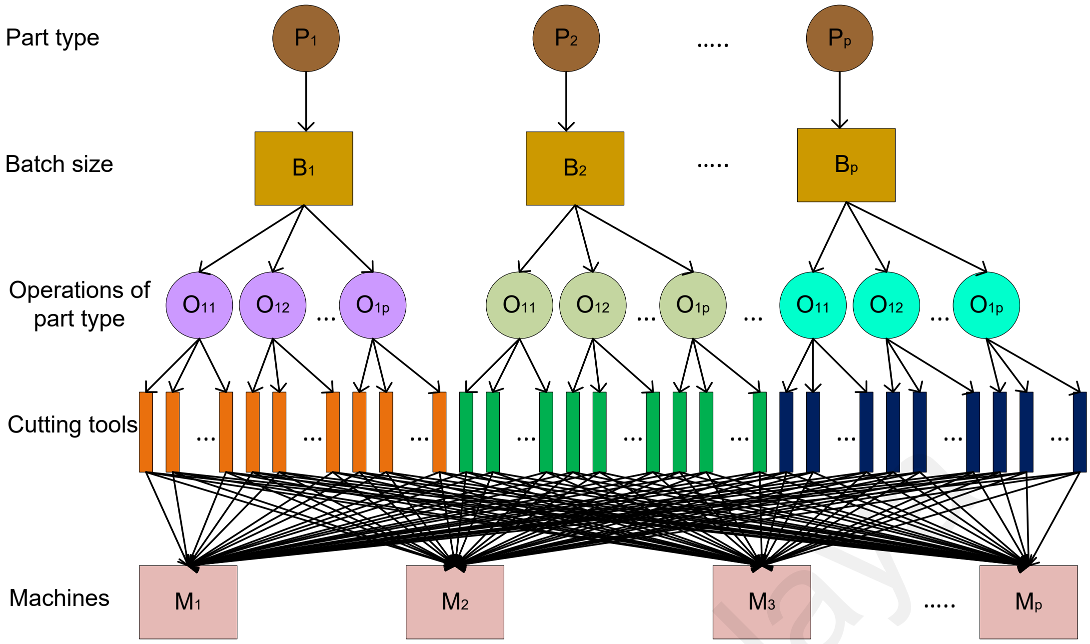

Figure 3.18: Hierarchical structure of production plan for FMC

Table 3.9: Transportation time between machines in FMC

Machine	M_1	M_2	…	M_{m-1}	M_m
M_1	-	t_{12}	…	$t_{1(m-1)}$	t_{1m}
M_2	t_{21}	-	…	$t_{2(m-1)}$	t_{2m}
…	…	…	-	…	…
M_{m-1}	$t_{(m-1)1}$	$t_{(m-1)2}$	…	-	$t_{(m-1)m}$
M_m	t_{m1}	t_{m2}	…	$t_{m(m-1)}$	-

In determining the production plan for FMC, one of the basic requirements is to ensure that the system operates in the optimal conditions, and that is reflected in the selection of suitable combination of machines and operations which satisfies the objectives of productivity. Therefore, the purpose of this model is to consider the selection problem of the best combination of machines and operations to obtain the minimization of system unbalance, makespan and total flow time in FMC.

3.5.4 Assumption

The following assumptions are taken in analyzing the FMC loading problem. Several parts of assumptions are adapted from Biswas and Mahapatra (2008) and Chen and Ho (2005):

1. The type of machines and the number of machines in FMC are known in advance. All the machining parts are processed in the same manufacturing facility.
2. The raw materials and cutting tool that have been prepared for machining process are available as necessary.
3. All of machines and part types are simultaneously available. A part type comprises of several operations. A number of parts are produced simultaneously in batches. Parts can be selected and processed in one or more machines and transported by conveyor.
4. A CNC machine can perform multiple functions of manufacturing operation (milling, drilling, boring, turning, reaming, etc.), and an operation is produced on potential machines equipped with the necessary tools to produce the various part types.
5. The part considered for processing on responding machines must be finished for all its operations before continuing to a new part.
6. All data of process plan are available.
7. The processing time of each operation is predetermined.
8. Loading, unloading and setup time are included in processing time or negligible.
9. The tool slots of magazines are not allowed to share and duplicate the cutting tools.
10. All the designs, layout and setup problems in FMC are already solved.

Real-time problems involving the congestion, traffic control, machine breakdown (failure or downtime), cutting tool breakdown, electricity failure, scraps, rework and failure of conveyor, robot, lack of materials and maintenance are not taken into consideration.

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3.5.5 Notation

The following is a list of the subscripts, variables and parameters used in the model.

Subscripts

$i = 1, 2, ..., N$, part type index in the FMC, where N is the total number of part type processed in FMC.

$i' = 1, ..., B(i)$: index of the i'-th part in batch size of part type i.

$j = 1, 2, ..., J(i)$, index for machining operations in the FMC, where $J(i)$ is the total number of operations of part i, $i = 1, 2, ..., N$.

$k, l, l' = 1, 2, ..., K$, index for CNC machines, where K is the total number of CNC machines in the FMC.

$K_{ii'j} = K(i, i', j)$: set of potential optional CNC machines for processing an operation j of the i'-th part in batch size of part type i, where $j = 1, 2, ..., J(i); i' = 1, 2, ..., B(i);$ $i = 1, 2, ..., N$. For instance, $K_{221} = \{1, 3\}$ shows that the first operation of the second part of part type 2 can be processed on the CNC machine 1 or machine 3.

Parameters

$B(i)$: Batch size of part i, $i = 1, 2, ..., N$.

H: length of the planning horizon (H = 8 hours).

T_k : the number of tool slots available on machine k, $k = 1, 2, ..., K$.

$p_{ii'jk}$: processing time of operation j of the i'-th part in batch size of part type i on machine k, where $j = 1, 2, ..., J(i); i' = 1, 2, ..., B(i);$ $i = 1, 2, ..., N$; $k = 1, 2, ..., K$.

$ts_{ii'jk}$: number of tool slots required for processing operation j of the i'-th part of part type i on machine k, where $j = 1, 2, ..., J(i); i' = 1, 2, ..., B(i);$ $i = 1, 2, ..., N$; $k = 1, 2, ..., K$

$t_{ii'kl}$: the transportation/traveling time from machine k to machine l for the i'-th part of part type i, where $i = 1, 2, ..., N; i' = 1, 2, ..., B(i);\ k, l = 1, 2, ..., K$.

$LT_{ii'k}$: the loading time of the i'-th part of part type I from loading station to machine k.

$ULT_{ii'l'}$: the unloading time of the i'-th part of part type I from machine l' to unloading station.

Decision variables

$$x_{ii'jk} = \begin{cases} 1, \text{if operation } j \text{ of } i'^{-th} \text{part of part type } i \text{ is assigned to machine } k \\ 0, \text{otherwise} \end{cases}$$

$$x_{ii'} = \begin{cases} 1, \text{ if } i'\text{-}th \text{ part of part type } i \text{ is selected for processing} \\ 0, \text{ otherwise} \end{cases}$$

$$x_{ii'k} = \begin{cases} 1, & \text{if } i'\text{-}th \text{ part of part type } i \text{ is loaded and} \\ & \text{assigned to machine } k \text{ from loading station} \\ 0, & \text{otherwise} \end{cases}$$

$$x_{ii'l'} = \begin{cases} 1, & \text{if } i'\text{-}th \text{ part of part type} i \text{ is unloaded and} \\ & \text{returned to unloading station from machine } l' \\ 0, & \text{otherwise} \end{cases}$$

$$x_{ii'jk} \times x_{ii'(j+1)l} = \begin{cases} 1, & \text{if operation } j \text{ of part } (i, i') \text{ completed on machine k} \\ & \text{is conveyed to machine } l \text{ to continue operation } (j+1) \\ & 0, \text{otherwise} \end{cases}$$

3.5.6 Mathematical model of machine loading problem

Three objectives are considered to model the MLP in FMC such as the system unbalance, makespan and the total flow time. A good production plan will make the FMC operate at high performance. A mixed integer linear programming (MILP) model is presented for determining the suitable solution of production plan of N part types over a limited pool of K CNC machines in the FMC. Due to the limitation of the operating time in machines, the machines are considered in the status of under-utilized (unused capacity of machine) or over-utilized (the overload of machine). In this study, the over-

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utilization of machines is allowed in the FMC. The model for selecting the machines and operations to satisfy the objectives of system is formulated based on the assumptions mentioned previously. According to recent practice, most researchers would usually neglect the transporting time in the MLP (Tiwari et al., 2007; Prakash et al., 2008; Arikan and Erol, 2012; Abazari et al., 2012; and Kumar, Murthy et al., 2012). In addition, they did not consider the allocation of each part in each batch size and so the all parts of part types have been assigned to the same machines. Therefore, in this research, the traveling time used based on the conveyor system to contribute to the makespan and total flow time, and each part of the part type is considered to be allocated to different machine in order to ensure the system is balanced.

The three objectives of this model are to minimize the system unbalance, makespan and total flow time for processing all operations of part types in the batch. The objective functions are described as follows:

(1) Minimization of the system unbalance: The balance of workload of machines is balancing the operating time on each machine in the system. It can improve the productivity by avoiding bottleneck machines and maintains the life of machines. This objective function is adapted from Basnet (2012) and Abazari at el. (2012) but is extended to consider the different allocation for each part of part type to different or same machines:

$$Min\ SU = \sum_{k=1}^{K} \left| H - \sum_{i=1}^{N} \sum_{i'=1}^{B(i)} \sum_{j=1}^{J(i)} x_{ii'jk} \times p_{ii'jk} \right| \tag{3.56}$$

where $i = 1, 2, ..., N$, *part type index and N is the total number of part type;* $i' = 1, ..., B(i)$: *index of the* $i'^{\text{-}th}$ *part in batch size of part type* i; $j = 1, 2, ..., J(i)$, *index for machining operations and* $J(i)$ *is the total number of operations of part* i, $i = 1, 2, ..., N$; $k = 1, 2, ..., K$, *index for CNC machines, where K is the total number of CNC machines in the FMC;* $p_{ii'jk}$: *processing time of operation* j *of the* $i'^{\text{-}th}$ *part in batch size of part type* i *on machine* k, *H= 8 hours = 480 (min) and decision variables* $x_{ii'jk} = 0, 1$.

(2) Minimization of makespan: Makespan is the total time to completely process all part types. The objective function is defined as follows:

$$Max\ C(i,i') = \max_{(i,i')}\Bigg[\sum_{k=1}^{K} x_{ii'k} \times LT_{ii'k} + \sum_{j=1}^{J(i)}\sum_{k=1}^{K} x_{ii'jk} \times p_{ii'jk} + \\ + \sum_{k=1}^{K}\sum_{l=1}^{K} t_{ii'kl} \times x_{ii'jk} \times x_{ii'(j+1)l} + \sum_{l=1}^{K} x_{ii'l'} \times ULT_{ii'l'}\Bigg] \tag{3.57}$$

where $k,l,l' = 1,2,...,K$, *index for CNC machines, where K is the total number of CNC machines and decision variables* $x_{ii'jk} \times x_{ii'(j+1)l}$, $x_{ii'k}$, $x_{ii'l'}$ *and* $x_{ii'jk}$.

In particular,

$x_{ii'k} \times LT_{ii'k}$: The loading time of part (*i', i*) from loading station to machine *k*

$\sum_{j=1}^{J(i)}\sum_{k=1}^{K} x_{ii'jk} \times p_{ii'jk}$: The process time of part (*i',i*) on machine *k*.

$\sum_{k=1}^{K}\sum_{l=1}^{K} t_{ii'kl} \times x_{ii'jk} \times x_{ii'(j+1)l}$: The traveling time of part (*i', i*) from machine *k* to machine *l* for processing the next operation (*j+1*).

$\sum_{l=1}^{K} x_{ii'l'} \times ULT_{ii'l'}$: The unloading time of part (*i', i*) from machine *l* to unloading station.

(3) Minimization of the total flow time: The total flow time comprises the total processing time and the transportation/traveling time between machines for processing the parts in the system. Similarly to objective (2), the objective function for total flow time can be expressed as:

$$Min\ TFT = \sum_{i=1}^{N}\sum_{i'=1}^{B(i)}\sum_{k=1}^{K} x_{ii'k} \times LT_{ii'k} + \sum_{i=1}^{N}\sum_{i'=1}^{B(i)}\sum_{j=1}^{J(i)}\sum_{k=1}^{K} x_{ii'jk} \times p_{ii'jk} + \\ + \sum_{i=1}^{N}\sum_{i'=1}^{B(i)}\sum_{j=1}^{J(i)}\sum_{k=1}^{K}\sum_{l=1}^{K} t_{ii'kl} \times x_{ii'jk} \times x_{ii'(j+1)l} + \sum_{i=1}^{N}\sum_{i'=1}^{B(i)}\sum_{l'=1}^{K} x_{ii'l'} \times ULT_{ii'l'} \tag{3.58}$$

Constraints

(1) The decision variables are binary (0-1 integers):

$$x_{ii'jk} = \begin{cases} 0 \\ 1 \end{cases} \text{ and } x_{ii'} = \begin{cases} 0 \\ 1 \end{cases} \tag{3.59}$$

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(2) The magazines of CNC machines must include enough tool slots for operation's assignment:

$$\sum_{i=1}^{N}\sum_{i'=1}^{B(i)}\sum_{j=1}^{J(i)} x_{ii'jk} \times ts_{ii'jk} \le T_k \tag{3.60}$$

where $k = 1, 2, ..., K$; $j = 1, 2, ..., J(i)$; $i' = 1, 2, ..., B(i)$; $i = 1, 2, ..., N$

(3) Once a part type is chosen, each operation of part type can be just processed by one machine. If a part type is not chosen, no CNC machine in FMC is used to produce any operation. This constraint is expressed as follows:

$$\sum_{k \in K(i,i',j)} x_{ii'jk} = x_{ii'} \text{ , where } j = 1, 2, ..., J_i, \; i = 1, 2, ..., N \tag{3.61}$$

3.5.7 Method in solving the machine loading in FMC

3.5.7.1 Background of Biogeography based Optimization (BBO)

(a) ***The optimality principle of BBO***

Biogeography is a subject to study the geographical distribution of the biological organisms. During the 1960s, the distribution of organisms was discovered and modeled based on the mathematical equations that describe the migration of species from one island to another islands in the nature (see Figure 3.19). The migration of species shows the existence in living environment, showing how new species survives and develops. An island is called any habitat when it is insulated geographically to other islands. The geographical regions suitable for the residences of the biological species have a high habitat suitability index (HSI). The features that involve the HSI comprise of diversity of vegetation and topographic features, rainfall, temperature and land region. The decision variables that specialize the habitability is known as the suitability index variables (SIVs), which are independent variables of the habitats, and HSI can be dependent variable. The habitats having a higher HSI will have a larger number of species, whereas the lower HSI habitats have the smaller number of species. The high-HSI habitats include numerous species emigrating to adjacent habitats. The rate of

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immigration of species in the high-HSI habitats is low due to the saturation of species. Thus, in high-HSI habitats, the rate of emigration is high due to good condition for species emigrate to the near habitats. The rate of immigration is high in the low-HSI habitats due to the sparseness of the species in the populations.

As the suitability of a habitat is directly related to the diversity of biology, the HSI of the habitat is higher when the habitat immigrates new species. Meanwhile, low-HSI habitats will have a lower number of species that can go extinct, will open many opportunities for immigrating new varieties of species. Therefore, the habitats with low HSI become more dynamic and flexible in the distribution of species than the habitats with high HSI. Thus, the biogeography is a way of the natural distribution of species, and is similar to the general issues' solutions. A good solution is identified according to the high-HSI island, and poor solution shows an island with the low HSI. The high-HSI solutions oppose the change more than the low-HSI solutions and contribute their features into low-HSI solutions. So, the poor solutions can admit many new features from better solutions. The replacement of new features to the low-HSI solution will improve the quality of these solutions better (Simon, 2008).

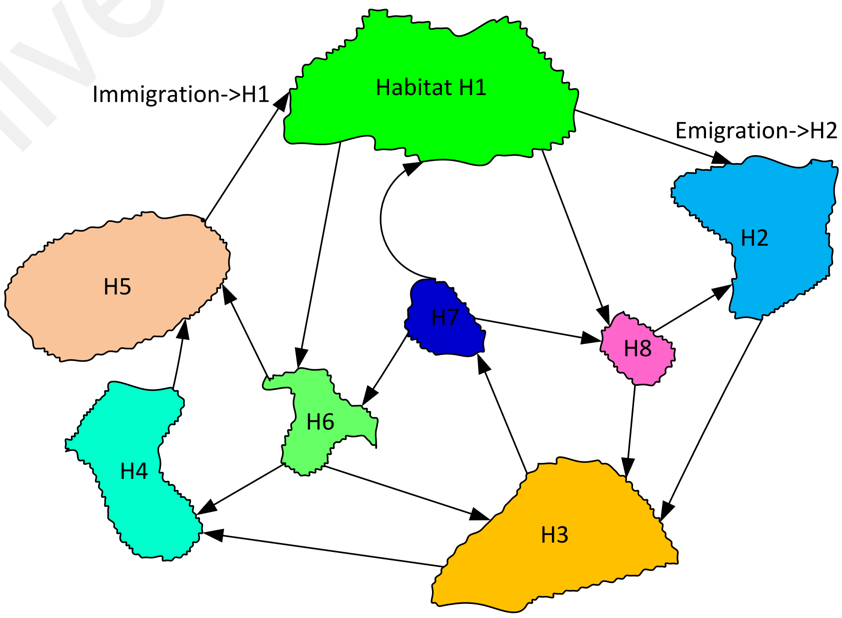

Figure 3.19: The migration process of species among the habitats

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The HSI value consists of the features of the habitats. Each feature is characterized by a value, and the HSI is considered as a function of those values. HSI are represented by SIVs. The mappings from SIVs to HSI are performed as follows (Ying, Min and Zheng, 2010).

$$Habitat \rightarrow (feature_1, feature_2, \cdots, feature_m) \rightarrow (SIV_1, SIV_2, \cdots, SIV_m) \rightarrow HSI$$

The migration rates comprising of the immigration and emigration rate of the habitat with S species are determined as follows (Boussaïd, Chatterjee, Siarry and Ahmed-Nacer, 2012; Rahmati and Zandieh, 2012; Simon, 2008).

$$\lambda_S = I\left(1 - \frac{S}{S_{\max}}\right) \tag{3.62}$$

$$\mu_S = E\left(\frac{S}{S_{\max}}\right) \tag{3.63}$$

where I is the maximum value of the possible immigration rate when no species exist on the habitat, and E is the maximum value of the emigration rate when the S_{max} number of species exists on the habitat is the busiest.

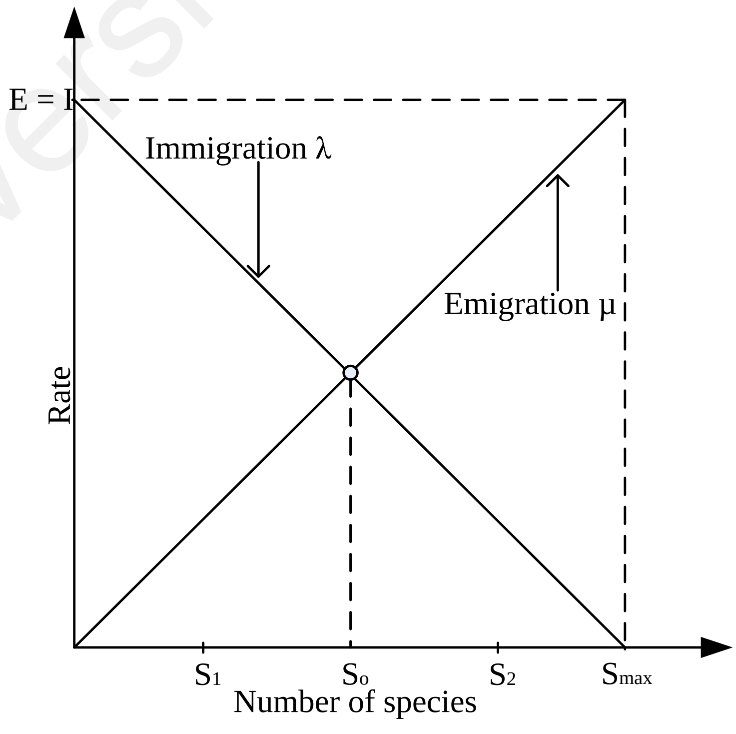

Figure 3.20: The model of species in a single habitat between two candidate solutions. In particular, S_1 is a poor solution while S_2 is a good solution (Simon, 2008).

Figure 3.20 shows the relationships of the islands' fitness involving the immigration λ and emigration rates μ. The equilibrium point S_o (number of species) is obtained at the intersection of the linear lines of immigration and emigration rates. At this point, the immigration rate λ is equal to the emigration rate μ. In the graph in Figure 3.20, S_2 is considered a good solution with high HSI because of its high emigration rate and low immigration rate whereas S_1 is a poor solution with low HSI due to a low emigration and high immigration rates.

(b) ***Migration operator***

The migration is an adaptive process for the changes in living environments of habitats by changing the SIV. Each habitat is modified according to the user defined probability value P_{mod}. The immigration rate is determined probabilistically and used to modify each SIV in the habitat. Another island is chosen with emigration rate μ, its SIV is randomly migrated to the selected island's SIV. A good solution is similar to the high-HSI island while a poor solution presented by a low-HSI island or habitat. A high-HSI island is capable of maintaining change more than low-HSI island. Useful information can be shared from the good solution to the poor solution to improve the ability of exploration in the algorithm (Jamuna and Swarup, 2012). The migration procedure of BBO is described in Figure 3.21.

Migration procedure:
1. Select habitat H_i with probability proportional to λ_i
2. **if** *rand*(0, 1) ≤ λ_i
3.   **for** j = 1 : n
4.   Select habitat H_j with probability proportional to μ_j
5.   **if** *rand*(0, 1) ≤ μ_j
6.   Randomly select an SIV σ from H_j
7.   Replace the corresponding variable with σ in H_i
8.   **end if**
9.   **end for**
10. **end if**

Figure 3.21: The migration procedure of BBO

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(c) ***Mutation operator***

The mutation is an operation to improve the diversity of the population in order to reduce the possibility of getting trapped in the local optima, and achieve a better solution. The elitism (copy few of the fittest/finest individuals into the next generation) is used to ensure the survival of the most potential individuals. The habitats with high and low HSI values are less possible to mutate than the habitats with the average HSI values. The mutation operator will allow the random modification of the habitat's SIV relying on the probability of mutation m in the case of E = I (Boussaïd et al., 2012; Jamuna and Swarup, 2012) as described in Figure 3.22. The mutation rate is determined as follows.

$$m(s) = m_{max} \times \left(1 - \frac{P_S}{P_{max}}\right) \tag{3.64}$$

where m_{max} is parameter defined by user and P_{max} = argmaxP_s, s = 1, 2, ..., P. P is a number of habitats, P_s is the probability of count probabilities which is computed from immigration and emigration rates λ_s and μ_s. The species count probability is determined as follows (Simon, 2008).

$$\dot{P}_s = \begin{cases} -(\lambda_s + \mu_s)P_s + \mu_{s+1}P_{s+1} & s = 0 \\ -(\lambda_s + \mu_s)P_s + \mu_{s-1}P_{s-1} + \mu_{s+1}P_{s+1} & 1 \le s \le s_{max} \\ -(\lambda_s + \mu_s)P_s + \mu_{s+1}P_{s+1} & s = s_{max} \end{cases} \tag{3.65}$$

The count of species in the island/habitat changes over time. The values such as λ_{s-1}, λ_s, λ_{s+1} and μ_{s-1}, μ_s, μ_{s+1} are the immigration and emigration rate of the habitats with s, s-1 and s+1 species, respectively. The parameters P_s, P_{s-1}, P_{s+1} are the species count probabilities of the habitat with s, s-1, s+1, respectively. Finally, s_{max} is the maximum value of the species count in the habitat.

According to Simon (2008) and Mo and Xu (2011), at the steady state, the species count probability is calculated by:

$$P_s = \frac{[v_1, v_2, \cdots, v_{n+1}]}{\sum_{i=1}^{n} v_i} \tag{3.66}$$

where $v_i = \begin{cases} \dfrac{n!}{(n-1-i)!(i-1)!} & (i = 1,..,i^+) \\ v_{n+2-i} & (i = i^+ + 1,..., n+1) \end{cases}$ in which i^+: smallest integer $\geq (n+1)/2$

For the straight line curves of migration process in the habitat, we determine some following parameters:

$$HSI = \frac{i}{N}; \quad \lambda_K = I\left(1 - \frac{K}{N}\right); \text{ and } \mu_K = \frac{E.K}{N} \tag{3.67}$$

Mutation procedure
1. **for** j = 1 : m
2. Use λ_i and μ_i to determine the probability proportional to P_i
3. Select SIV $H_i(j)$ with probability proportional to P_i
4. **If** *rand*(0,1) $\leq m_i$
5. Replace $H_i(j)$ with a randomly generated SIV
6. **end** if
7. **end** for

Figure 3.22: The mutation procedure of BBO

(d) ***The BBO algorithm procedure***

BBO is a natural inspired algorithm and a novel approach to solve NP-hard problems. It has some fundamental properties similar to genetic algorithm. The comparison of the similarity of BBO algorithm and Genetic algorithms (GA) in terms of definition and concepts have been reported by (Rahmati and Zandieh, 2012), as listed in Table 3.10. However, the initial population in the BBO is not eliminated among the various generations. Moreover, the concept of migration is utilized to modify the population and the fitness function is not employed to justify the population.

In BBO, the fitness function is only utilized for determining the migration ratios which are the immigration and emigration rates (Paslar, Ariffin, Tamjidy and Hong, 2014). The BBO procedure is described in Figure 3.23

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Table 3.10: Comparison in terms of the terminology between BBO and GA

	BBO	GA
1	Population-based	Population-based
2	Habitat (individual)	Chromosome (individual)
3	SIV	Gen
4	Habitats consisted of SIVs	Chromosomes consisted of Gens
5	Mutation operator	Mutation operator
6	Migration operators (immigration and emigration) No reproduction	Crossover operator Reproduction with P_{re} rate
7	Good solution is characterized by high HSI	Good solution is characterized by high fitness
8	A good habitat is one which has more diversity and species	A good chromosome is the one which has more value of fitness function
9	No individual of initial population discard during iterations but it is modified	Initial individuals can be discarded by GA operators during iterations

In recent years, BBO has shown potential applications in the manufacturing systems. It is used to handle the scheduling problem of FMS (Paslar et al., 2014), vehicle routing problem (Berghida and Boukra, 2014), flexible job shop scheduling problem (Rahmati and Zandieh, 2012) and job shop scheduling problems (Wang and Duan, 2014).

BBO procedure:
1. Initialize a population of habitats
2. **While** termination criteria not obtain
3. Evaluate HSI for each habitat
4. Determine S, λ and μ for each habitat
5. Modify habitats (*Migration*) based on λ and μ
6. **for** i = 1 : N
7. Decide probabilistically the habitat based on λ_i to immigrate to x_i
8. **if** *rand*(0, 1) < λ_i
9. **for** j = 1 : N
10. Select the emigrating habitat x_j with probability μ_j
11. **if** *rand*(0, 1) < μ_j
12. Replace a randomly selected decision variable (*SIV*) of x_i with its corresponding variable in x_j
13. **end if**
14. **end for**
15. **end if**
16. **end for**
Mutation operator
Elitism mechanism to gain the best habitats in the population from one generation to the next.
17. end while

Figure 3.23: The BBO procedure

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3.5.7.2 Background of non-dominated sorting procedure

An optimization issue involves one or multiple objective functions, the responsibility of exploring the most suitable solutions is known as multi-objective optimization. From the management point of view, such problems are considered as an MCDM process. There are many reasons why more attention is now focused on multiple objective problems which naturally reflect most real-world problems. Different solutions can produce trade-offs/balance among various objectives. A solution can be good for one objective but bad for another. Thus, its solutions should balance the benefits from the objectives enables the decision-makers to make decision easier and more accurate. Some definitions of non-dominated sorting solutions are extracted from Gen et al. (2008) and Simon (2013).

Domination: A solution x^* dominates a solution x $(x^* \succ x)$ when two following conditions are satisfied: $f_i(x^*) \leq \mathrm{f}_i(x), \forall i \in [1,k]$ and $f_j(x^*) < f_j(x), \exists j \in [1,k]$

Weak domination: A solution x^* dominates weakly a solution x $(x^* \succ x)$ if $f_i(x^*) \leq \mathrm{f}_i(x), \forall i \in [1,k]$

Nodiminated: if no solution x dominates a solution x^*, then solution x^* is called dominated.

To implement the sorting procedure of a population with size N following to non-dominated levels, we have to compare each solution with each other in the population to determine the non-dominated solutions. This procedure is continued to obtain the first non-dominated group of all population individuals and all individuals in the first non-dominated front are determined. Next, the solutions belonging to the first front are temporary discounted in order that the above procedure is repeated for finding the individual in next front (Deb, Pratap, Agarwal, and Meyarivan, 2002; Li, Pan, and Gao, 2011; Moradi, Fatemi Ghomi, and Zandieh, 2011; Palanikumar, Latha, Senthilkumar,

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and Karthikeyan, 2009). The non-dominated sorting process implemented for the population P will carry out a list of non-dominated solutions (see Figure 3.24). We used the following notations to present the non-dominated sorting procedure: (1) n_i, the number of individuals that dominate the individual i; (2) S_i, this set consists of the individuals that is being dominated by individual i; (3) F_1, the first front and (4) H, the current front contains the current individuals/solutions.

Non-dominated sorting procedure of population (P) (Deb et al., 2002)

for each $p \in P$	for each individual p in main population P do the following
Initialize $\mathrm{S}_p = 0$	This includes all individuals that are dominated by p
Initialize $\mathrm{n}_p = 0$	n_p as the number of individuals that dominate p
for each $q \in P$	
if $(p \prec q)$ then	if p dominates q then
$\mathrm{S}_p = S_p \cup \{q\}$	include q in S_p
else if $(q \prec p)$ then	if p is dominated by q then
$n_p = n_p + 1$	increment n_p
if $n_p = 0$ then	if no solution dominates p then
$F_1 = F_1 \cup \{p\}$	include p in the first front F
$i = 1$	Initialize the front counter $i = 1$
while $F_i \neq \phi$	
H=ϕ	
for each $p \in F_i$	for each member p in F_i
for each $q \in S_p$	modify each member fromthe set S_p
$n_q = n_q - 1$	decrement n_q by one
if $n_q = 0$ then $\mathrm{H} = \mathrm{H} \cup \{q\}$	if n_q is zero, q is a member of a list H
$i = i + 1$	
$F_i = \mathrm{H}$	current front is formed with all members in H

Figure 3.24: The non-dominated sorting procedure

- **Crowding distance:** Crowding distance is used to evaluate the density of solutions around a particular individual in the population (Deb et al., 2002). The crowding distance is calculated based on the determination of the Euclidian distance between each

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solution in a front according to multiple objectives. The steps to assign the crowding distance are described in Figure 3.25.

crowding distance assignment (L)
$l = \vert L \vert$ number of individuals/solutions in L
for each i, set $L[i]_{\text{distance}} = 0$ initialize distance
for each objective m
$L = \text{sort}(L, m)$ sorting using each objective value
$L[1]_{\text{distance}} = L[l]_{\text{distance}} = \infty$ set the boundary values
for $i = 2$ to $(l-1)$ for all other points
$L[i]_{\text{distance}} = L[i]_{\text{distance}} + (L[i+1].m - L[i-1].m)$
where $L[i].m$ is the value of the m^{th} objective function of the i^{th} individual in L.

Figure 3.25: The assignment procedure of crowding distance

- **Selection**

After non-dominated sorting and assigning the crowding distance in the population, the selection operator is conducted as follows.

(1) Non-domination rank i_{rank}: the individuals of F_i front have a rank as $i_{\text{rank}} = i$.

(2) Crowding distance $L[i]_{\text{distance}}$: $p <_n q$ if $p_{\text{rank}} < q_{\text{rank}}$ or if p and q are in the same front then the crowding distance should be larger.

3.5.7.3 The proposed steps for machine loading problem

The proposed approach for machine loading in FMC is described in Figure 3.26 with the steps as follows.

Step 1: Initial population: Initialize feasible solution.

Step 2: Duplicates: to check and estimate the individual duplications in population.

Step 3: Evaluate the objective function with the constraints.

Step 4: Operators: migration and mutation operators.

Step 5: Sort: ranks of individuals in population based on non-dominated sorting and crowding distance.

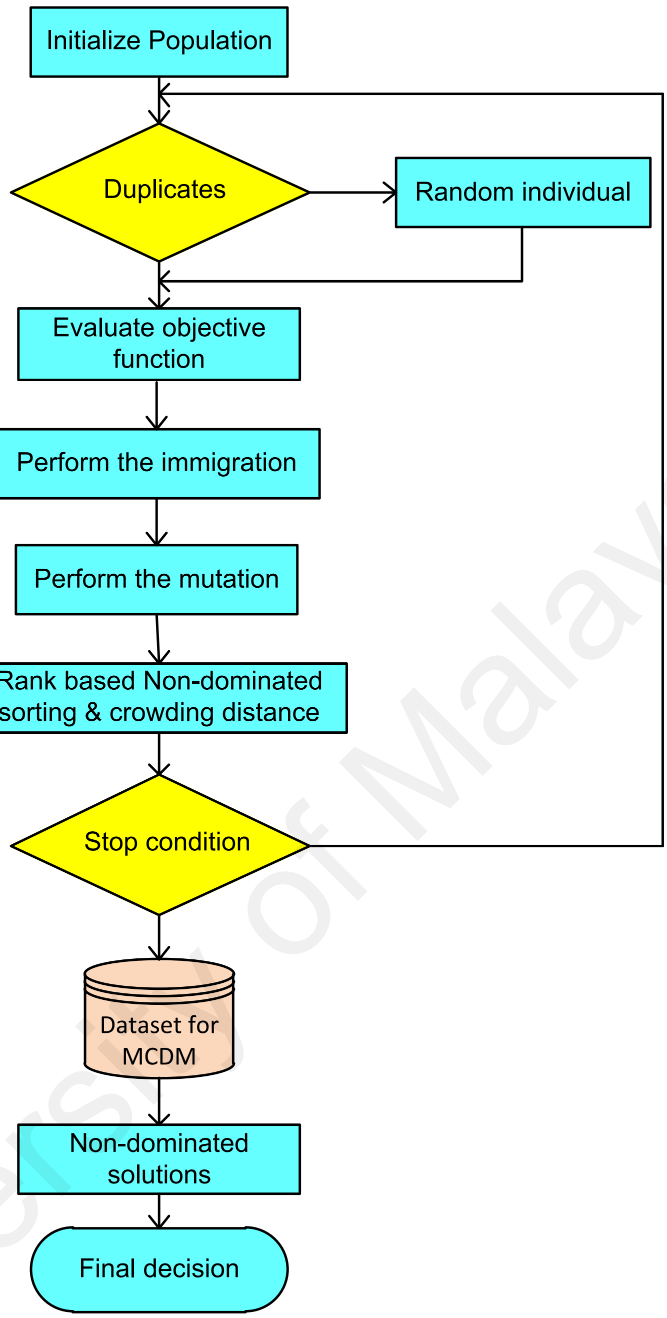

Figure 3.26: The proposed approach for machine loading in FMC

In order to implement this algorithm, we first create the initial population consisting of feasible solutions. Then, the operators of migration and mutation are applied in populations to create a new population consisting of individuals having more improvements. To take advantage of the best individuals in the new and old populations, a combined population is created and includes all the individuals. Therefore, the size of new population is doubled and it will undergo selective mechanism based on non-dominated sorting and crowding distance to form an entirely new population with the original size. This new population will continue to cycle until the solutions satisfy the requirements or the termination conditions is obtained. Figure 3.27 shows the steps of BBO. Moreover, the process of multiple objective BBO method is illustrated in Figure 3.28.

Step 1: Determine the initial parameters and population
Step 2: Check and estimate the duplicates
Step 3: Evaluate the habitat
Step 4: Implement the operators of migration and mutation
Step 5: Determine the rank of the habitats.
Step 6: Update the habitat population with double size.
Step 7: Sort and select elite habitats for next generation.
Step 8: If the terminating condition is satisfied,
the algorithm ends; else, go to step 2.

Figure 3.27: Main algorithm for determining the near-optimal solutions

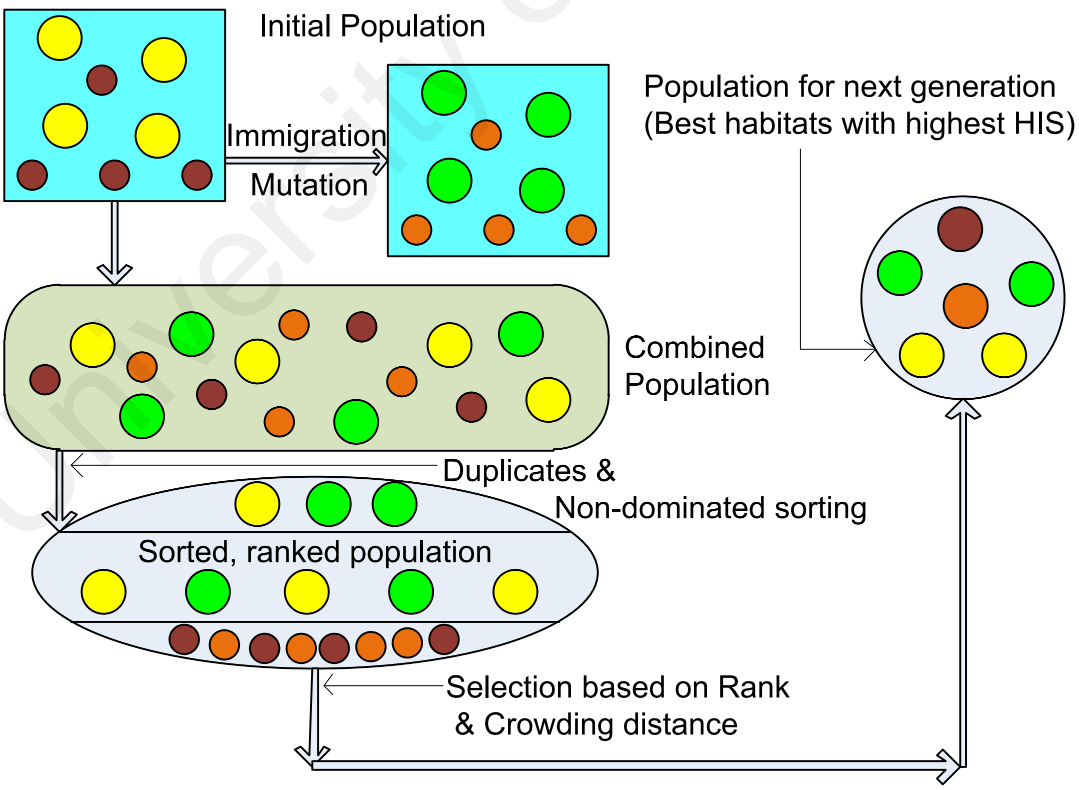

Figure 3.28: Process of the multiple objective BBO Algorithm (adapted from (Mohapatra, Benyoucef, and Tiwari, 2013)

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3.5.7.4 Implementation of non-dominated sorting BBO

(a) ***The initialization of the habitat***

For initiate algorithm, an initial population of solutions is generated. These solutions are presented by the structure of habitats. In this study, the approach used to create the initial population is based on the methods presented by Wang, Gao and Shao (2010), Rahmati and Zandieh (2012) and Paslar et al. (2014). In their methods, the two machines are chosen from the set of potential machines for each operation. For the aim of machines selection, a random number is generated within the interval [0, 1], if this random number is less than 0.8, a machine with a shorter processing time is prior to select; otherwise, a machine with longer processing time is selected.

(b) ***Representation of the habitat***

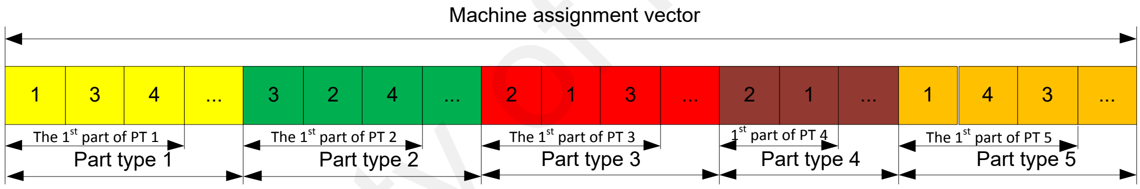

Figure 3.29: The presentation of habitat, adapted from (Paslar et al., 2014; Rahmati and Zandieh, 2012; Wang et al., 2010)

The presentation for the structure of the habitat is similar to the structure of the individuals in genetic algorithm. The structure of the habitat in this approach is adapted from Wang et al. (2010), Paslar et al. (2014), Rahmati and Zandieh (2012) and Gen et al. (2008) shown in Figure 3.29. This representation consists of vector for assigning suitable operations to the potential machines in the system. A habitat is scanned from the left to the right. The length of habitat is the same as the length of vector. The difference between this representation and others for MLP in the literature is that it includes the consideration of batch size of part type. It means that the length of habitat representation is equal to the total batch sizes of all the part types to be processed in FMC.

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Table 3.11: Process plan for FMC with 5 part types and 4 CNC machines

Part	Operation	Processing time			
		M1	M2	M3	M4
1	1	4	5	-	7
	2	-	3	2	-
	3	3	2	-	2
2	1	2	-	3	-
	2	-	7	9	6
	3	7	-	5	-
3	1	-	4	4	8
	2	5	6	7	-
	3	-	4	-	5
4	1	-	4	5	7
	2	6	-	6	7
5	1	4	-	5	7
	2	4	6	-	5
	3	3	4	2	-

For example, the scheme of the habitat seen in Figure 3.29 is based on the process plan (Table 3.11). The assignment vector is a vector of [1 3 4 … – 3 2 4 …– 2 1 3 … – 2 1… – 1 4 3…]. It means that the suitable machines are assigned to the corresponding operations of the first part of part types 1, 2, 3, 4, and 5 needed to be processed in the system. From the machine assignment vector, we can read the suitable solution as [Part type 1: (O_{11}, M1); (O_{12}, M3); (O_{13}, M4)…; Part type 2: (O_{21}, M3); (O_{22}, M2); (O_{23}, M4)…; Part type 3: (O_{31}, M2); (O_{32}, M1); (O_{33}, M3)…; Part type 4: (O_{41}, M2); (O_{42}, M1)…; and Part type 5: (O_{51}, M1); (O_{52}, M4); (O_{53}, M3)…].

(c) ***Migration operator***

Migration is an adaptive process in the biogeography environment. The mechanism of migration is used to immigrate and emigrate the species from a habitat to another. The probability ratio is utilized to determine the migration process which comprises of two processes of immigration and emigration. Both of these processes are represented by immigration rate λ_i and emigration rate μ_i. The selection of solution IH as the immigrating habitat IH depends on the immigration rate λ_i and solution EH as

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emigration rate depends on the emigration rate μ_i. The parameter values of migration rates can be determined as described in Eq. 3.67.

After choosing the immigrating and emigrating habitats, the operators of migration are completed based on the principles of the crossover operator in GA. Multi-point preservative crossover (MPX) described by Gen et al. (2008) is used for the process of migrating the representation of the habitat. MPX are applied for the migration operators in the vectors of machine assignment (Rahmati and Zandieh, 2012) as shown in Figure 3.30. The principles of MPX are implemented as follows (Paslar et al., 2014).

Step 1: For the operator of MPX migration on machine assignment vector, we randomly generate a vector comprising of values 0 and 1. This vector has the same length with the habitat size. The name of the vector is called Rand.

Step 2: Direct copies (same positions) of IH to the MH at Rand = 0.

Step 3: Direct copies (same positions) of EH to the MH at Rand = 1.

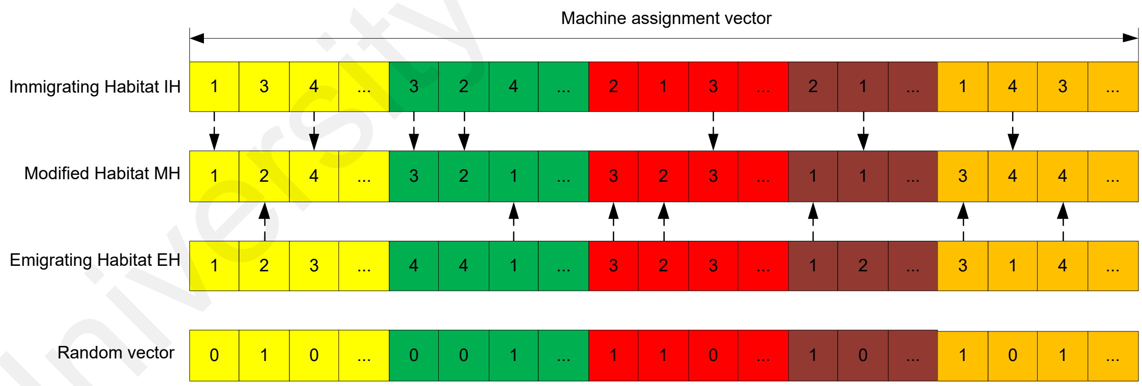

Figure 3.30: Migration operator of MPX

(d) ***Mutation operator***

Mutation is an operator of selection based on the probability of existence in the population. It is applied to maintain and to increase the diversity of solutions by modifying one or more chosen SIV of solution randomly. To apply the mutation operator for BBO algorithm, as shown in Figure 3.31, the principle of the implementation is adapted from Wang et al. (2010) and Gen et al. (2008).

Step 1: Choose the machine assignment vector of the habitat SIV.

Step 2: Randomly select two positions, and change each number with another potential machine from the set of alternative machines for these two operations.

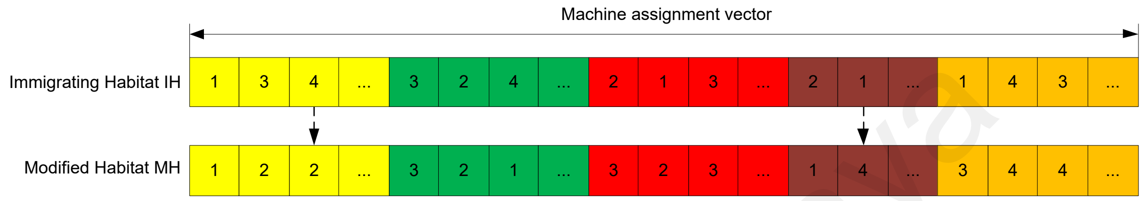

Figure 3.31: Mutation operator of vectors of machine assignment

(e) ***Evaluation of the habitat***

HSI is used to select and evaluate the habitat in BBO algorithm. HISI plays the critical role for determining the probability of habitat selection and being considered as fitness function in GA. The value of HSI depends on the objective function in the optimization problems.

(f) ***Updating the habitat's population***

In maintaining the elites in the habitat population, the combination of the initial population and modified habitat population after the migration operators is implemented. Thus, the size of the habitat population will be doubled as compared to the previous population. Then, the merged habitat population is sorted based on non-dominated sorting and crowding distance. Finally, the best elite habitats are chosen from the combined population to establish the new population with the original size for the next generation.

(g) ***Stopping criteria***

The stopping criteria are used to terminate the computational running time of algorithm after the process of repeating the migration operators to determine the most suitable solution. In this case, the maximum time is considered as the stopping criterion for computational process.

3.6 Summary

This chapter presents an integrated framework of multi-criteria analysis for machine tool selection and optimal machine loading in FMC.

Firstly, the preliminary evaluation of CNC machine tools is conducted based on the manufacturing goals to establish an FMC. The integrated approach of fuzzy linguistic preference based AHP and fuzzy COPRAS is developed to evaluate the most suitable machine tools of a set of the alternatives from the market.

Secondly, the finalization of decisions in machine tool selection from the first stage is implemented based on the newly proposed hybrid method of fuzzy ANP and COPRAS-G.

Finally, the machine loading problem is modeled to determine the most appropriate solutions of combination between machine tools and operations of part types with minimization of the system unbalance, makespan and total flow time in FMC. The non-dominated BBO approach is proposed to explore the best process plan in producing the numerous part types with different batch size in manufacturing cell.

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CHAPTER 4: RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results of fuzzy multi-criteria analysis for machine tool selection, and non-dominated sorting BBO approach for machine loading problem in FMC. Firstly, the integrated approach of fuzzy AHP and fuzzy COPRAS is developed to evaluate and select the preliminary machine tool from the marketplace with the aid of fuzzy preference relations. Secondly, the newly hybrid method of fuzzy ANP and COPRAS-G is proposed to determine the most suitable machine tool for implementing FMC at manufacturing SMEs. Finally, the result of sensitivity analysis is presented to prove the robustness of alternative ranking of machine tools.

Next, the chapter continues by presenting the analytical results of selecting the most appropriate combination of machines and operations for producing the part types in FMC. The result of non-dominated sorting BBO approach is used to explore the feasible solutions of machine loading problem. Data from two case studies are collected for use to run the BBO based on the literature and real conveyor in a manufacturing lab. The final decision of the best combination of machines and operations is carried out based on non-dominate sorting principle and is verified with other existing methods and LINGO software.

4.2 Preliminary evaluation of machine tools

4.2.1 Results on preliminary machine tool evaluation using FAHP and FCOPRAS

The survey designed for formulating the comparison decision matrix is conducted by the decision-makers with 10 attributes, which are extracted from literature and catalogues of CNC machines (cost-A1, power-A2, maximum spindle speed-A3, maximum tool diameter-A4, number of tools-A5, cutting feed-A6, traverse speed-A7,

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positioning precision accuracy-A8, machine dimension-A9 and table area-A10). They are shown on the decision hierarchical structure as in Figure 3.3, with five machining machines chosen as alternatives for decision-making process. The pair-wise comparison matrix of the attributes is collected with fuzzy linguistic assessment variables, as shown in Table 4.1, based on the data from questionnaire (see Appendix D).

Table 4.1: Pair-wise comparison matrix among the attributes of CNC machines

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Cost (A1)	*	M								
Power (A2)		*	P							
Maximum Spindle Speed (A3)			*	G						
Maximum Tool Diameter (A4)				*	MG					
Number of Tools (A5)					*	P				
Cutting Feed (A6)						*	G			
Traverse Speed (A7)							*	VP		
Positioning Precision Accuracy (A8)								*	VG	
Machine Dimension (A9)									*	P
Table Area (A10)										*

The (*) symbol in Table 4.1 presents the fuzzy number (0.5, 0.5, 0.5)

The pair-wise comparison matrix among the attributes of machines is created with 9 elements/cells to corresponding 9 judgments from the experts. The remainder of the elements within the matrix is calculated by applying Eqs. 3.1 – 3.11, outlined in Chapter 3. A MATLAB program is developed to determine the values of the remaining of elements in the decision matrix. The resulting elements are shown in Table F.1 (Appendix F). For example, to calculate the value of $\tilde{p}_{91}$ in the decision matrix, equations Eqs. 3.9-3.11 are utilized as follows:

$$\tilde{p}_{91} = (p_{91}^L, p_{91}^M, p_{91}^R)$$

$$p_{12}^L + p_{23}^L + p_{34}^L + p_{45}^L + p_{56}^L + p_{67}^L + p_{78}^L + p_{89}^L + p_{91}^R = \frac{(9-1)+1}{2} = \frac{9}{2}$$

$$\Rightarrow p_{91}^R = \frac{9}{2} - (p_{12}^L + p_{23}^L + p_{34}^L + p_{45}^L + p_{56}^L + p_{67}^L + p_{78}^L + p_{89}^L)$$

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$p_{91}^{M} = \frac{9}{2} - (p_{12}^{M} + p_{23}^{M} + p_{34}^{M} + p_{45}^{M} + p_{56}^{M} + p_{67}^{M} + p_{78}^{M} + p_{89}^{M})$

$p_{91}^{L} = \frac{9}{2} - (p_{12}^{R} + p_{23}^{R} + p_{34}^{R} + p_{45}^{R} + p_{56}^{R} + p_{67}^{R} + p_{78}^{R} + p_{89}^{R})$

Therefore, from the above equations, the value of element $\tilde{p}_{19} = (p_{19}^{L}, p_{19}^{M}, p_{19}^{R}) = \tilde{p}_{91}^{-1}$. According to Eqs.3.3-3.5, we have:

$p_{19}^{L} = 1 - p_{91}^{R};\ p_{19}^{M} = 1 - p_{91}^{M}; p_{19}^{R} = 1 - p_{91}^{L}.$

As there are some elements of Table F.1 (Appendix F) falling out of the interval [0,1], thus, according to Eq. 3.12, the transforming function f(x) = (x+0.9)/(1+2*0.9) is used to preserve the consistency of matrix, and the result is shown in Table F.2 (Appendix F).

The average values and weights of attributes are determined with Eq. 3.27 and Eq. 3.28, and the defuzzification of fuzzy triangular numbers is calculated using Eq. 3.29. Table 4.2 shows the results of average values, fuzzy weights and defuzzied weights of the attributes for decision-making process. Figure 4.1 presents a bar chart to illustrate the weights of attributes for evaluating the machine tool alternatives.

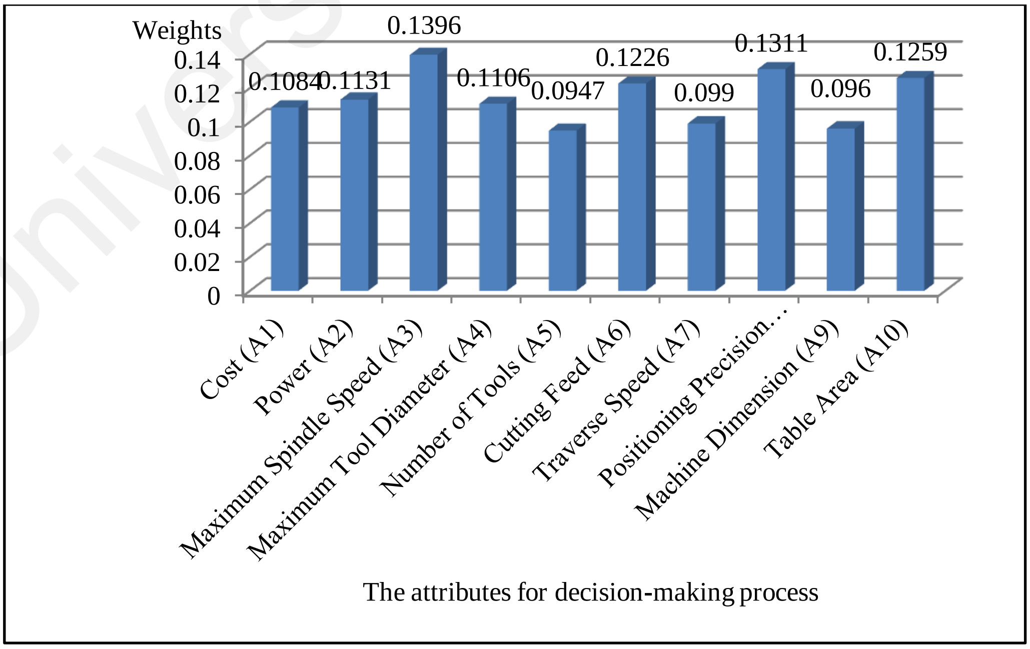

Figure 4.1: The weights/priorities of attributes

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Table 4.2: Weights of attributes

	Average	Weights/Priorities	Defuzzied Weights
A1	(0.24,0.48,0.66)	(0.04,0.10,0.19)	0.1084
A2	(0.30,0.48,0.68)	(0.05,0.10,0.20)	0.1131
A3	(0.45,0.63,0.78)	(0.07,0.13,0.22)	0.1396
A4	(0.35,0.48,0.63)	(0.05,0.10,0.18)	0.1106
A5	(0.29,0.41,0.54)	(0.04,0.08,0.16)	0.0947
A6	(0.42,0.55,0.67)	(0.06,0.11,0.19)	0.1226
A7	(0.30,0.43,0.57)	(0.05,0.09,0.17)	0.0990
A8	(0.44,0.59,0.72)	(0.07,0.12,0.21)	0.1311
A9	(0.26,0.41,0.57)	(0.04,0.08,0.17)	0.0960
A10	(0.40,0.54,0.72)	(0.06,0.11,0.21)	0.1259
Total	(3.45,5.00,6.55)		

The decision matrix is established based on the experts' judgments, as shown in Table 4.3. The experts use the fuzzy linguistic terms described in Table 3.3 to perform their assessment of each alternative against each attribute. Table 4.4 depicts the decision matrix with the presence of fuzzy numbers which has been converted from linguistic terms.

Table 4.3: Decision support matrix/trade-off matrix using fuzzy linguistic term

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Machine 1 (MC1)	H	L	H	M	M	M	M	VH	M	M
Machine 2 (MC2)	H	L	H	M	M	M	M	VH	M	M
Machine 3 (MC3)	H	L	M	H	VL	M	M	VH	M	M
Machine 4 (MC4)	H	L	M	H	VL	M	M	VH	M	M
Machine 5 (MC5)	H	L	H	H	M	M	M	VH	L	M

Table 4.4: The trade-off matrix/decision matrix using the fuzzy numbers

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Machine 1 (MC1)	(5,7,9)	(1,3,5)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(7,9,9)	(3,5,7)	(3,5,7)
Machine 2 (MC2)	(5,7,9)	(1,3,5)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(7,9,9)	(3,5,7)	(3,5,7)
Machine 3 (MC3)	(5,7,9)	(1,3,5)	(3,5,7)	(5,7,9)	(1,1,3)	(3,5,7)	(3,5,7)	(7,9,9)	(3,5,7)	(3,5,7)
Machine 4 (MC4)	(5,7,9)	(1,3,5)	(3,5,7)	(5,7,9)	(1,1,3)	(3,5,7)	(3,5,7)	(7,9,9)	(3,5,7)	(3,5,7)
Machine 5 (MC5)	(5,7,9)	(1,3,5)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(7,9,9)	(1,3,5)	(3,5,7)

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In the subsequent step, defuzzification of the values of the elements or cells in the trade-off matrix is implemented using Eq. 3.15. The results are shown in Table 4.5.

Table 4.5: Defuzzification of decision support matrix/trade-off matrix

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Machine 1 (MC1)	7.00	3.00	7.00	5.00	5.00	5.00	5.00	8.33	5.00	5.00
Machine 2 (MC2)	7.00	3.00	7.00	5.00	5.00	5.00	5.00	8.33	5.00	5.00
Machine 3 (MC3)	7.00	3.00	5.00	7.00	1.67	5.00	5.00	8.33	5.00	5.00
Machine 4 (MC4)	7.00	3.00	5.00	7.00	1.67	5.00	5.00	8.33	5.00	5.00
Machine 5 (MC5)	7	3	7	7	5	5	5	8.33	3	5

After defuzzification of the trade-off matrix is implemented, the normalization values of the elements in the matrix are calculated according to step 6 in fuzzy COPRAS method (see Section 3.3.2.2) and converted to the weighted normalized values by multiplying with the weights of the attributes according to Eq. 3.16. Finally, the weighted normalized decision support matrix is obtained as shown in Table 4.6.

Table 4.6: Weighted normalized decision matrix

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Weights	0.1084	0.1131	0.1396	0.1106	0.0947	0.1226	0.0990	0.1311	0.0960	0.1259
Optimization Direction	Min	Max	Max	Max	Max	Max	Max	Max	Min	Max
Machine 1 (MC1)	0.1084	0.1131	0.1396	0.0790	0.0947	0.1226	0.0990	0.1311	0.0960	0.1259
Machine 2 (MC2)	0.1084	0.1131	0.1396	0.0790	0.0947	0.1226	0.0990	0.1311	0.0960	0.1259
Machine 3 (MC3)	0.1084	0.1131	0.0997	0.1106	0.0316	0.1226	0.0990	0.1311	0.0960	0.1259
Machine 4 (MC4)	0.1084	0.1131	0.0997	0.1106	0.0316	0.1226	0.0990	0.1311	0.0960	0.1259
Machine 5 (MC5)	0.1084	0.1131	0.1396	0.1106	0.0947	0.1226	0.0990	0.1311	0.0580	0.1259
PIS	0.1084	0.1131	0.1396	0.1106	0.0947	0.1226	0.0990	0.1311	0.0058	0.1259
NIS	0.1084	0.1131	0.0997	0.079	0.0316	0.1226	0.0990	0.1311	0.0960	0.1259
	A1: Cost A2: Power A3: Maximum Spindle Speed A4: Maximum Tool Diameter A5: Number of Tools					A6 : Cutting Feed A7 : Traverse Speed A8 : Position Precision A9 : Machine Dimension A10: Table Area				

In the following step, after the weighted normalized decision matrix is obtained, Eq. 3.17, Eq. 3.18, Eq. 3.19, Eq. 3.21 and Eq.3.23 are used to determine the values of P_i, R_i, Q_i, N_i. The results are shown in Table 4.7. The PIS (Positive Ideal Solution) and NIS

(Negative Ideal Solution) are used to determine the ranking according to TOPSIS methodology.

Table 4.7: Results of the ranking for machine tool alternatives

	Pi	Ri	Qi	Ni	Rank	d(+)$_{Topsis}$	d(-)$_{Topsis}$	Cc Topsis	Rank$_{Topsis}$
Machine 1 (MC1)	0.9050	0.2044	1.0149	94.68%	2	0.0494	0.0747	.6019	2
Machine 2 (MC2)	0.9050	0.2044	1.0149	94.68%	2	0.0494	0.0747	.6019	2
Machine 3 (MC3)	0.8336	0.2044	0.9435	88.02%	3	0.0838	0.0316	.2738	3
Machine 4 (MC4)	0.8336	0.2044	0.9435	88.02%	3	0.0838	0.0316	.2738	3
Machine 5 (MC5)	0.9366	0.1660	1.0719	100%	1	0.0380	0.0895	.7020	1

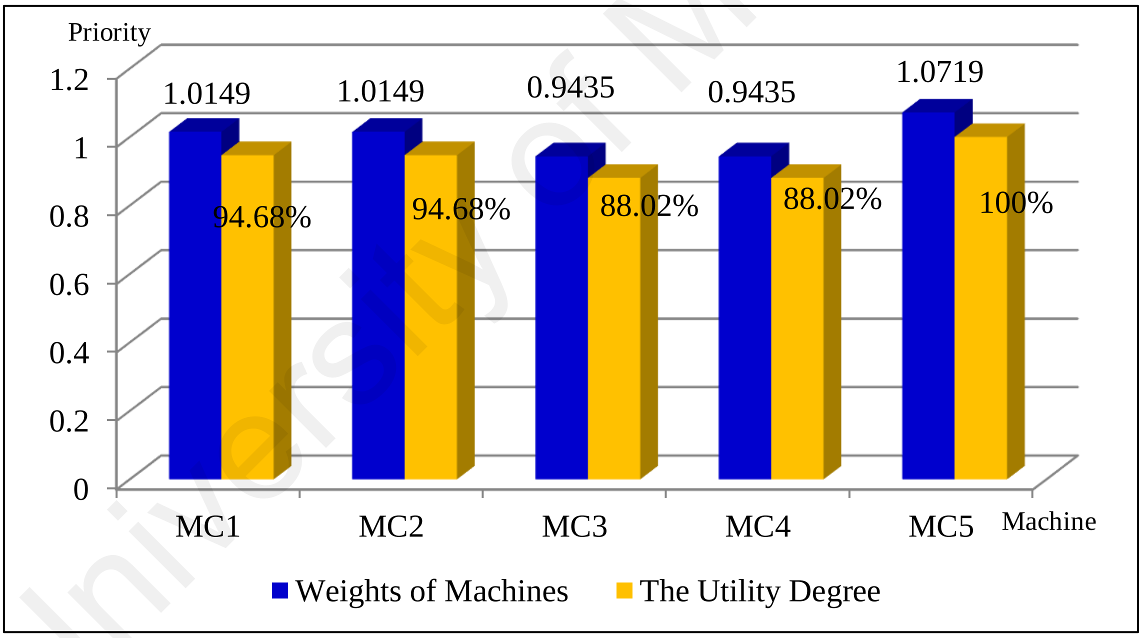

Figure 4.2: Ranking of alternatives

The results from Table 4.7 and Figure 4.2 and Figure 4.3 show that the ranking of alternatives is as follows: MC5>MC2 > MC1 > MC3=MC4 (see Section 4.2.2). Therefore, according to the collected data, MC5 is the best alternative with higher-ranking rate of the closeness coefficient for machine tool selection.

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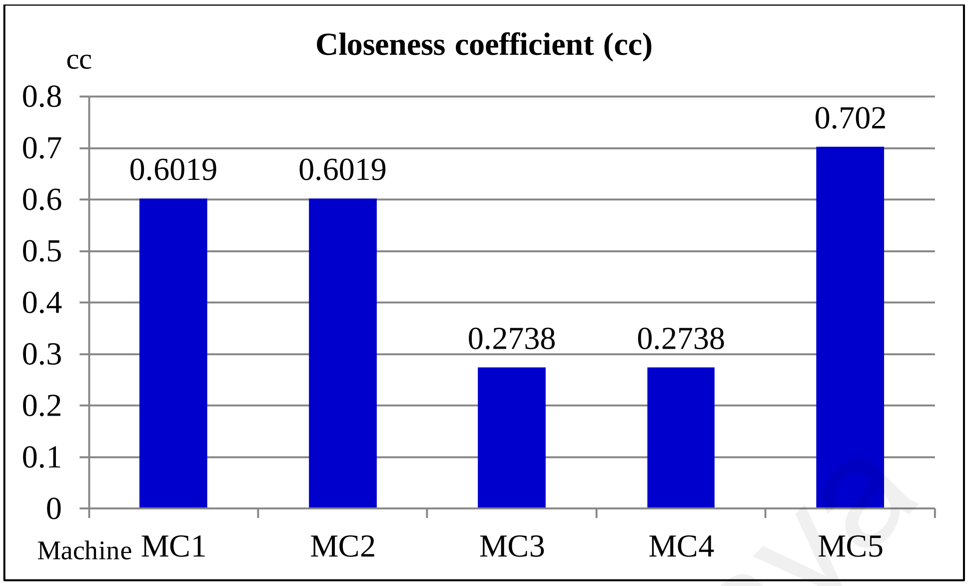

Figure 4.3: Closeness coefficient of machine tool alternatives

4.2.2 Discussion on preliminary MTS

Evaluating machine tools for the implementation of manufacturing systems in production enterprises is a complex task which requires proper consideration in the technique and systems engineering management. The decision needs to take into account various factors to obtain the manufacturing goals and the capacity of the enterprise, and contains both mixtures of quantitative and qualitative factors. To overcome this problem, the model is developed based on the fuzzy AHP with consideration of fuzzy linguistic preference relation and fuzzy COPRAS to collect and analyze the judgments of experts for the selected attributes and the potential alternatives.

The MCDM model has considered 10 attributes for evaluating machine tools, as listed in Table 4.1. The weightage of spindle speed is ranked the highest because this is a very important criterion to improve the productivity of manufacturing company. The second highest ranked criterion is the positioning precision accuracy to ensure the quality of product. Other significant criteria are table area, cutting feed, and power for improved productivity and the capacity for processing large-sized product. The cost of machine tool is also a concern for small and medium enterprises. The final assignment of priority order for the attributes of machine tool is reasonable according to expert's judgments, and also suitable for many cases in practice at manufacturing companies. Five alternatives of CNC machine tools are selected and their ranking is determined based on fuzzy COPRAS based on weights from fuzzy AHP. This integrated approach has significantly reduced the required number of experts' judgments.

The method of making decisions based on the experts' judgments may result in inconsistency, since it depends on the experience and knowledge of the decision-makers. Thus, results can differ when different groups of experts are selected as evaluators. Thus, the aggregation of fuzzy sets is used to aggregate the experts' judgments in the group. It is the duty of managers to carefully choose participants having the appropriate experience and knowledge. For example, in this study, the decision-maker have listed that the cutting feed is considered more important than the number of cutting tools. This shows that cutting performance may be appropriate for CNC machine considerations, but for a production system a greater number of cutting tools gives better system flexibility.

The results of the proposed method show that CNC machine 1 and CNC machine 3 have the same ranking. In this case the attributes need to be scrutinized more carefully, as CNC machine 2 is better than CNC machine 1 at high-value attributes such as maximum spindle speed (MC2: 10.000min^{-1} > MC1: 6000min^{-1}). The result is validated with the classic TOPSIS method in Figure 4.3.

In conclusion, in today's manufacturing environment, decision-making is a difficult and time-consuming process that involves many attributes in today's manufacturing environment. In most cases, these attributes can sometime be imprecise and vague and are very difficult to be defined numerically. The integration of fuzzy AHP and Fuzzy COPRAS has shown significant advantage in data collection for processing uncertain information on machine tool evaluation. In particular, the fuzzy linguistic preference relation is used to determine the elements of decision matrix based on experts' judgments. Using this approach, the number of expert judgment can be significantly reduced while still ensuring the consistence of fuzzy AHP enabling a rapid decision-making process. This is a practical and applicable method for the decision-making process and helps engineers and managers to interpret information by modeling the quantitative and qualitative input data.

4.3 Finalized decision on MTS using hybridization of FANP and COPRAS-G

4.3.1 Results on final decision of MTS

Appropriate machine tool selection is a problem of the integrated production planning and decision analysis for FMC. One of the aims in finalizing decision of machine selection is to choose the most suitable machine tool from the set of the potential machines in the market for implementing FMC from selected machines in Section 4.2. The survey (in Appendix E) is conducted to carefully consider more attributes and their interactions in structure of fuzzy ANP. The experts' judgments are used to formulate the pair-wise comparison matrix by decision-makers with twelve attributes in Table 3.4, which are extracted from the literature and catalogues of CNC machines (Productivity (A1), Flexibility (A2), Space (A3), Adaptability (A4), Precision (A5), Reliability (A6), Safety (A7), Maintenance and Service (A8), Cost (A9), Installation easiness (A10), User friendliness (A11) and Green Standard (A12)). They are shown on the decision hierarchical structure as in Figure 3.8 and explained in Table 3.4. Five machines are chosen as alternatives (from Mazak, Seiki, Romi, Nakamura and Okuma) for the decision-making process.

The pair-wise comparison of the attributes is populated with fuzzy linguistic variables, as shown in Table 3.5. Table F.3 (Appendix F) presents a pair-wise comparison matrix of the attributes in machine tool selection. The inter-dependence pair-wise comparison matrix among the attributes is formulated as in Table F.4 (Appendix F). The other matrices are shown in a similar manner. MATLAB programming codes and Excel calculations are used to carry out all the results for finalizing decision. The weights of the attributes in pair-wise comparison matrices are calculated using fuzzy ANP approach, which is mentioned in Section (3.4.2.3). All the weights are assigned and rearranged in the columns to formulate the inter-dependence matrix W_{22}, shown in Table F.5 (Appendix F). The total weights of the attributes for decision-making process are determined by equation Eq. 3.34 (by multiplying the inter-dependence matrix with the matrix of local weights, which is presented as a column in Table 4.8), and this results are shown in column of total weight of Table 4.8. The precision, cost, maintenance and service, productivity are the most important attributes with high weights. In practice, these are also the most interested attributes, firstly for considering when to invest in machine tools in manufacturing facility, as well as to improve the performance in manufacturing environment.

For COPRAS-G approach, the decision support matrix in Table F.6 (Appendix F) is formulated by grey numbers, which is shown in Table 3.6. The normalization of data in decision matrix is determined by equations Eq. 3.44 and Eq. 3.45. The weighted normalized decision support matrix is calculated through equations Eq. 3.47 and Eq. 3.48. These results are depicted in Table F.7 (Appendix F). The weights of alternatives (MC1, MC2, MC3, MC4 and MC5) are determined by equations Eqs. (3.50 – 3.55).

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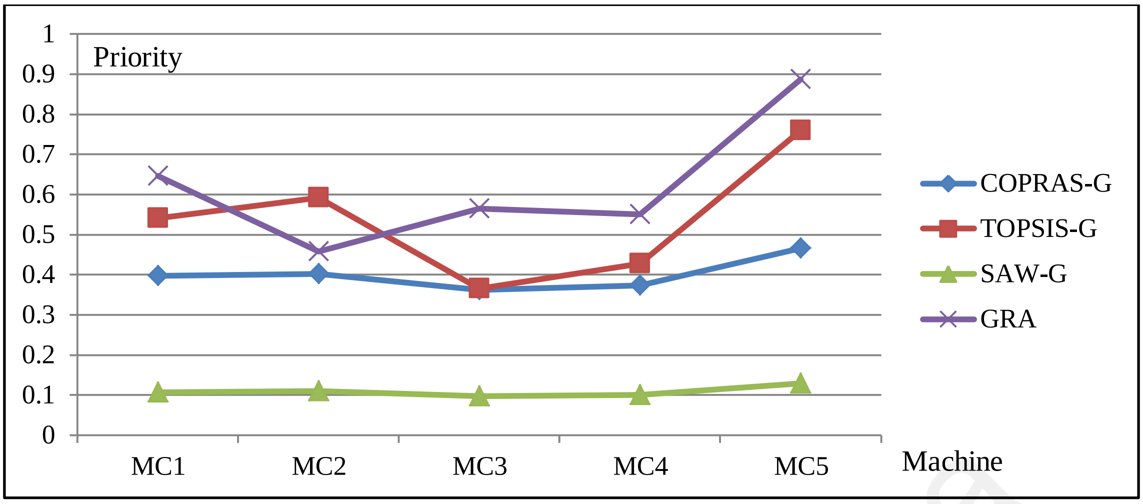

Figure 4.4: The weights of alternatives

Table 4.8: The weights of the attributes

No.	Symbol	Attributes	Local Weights	Total weights
1	A1	Productivity	0.115	0.186855
2	A2	Flexibility	0.06688	0.145027
3	A3	Space	0.023877	0.074267
4	A4	Adaptability	0.070874	0.134205
5	A5	Precision	0.1603	0.30403
6	A6	Reliability	0.050301	0.118758
7	A7	Safety	0.054072	0.115959
8	A8	Maintenance & Service	0.10919	0.23503
9	A9	Cost	0.16286	0.289891
10	A10	Installation easiness	0.037417	0.109151
11	A11	User friendliness	0.073498	0.143141
12	A12	Green standard	0.075727	0.143678

Table 4.9: The ranking of alternatives

Ranking	COPRAS-G	Ranking	TOPSIS-G	Ranking	SAW-G	Ranking	GRA	Ranking
MC1	0.3971	3	0.54165	3	0.10758	3	0.64628	2
MC2	0.40208	2	0.59227	2	0.10983	2	0.45803	5
MC3	0.36166	5	0.36531	5	0.097338	5	0.56467	3
MC4	0.37259	4	0.4278	4	0.1008	4	0.55004	4
MC5	0.46655	1	0.75932	1	0.12949	1	0.88779	1

Finally, the weights of alternatives are shown in Table 4.9 and compared with the results, which are carried out by other methods such as TOPSIS-G, SAW-G and GRA, which is shown in Figure 4.4. The methods show that MC5 is the most suitable machine. Three methods (COPRAS-G, TOPSIS-G and SAW-G) resulted in the same priority order in machine tool selection (MC5>MC2>MC1>MC4>MC3), whereas GRA approach resulted in a different priority order (MC5>MC1>MC3>MC4>MC2). In summary, decision maker is encouraged to use the sensitivity analysis for checking the robustness of the alternatives' ranking.

4.3.2 Sensitivity analysis

The sensitivity analysis is carried out for COPRAS-G and GRA to verify the robustness of the ranking. A sensitivity analysis is a technique used to exchange each attribute weight with another attribute while the weights of other attributes remain unchanged (Kang, Lee, and Yang, 2012; Önüt et al., 2009; Pang and Bai, 2013; Vinodh, Anesh Ramiya and Gautham, 2011). We choose to switch the weights of 2 attributes from the set of 12 attributes. Therefore, 66 different calculations (12!/(2!(12-2)!)) are implemented for the sensitivity analysis. Table 4.10 shows one of these modifications. Different names are given for each calculation. For example; QQ_{12} means the weights of attribute 1 and attribute 2 are switched, and QQ_{23} means the weights of attribute 2 and attribute 3 are switched. With the new weights of the attributes, the weighted normalized decision support matrix is re-calculated and the weights of alternatives are determined again for each modification. Then, the alternatives are re-ranked.

The results of sensitivity analysis are shown in Table 4.11, Figure 4.5 (for the fuzzy ANP and COPRAS-G), and Figure 4.6 (for the fuzzy ANP and GRA). For example, for QQ, that is, the weight of productivity (A1) becomes 0.145027 and flexibility (A2) becomes 0.186885, and the priorities of machine tools MC1, MC2, MC3, MC4 and MC5 are 0.39841, 0.40082, 0.3604, 0.3739 and 0.46646, respectively.

Table 4.10: The weights of alternatives when to exchange the weights of attributes (fuzzy ANP & COPRAS-G)

	MC1	MC2	MC3	MC4	MC5
QQ_{12}	0.39841	0.40082	0.3604	0.3739	0.46646
QQ_{13}	0.40474	0.40365	0.36322	0.37327	0.45511
QQ_{14}	0.39808	0.40345	0.3594	0.37357	0.46549
QQ_{15}	0.39354	0.40111	0.36531	0.36904	0.47099
QQ_{16}	0.40248	0.40048	0.36005	0.37518	0.4618
QQ_{17}	0.40331	0.39904	0.35372	0.3788	0.46513
QQ_{18}	0.39172	0.40192	0.36752	0.37248	0.46636
QQ_{19}	0.3954	0.40288	0.36245	0.36711	0.47216
$QQ_{1.10}$	0.40269	0.39788	0.35746	0.37819	0.46378
…	…	…	…	…	…
$QQ_{10.12}$	0.39894	0.4017	0.35889	0.37444	0.46602
$QQ_{11.12}$	0.39712	0.40207	0.36164	0.37261	0.46656

Table 4.11: The weights of alternatives when to exchange the weights of attributes (fuzzy ANP & GRA)

	MC1	MC2	MC3	MC4	MC5
QQ_{12}	0.61842	0.45821	0.56462	0.54929	0.88779
QQ_{13}	0.61658	0.45839	0.56416	0.56779	0.88779
QQ_{14}	0.61812	0.46433	0.56458	0.54912	0.88779
QQ_{15}	0.71468	0.45872	0.56467	0.59682	0.88779
QQ_{16}	0.62627	0.45803	0.56467	0.54886	0.87903
QQ_{17}	0.62667	0.45833	0.56483	0.55872	0.88779
QQ_{18}	0.67369	0.45803	0.51416	0.55004	0.88779
QQ_{19}	0.69903	0.45803	0.56467	0.58828	0.87929
…	…	…	…	…	…
$QQ_{1.11}$	0.61819	0.50723	0.56467	0.54919	0.88779
$QQ_{10.12}$	0.65192	0.45803	0.55919	0.55575	0.88779
$QQ_{11.12}$	0.64628	0.45804	0.5646	0.55004	0.88779

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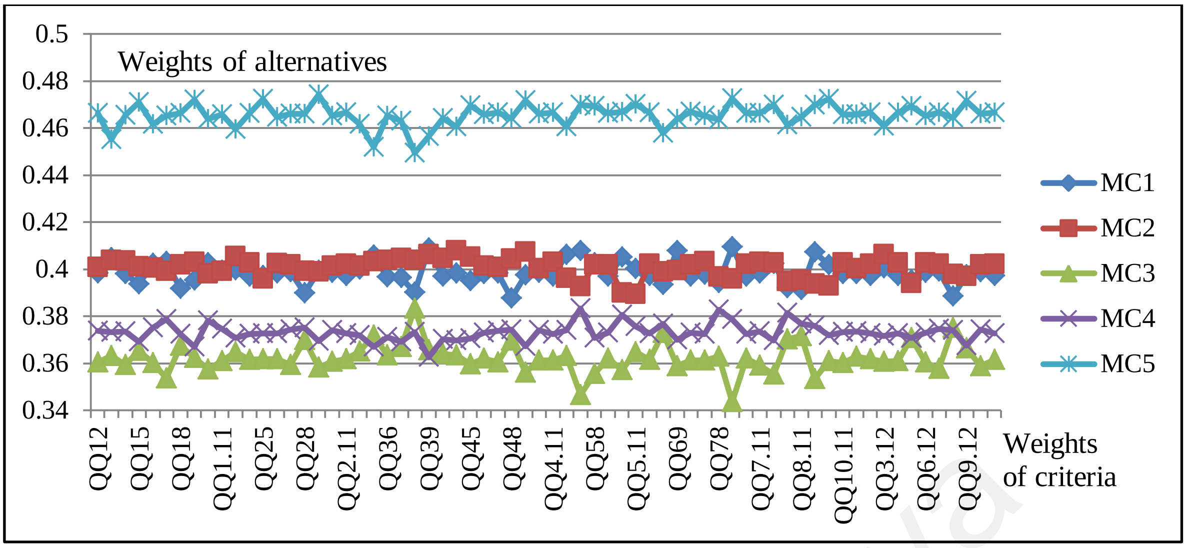

Figure 4.5: Sensitivity analysis of the alternatives (Fuzzy ANP and COPRAS-G)

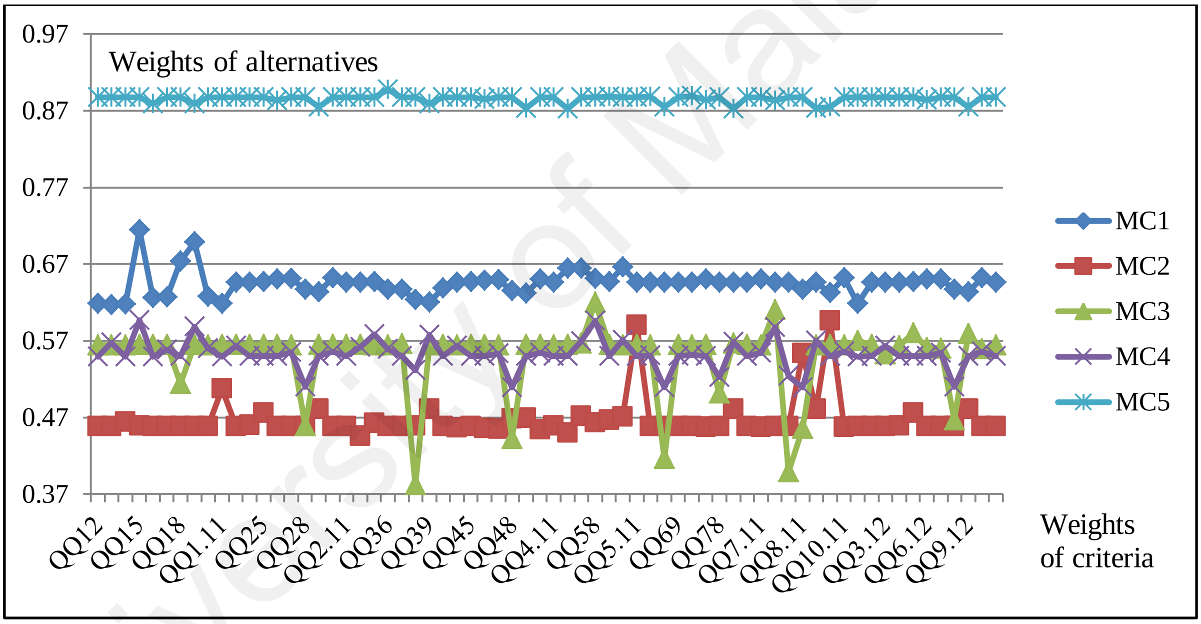

Figure 4.6: Sensitivity analysis of the alternatives (Fuzzy ANP and GRA)

As shown in Figure 4.5 and Figure 4.6, MC 5 is always the best alternative in all 66 cases of computation. For COPRAS-G, there are 44 changes in the rankings over all the cases and 45 changes for GRA. Moreover, the ranking of alternatives in the GRA method changed more dramatically than the COPRAS-G approach when switching the weights of attributes. This verifies that the proposed integrated approach of the fuzzy ANP and COPRAS-G is a potential method for a fuzzy multi-attribute decision-making process.

4.3.3 Discussion on final decision of machine tool selection

Appropriate machine selection for the implementation of production systems in manufacturing enterprises is a challenging task, combining the factors of system techniques and management. This selection involves many different quantitative and qualitative factors to ensure production goals and the capacity of enterprise. The hybrid approach of fuzzy ANP and COPRAS-G has been proven to provide an effective decision when evaluating suitable machines to be implemented in the manufacturing system. This methodology is useful to assist decision-makers due to the following benefits. First, fuzzy logic is capable of handling the imprecise, vague and uncertain information from the decision-makers' judgments. Second, the influence of the interactions between the attributes is considered in the fuzzy ANP method when determining the weights of the attributes (Table 4.8). Finally, the COPRAS-G method allows the uncertain information of the attributes to be expressed in interval values and be used to obtain the ranking of alternatives (Table 4.9, Figure 4.4). The results show that four highest-priority, most important attributes for machine selection are precision, cost, maintenance and service and productivity. This is entirely consistent with common practice in the manufacturing sector because precision is a factor in obtaining a quality product, cost is beneficial factor in finance, maintenance and service ensures the equipment operates continuously, avoiding undesirable stochastic events such as breakdown, and solve technique problems quickly and costly, and finally the productivity allows the enterprise to achieve sufficient production performance to satisfy the customers’ demand. In addition, three new attributes, related to ergonomics and environment are also considered, namely, the ease of installation, user friendliness and green standards, but they do not substantially contribute to the rankings. This shows that the manufacturing enterprises have not paid much attention to these factors.

As mentioned in the sensitivity analysis, the integrated approach of the fuzzy ANP and COPRAS-G as a multi-attribute decision-making model in machine tool selection is robust and manageable. This proposed method shows the following advantages over the existing work. First, this model includes the interaction of attributes when evaluating the alternatives with the fuzzy ANP and includes three new additional attributes (ease of installation, user friendliness and green standards). Second, the number of pairwise comparisons is reduced, and the consistency ratio and super-matrix, which require the large computational effort, are not necessary in the fuzzy ANP. Finally, COPRAS-G easily solves problems with a large number of alternatives. The present findings, however, must be interpreted in the context of a number of potential limitations. The interaction of alternatives at the detailed level of sub-attributes is not considered.

In addition, several practical implications of the proposed approach need to be made clearer. First, experts are required to interact and make many judgments. Thus, it takes time for the decision-makers to achieve an effective decision with high levels of confidence. Second, the ease of extending this model by adding or subtracting few attributes or alternatives will help managers to be flexible in selection and evaluation. Moreover, this method is based on the opinions of experts, which means it can produce inconsistent results. The results depend on the experience and knowledge of the decision-makers. If different groups of experts are selected, the results will be different. Therefore, the managers need to select the participants carefully who have an appropriate level of experience and knowledge in the subject.

In conclusion, this study contributes to the body of knowledge by providing a MADM model comprising three phases and presenting a hybrid approach of fuzzy ANP and COPRAS-G to select the most suitable machine tool, based on twelve attributes. In particular, in the first phase a team discusses together to determine the attributes and a

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set of potential alternatives. The second phase is to determine the interaction and weights of the attributes with the fuzzy ANP. The third phase is to evaluate the ranking of alternatives based on COPRAS-G. The obtained results are compared with other methods of TOPSIS-G, SAW-G and GRA. Finally, a sensitivity analysis is conducted to verify the robustness of the ranking and further support the decision when selecting the final solution. In general, these results show that this approach is a flexible tool and reaches a final effective decision in machine tool selection for FMC implementation.

4.4 Results on machine loading problem in FMC

After the process of machine tool selection is implemented in the previous phase, four machine tools of five alternatives (MC5, MC2, MC1 and MC4) are chosen to establish the flexible manufacturing cell (FMC) based on the layout as suggested in Figure 3.17. These four machines are placed surrounding the conveyor to build an FMC with the positions of the machine's labelled as "CNC Machine 1 (CNC-M1), CNC machine 2 (CNC-M2), CNC machine 3 (CNC-M3) and CNC machine 4 (CNC-M4)". The non-dominated sorting BBO (NSBBO) methodology is proposed to determine the most suitable process plan to derive the part types in FMC.

Finding a realistic production plan is extremely difficult because it involves confidential business technology. The factors of processing time and traveling time are not easy to obtain. The production companies usually cannot stop the production line so for test in the studies because of the competitiveness of economics. Therefore, the actual production plan for this study is adapted from previous studies (Mukhopadhyay, Midha and Krishna, 1992) with added new data of traveling time to build a model of flexible manufacturing cells to simulate the practice at the manufacturing SMEs. In this study, the FMC consists of four machines and conveyor system for conveying the part type.

In this section, the BBO methodology combined with non-dominated sorting procedure is applied for two case studies to find the most suitable process plan which satisfies three objectives of minimizing system unbalance, makespan and total flow time.

4.4.1 Data preparation of process plan

In this study, the processing time and traveling time between machines are important parameters to determine the most suitable combination of machines and operations. In particular, the processing time in process plan is extracted from the research of Mukhopadhyay et al. (1992), and the traveling time is designed based on the length and speed of conveyor system. The machines are capable of operating two shifts in a day (one shift for 8 hours), meaning over-utilization of machines is permitted. The database of traveling time between machines and loading/unloading stations are shown as in Table 4.12.

Table 4.12: The traveling time between machines in FMC (min)

	CNC machine 1	CNC machine 2	CNC machine 3	CNC machine 4
L/UL	2	4	8	10
CNC machine 1	-	2	6	8
CNC machine 2	10	-	4	6
CNC machine 3	6	8	-	3
CNC machine 4	4	4	10	-

4.4.2 Parameters of NSBBO

To examine the applicability of proposed BBO method and non-dominated sorting procedure, a computational program was developed based on MATLAB software to be executed on an Intel® core™ i5-2410M 2.3GHz personal computer with 4GB DDR3 memory running Microsoft Windows 7. The parameters of BBO method are defined in this study, after checking a number of experimentations, are as follows:

- The habitat size (population size): 50

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- Maximum migration and immigration rate of each habitat: E = I = 1.
- Mutation probability m_{max}: 0.01 and Terminal criteria: number of iteration is 1000
- Immigration and emigration rates are determined based on equations Eqs. 3.62, 3.63 and 3.67. Mutation rates are calculated using equations Eqs. 3.64 and 3.66.

4.4.3 Testbed Data

To prove the applicability of the NSBBO and determine the most suitable solution for machine loading problem in FMC with minimization of system unbalance, makespan and total flow time, two testbed sets are adapted from the literature (Mukhopadhyay et al., 1992). The traveling time is selected based on the conveyor system (Table 4.12).

4.4.3.1 Case Study 1

In FMC, four CNC machines (CNC-M1, CNC-M2, CNC-M3 and CNC-M4) are considered to produce five part types with the different batch sizes. Each part type comprises of one to three operations. The data input of the proposed method consists of processing time, traveling time and constraint on the tool slots in FMC. The numbers in Table 4.13 show the batch size, operation index, and processing time (tool slots), respectively.

Table 4.13: Process plan for case study 1 (adapted from Mukhopadhyay et al. (1992))

Part type	Part 1			Part 2		Part 3	Part 4			Part 5
Batch size	6			9		8	12			16
Operation index	1	2	3	1	2	1	1	2	3	1
CNC machine 1		12(2)								15(2)
CNC machine 2	10(1)			9(1)			14(2)		12(1)	
CNC machine 3				9(1)	6(2)		14(2)	12(1)		
CNC machine 4			7(1)	9(1)		12(1)				

(Source: permissions obtained from Taylor and Francis with reference number LA/TPRS/P5218 on 12 October 2015)

The purpose is to determine the most suitable combination of machine and operation with satisfaction of tool slots. For instance, in this process plan, the operation 1 of part

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type 2 can be processed in CNC-M2, CNC-M3 and CNC-M4 with one tool slot, and operation 1 of part type 4 can be processed in CNC-M2 and CNC-M3 with 2 tool slots. These are optional operations which are needed to be processed, and create the flexibility of FMC. So, our aim is to find which machine tools and operations is suitable for producing in FMC in order that the system unbalance, makespan and total flow time in manufacturing cell are minimized and satisfies the constraint of tool slots.

Table 4.14 presents the potential solutions obtained from BBO approach and non-dominated sorting procedure. These solutions show the most combination of CNC machines and the machining operations with satisfying three objectives of minimum system unbalance, makespan and total flow time. Figure 4.7 shows all the non-dominated solutions from a run of non-dominated BBO on three objectives until all the batch sizes of part types are completed with the machining process.

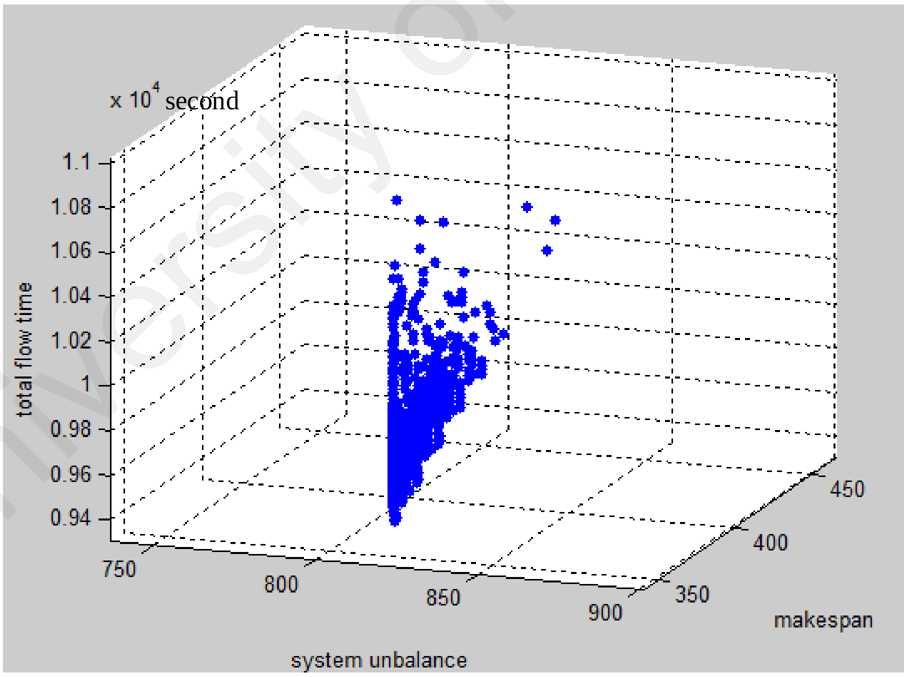

Figure 4.7: The non-dominated solutions from a run of non-dominated BBO

As seen in Table 4.14, the best solution for case study 1 is vector of allocating the operations into the machines which is presented as follows: All the parts of part types 1 are assigned to machine with the sequence [2 1 4]. It means that operations 1, 2 and 3 of part type 1 is assigned to machine 2, machine 1 and machine 4, respectively.

Table 4.14: The potential solution for the machine loading (SU=819, MK=353, TFT=9448)

Batch No	Part No.	Operation 1	Operation 2	Operation 3	Completion time(s)
1	1	Machine 2	Machine 1	Machine 4	132
	2	2	1	4	139
	3	2	1	4	151
	4	2	1	4	313
	5	2	1	4	340
	6	2	1	4	352
2	1	3	3	0	34
	2	4	3	0	145
	3	3	3	0	49
	4	3	3	0	64
	5	3	3	0	79
	6	3	3	0	94
	7	3	3	0	109
	8	3	3	0	124
	9	3	3	0	139
3	1	4	0	0	41
	2	4	0	0	53
	3	4	0	0	65
	4	4	0	0	77
	5	4	0	0	89
	6	4	0	0	101
	7	4	0	0	113
	8	4	0	0	125
4	1	2	3	2	257
	2	2	3	2	269
	3	2	3	2	281
	4	2	3	2	293
	5	2	3	2	305
	6	2	3	2	317
	7	3	3	2	211
	8	2	3	2	329
	9	2	3	2	223
	10	2	3	2	341
	11	3	3	2	245
	12	3	3	2	**353**
5	1	1	0	0	72
	2	1	0	0	87
	3	1	0	0	102
	4	1	0	0	117
	5	1	0	0	132
	6	1	0	0	159
	7	1	0	0	174

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	8	1	0	0	189
	9	1	0	0	204
	10	1	0	0	219
	11	1	0	0	234
	12	1	0	0	249
	13	1	0	0	264
	14	1	0	0	279
	15	1	0	0	294
	16	1	0	0	321

For part type 2, most of operations are assigned to sequence of machine [3 3]. It means that the operations 1 and 2 of part type 2 are assigned to machine 3. However, the second part of part type 2 is assigned to sequence [4 3] to make the system unbalance. It means that the operations 1 and 2 of second part in batch size of part type 2 are assigned to machine 4 and machine 3, respectively. Similarity, we can read the sequence of assignment as described in Table 4.14.

4.4.3.2 Case Study 2

Case Study 2 is similar to Case 1 but the number of part type is increased, increasing the complexity of the problem. The FMC is considered with four CNC machines to produce the number of part types with different batch sizes. For instance, the process plan consists of 8 part types in Table 4.15. The batch size for each part type is 8, 9, 13, 16, 9, 10, 12 and 13, respectively. The parameters of processing time and traveling are explained as in Case Study 1. In this process plan, the number of optional operation is large, so the production process becomes more flexible. It means that the opportunity for combining the machines and operations is considerable. Table 4.16 shows the best solution for selecting the most appropriate combination of machines and operations in FMC. Figure 4.8 shows all the non-dominated sorting solutions from a run of NSBBO until all the batch sizes are completed with the process. Figure 4.9 presents the relationship between makespan and total flow time as a Pareto front.

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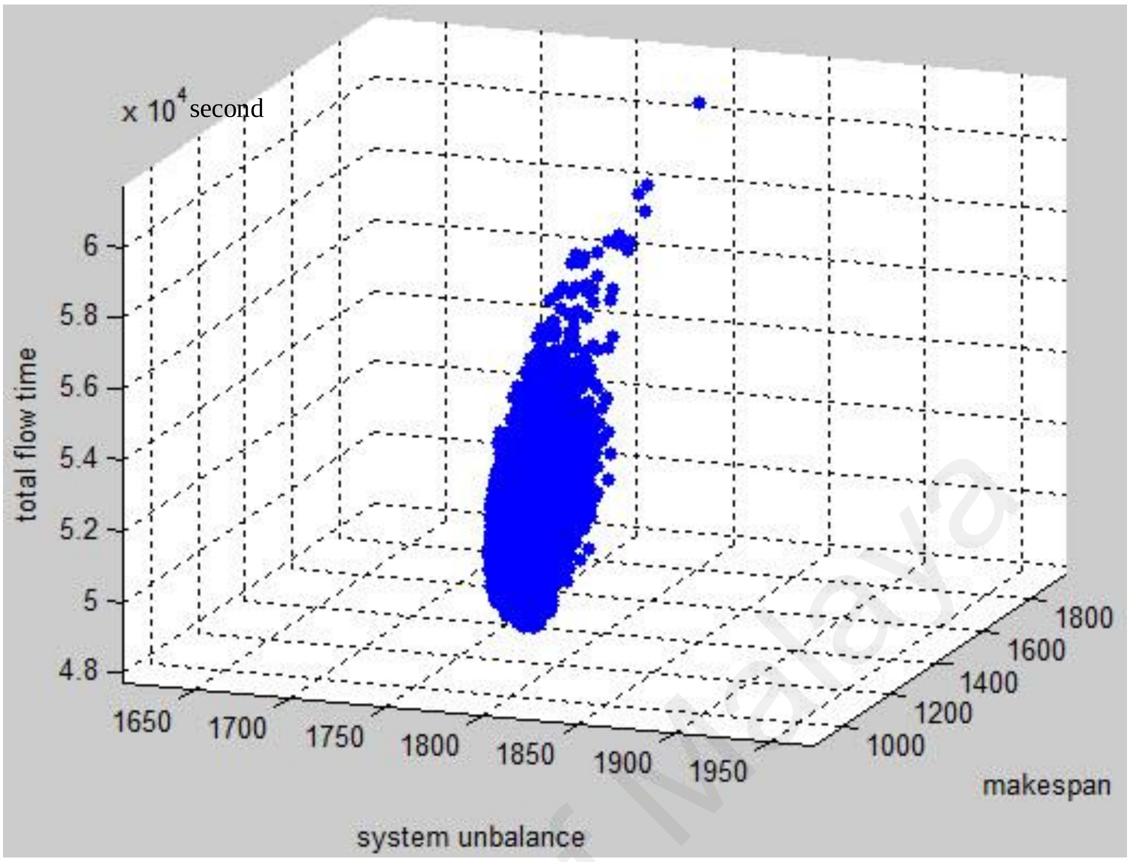
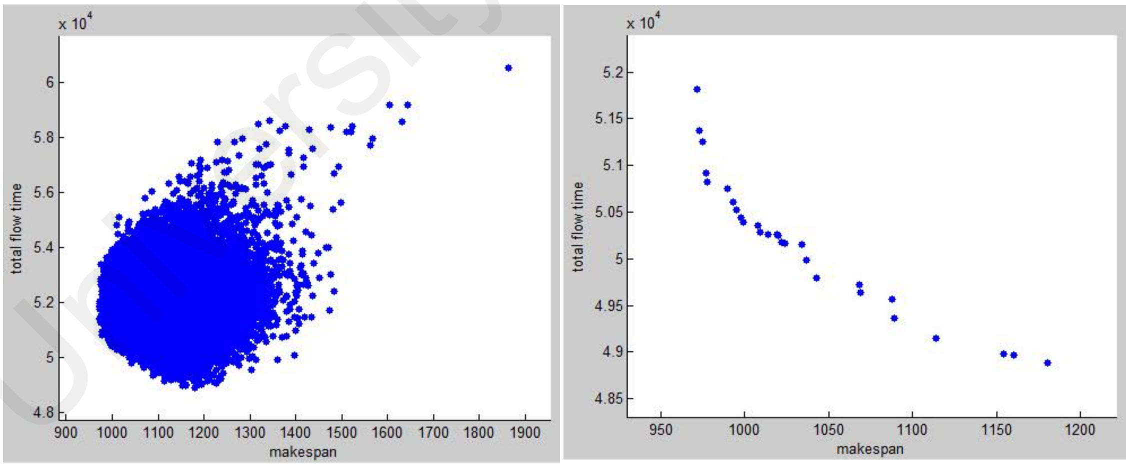


Figure 4.8: The non-dominated sorting solutions from a run of NSBBO with three objectives



(a) all the non-dominated sorting solutions (b) potential non-dominated sorting solutions

Figure 4.9: Relationship between makespan and total flow time (s) from a run of NSBBO

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Table 4.15: Process plan for case study 2 adapted from Mukhopadhyay et al. (1992))
Permissions obtained from Taylor and Francis with reference number LA/TPRS/P5218 on 12 October 2015

Part type	Part 1	Part 2			Part 3		Part 4		Part 5		Part 6			Part 7			Part 8		
Batch size	8	9			13		6		9		10			12			13		
Operation index	1	1	2	3	1	2	1	2	1	2	1	2	3	1	2	3	1	2	3
CNC machine 1		25(1)			26(2)								21(1)	19(1)	13(1)		25(1)	7(1)	24(3)
CNC machine 2				22(1)					22(2)	25(1)		7(1)	21(1)		13(1)		25(1)	7(1)	
CNC machine 3	18(1)					11(3)	14(1)		22(2)			7(1)		19(1)	13(1)				
CNC machine 4		25(1)	24(1)		26(2)			19(1)			16(1)	7(1)				23(3)			

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These solutions were obtained for the most combination of 4 CNC machines and 8 part types with different batch sizes to satisfy three objectives of minimum system unbalance, makespan and total flow time. These solutions support the decision makers in machine selection decisions to derive the operations of each part types.

Table 4.16: The most suitable combination of machine and operation in FMC for case study 2

Part No.	Part type	Batch size	Operation 1	Operation 2	Operation 3
1	1	8	3	0	0
2			3	0	0
3			3	0	0
4			3	0	0
5			3	0	0
6			3	0	0
7			3	0	0
8			3	0	0
9	2	9	4	4	2
10			1	4	2
11			4	4	2
12			4	4	2
13			4	4	2
14			1	4	2
15			4	4	2
16			1	4	2
17			4	4	2
18	3	13	1	3	0
19			1	3	0
20			1	3	0
21			1	3	0
22			1	3	0
23			1	3	0

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24			1	3	0
25			4	3	0
26			1	3	0
27			1	3	0
28			1	3	0
29			1	3	0
30			1	3	0
31	4	6	3	4	0
32			3	4	0
33			3	4	0
34			3	4	0
35			3	4	0
36			3	4	0
37	5	9	2	2	0
38			3	2	0
39			3	2	0
40			3	2	0
41			3	2	0
42			3	2	0
43			3	2	0
44			3	2	0
45			3	2	0
46	6	10	4	2	2
47			4	2	2
48			4	2	2
49			4	2	2
50			4	3	2
51			4	2	2
52			4	2	2
53			4	2	2
54			4	2	2

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55			4	3	2
56	7	12	3	3	4
57			3	2	4
58			3	3	4
59			3	3	4
60			3	3	4
61			3	3	4
62			3	2	4
63			3	3	4
64			3	2	4
65			3	2	4
66			3	3	4
67			3	3	4
68	8	13	1	2	1
69			1	2	1
70			2	2	1
71			2	2	1
72			2	1	1
73			1	2	1
74			1	2	1
75			1	2	1
76			1	2	1
77			1	2	1
78			1	2	1
79			1	2	1
80			1	2	1
System Unbalance: 1793; Makespan: 978; Total Flow Time: 50828					

The most suitable combination of machines and operation of each part of part type with different batch size is described as in Table 4.16. The optional operations of part type are assigned to obtain the optimal objectives of system unbalance, makespan and total flow time. For example, part type 2 is assigned according to sequence of [4 4 2] and [1 4 2]. In particular, the operations 1, 2 and 3 of first part of part type 2 in batch size are allocated to CNC machines 4, 4 and 2. However, the operations 1, 2 and 3 of the second part of part type 2 in batch size are assigned to CNC machines 1, 4 and 2. Clearly, these machine assignments are different to obtain the system unbalance of each machine. Similarly, the operations of other part types can be interpreted in the same manner.

The proposed model of multi-criteria machine loading in FMC is solved using the principle of BBO and non-dominated sorting procedure. In this study, three objectives of minimizing SU, makespan and total flow time were chosen. Minimizing the total flow time will make the workload unbalanced with the larger queues closed to the most heavily used machines. In two case studies, the overloading on CNC machines is permitted. The traveling time is collected from conveyor handling system. However, it is difficult to take data of a real process plan from the industry and it was one of the major drawbacks of this research. The chosen solutions of the most suitable combination of machine and operation must satisfy the three objectives using the non-dominated sorting. However, it is important to realize that two of three objectives are dependent with each other and are not conflicting with one another. Therefore, the surface of Pareto frontier is difficult to demonstrate in these cases. The results obtained are compared with solution achieved from LINGO optimization software (B&B) to prove that application of non-dominated sorting BBO is suitable for finding the feasible solutions for multi-criteria machine loading in FMC. The best solution obtained for two case studies by the proposed approach in terms of selection of machines and operations' allocation to minimize system unbalance, makespan and total flow time have been reported in Table 4.14 and Table 4.16.

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This study does not only present a multi-criteria machine loading model for FMC, it also aims at providing an integrated procedure of BBO and non-dominated sorting for exploring the best possible solutions. The results obtained by proposed NSBBO are compared with four existing algorithms available in the literature (see Table 4.17). These algorithms include GA reported in Abazari et al. (2012), modified Immune Algorithm presented in Prakash, Khilwani, Tiwari and Cohen (2008), multi-stage programming approach in Nagarjuna et al. (2006) and heuristic approach proposed by Mukhopadhyay et al. (1998).

Table 4.17: Comparison of the results obtained on the system unbalance by different methods

Problem number	Total number of part types	B&B	Prakash et al. (2008)	Nagarjuna et al. (2006)	Mukhopadhyay et al. (1992)	Abazari et al. (2012)	Suggested NSBBO
1	8	81	318	122	122	81	1793
2	6	202	**524**	202	202	202	**316**
3	5	72	**312**	130	**286**	72	**156**
4	5	**819**	**819**	**819**	**819**	**819**	**819**
5	6	133	**536**	219	**364**	133	**289**
6	6	178	**518**	**265**	**265**	178	**236**
7	6	147	477	183	147	147	**99**
8	7	111	677	288	459	111	1246
9	7	**309**	333	**309**	315	**309**	**309**
10	6	184	**272**	**271**	**320**	184	**221**

As seen in Table 4.17, the proposed NSBBO for MLP in FMC has obtained a globally optimal solution of all the problems and its performance is comparable to other existing methods in the literature. The results of NSBBO is considerably better than those of Parakash et al. (2008) and Mukhopadhway et al. (1992), and competitive when compared with results of Nagarjuna et al. (2006). However, the result of NSBBO is acceptable when compared with one of Abazari et al. (2012). Because NSBBO method considers multiple objective solutions, the best solution is identified based on the trade-off or balance among the values of objectives (system unbalance, makespan and total flow time) and is different from finding the best solution in single objective problem. Moreover, one more difference between results of NSBBO with other methods is consideration of completion of the desired batch sizes of FMC. As seen in Table 4.17, the system unbalance of FMC has been reported in the case of completing all the batch size of part types. Parakash et al. (2008), Nagarjuna et al. (2006), Mukhopadhyay et al. (1992), and Abazari et al. (2012) have ignored the consideration of the completion of all the batch sizes of part types. Thus, problem 1 and problem 8 have very large values of system unbalance. Looking back at the results of Case Studies 1 and 2, it is easy to see that makespan in Case Study 2 is greater than 480 minutes which describes the time of the first shift in a day. Therefore, it is essential to suggest that FMC should continue operating the second shifts to complete all the part types with desired batch sizes. This is very convenient to assess the delivery time for the valued customers.

Globalization process of business motivates the manufacturing SMEs to apply the advanced manufacturing technology, especially in implementing manufacturing cell to produce competitive products in the market. A multi-criteria machine assignment model was presented to determine the most suitable combination machines and operations in FMC. The proposed model takes into account numerous real parameters comprising of the capacity of machines, tool magazines, processing time, and traveling time and allows the overloading status of machines. Due to the complexity in manufacturing cell, the adoption of integrated approach on manufacturing goals to obtain the objectives of minimization of system unbalance, makespan and total flow time is possible. A feasible integrated solution approach NSBBO based on the biogeography based optimization (BBO) and non-dominated sorting is proposed to generate the most suitable process plans in the context of manufacturing SMEs. The explored results are verified based on the LINGO software.

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Thus, it is proved that the proposed NSBBO approach is general enough and applicable to a variety of manufacturing enterprises for FMC.

4.5 Summary

Firstly, the various experiments for machine tool selection are successfully conducted in uncertain manufacturing environment. The preliminary evaluation and final decision of machine tool selection are implemented based on FAHP-FCOPRAS and FANP-COPRAS-G approaches, respectively. The advantages of these proposed approaches are to reduce the experts' judgments need to be collected and to consider the interactions of the attributes. In each of the experiments, the rankings of machine alternatives have been compared with the rankings of existing methods based on experts' judgments, and sensitivity analysis is carried out to evaluate the robustness of the rankings. The results highlighted that the developed approaches are flexible and potential in effective MCDM process for machine tool selection.

Secondly, the results of machine loading problem in FMC are presented by developing the NSBBO method to select the most suitable combination of machine tools and operations. The non-dominated sorting procedure is used to determine the best solution in feasible solution space. The aim of MLP is to obtain the performance of FMC by minimizing the system unbalance, makespan and total flow time. The NSBBO is applied for two case studies of FMC with consideration of traveling time of conveyor system. Moreover, the result of NSBBO is compared with other methods in the literature in terms of the system unbalance of ten problems with different FMC sizes. The results show that the NSBBO method is potential in achieving near-optimal (and in some cases optimal) solutions which satisfy multiple objectives of minimization of system unbalance, makespan and total flow time for MLP of FMC.

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CHAPTER 5: VALIDATION USING FLEXSIM SIMULATION

5.1 Introduction

This chapter presents a simulation model of FMC based on the solutions of machine loading obtained from Table 4.14 and Table 4.16 (see Chapter 4). The simulation model is used to observe the behavior and the system's performance. The performance indicators of FMC are identified as system unbalance, makespan and total flow time. The purpose of the simulation process is to validify that the newly design FMC has the potential applicability in manufacturing SMEs. In this chapter, the construction of simulation model of FMC is descrbed and then the results and discussion are carried out based on the experiments of simulation runs.

5.2 Simulation model

Discrete event simulation is a widely used technique to analyze and understand the behaviors and characteristics of general production systems. It is a valuable tool to evaluate potential candidates of configurations of systems and operational strategies to aid the process of decision making in manufacturing engineering. As a computationally expensive tool, the increase in computer power and memory has further increased the use of discrete event simulation in recent years (Negahban and Smith, 2014).

To obtain the purpose mentioned above, FlexSim software was used to simulate the FMC with the aim of aiding the organizations to have the best information and knowledge on the resources when the description of the relationship of the components in the systems is very difficult to express mathematically. The practical model is built based on the objects and interfaces in FlexSim simulation environment. Development of the model comprises of five basic steps, which consist of developing a layout, connecting the objects, detailing the objects, running the models and review the output. FlexSim is a powerful software to

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achieve an in-depth knowledge and deeper insight of complex and uncertain systems. When – and only when-the relationship of the elements in the systems are clearly understood, the systems can then be improved (Nordgren, 2003). The procedure of simulation is described in Figure 5.1.

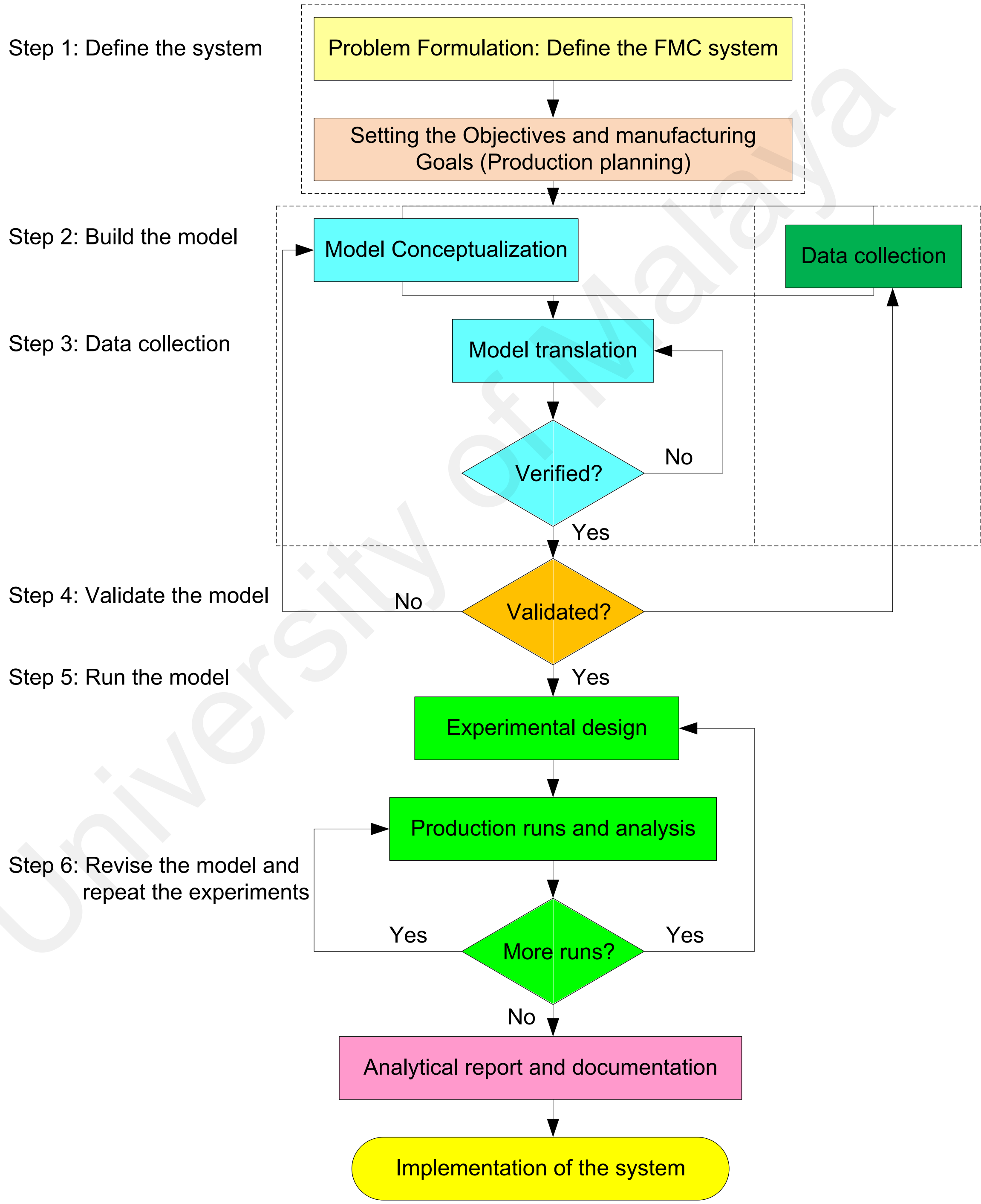

Figure 5.1: The steps of simulation procedure (adapted from Banks, Nelson, and Nicol (2009 and Carrie (1988)

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The objectives of simulation model are (1) To verify the results obtained from non-dominated sorting BBO in selecting the most suitable combination of machines and operations for processing in FMC; (2) To evaluate the capacity of machine utilization. The simulation model is applied in the scope of the FMC of SME manufacturing environment where many part types are produced on suitable CNC machine tools and transported among the machines by material handling system (conveyor) for conveying the part types.

The validation is conducted by comparing the results of the proposed model with those of the real system. In FMC simulation, if the system has not normally built yet, so this is impossible. However, the system is already in existence, the problem of validation does not usually arise. The only thing that we can do is to ensure the validity of the data supplied from the proposed process plan. In this study, simulation model is used to estimate the performance's indicators of system unbalance, makespan and total flow time.

5.3 Implementation of FMC simulation model in FlexSim

Each part type, called item types in simulation model, is connected with a particular name and label to be distinguished for simulation purposes, as depicted in Table 5.1. The allocation and processing time of operations are extracted from Chapter 4 (Tables 4.12-4.16 for two case studies).

Table 5.1: The item types of part types for production in case study 1

Item	Par type	Batch size	Color of Item Label	Sequence and processing time
ItemType1	1	6	black	(O1, MC2, 10 min) >>> (O2, MC1, 12 min) >>> (O3, MC4, 7 min)
ItemType2	2	9	red	(O1, MC3, 9 min) >>> (O2, MC3, 6 min)
ItemType3	3	8	yellow	(O1, MC4, 12 mins)
ItemType4	4	12	blue	(O1, MC3, 14 mins) >>> (O2, MC3, 12 mins) >>> (O3, MC2, 12 min)
ItemType5	5	16	pink	(O1, MC1, 15 min)

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The FMC is modeled based on fixed resources (source, conveyor, machine, queue, sink, etc.) and mobile resources (task executors such as transports, operator, etc.) in FlexSim simulation environment. The fixed resources comprise of four CNC machines, which are described as MC1, MC2, MC3 and MC4 for processing various part types with required batch sizes. The machined parts are called flowitem in FlexSim, which are entities that flow through a model. The fixed resources (CNC machines) will send and received the flowitems. The conveyor is used to transport the parts between the objects (source, machine, sink, etc.) in the model. Part types are moved from source to machine for processing and from machine to sink for storage. Figure 5.2 shows the designed cell in FlexSim environment.

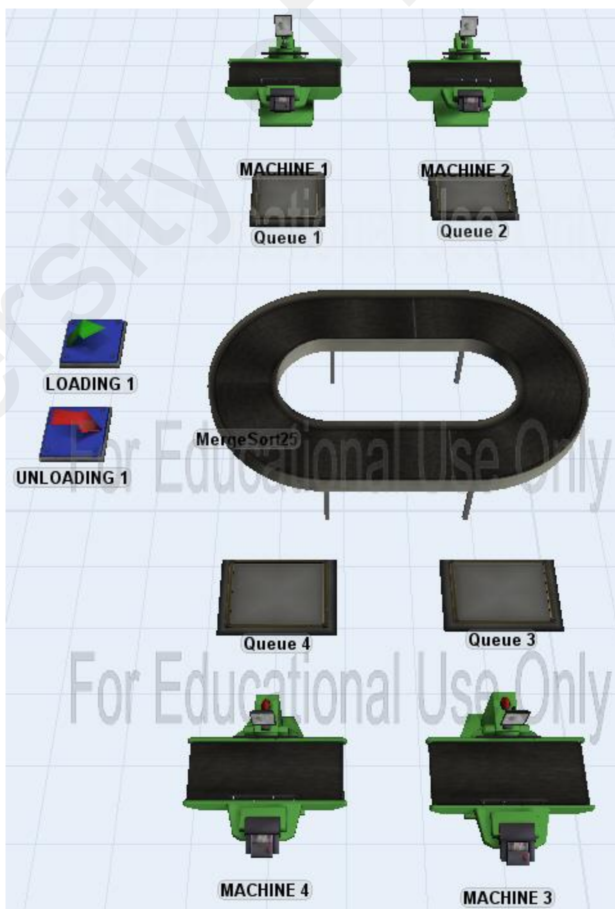

Figure 5.2: Simulation model of FMC in FlexSim

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Table 5.2 lists the equipment used to establish the FMC. The simulation model of FMC is implemented in FlexSim with objects that represent the components of system as described in Table 5.3.

Table 5.2: Objects presents equipment in FMC model

Objects	Resource name	Description	Capacity
Fixed resources	MC1	CNC machine 1	1
	MC2	CNC machine 2	1
	MC3	CNC machine 3	1
	MC4	CNC machine 4	1
	Conveyor	Transporting parts	1

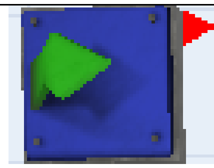
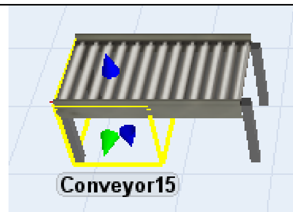
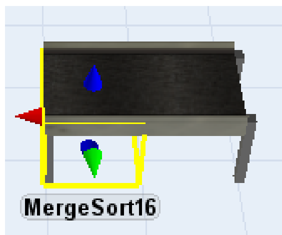
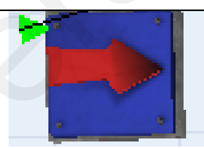
The experiment of simulation runs aims to validate the results obtained in Table 4.14 and Table 4.16 (see Chapter 4). The performance indicators used to measure the similarity between the simulation model and proposed BBO approach are the system unbalance, makespan and total flow time when the total part types are completed all operations and stored by the queue.

The inputs of simulation process are summarized as follows:

- The processing time of each operation of each part type in each CNC machine.
- The sequence and routing of part enter in the FMC to produce many various operations of part types in the different CNC machines with the pre-determine batch sizes as required by customer's demand. The routing of part in the cell is correctly suitable for operations' assignment into machines which is suggested by the non-dominated sorting BBO approach.

The output is the comparison of the performance's indicators (system unbalance, makespan and total flow time) for the two models of simulation and numerical study.

Table 5.3: The main components (Objectives/Elements) in the FlexSim simulation

Components	Visualization	Function
Sources		The Sources is used to create the part types and define the arrival schedule and quality of part types.
Conveyor		Conveyor is used to convey the part types to machines. It has a single input and output. The main parameters of conveyor are length, width, radius, speed and capacity.
MergeSoft		Transport the part types to machines for processing. MergeSoft has multiple inputs and multiple outputs which is more convenient to control the production flow. The length, speed, capacity, location of input port and output port are considered the main parameters for specializing the characteristics of MergeSoft.
Processors		Processor is shown as a CNC machine to processing the part in the manufacturing cell. The main properties of the processors are processing time and capacity.
Sink		Sink is the destination of the part type. It is used to destroy items/part after processing

5.4 Simulation results

In order to validate the results of solution for machine loading in FMC in terms of system unbalance, makespan and total flow time, the processing time, traveling time and operations for each machine determined to produce the part type are assigned based on Tables 4.12-4.16. The solutions of the most suitable combination of machines and operation in FMC are determined based on the NSBBO approach. Figure 5.3 describes the FMC model and its results in FlexSim simulation environment.

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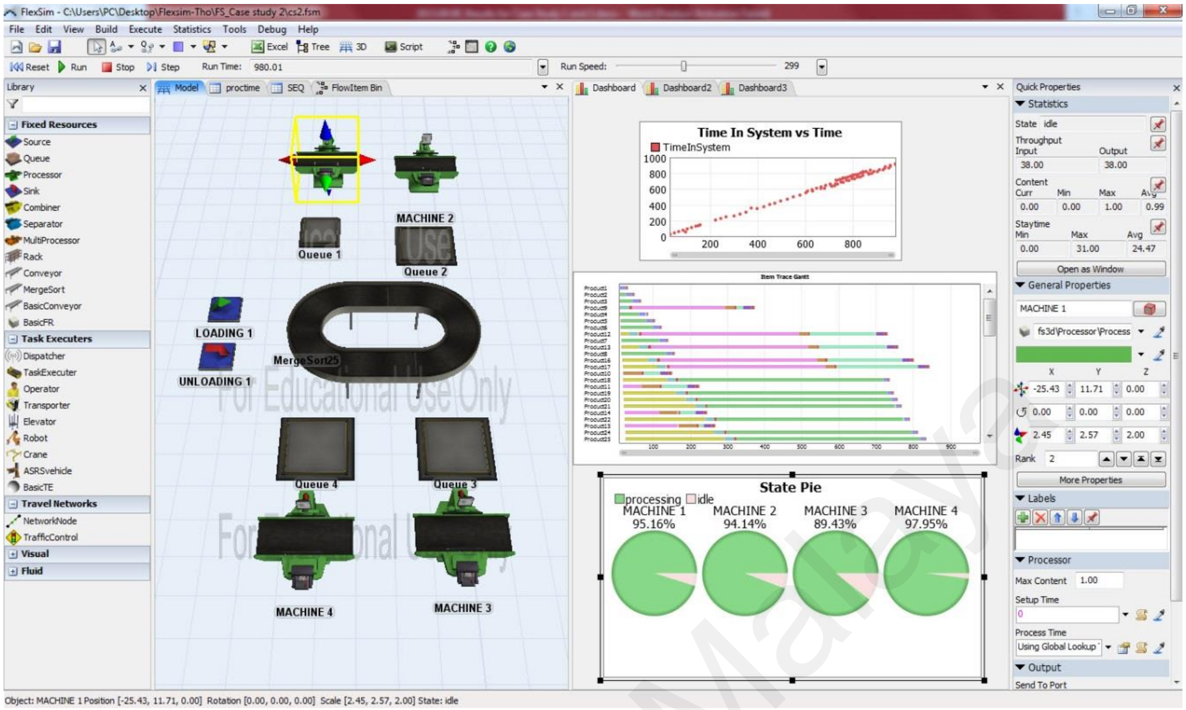

Figure 5.3: FMC in FlexSim simulation environment

The statistics of the state of CNC machines in FMC is described as a pie chart in Figure 5.4. For Case Study 1, as described in Figure 5.4a, shows that CNC machine MC1 was idle for 12.11% of the total simulation time, and was busy for 87.89% of the time. Similarly, other machines, MC2, MC3 and MC4 show percentages of busy time at 92.96%, 87.89%, and 41.41%, respectively. This last metric is also known as the machine utilization. Machine MC2 had the highest utilization rate in FMC whereas machines MC3 and MC1 had the balance rate of utilization. The optional operations of part types 2 and 4 (Case Study 1) are common assigned to Machines 2 and 3. Therefore, these machines possess high utilization rate.

Figure 5.4b shows the utilization rate of each machine in FMC in Case Study 2. Since this case has 8 part types with large batch sizes, there are many optional operations of part types needed to be considered. Thus, the utilization of machine becomes more flexible and easier to obtain the trade-off among each machine. Figure 5.4b depicts that CNC machine

MC1 was idle for 6.47% of the total simulation time, and busy for 95.53% of the time. Similarly, other machines, MC2, MC3 and MC4, percentages of the busy time were recorded at 93.53%, 91.99%, and 97.04%, respectively. Most of machines in FMC obtained the very high utilization rate, with machine MC4 having the highest rate of 97.04% busy time.

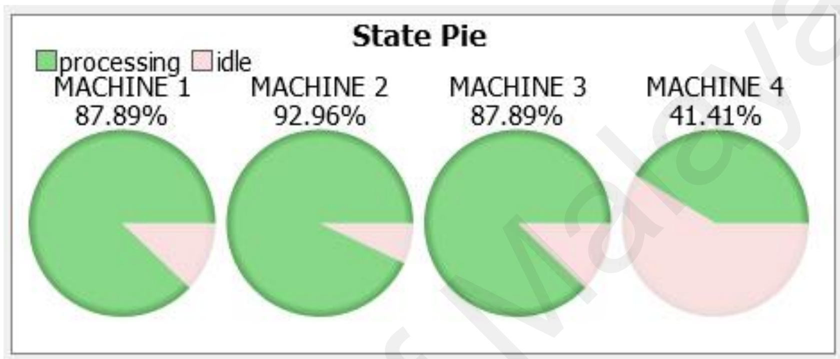

Figure 5.4a: Case study 1

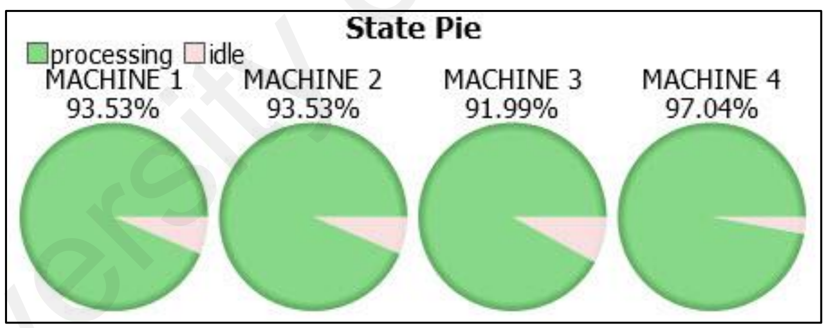

Figure 5.4b: Case study 2

Figure 5.4: The statistics of the state of CNC machines in FMC of simulation model

Figure 5.5 shows the work in progress (WIP) vs time in the FMC of the simulation process. It describes the WIP will be reduced if when the running time of simulation is increased. The WIP will be zero when the running time obtains the values of the makespan 355.01min (Figure 5.5a for Case 1) and 978min (Figure 5.5b for Case 2), and FMC completes the machining process to obtain the desired batch sizes.

Figue 5.5a: Case study 1

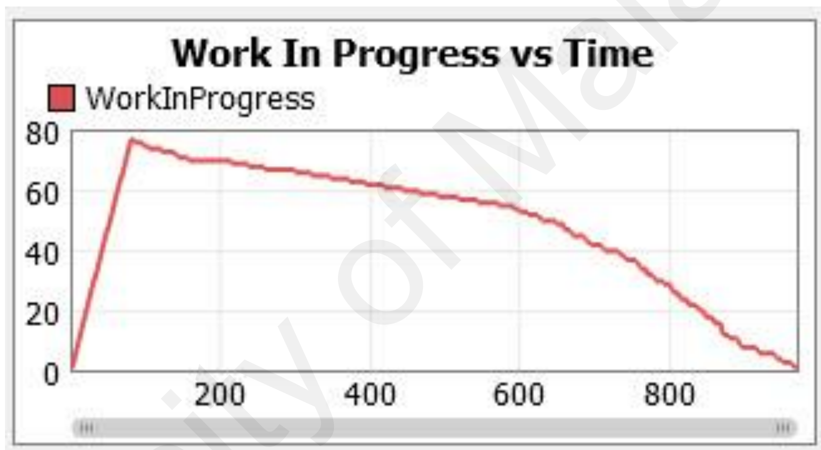

Figure 5.5b: Case study 2
Figure 5.5: Work In Progress (WIP) vs Time

Figure 5.6 shows the average staytime for each machine to complete the simulation process of FMC (Figure 5.6a for Case Study 1 and Figure 5.6b for Case Study 2).

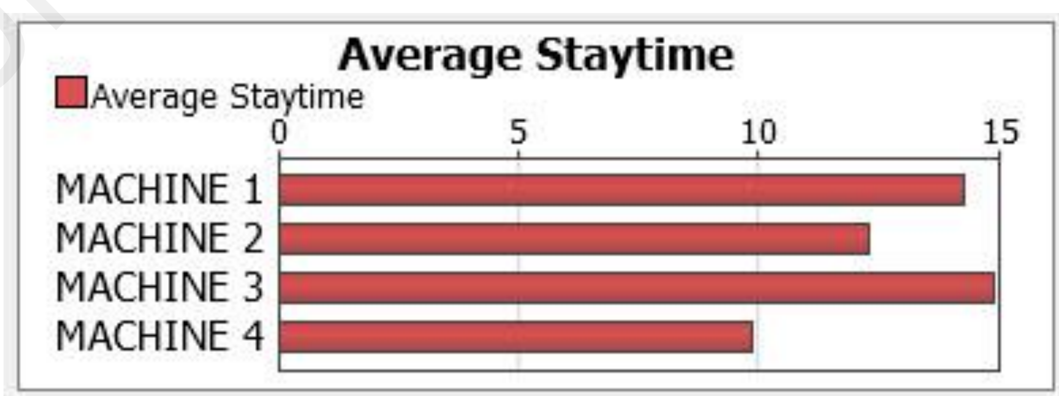

Figure 5.6a: Case study 1

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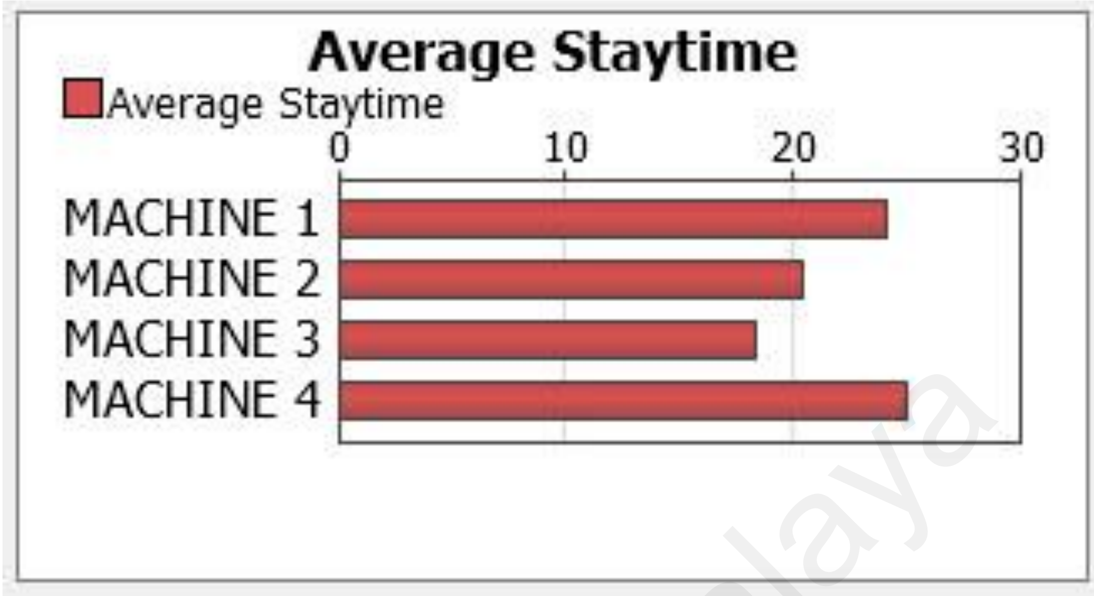

Figure 5.6b: Case study 2
Figure 5.6: Average Staytime of each machine

Figure 5.7 shows the item type trace of each machine in FMC is based on the arrival schedule of the part types and the loading time to machines. The simulation run time to complete all the batch sizes of Case Study 1 for 5 part types (51 items) is 355.01 min (Figure 5.7a) and Case Study 2 for 8 part types (81 items) is 978 min (Figure 5.7b). From this Trace Gantt, the values of makespan and total flow time are also calculated to be compared with the analytical results of NSBBO. Table 5.4 shows the comparison of system unbalance, makespan and total flow time from NSBBO analytical and simulation experiments. In particular, the system unbalance is determined from Figure 5.4 on the machine utilization rate. The Figures 5.8a and 5.8b describe the bar chart of comparison for Case Study 1 and Case Study 2, respectively. Based on Table 5.4, it can be shown that the result of NSBBO is quite similar to results of the FlexSim simulation. It means that FlexSim simulation of FMC can be a powerful tool to validate the proposed model, and results of NSBBO are competitive and potential to explore the most appropriate process planning.

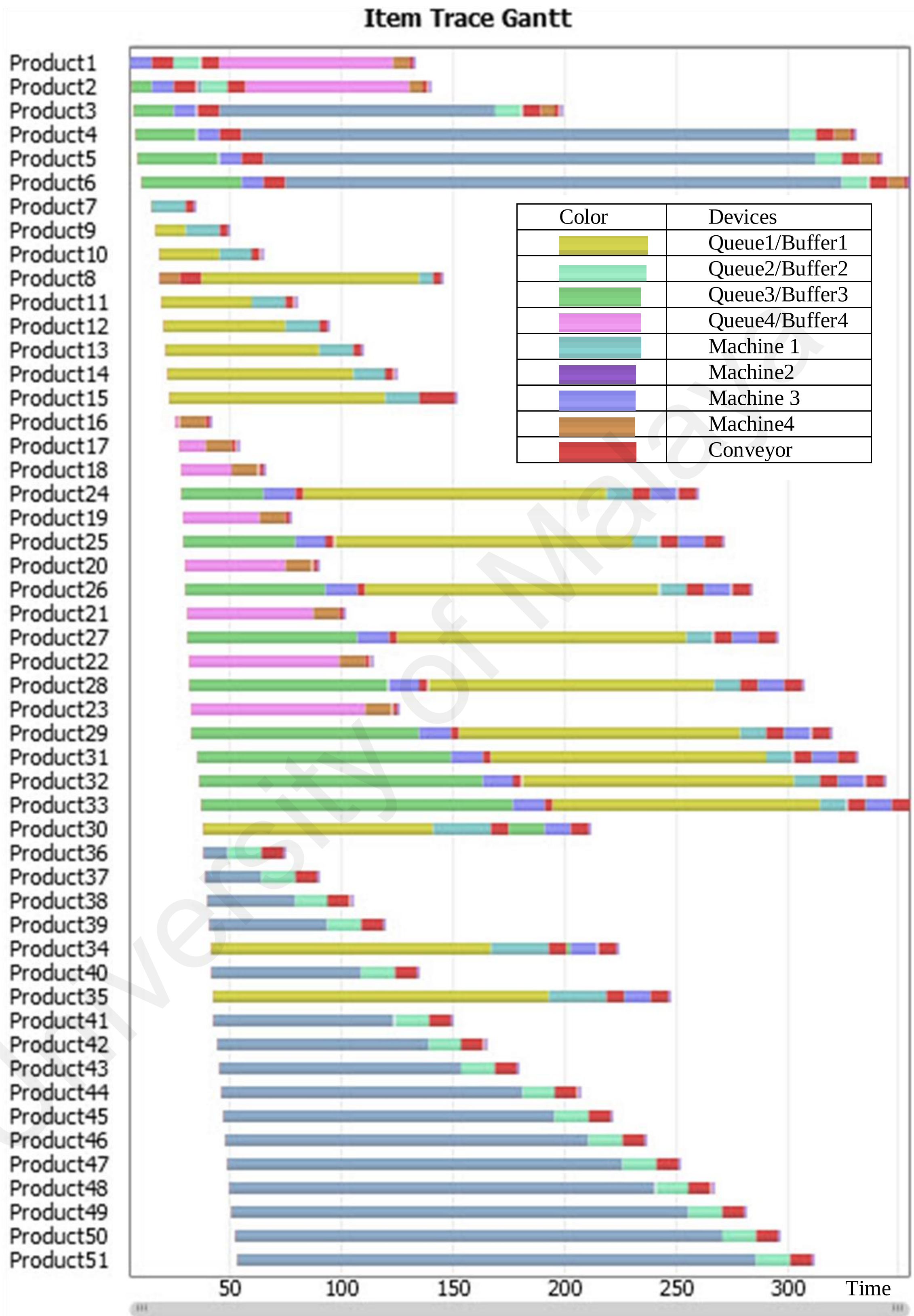

Figure 5.7a: Case study 1

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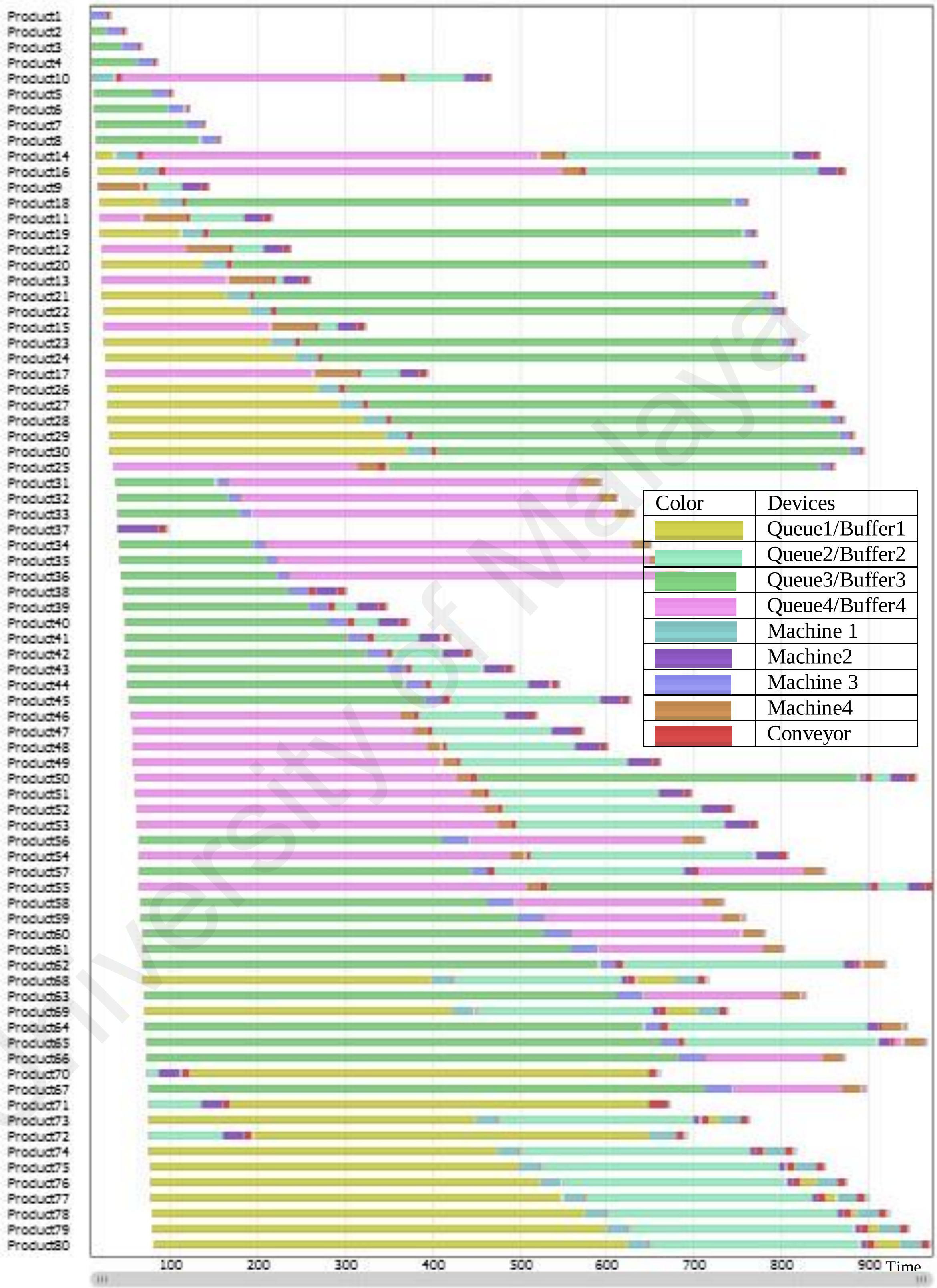

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Figure 5.7b: Case study 2

Figure 5.7: Item Type Trace Gantt

Table 5.4: The comparison of system unbalance, makespan and total flow time (min)

	Case study 1			Case study 2		
Performance index	Simulation	NSBBO	Error	Simulation	NSBBO	Error
System unbalance	818.936	819	0.06%	1739.36	1793	3%
Makespan	355.01	353	0.57%	973.01	978	0.5%
Total flow time	9532.6	9448	0.89%	50560.01	50858	0.6%

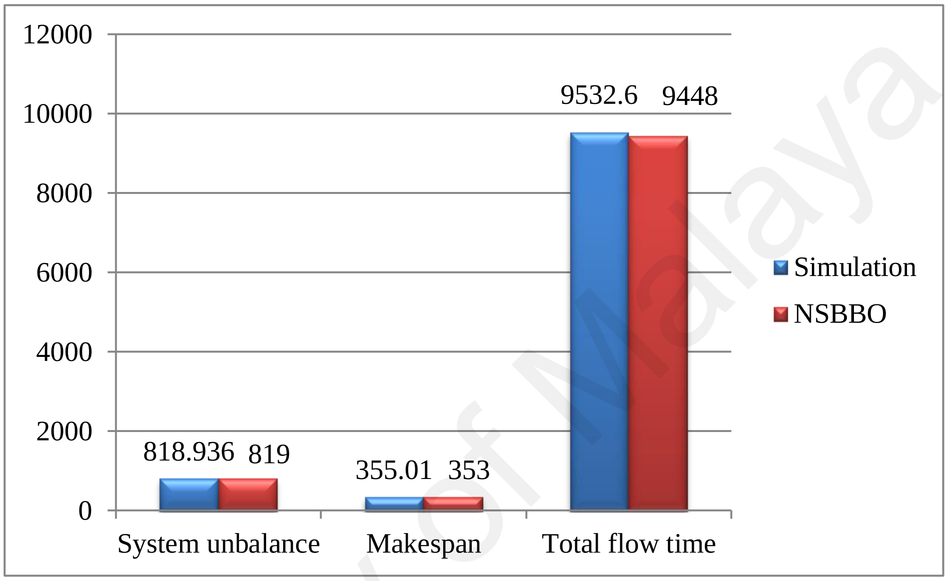

Figure 5.8a: Case study 1

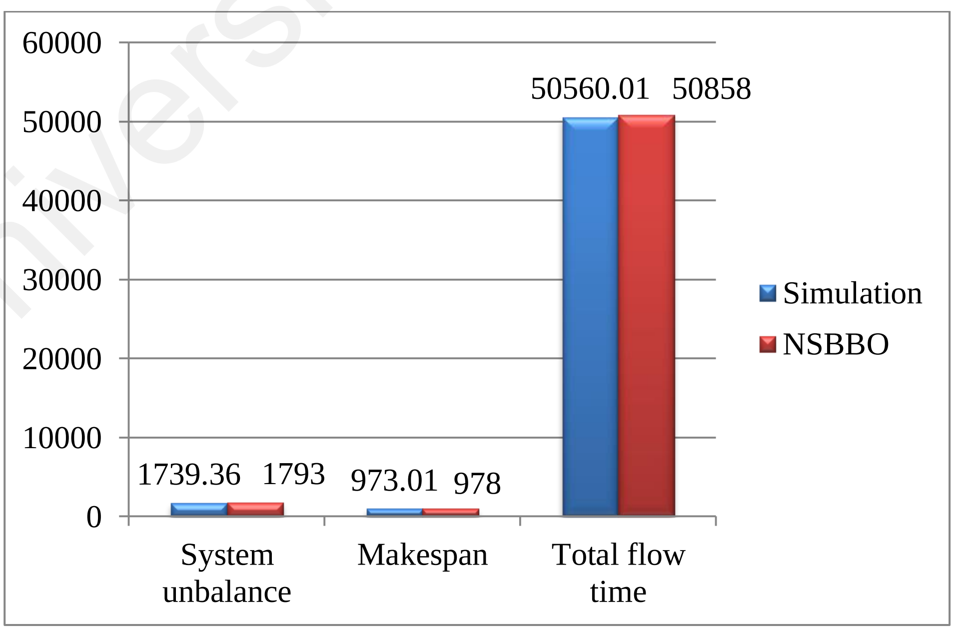

Figure 5.8b: Case study 2

Figure 5.8: Comparison of performance index between NSBBO and simulation

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A simulation technique is used to evaluate the designed flexible manufacturing cell in terms of productivity to produce various part types with the corresponding batch sizes from customers' demand. From the results of the comparison between the two models of simulation and analytical non-dominated sorting BBO method, it can be seen that the proposed FMC model is able to complete the process planning and achieve batch size as required. The simulation model also shows the status of each CNC machine to improve the machine's utilization and evaluate the total performance of FMC.

5.5 Summary

In this chapter, the simulation of proposed FMC model has been conducted to validate and verify the accuracy of computational results from the previous chapters of the thesis. The objective of this is to prove that the computational model proposed is effective and practical to develop the real applications in manufacturing SMEs.

The newly design FMC system consists of four CNC machines, conveyor systems and buffers are connected together and controlled by a computer workstation. The simulation results and experiment runs on the comparison of performance indicators such as system unbalance, makespan and total flow time confirm the reasonableness of the designed cell.

The simulations are carried out based on two case studies, a case study for 5-part types and a case study for 8 part types with various desired batch sizes from customer's demand. The experiment and simulation of the newly design FMC is implemented for the most appropriate process plan determined by the computational method described in Chapter 4. The results confirmed the capacity of the ability to complete the part types with different batch sizes, and the proposed model is potential to be implemented in practice at manufacturing SMEs of the local as well as in other developing countries.

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CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

Globalization process of business promotes the introduction and strong development of SMEs in the application of advanced manufacturing technology to create competitive values. FMC is a major factor in this issue due to the flexibility and efficiency in production. To achieve the flexibility and effectiveness of FMC, the issue of machine tool selection and machine loading were considered in this thesis. The research work involved the development of methods to solve the problem in designing FMC and has important significance to contribute to the body of knowledge in this field. Moreover, the results of this research work can be implemented in various applications in manufacturing SMEs of developing countries.

6.1 Conclusions

The machine selection was integrated with machine loading problems in particular to aid the decision as a result of the compromise for the implementation of FMC. In this research, a multi-criteria integrated analysis methodology for machine tool selection and machine loading is proposed for developing the flexible manufacturing cells to be implemented in manufacturing SMEs. The simulation model was used to prove the practical applicability of proposed framework at enterprises through simulation behavior of operation of FMC. The main contributions of this research are as follows:

- Developing the fuzzy preference relations based AHP and fuzzy COPRAS for machine tool selection to establish the FMC.
- Finalizing the decision in machine tool selection based on the development of hybrid approach of fuzzy ANP and COPRAS-G with the consideration of interactions of attributes.

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- Developing a non-dominated sorting Biogeography Based Optimization for finding the best solutions of process plan to give the most suitable combination of operations and machines in FMC.
- Simulation was carried out to validate the proposed machine loading model.

In addition, the novelty of this research is also identified as follows:

- The integrated approach of fuzzy linguistic preference based AHP and fuzzy COPRAS for evaluating the machine tools.
- The hybrid method of fuzzy ANP and COPRAS-G was developed for making the final decision in machine tool selection. The interaction of attributes of machines was considered, and few new attributes were included.
- The mathematical model of machine loading problem in FMC was developed. In particular, the different allocation of each part in batch size was considered.
- The non-dominated sorting BBO was adapted to determine the most suitable solutions of machine loading problem.

Furthermore, this research also presented several significant findings as follows:

1. In the proposed decision making framework of Fuzzy Linguistic Preference based AHP and Fuzzy COPRAS, a computation program based on MATLAB was developed for machine tool selection in uncertain environments. The integration of fuzzy AHP and Fuzzy COPRAS has shown significant advantage in data collection for processing uncertain information on machine tool evaluation. In particular, the fuzzy linguistic preference relation was used to determine the elements of decision matrix based on experts' judgments. In the MCDM model of fuzzy AHP and fuzzy COPRAS, ten attributes were considered for evaluating machine tools. This integrated approach has significantly reduced the required number of experts' judgments. This is a practical and applicable method for

the decision-making process and helps engineers and managers to interpret information by modeling the quantitative and qualitative input data.

2. The multi-criteria analysis based on hybrid method of fuzzy ANP and COPRAS-G: The hybrid approach of fuzzy ANP and COPRAS-G has been proven to provide an effective decision when evaluating suitable machines to be implemented the flexible manufacturing cells. This methodology is useful for supporting the decision-makers due to the following benefits. First, fuzzy logic is capable of handling the imprecise, vague and uncertain information from the decision-makers' judgments. Second, the influence of the interactions between the attributes is considered in the fuzzy ANP method when determining the weights of the attributes. Finally, the COPRAS-G method allows uncertain information of the attributes to be expressed in interval values which is then used to obtain the ranking of alternatives.

3. A sensitivity analysis was carried out to prove that the integrated approach of the fuzzy ANP and COPRAS-G is a multi-attribute decision-making model in machine tool selection and is robust and manageable. This approach shows the following advantages over previous work. First, this model includes the interaction of attributes when evaluating the alternatives with the fuzzy ANP and includes three new additional attributes (ease of installation, user friendliness and green standards). Secondly, the number of pairwise comparisons is reduced, and the consistency ratio and super-matrix, which require large computational effort, are not necessary in the fuzzy ANP. Finally, COPRAS-G can easily solve problems with a large number of alternatives.

4. Two wise steps are successfully established for the selection of machine tools to completely implement flexible manufacturing cell. The proposed methods can be applied in both cases of single decision making and group decision making with consideration of

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evaluation criteria for the formation of manufacturing cells. These methods simultaneously allow the evaluation of large number of alternatives.

5. The model of multi-criteria selection of machines and operations to produce the part type in FMC was proposed using the principle of Biogeography Based Optimization and non-dominated sorting procedure. The multiple objectives are in minimizing the system unbalance, makespan and total flow time. The NSBBO was proposed to explore the feasible space of suitable solutions for the most suitable combination of machine and operation, satisfying three objectives. The results obtained were compared with solutions achieved from LINGO and other studies from the literature.

6. A simulation study was successfully implemented to show the practical applicability of the proposed FMC model in producing various part types with different batch sizes in manufacturing SMEs. The discrete event simulation comprises the graphical modeling to perform a visualization of allocation execution of part type into machines, and simulation results are used to validate the output of numerical study of machine loading problem on its performance indices of system unbalance, makespan and total flow time. The graphical simulation model has made the evaluation of FMC easier, and provided better insight and deep understanding on system operation through evaluating the cell's behavior and performance. The outcome of simulation model highlighted that there was no significant difference between simulation and numerical studies and capacity of implementation in the practice at manufacturing SMEs.

7. The overall proposed framework developed in this thesis is a synthesis of three phases of selecting preliminary machine tools, finalization of machine selection decision is then solved to establish a FMC; and then, the most suitable process plans are gained for introducing the operations of part types into the most appropriate machine tool to process.

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The proposed framework of this research has been validated by a simulation discrete event model in FlexSim. The results highlighted that this framework have some practical implications. It can be used for investing the right machines and verify the most appropriate process plan for implementing the FMC at manufacturing SMEs to produce the part types with required batch sizes of customers.

6.2 Recommendations for Future Works

In order to pursue this research application to be effective in all aspects of manufacturing cells, there are some possible areas are suggested for future studies:

- For decision making in machine tool selection, the attributes of machine tools are hypothesized as independent factors affecting the decision-making without consideration of their interactions and inter-dependence. Therefore, the fuzzy ANP (Analytic Network Process) can be further developed and implemented based on fuzzy linguistic preference relations to reduce the number of experts' judgments needed to be collected and its hybrid approaches with many different methods (fuzzy PROMETHEE, fuzzy ELECTRE, fuzzy VIKOR, fuzzy SAW, fuzzy ARAS and fuzzy TOPSIS) can be considered as an interest to evaluate a large number of alternatives. Future studies on the proposed approach can continue to develop the process plan for machine tools because of the promising capacity of the fuzzy ANP and COPRAS-G to handle the processing time, costs (tools, setup, machining, etc.) and other factors using fuzzy and grey numbers (interval values). In addition, there are several other critical issues for future research that do not directly affect the results, such as considering the fuzzy linguistic preference relations, expert systems to reduce the number of judgments in the pairwise comparison matrix and integrating the proposed method with ANFIS (Adaptive Neuro Fuzzy Inference System) to reduce the inputs/attributes.

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- As an extension to this research, actual case studies at a manufacturing company can be carried out to assess the FMC. The proposed model of machine loading can be considered with the additional resources such as jigs/fixtures, material handling systems (robots, AGVs) and the constraints on availability of resources. Then, sequencing and scheduling of flexible manufacturing cell for the selected machines and operations can be suggested for further extension in uncertain and stochastic manufacturing environment. Furthermore, the parameters of processing time of operations and traveling time of machining parts can be addressed in the context of fuzzy numbers and grey numbers where the uncertain information exists in the manufacturing environment. The fuzzy resources and stochastic machine assignment problems is another direction for future research. Finally, one future possible area of this research is to develop a multi-agent based machine assignment, sequencing, scheduling and integration system for exchanging effectively information in real manufacturing cell of SMEs.
- The continuation for the development of NSBBO to include the variations of migration rates should be explored and compared with NSGA-II and SPEA-2 in terms of performance indicators. Moreover, the constraints handling methods can also be combined with NSBBO to solve constrained multi-objective machine loading problems.

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LIST OF PUBLICATIONS AND PAPERS PRESENTED

Conference papers

[1] **H-T Nguyen**, SZM Dawal, Y. Nukman, F. Tahriri, H. Aoyama. Selecting a CNC machine tool using the Intuitionistic Fuzzy TOPSIS approach for FMC. *International Conference on Mechanical and Manufacturing Engineering* (ICME2012), 20-21 Nov 2012 at Johor, Malaysia.

[2] Siti Zawiah Md Dawal, Nukman Yusoff, **Nguyen Huu Tho**, Hideki Aoyama. Multi-Attribute decision making for CNC machine tool selection in FMC based on the integration of the improved consistent fuzzy AHP and TOPSIS. *5th AUN/Seed-Net Regional Conference on Manufacturing Engineering*, Manila, Philippines (5-6Nov2012).

Journal Articles

[3] **H-T Nguyen**, SZM Dawal, Y. Nukman, F. Tahriri, H. Aoyama (2013). Selecting a CNC machine tool using Intuitionistic Fuzzy TOPSIS approach for FMC, *Applied Mechanics and Materials* (Vol. 315), 2013, 196-205 (published, SCOPUS-indexed).

[4] Siti Zawiah Md Dawal, Nukman Yusoff, **Huu-Tho Nguyen**, Hideki Aoyama (2013). Multi-Attribute decision making for CNC machine tool selection in FMC based on the integration of the improved consistent fuzzy AHP and TOPSIS, *ASEAN Engineering Journal* Part A Vol. 3 No. 2 (published, SCOPUS-indexed).

[5] **Huu-Tho Nguyen**, Siti Zawiah Md Dawal, Yusoff Nukman, Hideki Aoyama (2014). A hybrid approach for fuzzy multi-attribute decision making in machine tool selection with

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[6] **Huu-Tho Nguyen**, Siti Zawiah Md Dawal, Yusoff Nukman, Hideki Aoyama, Keith Case (2014). An integrated approach for machine tool evaluation based on improved consistent fuzzy AHP and fuzzy COPRAS. *PLoS One* (ISSN: 1932-6203). (published in Q1 ISI-indexed).

[7] Siti Zawiah Md Dawal, Farzad Tahriri, Yap Hwa Jen, Keith Case, **Nguyen Huu Tho**, Aliq Zuhdi, Maryam Mousavi, Atefeh Amindoust, Novita Sakundarini (2015). Empirical evidence of AMT practices and sustainable environmental initiatives in malaysian automotive SMEs. *International Journal of Precision Engineering and Manufacturing* (ISSN: 2234-7593) 16(6) 1195-1203 (published in Q2 ISI-indexed).

[8] **Huu-Tho Nguyen**, Siti Zawiah Md Dawal, Yusoff Nukman, Hideki Aoyama, Achmad P. Rifai (2015). Multi-criteria analysis for machine loading in FMC using non-dominated sorting BBO. *Computers and Operations Research*. Under review (Q1 ISI-indexed).

[9] **Huu-Tho Nguyen**, Siti Zawiah Md Dawal, Yusoff Nukman, P. Rifai A, Hideki Aoyama (2016). An integrated MCDM model for conveyor equipment evaluation and selection in FMC based on a fuzzy AHP and fuzzy ARAS in the presence of vagueness. *PLoS ONE 11(4): e0153222. doi:10.1371/journal.pone.0153222*. Published (Q1 ISI-indexed).

[10] **Huu-Tho Nguyen**, Siti Zawiah Md Dawal, Yusoff Nukman, Hideki Aoyama (2015). Validation of optimal loading decision for flexible manufacturing cell based on

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Other activities

- Reviewer of manuscript (No.: 140031) for Journal of Information Science and Engineering (ISSN: 1016-2364)

- Reviewer of manuscript (No.: Engineering-14-191) for Journal of Industrial Engineering & Management (ISSN: 2169-0316)

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APPENDIX

Appendix A: Previous works in machine tool selection

Author	Year	Focus area	Description and Solution
Ic YT, Yurdakul M, Eraslan E	2012	Machining center selection	To rank the machining center based on the components with a model using Analytic Hierarchy Process (AHP)
Ayağ Z, Gürcan Özdemir R	2012	Evaluating machine tool alternatives	Fuzzy ANP is used to determine the weights of attributes and TOPSIS for calculating the ranking of machine tool alternatives
Taha Z, Rostam S	2011	Decision support system for machine tool selection	Fuzzy AHP and ANN is combined to evaluate the ranking of machine tools
Taha Z, Rostam S	2011	Decision support system for machine tool selection	Fuzzy AHP and PROMETHEE
Samvedi A, Jain V, Chan FTS	2011	Machine tool selection	Fuzzy AHP and GRA are used to analyze and evaluate the machine tools
Ayağ Z, Özdemir R	2011	An intelligent approach to machine tool selection	Fuzzy ANP
Paramasivam V, Senthil V, Rajam Ramasamy N	2011	Decision making in equipment selection	Digraph and matrix, AHP and ANP are integrated to select the equipment
Alberti M, Ciurana J, Rodríguez CA, Özel T	2011	Machine tool selection	Design of a decision support system for machine tool selection based on machine characteristics and performance tests using Artificial Neural Network (ANN)
Chakraborty S	2011	Decision making in manufacturing environment	Applications of the MOORA method for ranking alternatives
Ozgen A, Tuzkaya G, Tuzkaya UR, Ozgen D	2011	A Multi-Criteria Decision Making Approach for Machine Tool Selection in a Fuzzy Environment	Modified DELPHI, AHP, PROMETHEE, Fuzzy Set
Qi J	2010	Machine tool selection model based on fuzzy MCDM approach	Fuzzy Logic
Tsai JP, Cheng HY, Wang SY, Kao YC	2010	Multi-criteria decision making method for selection of machine tool	AHP (Expert Choice)
Yurdakul M, İç YT	2009	Analysis of the benefit generated by using fuzzy numbers in a TOPSIS model developed for machine tool selection problems	Fuzzy TOPSIS
İç YT, Yurdakul M	2009	Development of a decision support system for machining center selection	Fuzzy AHP and Fuzzy TOPSIS
Abdi M	2009	Fuzzy multi-criteria decision model for evaluating reconfigurable machines	Fuzzy AHP
Balaji CM, Gurumurthy A, Kodali R	2009	Selection of a machine tool for FMS using ELECTRE III-a case study	ELECTRE III
Önüt S, Soner Kara S, Efendigil T	2008	A hybrid fuzzy MCDM approach to machine tool selection	Fuzzy AHP and Fuzzy TOPSIS
Durán O, Aguilo J	2008	Computer-aided machine-tool selection based on a Fuzzy-AHP approach	Fuzzy AHP

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Dağdeviren M	2008	Decision making in equipment selection: an integrated approach with AHP and PROMETHEE	AHP and PROMETHEE
Bo S, Hua C, Laihong D, Yadong F	2008	Machine Tools Selection Technology for Networked Manufacturing	AHP
Ayağ Z	2007	A hybrid approach to machine-tool selection through AHP and simulation	AHP and Simulation
Ertuğrul İ, Güneş M	2007	Fuzzy Multi-criteria Decision Making Method for Machine Selection	Fuzzy TOPSIS
Rao RV	2007	Machine Selection in a Flexible Manufacturing Cell	GTMA, SAW, WPM, AHP, TOPSIS
Ayağ Z, Özdemir R	2006	A fuzzy AHP approach to evaluating machine tool alternatives	Fuzzy AHP
Chtourou H, Masmoudi W, Maalej A	2005	An expert system for manufacturing systems machine selection	ES
Arslan M, Catay B, Budak E	2004	A decision support system for machine tool selection	Multi-criteria weighted average
Yurdakul M	2004	AHP as a strategic decision-making tool to justify machine tool selection	AHP
Wang TY, Shaw CF, Chen YL	2000	Machine selection in flexible manufacturing cell: a fuzzy multiple attribute decision-making approach	Fuzzy Logic
Lin ZC, Liu QY	1997	Selection of coordinate measuring machines by the neural network method	Neural Network machine learning
Lin ZC, Yang CB	1996	Evaluation of machine selection by the AHP method	AHP
Myint S, Tabucanon MT	1994	A multiple-criteria approach to machine selection for flexible manufacturing systems	AHP and GP
Tabucanon MT, Batanov DN, Verma DK	1994	Decision support system for multicriteria machine selection for flexible manufacturing systems	AHP (Expert Choice) and ES

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Appendix B: Criteria and Sub-Criteria for Machine tool selection

Authors	Sample	Inputs (Criteria)	Sub-criteria	Outputs (Alternatives)
Ic YT, Yurdakul M, Eraslan E	20 Machines	1. Stiffness	1. Structure (Frame)	1. Mazak
		2. Damping Capacity	2. Spindle/Bearing	2. Okuma
		3. Thermal Stability	3. Guides	3. Excel
		4. Speed Capacity	4. Feed Drive	4. Milltronics
		5. Accuaracy		5. Eagle
				6. Challenger
				7. Fadal
				8. Hyundai
				9. Matsuura
				10. Moriseiki
Ayağ Z, Gürcan Özdemir R	3 machines	1. Productivity	1. Spindle speed	1. Machine A1
			2. Power	2. Machine A2
			3. Cutting feed	3. Machine A3
			4. Traverse speed	
		2. Flexibility	4. Number of tools	
			5. Rotary table	
		3. Space	6. Machine dimensions	
		4. Adaptability	7. CNC type	
			8. Number of taper	
		5. Precision	9. Repeatability	
			10. Thermal deformation	
		6. Reliability	11. Bearing failure rate	
			12. Reliability of drive system	
		7. Safety and environment	13. Mist collector	
			14. Safety door	
			15. Fire extinguisher	

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		8. Maintenance and service	16. Repair service	
			17. Regular maintenance	
Taha Z, Rostam S	118 CNC turning center machines	1. Work envelope (main spindle)	1. Turning diameter	1. Nakamura
		2. Components (head spindle)	2. Turning length	2. Mazak
		3. Tooling (carrier)	3. Standard chuck diameter	3. Romi
		4. Axes specification	4. Bar capacity	4. Doosan
		5. General	5. Top rpm	
			6. Horse power	
			7. Number of turning tools	
			8. Standard number of axes	
			9. Machine weight	
			10. Floor layout	
Taha Z, Rostam S	118 CNC turning centre	1. Work envelope	1. Turning diameter	1. Nakamura
		2. Headstock	2. Top RPM	2. Mazak
		3. Tooling	3. Number of turning tools	3. Romi
		4. Axes specification	4. Number of axes	4. Doosan
		5. General	5. Machine weight	
			6. Floor layout	
			7. Horse power	
Samvedi A, Jain V, Chan FTS	4 machining centres	1. Cost		1. Machining centre 1
		2. Operative flexibility		2. Machining centre 2
		3. Installation easiness		3. Machining centre 3
		4. Maintainability and serviceability		4. Machining centre 4

		5. Productivity		
		6. Machine tool compatibility		
		7. Safety		
		8. User friendliness		
Ayağ Z, Özdemir R	3 Machine tools	1. Improved customer satisfaction (ICS)\Increased productivity	1. Spindle speed	1. Machine tool 1
			2. Main power	2. Machine tool 2
			3. Cutting feed	3. Machine tool 3
			4. Traverse speed	
		2. ICS\Higher flexibility	5. Tool change time	
			6. Capacity of rotary table	
			7. Average set-up time for product change	
		3. ICS\Effective use of space	8. Machine dimensions	
			9. Area for accessories	
			10. Difficulty degree to locate in-site	
		4. Increased profitability (IPF)\Better adaptability	11. DNC integration	
			12. CNC capacity	
			13. Upgradeability	
		5. IPF\Better precision and accuracy	14. Repeatability	
			15. Thermal deformation	
			16. Checking probe installed	
		6. IPF\Increased	17. Bearing failure	

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		reliability	rate	
			18. Reliability of drive system	
			19. Reliability of computer-controlled system	
		7. IPF\More safety and environment	20. Operator training for safety	
			21. Proportion of recycling components	
			22. Safety accessories (i.e. mist collector)	
		8. IPF\Satisfied maintenance and service	23. Specialized training	
			24. On-time repair service	
			25. Regular maintenance	
Paramasivam V, Senthil V, Rajam Ramasamy N	5 alternatives		1. Price	1. Machine 1
			2. Weight	2. Machine 2
			3. Power	3. Machine 3
			4. Spindle Speed	4. Machine 4
			5. Spindle Diameter	5. Machine 5
			6. Stroke length	
Alberti M, Ciurana J, Rodríguez CA, Özel T	5 machine tools		1. Temperature control	1. Machine tool MT1
			2. Machine accuracy	2. Machine tool MT2
			3. Acceleration	3. Machine tool MT3
			4. Acceleration	4. Machine tool MT4
			5. Volume	5. Machine tool MT5
			6. Machine tool cost	
Chakraborty S	21 CNC machines		1. Capital cost	1. YANG
			2. Spindle spped	2. YCM

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	(lathes)		range	
			3. Tool capacity	3. VTURN
			4. Rapid traverse rate of X-axis	4. FEMCO
			5. Rapid traverse rate of Z-axis	5. EX
			6. Maximum machining diameter	6. ECOCA
			7. Maximum machining length	7. TOPPER
				8. ATECH
Ozgen A, Tuzkaya G, Tuzkaya UR, Ozgen D	5 alternati ves	1. Cost related specifications	1. Investment costs	1. Alternative P1
			2. Operating costs	2. Alternative P2
			3. Maintenance costs	3. Alternative P3
			4. Revision costs	4. Alternative P4
		2. Technical specification	5. Capacity	5. Alternative P5
			6. Setup and adjusting time	
			7. Installation easiness	
			8. Revision and upgradeability	
		3. Operational specifications	9. Flexibility	
			10. Productivity	
			11. User friendliness	
			12. Safety	
		4. Quality related specifications	13. Accuracy	
			14. After sales maintenance and service possibilities	
			15. Durability	
Qi J	Three CNC wirecut	1. Process quality	1. Dimension accuracy	1. CNC wirecut EDM 1
			2. Shape accuracy	2. CNC wirecut

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	EDM			EDM 2
			3. Positioning accuracy	3. CNC wirecut EDM 3
			4. Surface roughness	
		2. Delivery time	5. Cutting time	
			6. Auxiliary time	
		3. Resource consumption	7. Main material consumption	
			8.Auxiliary material consumption	
			9.Energy consumption	
		4. Cost	10. Operation cost	
			11.Maintenance cost	
			12.Depreciation of machine	
		5. Environment impact	13. Noise	
			14. Waste	
		6. Ergonomical aspect	15. Safety	
			16.Labour intension	
			17. Simplicity	
			18. Operator comfort	
Tsai JP, Cheng HY, Wang SY, Kao YC	Three 4-axis CNC vertical machining centers	1. Capacity	1. Productivity: Spindle speed, Power, Cutting Feed, Traverse feed.	1. Machine A
			2. Flexibility: Number of tools; Rotary table	2. Machine B
			3. Adaptability: CNC type Taper nr.	3. Machine C

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			4. Precision: Repeatability Thermal Deformation	
		2. Space	5. Floor space requirement	
			6. Maximum machine hight	
		3. Maintenance & service	7. Training	
			8. Repair service	
			9. Regular Maintenance	
		4. Safety & Environment	10. Mist collector	
			11. Safety door	
			12. Fire extinguisher	
		5. Reliability	13. Bearing failure rate	
			14. Reliability of drive system	
		6. Cost	15. Initial cost	
			16. Running cost	
Yurdakul M, İç YT	16 machine tools		1. Table area	1. Mazak
			2. Maximum spindle speed	2. Okuma
			3. Power	3. Matsuura
			4. Tool number	4. Moriseiki
			5. Tool change time	5. Dahil
			6. Maximum tool diameter	6. Hyundai
			7. Positioning accuracy	7. Excel
				8. Challenger
				9. Leadwel
				10. Eagle
				11. Awea
				12. Taksan

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İç YT, Yurdakul M	10 machining centers	1. Guides	1. Box	1. Mazak
			2. Linear-ball bearing	2. Matsuura
			3. Linear-cylindrical bearing	3. Okuma
			4. Hydrostatic	4. Moriseiki
		2. Spindle/bearing	5. Ball bearing	5. Excel
			6. Angular contact ball bearing	6. Hyundai
			7. Cylindrical bearing	
			8. Hybrid bearing	
			9. If chiller unit or other cooling capacities exist (for all bearing types)	
		3. Feed drive	10. Ball-screw-single nut	
			11. Ball-screw-double nut	
			12. Double ball-screw	
			13. Ball-screw-fixed both end/or preloaded	
			14. Linear motor	
			15. If ball-screw cooling (effective coolant oil or circulated through the hollow ball-screws) exist	
		4. Structure	16. Cast-iron	
			17. Special design or special materials used	
Abdi M	3	1. Manufacturing	1. Setup time	1. Machine EC1

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	machine s	process reconfigurability (Process)\Capacit y	2. Changeover time	2. Machine EC2
			3. Variety	3. Machine EC3
		2. Process\Function	4. New product introduction	
			5. Mobility	
			6. Volume	
		3. Cost\Operating cost	7. Labour	
			8. Maintenance	
			8. Work in process	
			9. Changeover cost	
		4. Cost\Capital cost	10. Price	
			11. Install	
			12. Tools and fixtures	
		5. Cost\Overhead		
		6. Quality\Convenie nce of use		
		7. Quality\Reliability		
		8. Quality\Accuracy		
		9. Quality\Compatibi lity		
		10. Performance\Effic iency		
		11. Performance\Risk		
		12. Performance\Safet y		
Balaji CM, Gurumurthy A,	5 CNC machine	1. Operational attributes	1. Maximum swing over bead in	1. CNC ECONO26

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Kodali R	lathes		mm	
			2. Maximum swing over carriage in mm	2. CNC AUTOMANN26 V1
			3. Distance between centers in mm	3. CNC AUTOMANN26 V2
			4. Maximum turning length in mm	4. CNC AUTOMANN26 V3
			5. Minimum spindle speed in rpm	5. SMARTURN
			6. Maximum spindle speed in rpm	
			7. Spindle motor power in kW	
			8. Tail stock quill diameter in mm	
			9. Tail stock quill stroke in mm	
			10. Maximum X-axis travel in mm	
			11. Maximum Z-axis travel in mm	
			12. Rapid feed rate in X-direction in mm/min	
			13. Rapid feed rate in Z-direction in mm/min	
			14. Positioning accuracy in X-direction in mm	
			15. Positioning accuracy in Z-direction in mm	
			16. Repeatability in X-direction in	

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			mm	
			17. Repeatability in Z-direction in mm	
		Physical attributes	18. Machine length in mm	
			19. Machine width in mm	
			20. Tool holding capacity	
Önüt S, Soner Kara S, Efendigil T	4 vertical CNC machining centers	1. Cost		1. Machine tool MC1
		2. Operative flexibility		2. Machine tool MC2
		3. Installation easiness		3. Machine tool MC3
		4. Maintainability and serviceability		4. Machine tool MC4
		5. Productivity		
		6. Compatibility		
		7. Safety		
		8. User friendliness		
Durán O, Aguilo J	3 alternatives	1. Flexibility		1. Machine tool MT1
		2. Operation easiness		2. Machine tool MT2
		3. Reliability		3. Machine tool MT3
		4. Quality		
		5. Implementation easiness		
		6. Maintainability		
Dağdeviren M	5 alternatives	1. Price		1. Milling machine MM1
		2. Weight		2. Milling machine MM2
		3. Power		3. Milling

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				machine MM3
		4. Spindle		4. Milling machine MM4
		5. Diameter		5. Milling machine MM5
		6. Stroke		
Bo S, Hua C, Laihong D, Yadong F	5 machine tools	1. Machining precision	1. Highest precision	1. CW11000-1-2105138
			2. Lowest precision	2. C6130-2103084
			3. Surface roughness	3. C6140-2103090
		2. Task machining degree		4. CM6125A-2101373
		3. Machining dimension	4. Maximal length	5. STAR-TURN1200
			5. Maximal diameter	
			6. Minimum diameter	
		4. Machining cost	7. Operation cost	
			8. Transportation cost	
		5. Credibility factor	9. Enterprise grade	
			10. Cooperation credibility	
		6. Production time	11. Manufacturing time	
			12. Preparing time	
Ayağ Z	6 machine tools	1. Productivity	1. Spindle speed	1. Machine tool M1
			2. Power	2. Machine tool M2
			3. Cutting feed	3. Machine tool M3
			4. Traverse speed	4. Machine tool M4
		2. Flexibility	5. Number of tools	5. Machine tool M5
			6. Rotary table	6. Machine tool

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				M6
		3. Space	7. Machine dimensions	
		4. Adaptability	8. CNC type	
			9. Taper no.	
		5. Precision	10. Repeatability	
			11. Thermal deformation	
		6. Reliability	12. Bearing failure rate	
			13. Reliability of drive system	
		7. Safety and environment	14. Mist collector	
			15. Safety door	
			16. Fire extinguisher	
			17. Training	
		8. Maintenance and service	18. Repair service	
			19. Regular maintenance	
Ertuğrul İ, Güneş M	3 machines	1. Quality		1. Machine 1
		2. Payment terms		2. Machine 2
		3. After-sale service		3. Machine 3
		4. Capacity		
		5. Technology		
Rao RV	10 machines	1. Total purchasing cost		1. Alternative 1
		2. Total floor space		2. Alternative 2
		3. Total number of machines in a machine group of the FMC		3. Alternative 3
		4. Productivity.		4. Alternative 4
				5. Alternative 5
				6. Alternative 6
				7. Alternative 7

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				8. Alternative 8
				9. Alternative 9
				10. Alternative 10
Ayağ Z, Özdemir R	3 CNC vertical turning centers	1. Productivity	1. Spindle speed	1. Maho
			2. Power	2. Hass
			3. Cutting feed	3. Seiki
			4. Traverse speed	
		2. Flexibility	5. Number of tools	
			6. Rotary table	
		3. Space	7. Machine dimensions	
		4. Adaptability	8. CNC type	
			9. Taper nr.	
		5. Precision	10. Repeatability	
			11. Thermal deformation	
		6. Reliability	12. Bearing failure rate	
			13. Reliability of drive system	
		7. Safety and environment	14. Mist collector	
			15. Safety door	
			16. Fire extinguisher	
			17. Training	
		8. Maintenance and service	18. Repair service	
			19. Regular maintenance	
Chtourou H, Masmoudi W, Maalej A	5 machines	1. Number of machines		1. Machine M1
		2. Mean number of batches waiting		2. Machine M2
		3. Mean waiting time of a batch		3. Machine M3
		4. Mean machine utilization rate		4. Machine M4

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		5. Maximum allowable utilization rate		5. Machine M5
		6. Minimum allowable utilization rate		
		7. Utilization sate		
		8. Diagnosed problem		
		9. List of all machine departments		
		10. List of machine departments with a machine lack problem		
		11. List of machine departments with a machine surplus problem		
		12. Mean tardiness (actual cycle value)		
		13. mean advance (actual cycle value)		
		14. Manufacturing system sate according to the no performance deterioration constraint		
		15. Mean tardiness (last cycle value)		
		16. mean advance (last cycle value)		
		17. Solution of approach cycle number.		
Arslan M, Catay B, Budak E	33 machining centers	1. Productivity	1. Speed	
			2. Power	
			3. Cutting feed	
			3. Tool change time	
			4. Rapid speed	
			5. Pallet changer	

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		2. Flexibility	6. Number of tools	
			7. Rotary table	
			8. Number of pallets	
			9. Index table	
			10. CNC type	
			11. U or V axis	
			12. Head changer	
			13. Spindle power	
		3. Space	14. Machine dimensions	
			15. Auxiliary equipment (loading/unloading, material handling, quality)	
		4. Adaptability	15. CNC type	
			16. Number of tools	
			17. taper number	
		5. Precision	18. Axis precision	
			19. Repeatability	
			20. Thermal stability	
			21. Static and dynamic rigidity	
		6. Cost	22. Machining procurement cost	
		7. Reliability	23. Bearing failure rate	
			24. Reliability of drive system, etc.	
		8. Safety and environment	25. Mist collector	
			26. Safety door	
			27. Fire extinguisher	
		9. Maintenance and service	28. Training	
			29. Repair service	
			30. Spare parts	
			31. Regular	

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			maintenance	
Yurdakul M	4 vertical machining centers	1. Cost	1. Direct material	VTC-200B (3 Axis)
			2. Direct labor	FJV-250 (3 Aixs)
			3. Factory overhead	VARIAXIS 500 (5 Axis)
			3.1 Factory overhead\Depreciation on machinery	Conventional
			3.2 Factory overhead\Materials handling and storage	
			3.3 Factory overhead\Production planning	
			3.4 Factory overhead\Quality	
			3.5 Factory overhead\Machine set-up	
			3.6 Factory overhead\Machine maintenance and suppliers	
		2. Quality	4. Process quality	
			5. Actual machining time	
			6. Set-up time	
			7. Number of operations/parts	
		3. Delivery	8. Time from order to delivery	
			9. On-time shipments	
			10. Shipment accuracy	
Wang TY, Shaw CF, Chen YL	10 alternati	1. Total purchasing cost		1. Alternative 1

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	ves	2. Total floor space		2. Alternative 2
		3. total machine number		….
		4. Productivity		10. Alternative 10
Lin ZC, Yang CB	3 alternatives	1. Machine procedures		1. Conventional machine
		2. Lead time		2. NC machine
		3. Labor cost		3. FMC
		4. Operation shift		
Myint S, Tabucanon MT	7 alternatives	1. Investmant cost	1. Machines	1. Alternative 1
			2. Pallet and fixture	2. Alternative 2
			3. Transportation cost	3. Alternative 3
			4. Warehousing	4. Alternative 4
			5. Material handling	5. Alternative 5
			6. Tool	6. Alternative 6
			7. Software	7. Alternative 7
			8. Planned and training	
		2. Capacity	9. Planned capacity	
			10. Reserved capacity	
		3. Flexibility	11. Batch size	
			12. Throughput	
			13. Routing	
			14. Future potential	
			15. Part complexity	
		4. Utilization rate	16. Disturbed time	
			17. Shift in	
			18. Operation & Org. prob	

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			19. Prod. prob	
		5. Unit cost	20. Labour cost	
			21. Capital cost	
			22. Maintenance cost	
			23. Repair cost	
		6. Economic risk	24. Market product	
			25. Change tech.	
			26. Operation change	
Tabucanon MT, Batanov DN, Verma DK	7 alternatives	1. Flexibility of machine	1. Adaptability of machine to tooling	1. Alternative 1
		2. Adaptability of machine	2. Adaptability of machine to manpower	2. Alternative 2
		3. Total cost of machine	3. Adaptability of machine to MHS	3. Alternative 3
		4. Continuous operation of machine	4. Adaptability of machine to CS	4. Alternative 4
		5. Special feature of machine	5. Reliability of machine	5. Alternative 5
		6. Total productivity of machine	6. Maintainability of machine	6. Alternative 6
		7. Power and space requirements of machine	7. Service backup of machine	7. Alternative 7
			8. Spares availability of machine	
			9. Multi-tool operation in machine	
			10. Rapid traverse of machine	
			11. Unmanned operation of	

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			machine	
			12. Power consumed by machine	
			13. Space occupied by machine	

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Appendix C: Previous works on machine loading problem

No	Author	Year	Description and Research Objectives	Research Methodology
1	Chen & Ho	2005	To determine the production planning for flexible manufacturing system (FMS) with satisfied multiple objectives such as minimization of total flow time, machine workload unbalance, greatest machine workload, and total tool cost.	Effective Multi-objective GA (EMOGA)
2	Keung & Lee	2001	To simultaneously minimize both the number of tool switches and the number of tool switching instances in FMS.	Genetic algorithms (GA)
3	Goswami & Tiwari	2006	Minimization of system unbalance and maximization of throughput are considered as two main objectives of loading problem.	Reallocation-based heuristic
4	Swarnkar & Tiwari	2004		0-1 integer programming formulation using a hybrid algorithm based on TS and SA
5	Almutawa et al.	2005	To optimize the number of machines acquired for batch processing	Mathematical modeling and simulation, Linear programming, B&B in LINGO, LINDO, MATLAB, ARENA
6	Yogeswaran et al.	2009	Minimization of system unbalance and maximization of throughput	The methods GA and SA were developed based on crossover operators and mutation operators
7	Mahdavi et al.	2008	To minimize the machining cost, set-up cost and material handling cost	The 0-1 integer linear programming model is established and Pareto-based ant colony optimization (P-ACO) is proposed.
8	Kazerooni et al.	1997	Fuzzy approach to real-time operation selection	Fuzzy membership function and simulation techniques and dispatching rules
9	Yang & Wu	2002	Minimize the difference between maximum and minimum workloads of all the machine resources in each batch	MIP model and a GA-based method
10	Tiwari et al.	2006	To minimize SU, maximize TH, the combination of minimum SU + maximum TH)	Using constraints-based Fast Simulated Annealing Algorithm (FSAA)
11	Mahdavi et al.	2011	A bi-objective operation allocation and material handling equipment selection problem in FMS with the aim of minimizing the machine operation, material handling, machine setup costs and maximization of the machine utilization.	A modified chaotic ant swarm simulation based optimization (CASO)

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12	Atmani & Lashkari	1998	To minimize the total costs of operations, material handling and set-ups.	A linear, 0-1 integer programming model.
13	Mukhopadhyay et al.	1998	Minimizing the system unbalance	SA
14	Shouman et al.		To minimize SU and maximize TH	Integer programming, GA
15	Tiwari et al.	1997	To reduce SU and thereby maximize TH	Heuristic and Petri Net
16	Binghai et al.	2004	To minimize the number of tool changes and minimization of the imbalance in each machine	Heuristic algorithm
17	Vidyarthi & Tiwari	2001	Minimization of SU and maximization of TH	The job sequence is determined by evaluating the membership function of each job to characteristics such as batch size, essential operation processing time, and optional operation processing time
18	Koşucuoğlu & Bilge	2012	Minimization of the total distance traveled by parts	Mathematical programming (MP) models and Genetic Algorithms (GA), the Mixed-integer nonlinear programming (MINLP) models
19	Kim et al.	2012	To balance the workloads assigned to machines	Integer linear programming model, and the bin-packing algorithms
20	Berrada & Stecke	1986	To assign the machine tools, operations and associated cutting tools required for part types selected to be produced simultaneously for balancing the workload on all machines	Branch and Bound Algorithms
21	Prakash et al.	2008	To minimize SU and maximize TH	An Adaptive Hierarchical Ant Colony Optimization (AHACO) is proposed to compare with GA, SA, AIS, ACO, TS, SPT, LPT, LIFO, FIFO
22	Slomp & Stecke	2011	To change the current production control hierarchy	Algorithms for selecting and sequencing operations
23	Tripathi et al.	2005	To optimize the processing and transportation cost and time	Multi-agent modeling approach
24	Kumar et al.	2012	Minimization of SU and maximization of TH	Meta-hybrid heuristic technique based on GA and PSO
25	Keung et al.	2001	Minimization of tool switches and minimization of tool switching instances.	A novel Genetic Algorithm GA
26	Moon et al.	2002	The total production time for production order is minimized and workloads among the machine tools are balanced.	0-1 integer programming model and a GA approach based on a topological sort technique is developed.

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27	Lee et al.	2003	To perform the operation sequence and tool selection simultaneously to minimize tool waiting time when tool is absent.	
28	Mandal et al.	2010	To maximize TH and minimize the SU and makespan.	GA, SA, AIS
29	Babu Nanvala & Awari	2011	Minimization of SU and Maximization of TH	Mixed Integer or 0-1 programming; (1) The Mathematical approaches, (2) The heuristic approaches, (3). The Artificial Intelligence-based approaches.
30	Prabaharan et al.	2006	To generate joint operation-tool schedule in an FMC	Two heuristic algorithms, priority dispatching rules algorithm (PDRA) and SA algorithm. The results are compared with SPT, LPT, SRPT, LRPT, SIO, LIO, SDT, LDT.
31	Guldogan	2011	Machine tool selection and operation allocation to obtain the optimum machine park.	MCDM, the knowledge-based expert system; and to find the optimal machine park with the use of genetic algorithm GA.
32	Goswami et al.	2008	Minimization of make-span in a FMS	Tool and part grouping is performed using "principle component analysis", and tool allocation has been carried out using priority-based approach by developing a potency index.
33	Tiwari et al.	2007	Minimization of SU and maximization of TH	Heuristics and GA
34	Turkcan et al.	2007	Minimization of manufacturing cost (machining cost, tooling cost, non-machining cost) and minimization of the total weighted tardiness	
35	Prakash et al.	2007	Min SU, Max TH	GA, SA, AIS, ACO, TS
36	Kumar & Shanker	2000	Direct constraint=context-dependent genes and indirect constraint-the penalty function approach.	GA for mixed integer programming MIP
37	Arıkan & Erol	2012	Maximize the weighted sum of part and minimize the system unbalance	SA+TS
38	Basnet	2012	Minimize the system unbalance	Hybrid genetic algorithm GA
39	Jahromi & Tavakkoli-Moghaddam	2012	To minimize the production costs such as machining costs, setup costs, material handling costs, and tool movement costs.	Heuristic methods, B&B algorithm.
40	Abazari et al.	2012	Minimize the cost associated with the under-utilized and over-utilized times (min SU)	Linear mathematical programming model and GA

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41	Kumar et al.	2006	Min SU, Max TH and multi-objectives (SU+TH)	Constraint-based genetic algorithm GA
42	Guerrero	1999	To balance the workload	Mixed Integer Linear Programming.
43	Pandey	2011	Min SU and Max TH	AIS-Artificial Immune System
44	Deroussi & da Fonseca	2009	To minimize the makespan	Hybrid ACO-Ant colony optimization
45	Jahromi et al.	2011	To minimize the machining cost, setup cost, material handling cost.	Ant Colony Optimization ACO
46	Arikan & Erol	2006	To joint operation of part selection, operation assignment and tool magazine configuration.	SA & TS
47	Jahromi & Najafi	2011	To minimize the machining cost, setup cost, material handling cost for multi-objective problem.	Grouping GA
48	Jang et al.	2005	To balance the workload on machines	Hopfield Networks for 0-1 mixed integer programming problems.
49	Swarnkar & Tiwari	2004	Loading solutions with minimization of system unbalance and maximization of throughput	A generic 0-1 integer programming formulation; A hybrid algorithm of TS and SA
50	Goswami & Tiwari	2006	Minimization of SU and maximization of TH	Heristic algorithm
51	Chen & Ho	2005	To minimize the total flow time, machine workload unbalance, greatest machine workload and total tool cost.	An efficient multi-objective genetic algorithm EMOGA is proposed to solve the problem of production planning of FMS.
52	Almutawa et al.	2005	The optimum number of machines of each type and the optimum time delay between stages such as the system cost is minimized.	Linear programming in MATLAB, B&B algorithm in LINDO/LINGO; Simulation modeling in ARENA
53	Yogeswaran et al.	2009	Min SU + Max TH	GA with different crossovers and mutations
54	Mahdavi et al.	2008	Minimizing machining cost, set-up cost and material handling cost	0-1 integer programming; ACO base on Pareto Optimal solution
55	Mishra et al.	2006	The machine tool selection and operation allocation.	Quick Converging Simulated Annealing (QCSA) for fuzzy goal-programming model.
56	Chan et al.	2005	To minimize the total machining cost, setup cost and material handling cost	AIS-Artificial Immune System
57	Kumar et al.	1987	Decision-making	min-max approach
58	Kumar et al.	2004	Minimization of SU and maximization of TH	A fuzzy-based solution approach and extened neuro fuzzy petri net
59	Yusof et al.	2011	Minimize the SU as well as increase throughput	Harmony Search Algorithm
60	Chan et al.	2004	Min SU and Max TH	SA, a generic 0-1 mixed integer programming formulation

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61	Prakash et al.	2008	To minimize SU and maximize TH	AIS-Artificial Immune System
62	Biswas & Mahapatra	2008	To minimize the SU	Constraints: the availability of machining time and tool slots, PSO algorithm
63	Gamila & Motavalli	2003	Minimize the summation of maximum completion time, material handling time, and total processing time	0-1 mixed integer programming problem.
64	Salveson, M	1956		
65	Lee et al.	2003	To minimize tool waiting time when the tool is absent.	A simulation software and experiments, dispatching rules used is SPT, EDD, FCFS
66	Buyurgan et al.	2004	A heuristic approach for tool selection in FMS; the proposed method selects tool types with high L/S ratios by considering tool alternatives for operations assigned to each machine.	Several approaches related to loading and tool allocation problems in FMS.
67	Gupta	1999	Makespan; Mean flowtime; Mean tardiness	8 dispatching rules investigated in this study. There are FCFS (First-Come, First-Service), LCFS (Last-Come First-Service); SPT (Shortest Processing Time); LPT (Longest Processing Time); LREM (Least Remaining Processing Time); MREM (Most Remaining Time); LTOP (Least Total Processing Time); MTOP (Most Total Processing Time)
68	Nayak & Acharya	1998	A three stage approach to solving part type selection, machine loading and part type volume determination problems; maximize the part types in each batch.	
69	Rai et al.	2002	To minimize the total cost of machining operation, material handling and set-up	GA-Genetic Algorithm
70	Chan & Swarnkar	2006	To minimize total machining cost, total set-up cost; total material handling cost.	A fuzzy goal programming approach
71	Lee et al.	2000	To minimize the workload of the machine	Dispatching rules such as SJT; SPT; MOR; MWR; SDT; SMT; PWR; POR; SQ; SW
72	Sawik	1997	To balance the station workloads and to minimize station-to-station product transfer time	The weighting method and the interactive search for a set of weights
73	Sawik	1998	To balance station workloads and minimize total interstation transfer time.	Workloads are balanced using a linear relaxation-based heuristic and then assembly routes are selected based on a network flow model.
74	Sarma et al.	2002	To minimize SU, maximize TH	Tabu search TS heuristic

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75	Mussa I. Mgwatu	2011	Decisions of part selection, machine loading, machining optimization and part scheduling sub-problem.	MIP, LINGO
76	Ming Liang	1993	Bi-criteria models	LINGO
77	Ming Liang	1994	The part selection, machine loading, machining speeds are adjusted for all possible job-tool-machine combination.	MIP, LINGO
78	Biswas & Mahapatra	2007	Min SU	PSO
79	Ponnambalam & Kiat	2008	Min SU + Max TH	PSO, compared with GASA, PSO+PBLS, PSO+PBLS; PSO+JiBIS
80	Nagarjuna et al.	2006	Minimize SU	Literature review of 4 methods: (1) Mathematical programming approach; (2) Multi-criteria decision-making approaches; (3) Simulation-based approaches; (4) Heuristic-based approaches.
81	Yusof et al.	2011	Min SU as well as increase TH	Hybrid GA and Harmony Search algorithm
82	Ho & Hsieh	2005	To minimize the number of tool-shortage occurrences and balancing the workload between machines	Fuzzy c-mean, SA algorithm and an optimal tool-assignment algorithm
83	Grieco et al.	2001	review for approaches of machine loading	
84	Kim & Yano	1997	To minimize the maximization overload across machine groups is an excellent objective. The results also indicate that reducing the number of machine of machine groups and balancing workloads among the machine help to reduce makespan.	Makespan, Mean Tardiness, Mean Flow Time; Dispatching rules such as SPT (Short processing time); MDDI (modified due date); MDD2, MDD3, MDD4, MOD2 (modified operation due date), SLACK2, SLACK/RMOP2 (slack per remaining operation), SLACK/RMWK2, (slack divied by remaining work), COVERT2 (cost cover time). ATC2 (apparent tardiness cost), PWKR2 (processing time divided by remaining work), MWKR2 (most work remaining), and FIFO (first in first out).

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85	Stecke	1983	(1) Balance the assigned machine processing times; (2) Minimize the number of movements from machine to machine, or equivalently, maximize the number of consecutive operations on each machine; (3) Balance the workload per machine for a system of groups of pooled machines of equal sizes. (4). Unbalance the workload per machine for a system of groups of pooled machines of unequal sizes. (5) Fill the tool magazines as densely as possible. (6) Maximize the sum of operations priorities.	Non-linear 0-1 mixed integer programs.
86	Selvaraj	2011	Min SU, Max TH	MIP, GA, FlexSim Simulation software
87	Kato et al.	1993	(1) Formulation of part-tool group; (2) Assignment of groups to machines; (3) minimization of the total number of required tools; constraints such as available machining time, desired machine utilization rate; the magazine capacity constraint.	Branch and Bound Algorithms; Branch and Backtrack Algorithm
88	Soolaki, and Zarrinpoor	2014	Minimize machining cost, material-handling cost, setup cost, and maximum machine workload time and tool life.	A genetic algorithm (GA)

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Appendix D: Questionnaire design for machine tool selection using FAHP and FCOPRAS

The purpose of questionnaire design is to determine the weight priorities of the selected attributes for multi-attribute decision-making process in the most suitable CNC machine tool selection to implement a flexible manufacturing cell and satisfy the Small and Medium Enterprise's (SME) manufacturing goals is to produce few types of parts. The result is only used for the academic research purpose. The questionnaire should be completed by the experienced experts understanding the CNC machine tools as well as manufacturing system and technology. The following questions refer a questionnaire hierarchical structure (table below) to determine the importance of the attributes and the weight priorities of alternatives by **putting check marks** on the pair-wise comparison matrices. An example is shown below. Question: **How important is "cost" attribute when it is compared with "power" attribute for machine tool selection**.

Linguistic Variables
1=equal important (0.3,0.5,0.7)
3=Moderately important (0.5,0.7,0.9)
5=Strongly important (0.7,0.9,1)
7=Very strongly important (0.9,1,1)

Questionnaire form used to compare the machine tool selection attributes

How important the attribute is chosen for decision-making in machine selection when compared with other attributes. Please fill in the form for your judgments.

Cost	7	5	3	**1**	3	5	7	Power
Power	7	5	3	**1**	3	5	7	Maximum spindle speed
Maximum spindle speed	7	5	3	**1**	3	5	7	Maximum tool diameter
Maximum tool diameter	7	5	3	**1**	3	5	7	Number of tools
Number of tools	7	5	3	**1**	3	5	7	Cutting feed
Cutting feed	7	5	3	**1**	3	5	7	Traverse speed
Traverse speed	7	5	3	**1**	3	5	7	Positioning Precision (accuracy)
Positioning Precision (accuracy)	7	5	3	**1**	3	5	7	Machine dimension
Machine dimension	7	5	3	**1**	3	5	7	Table area
Table area	7	5	3	**1**	3	5	7	cost

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Section 2: **Evaluating the attributes for each machine**

Linguistic variables	Triangular fuzzy scale
Very Low (VL)	(1,1,3)
Low (L)	(1,3,5)
Medium (M)	(3,5,7)
High (H)	(5,7,9)
Very High (VH)	(7,9,9)

According to your opinion, how attribute for each machine. Please mark (VL, L, M, H or VH) the below table. For example: Machine 1 has a very high cost. We mark "VH" in row "cost" and column "machine 1"

Attributes/Machines	Machine 1	Machine 2	Machine 3	Machine 4	Machine 5
Cost					
Power					
Maximum spindle speed					
Maximum tool diameter					
Number of tools					
Cutting feed					
Traverse speed					
Positioning Precision (accuracy)					
Machine dimension					
Table area					

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Appendix E: Questionnaire design for decision finalization in machine tool selection using FANP and COPRAS-G

The purpose of the questionnaire design is to determine the weights/priorities of the selected attributes for multi-attributes decision-making process in the most suitable CNC machine tool selection to implement a Flexible Manufacturing Cell (FMC), satisfying the Small and Medium Enterprise's (SME) requirements of manufacturing, which is needed to produce few types of parts. The results are used for the academic and reference of the automotive industry in Malaysia. The questionnaire should be completed by the experts or operators understanding the CNC machine tools as well as the manufacturing system technology. The following questions refer a questionnaire hierarchical structure (below table) to determine the importance of the attributes and the weights/priorities of alternatives by putting check marks on the pair-wise comparison matrices. An example is shown as follows.

The scale number for pair-wise comparisons	
1	Just equal
2	Equally important
3	Weakly more important
4	Strongly more important
5	Very strongly more important
6	Absolutely more important

Question: How important is attribute 1 when it is compared with attribute 2 for machine tool selection? If Attribute 1 is more important than Attribute 2, please mark the scale number on the left. If Attribute 2 is more important than Attribute 1, please mark on the right. Please choose 1, 2, 3, 4, 5, and 6 for important level.

Attribute 1	Scale number for pair-wise comparisons											Attribute 2
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	Flexibility
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	Space
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	Adaptability
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	Precision
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	Reliability
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	Safety
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Productivity	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Space
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Adaptability
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Precision
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Reliability
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Safety
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Space	6	5	4	3	2	**1**	2	3	4	5	6	Adaptability
Space	6	5	4	3	2	**1**	2	3	4	5	6	Precision
Space	6	5	4	3	2	**1**	2	3	4	5	6	Reliability
Space	6	5	4	3	2	**1**	2	3	4	5	6	Safety
Space	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Space	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Space	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Space	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Space	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Precision
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Reliability
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Safety

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Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Reliability
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Safety
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Precision	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	Safety
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Safety	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Safety	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Safety	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Safety	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Safety	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Maintenanc&Serv	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Maintenanc&Serv	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Maintenanc&Serv	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Maintenanc&Serv	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Cost	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Cost	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Cost	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Installation easiness	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness

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Installation easiness	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
User friendliness	6	5	4	3	2	**1**	2	3	4	5	6	Green standard

Section 2: Questionnaire form was used to compare the attributes to each attribute to build inner-dependence matrices of the attributes. For instance, the questionnaire for the target <PRODUCTIVITY>

Question: For the target "**productivity**", how important? The influence level of the attribute 1 with respect to the satisfaction of the target when it is compared with the attribute 2? If Attribute 1 is more important than Attribute 2. Please mark the scale number (1, 2, 3, 4, 5, and 6) on the left. If Attribute 2 is more important than Attribute 1, please mark on the right.

Attribute 1	**Scale number for pair-wise comparisons**											**Attribute 2**
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Space
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Adaptability
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Precision
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Reliability
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Safety
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Flexibility	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Space	6	5	4	3	2	**1**	2	3	4	5	6	Adaptability
Space	6	5	4	3	2	**1**	2	3	4	5	6	Precision
Space	6	5	4	3	2	**1**	2	3	4	5	6	Reliability
Space	6	5	4	3	2	**1**	2	3	4	5	6	Safety
Space	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv

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Space	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Space	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Space	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Space	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Precision
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Reliability
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Safety
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Adaptability	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Reliability
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Safety
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Precision	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Precision	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	Safety
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Reliability	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Safety	6	5	4	3	2	**1**	2	3	4	5	6	Maintenance&Serv
Safety	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Safety	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Safety	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Safety	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Maintenanc&Serv	6	5	4	3	2	**1**	2	3	4	5	6	Cost
Maintenanc&Serv	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness

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Maintenanc&Serv	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Maintenanc&Serv	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Cost	6	5	4	3	2	**1**	2	3	4	5	6	Installation easiness
Cost	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Cost	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
Installation easiness	6	5	4	3	2	**1**	2	3	4	5	6	User friendliness
Installation easiness	6	5	4	3	2	**1**	2	3	4	5	6	Green standard
User friendliness	6	5	4	3	2	**1**	2	3	4	5	6	Green standard

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Appendix F: Decision matrix

Table F.1: The fuzzy linguistic reference relation matrix with attributes

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	(0.5,0.5,0.5)	(0.3,0.5,0.7)	(-0.2,0.1,0.5)	(0.0,0.5,1.0)	(0.0,0.7,1.4)	(-0.5,0.3,1.2)	(-0.3,0.7,1.7)	(-0.8,0.2,1.3)	(-0.4,0.7,1.8)	(-0.9,0.3,-0.5)
A2	(0.3,0.5,0.7)	(0.5,0.5,0.5)	(0.0,0.1,0.3)	(0.2,0.5,0.8)	(0.2,0.7,1.2)	(-0.3,0.3,1.0)	(-0.1,0.7,1.5)	(-0.6,0.2,1.1)	(-0.2,0.7,1.6)	(-0.7,0.3,1.4)
A3	(0.5,0.9,1.2)	(0.7,0.9,1.0)	(0.5,0.5,0.5)	(0.7,0.9,1.0)	(0.7,1.1,1.4)	(0.2,0.7,1.2)	(0.4,1.1,1.7)	(-0.1,0.6,1.3)	(0.3,1.1,1.8)	(-0.2,0.7,1.6)
A4	(0.0,0.5,1.0)	(0.2,0.5,0.8)	(0.0,0.1,0.3)	(0.5,0.5,0.5)	(0.5,0.7,0.9)	(0.0,0.3,0.7)	(0.2,0.7,1.2)	(-0.3,0.2,0.8)	(0.1,0.7,1.3)	(-0.4,0.3,1.1)
A5	(-0.4,0.3,1.0)	(-0.2,0.3,0.8)	(-0.4,-0.1,0.3)	(0.1,0.3,0.5)	(0.5,0.5,0.5)	(0.0,0.1,0.3)	(0.2,0.5,0.8)	(-0.3,0.0,0.4)	(0.1,0.5,0.9)	(-0.4,0.1,0.7)
A6	(-0.2,0.7,1.5)	(0.0,0.7,1.3)	(-0.2,0.3,0.8)	(0.3,0.7,1.0)	(0.7,0.9,1.0)	(0.5,0.5,0.5)	(0.7,0.9,1.0)	(0.2,0.4,0.6)	(0.6,0.9,1.1)	(0.1,0.5,0.9)
A7	(-0.7,0.3,1.3)	(-0.5,0.3,1.1)	(-0.7,-0.1,0.6)	(-0.2,0.3,0.8)	(0.2,0.5,0.8)	(0.0,0.1,0.3)	(0.5,0.5,0.5)	(0.0,0.0,0.1)	(0.4,0.5,0.6)	(0.4,0.6,0.9)
A8	(-0.3,0.8,1.8)	(-0.1,0.8,1.6)	(-0.3,0.4,1.1)	(0.2,0.8,1.3)	(0.6,1.0,1.3)	(0.4,0.6,0.8)	(0.9,1.0,1.0)	(0.5,0.5,0.5)	(0.9,1.0,1.0)	(0.4,0.6,0.8)
A9	(-0.8,0.3,1.4)	(-0.6,0.3,1.2)	(-0.8,-0.1,0.7)	(-0.3,0.3,0.9)	(0.1,0.5,0.9)	(-0.1,0.1,0.4)	(0.4,0.5,0.6)	(0.0,0.0,0.1)	(0.5,0.5,0.5)	(0.0,0.1,0.3)
A10	(1.5,0.7,1.9)	(-0.4,0.7,1.7)	(-0.6,0.3,1.2)	(-0.1,0.7,1.4)	(0.3,0.9,1.4)	(0.1,0.5,0.9)	(0.1,0.4,0.6)	(0.2,0.4,0.6)	(0.7,0.9,1.0)	(0.5,0.5,0.5)

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Table F.2: Transforming results of the fuzzy linguistic reference relation matrix with function f(x)= (x+0.9)/(1+2x0.9)

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	(0.5,0.5,0.5)	(0.43,0.5,0.57)	(0.25,0.36,0.5)	(0.32,0.5,0.68)	(0.32,0.57,0.82)	(0.14,0.43,0.75)	(0.21,0.57,0.93)	(0.04,0.39,0.79)	(0.18,0.57,0.96)	(0.0,0.43,0.14)
A2	(0.43,0.5,0.57)	(0.5,0.5,0.5)	(0.32,0.36,0.43)	(0.39,0.5,0.61)	(0.39,0.57,0.75)	(0.21,0.43,0.68)	(0.29,0.57,0.86)	(0.11,0.39,0.71)	(0.25,0.57,0.89)	(0.07,0.43,0.82)
A3	(0.5,0.64,0.75)	(0.57,0.64,0.68)	(0.5,0.5,0.5)	(0.57,0.64,0.68)	(0.57,0.71,0.82)	(0.39,0.57,0.75)	(0.46,0.71,0.93)	(0.29,0.54,0.79)	(0.43,0.71,0.96)	(0.25,0.57,0.89)
A4	(0.32,0.5,0.68)	(0.39,0.5,0.61)	(0.32,0.36,0.43)	(0.5,0.5,0.5)	(0.5,0.57,0.64)	(0.32,0.43,0.57)	(0.39,0.57,0.75)	(0.21,0.39,0.61)	(0.36,0.57,0.79)	(0.18,0.43,0.71)
A5	(0.18,0.43,0.68)	(0.25,0.43,0.61)	(0.18,0.29,0.43)	(0.36,0.43,0.5)	(0.5,0.5,0.5)	(0.32,0.36,0.43)	(0.39,0.5,0.61)	(0.21,0.32,0.46)	(0.36,0.5,0.64)	(0.18,0.36,0.57)
A6	(0.25,0.57,0.86)	(0.32,0.57,0.79)	(0.25,0.43,0.61)	(0.43,0.57,0.68)	(0.57,0.64,0.68)	(0.5,0.5,0.5)	(0.57,0.64,0.68)	(0.39,0.46,0.54)	(0.54,0.64,0.71)	(0.36,0.5,0.64)
A7	(0.07,0.43,0.79)	(0.14,0.43,0.71)	(0.07,0.29,0.54)	(0.25,0.43,0.61)	(0.39,0.5,0.61)	(0.32,0.36,0.43)	(0.5,0.5,0.5)	(0.32,0.32,0.36)	(0.46,0.5,0.54)	(0.46,0.54,0.64)
A8	(0.21,0.61,0.96)	(0.29,0.61,0.89)	(0.21,0.46,0.71)	(0.39,0.61,0.79)	(0.54,0.68,0.79)	(0.46,0.54,0.61)	(0.64,0.68,0.68)	(0.5,0.5,0.5)	(0.64,0.68,0.68)	(0.46,0.54,0.61)
A9	(0.04,0.43,0.82)	(0.11,0.43,0.75)	(0.04,0.29,0.57)	(0.21,0.43,0.64)	(0.36,0.5,0.64)	(0.29,0.36,0.46)	(0.46,0.5,0.54)	(0.32,0.32,0.36)	(0.5,0.5,0.5)	(0.32,0.36,0.43)
A10	(0.86,0.57,1.0)	(0.18,0.57,0.93)	(0.11,0.43,0.75)	(0.29,0.57,0.82)	(0.43,0.64,0.82)	(0.36,0.5,0.64)	(0.36,0.46,0.54)	(0.39,0.46,0.54)	(0.57,0.64,0.68)	(0.5,0.5,0.5)

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Table F.3: Pair-wise comparison matrix of the attributes in machine tool selection

Attributes	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
Productivity	(1,1,1)	(1/2,1,3/2)	(5/2,3,7/2)	(2,5/2,3)	(1/3,2/5,1/2)	(2,5/2,3)	(3/2,2,5/2)	(2/5,1/2,2/3)	(1/3,2/5,1/2)	(2,5/2,3)	(1/2,1,3/2)	(2/3,1,2)
Flexibility	(2/3,1,2)	(1,1,1)	(2,5/2,3)	(1/3,2/5,1/2)	(1/3,2/5,1/2)	(1/2,1,3/2)	(1/2,1,3/2)	(2/5,1/2,2/3)	(1/3,2/5,1/2)	(1,3/2,2)	(2/3,1,2)	(1,3/2,2)
Space	(2/7,1/3,2/5)	(1/3,2/5,1/2)	(1,1,1)	(2/5,1/2,2/3)	(1/3,2/5,1/2)	(1,3/2,2)	(3/2,2,5/2)	(1/3,2/5,1/2)	(1/3,2/5,1/2)	(2/5,1/2,2/3)	(2/3,1,2)	(1/2,1,3/2)
Adaptability	(1/3,2/5,1/2)	(2,5/2,3)	(3/2,2,5/2)	(1,1,1)	(1/3,2/5,1/2)	(1/2,1,3/2)	(1,3/2,2)	(2/5,1/2,2/3)	(1/3,2/5,1/2)	(1,3/2,2)	(1/2,2/3,1)	(1,3/2,2)
Precision	(2,5/2,3)	(2,5/2,3)	(2,5/2,3)	(2,5/2,3)	(1,1,1)	(2,5/2,3)	(1,3/2,2)	(3/2,2,5/2)	(2,5/2,3)	(2,5/2,3)	(1/2,1,3/2)	(1/2,1,3/2)
Reliability	(1/3,2/5,1/2)	(2/3,1,2)	(1/2,2/3,1)	(2/3,1,2)	(1/3,2/5,1/2)	(1,1,1)	(2/3,1,2)	(2/5,1/2,2/3)	(1/3,2/5,1/2)	(1/2,1,3/2)	(2/3,1,2)	(1,3/2,2)
Safety	(2/5,1/2,2/3)	(2/3,1,2)	(2/5,1/2,2/3)	(1/2,2/3,1)	(1/2,2/3,1)	(1/2,1,3/2)	(1,1,1)	(1/2,1,3/2)	(2/5,1/2,2/3)	(1,3/2,2)	(2/5,1/2,2/3)	(2,5/2,3)
Main..& ser..	(3/2,2,5/2)	(3/2,2,5/2)	(2,5/2,3)	(3/2,2,5/2)	(2/5,1/2,2/3)	(3/2,2,5/2)	(2/3,1,2)	(1,1,1)	(2/7,1/3,2/5)	(1/2,2/3,1)	(3/2,2,5/2)	(1/2,1,3/2)
Cost	(2,5/2,3)	(2,5/2,3)	(2,5/2,3)	(2,5/2,3)	(1/3,2/5,1/2)	(2,5/2,3)	(3/2,2,5/2)	(5/2,3,7/2)	(1,1,1)	(2,5/2,3)	(1,3/2,2)	(1,3/2,2)
Installation easiness	(1/3,2/5,1/2)	(1/2,2/3,1)	(3/2,2,5/2)	(1/2,2/3,1)	(1/3,2/5,1/2)	(2/3,1,2)	(1/2,2/3,1)	(1,3/2,2)	(1/3,2/5,1/2)	(1,1,1)	(1/2,1,3/2)	(1/3,2/5,1/2)
User friendliness	(2/3,1,2)	(1/2,1,3/2)	(1/2,1,3/2)	(1,3/2,2)	(2/3,1,2)	(1/2,1,3/2)	(3/2,2,5/2)	(2/5,1/2,2/3)	(1/3,2/3,1)	(2/3,1,2)	(1,1,1)	(2/5,1/2,2/3)
Green standard	(1/2,1,3/2)	(1/2,2/3,1)	(2/3,1,2)	(1/2,2/3,1)	(2/3,1,2)	(1/2,2/3,1)	(1/3,2/5,1/2)	(2/3,1,2)	(1/3,2/3,1)	(2,5/2,3)	(3/2,2,5/2)	(1,1,1)

Table F.4: Inter-dependence pair-wise comparison matrix of the attributes with respect to the productivity

Attributes	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	To Productivity
Flexibility	(1,1,1)	(3/2,2,5/2)	(2/3,1,2)	(2/5,1/2,2/3)	(1,3/2,2)	(1/2,2/3,1)	(2/5,1/2,2/3)	(1/3,2/5,1/2)	(1,3/2,2)	(3/2,2,5/2)	(1/2,1,3/2)	0.076863
Space	(2/5,1/2,2/3)	(1,1,1)	(1/2,2/3,1)	(1/3,2/5,1/2)	(3/2,2,5/2)	(3/2,2,5/2)	(3/2,2,5/2)	(1/3,2/5,1/2)	(1/2,2/3,1)	(1/2,1,3/2)	(2/5,1/2,2/3)	0.066367
Adaptability	(1/2,1,3/2)	(1,3/2,2)	(1,1,1)	(1/3,2/5,1/2)	(2/3,1,2)	(1/2,1,3/2)	(1/3,2/5,1/2)	(1/3,2/5,1/2)	(2/3,1,2)	(1/3,2/5,1/2)	(1/2,2/3,1)	0.057408
Precision	(3/2,2,5/2)	(2,5/2,3)	(2,5/2,3)	(1,1,1)	(2,5/2,3)	(2,5/2,3)	(2,5/2,3)	(1/3,2/5,1/2)	(2,5/2,3)	(1,3/2,2)	(1/2,2/3,1)	0.15732
Reliability	(1/2,2/3,1)	(2/5,1/2,2/3)	(1/2,1,3/2)	(1/3,2/5,1/2)	(1,1,1)	(1,3/2,2)	(2/5,1/2,2/3)	(1,3/2,2)	(1,3/2,2)	(2/5,1/2,2/3)	(3/2,2,5/2)	0.067318
Safety	(1,3/2,2)	(2/5,1/2,2/3)	(2/3,1,2)	(1/3,2/5,1/2)	(1/2,2/3,1)	(1,1,1)	(2/5,1/2,2/3)	(1/3,2/5,1/2)	(2/3,1,2)	(2/3,1,2)	(2/5,1/2,2/3)	0.046665
Main..& ser..	(3/2,2,5/2)	(2/5,1/2,2/3)	(2,5/2,3)	(1/3,2/5,1/2)	(3/2,2,5/2)	(3/2,2,5/2)	(1,1,1)	(2/3,1,2)	(3/2,2,5/2)	(1,3/2,2)	(1/2,1,3/2)	0.12076
Cost	(2,5/2,3)	(2,5/2,3)	(2,5/2,3)	(2,5/2,3)	(1/2,2/3,1)	(2,5/2,3)	(1/2,1,3/2)	(1,1,1)	(3/2,2,5/2)	(1,3/2,2)	(3/2,2,5/2)	0.15807
Installation easiness	(1/2,2/3,1)	(1,3/2,2)	(1/2,1,3/2)	(1/3,2/5,1/2)	(1/2,2/3,1)	(1/2,1,3/2)	(2/5,1/2,2/3)	(2/5,1/2,2/3)	(1,1,1)	(3/2,2,5/2)	(3/2,2,5/2)	0.070357
User friendliness	(2/5,1/2,2/3)	(2/3,1,2)	(2,5/2,3)	(1/2,2/3,1)	(3/2,2,5/2)	(1/2,1,3/2)	(1/2,2/3,1)	(1/2,2/3,1)	(2/5,1/2,2/3)	(1,1,1)	(2/5,1/2,2/3)	0.070523
Green standard	(2/3,1,2)	(3/2,2,5/2)	(1,3/2,2)	(1,3/2,2)	(2/5,1/2,2/3)	(3/2,2,5/2)	(2/3,1,2)	(2/5,1/2,2/3)	(2/5,1/2,2/3)	(3/2,2,5/2)	(1,1,1)	0.10835

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Table F.5: The inter-dependence matrix of the attributes W_{22}

Productivity	1	0.077848	0.089181	0.08334	0.11799	0.088157	0.10358	0.05466	0.046724	0	0.12007	0.095887
Flexibility	0.076863	1	0.076579	0.084469	0.080939	0.083186	0.078563	0.084036	0.089782	0.0364	0.12041	0.080237
Space	0.066367	0.080018	1	0.061272	0.079984	0.066753	0.07019	0.087422	0.0045779	0	0	0.036942
Adaptability	0.057408	0.065405	0.056664	1	0.073887	0.090778	0.07294	0.098473	0.055963	0.11153	0.031523	0.056669
Precision	0.15732	0.12475	0.13151	0.13742	1	0.11194	0.11049	0.086291	0.25052	0.34902	0.20644	0.18958
Reliability	0.067318	0.079689	0.076451	0.061314	0.081821	1	0.080166	0.097982	0.083529	0	0.037152	0.062474
Safety	0.046665	0.088325	0.079206	0.054097	0.078235	0.076534	1	0.083527	0.075192	0	0.043242	0.052196
Main..& ser..	0.12076	0.11621	0.1069	0.1139	0.10619	0.10025	0.10565	1	0.20194	0.17252	0.17721	0.17708
Cost	0.15807	0.1242	0.15348	0.17727	0.11992	0.11468	0.12473	0.12552	1	0.28655	0.19197	0.18547
Installation easiness	0.070357	0.074285	0.070637	0.096828	0.080247	0.083083	0.071901	0.11077	0.064137	1	0.071995	0.017999
User friendliness	0.070523	0.083991	0.080445	0.040554	0.074793	0.081979	0.072954	0.084733	0.10268	0.043968	1	0.045469
Green standard	0.10835	0.085281	0.078945	0.089533	0.10599	0.10266	0.10883	0.086593	0.024946	0	0	1

Table F.6: The decision support matrix for alternatives with grey numbers

MC~A	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
MC1	[4, 6]	[4, 6]	[4, 6]	[4, 6]	[6, 8]	[8, 9]	[6, 8]	[8, 9]	[8, 9]	[6, 8]	[6, 8]	[4, 6]
MC2	[6, 8]	[4, 6]	[4, 6]	[6, 8]	[8, 9]	[6, 8]	[4, 6]	[6, 8]	[6, 8]	[4, 6]	[4, 6]	[4, 6]
MC3	[6, 8]	[4, 6]	[4, 6]	[4, 6]	[6, 8]	[6, 8]	[2, 4]	[2, 4]	[6, 8]	[4, 6]	[6, 8]	[6, 8]
MC4	[4, 6]	[4, 6]	[6, 8]	[4, 6]	[6, 8]	[6, 8]	[6, 8]	[4, 6]	[6, 8]	[6, 8]	[6, 8]	[4, 6]
MC5	[8, 9]	[6, 8]	[6, 8]	[6, 8]	[8, 9]	[6, 8]	[6, 8]	[8, 9]	[6, 8]	[6, 8]	[8, 9]	[6, 8]

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Table F.7: The weighted normalized decision support matrix for alternatives

MC~A	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
MC1	[0.0230; 0.0345]	[0.0215; 0.0322]	[0.0102; 0.0154]	[0.0185; 0.0278]	[0.0480; 0.0640]	[0.0260; 0.0293]	[0.0240; 0.0320]	[0.0588; 0.0661]	[0.0635; 0.0715]	[0.0211; 0.0282]	[0.0249; 0.0332]	[0.0198; 0.0297]
MC2	[0.0345; 0.0460]	[0.0215; 0.0322]	[0.0102; 0.0154]	[0.0278; 0.0370]	[0.0640; 0.0720]	[0.0195; 0.0260]	[0.0160; 0.0240]	[0.0441; 0.0588]	[0.0477; 0.0635]	[0.0141; 0.0211]	[0.0166; 0.0249]	[0.0198; 0.0297]
MC3	[0.0345; 0.0460]	[0.0215; 0.0322]	[0.0102; 0.0154]	[0.0185; 0.0278]	[0.0480; 0.0640]	[0.0195; 0.0260]	[0.0080; 0.0160]	[0.0147; 0.0294]	[0.0477; 0.0635]	[0.0141; 0.0211]	[0.0249; 0.0332]	[0.0297; 0.0396]
MC4	[0.0230; 0.0345]	[0.0215; 0.0322]	[0.0154; 0.0205]	[0.0185; 0.0278]	[0.0480; 0.0640]	[0.0195; 0.0260]	[0.0240; 0.0320]	[0.0294; 0.0441]	[0.0477; 0.0635]	[0.0211; 0.0282]	[0.0249; 0.0332]	[0.0198; 0.0297]
MC5	[0.0460; 0.0517]	[0.0322; 0.0430]	[0.0154; 0.0205]	[0.0278; 0.0370]	[0.0640; 0.0720]	[0.0195; 0.0260]	[0.0240; 0.0320]	[0.0588; 0.0661]	[0.0477; 0.0635]	[0.0211; 0.0282]	[0.0332; 0.0373]	[0.0297; 0.0396]

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Appendix G: Program for case study 2

```
%• Clean screen and previous data history
clear all
clc
clf
close all

%• Declare the inputs for computing program
%• Declare the information inputs of part types in FMC
parts = 8; machines = 4;
% • Declare the batch size for each part type needed to be processed. Example, batch_size=[1 1 1 1 1];
batch_size = [8 9 13 6 9 10 12 13];
total_parts = sum(batch_size);
number_of_operation = [1 3 2 2 2 3 3 3];
cum_number_of_operation = [1 4 6 8 10 13 16 19];
cum_number_of_operation_all = 0;
for a = 1:parts
   number_of_operation_all(a) = number_of_operation(a) * batch_size(a);
   cum_number_of_operation_all=cum_number_of_operation_all + number_of_operation_all(a);
   cum_all_num_ope(a) = cum_number_of_operation_all;
end
%• The operation of part type
ope = [1 0 0; 1 2 3; 1 2 0; 1 2 0; 1 2 0; 1 2 3; 1 2 3];
%• Processing time for each operation of part type
procs_time = [18 0  0; 25 24 22; 26 11 0; 14 19 0; 22 25 0; 16 7  21; 19 13 23; 25 7  24];
processing_time=[];
for a = 1:parts
   for b = 1:batch_size(a)
      processing_time = [processing_time;procs_time(a,:)];
   end
end
numero_uno = length(processing_time(1,:)) * length(processing_time(:,1));
hearts=1;
for a=1:parts
   for b=1:batch_size(a)
      proc_time(hearts,:) = procs_time(a,:);
      hearts = hearts+1;
   end
end
hearts=1;
for a=1:parts
   for b=1:batch_size(a)
      number_of_operations(hearts) = number_of_operation(a);
      hearts=hearts+1;
   end
end
%• Cutting tools available
tools=[1 0 0; 1 1 1; 2 3 0; 1 1 0; 2 1 0; 1 1 1; 1 1 3; 1 1 3;];
%• CNC machines need to process 8 part types
%• For each part type
machine(:,:,1) = [3 0 0; 0 0 0; 0 0 0];          % part type 1
machine(:,:,2) = [1 4 0; 4 0 0; 2 0 0];          % part type 2
machine(:,:,3) = [4 1 0; 3 0 0; 0 0 0];
machine(:,:,4) = [3 0 0; 4 0 0; 0 0 0];
machine(:,:,5) = [2 3 0; 2 0 0; 0 0 0];
```

```
machine(:,:,6) = [4 0 0; 4 2 3; 2 1 0];
machine(:,:,7) = [3 1 0; 2 3 1; 4 0 0];
machine(:,:,8) = [1 2 0; 2 1 0; 1 0 0];
%                    ope
%• Available machines for part types
number_of_available_machine=[1 0 0; 2 1 1; 2 1 0; 1 1 1; 2 1 0; 1 3 2; 2 3 1; 2 2 1];
hearts=1;
for a=1:parts
   for b=1:batch_size(a)
      number_of_available_machines(hearts,:)=number_of_available_machine(a,:);
      hearts=hearts+1;
   end
end
hearts=1;
for a=1:parts
   for b=1:batch_size(a)
      machines(:,:,hearts)=machine(:,:,a);
      hearts=hearts+1;
   end
end
% • Declare the transportation/traveling time with information from Machine M1 M2 M3 M4
transport_time=[2  4  2  2];
transport_time_loading=2;
transport_time_unloading=2;
% Declare the paprameters of algorithm
pop_size=50; H=8*60; E=1; I=1;
Iteration=1;
%• Computation process
load_time=1:total_parts;
%• Initialize Solution------------------------------
for c=1:pop_size
   ini_hab = zeros(total_parts,max(number_of_operations));
   for a = 1:total_parts
      for b = 1 : number_of_operations(a)
         ini_hab(a,b) = machineses(b, randi(number_of_available_machines(a,b)), a);
      end
   end
   initial_habita(:,:,c) = ini_hab;
end
% Constraint adjustment
% Cycle
for c = 1 : pop_size
   for a = 1 : total_parts
      cyc = 1;
      for b = 2 : max(number_of_operation)
         if initial_habitat(a,b,c) < initial_habitat(a,b-1,c)  &&  initial_habitat(a,b,c)~=0
            cyc = cyc+1;
         end
      end
      cycle(a,:,c) = cyc;
   end
end
bigg = max(cycle);
bggst = max(bigg);
exs = parts*bggst;
traveling_time = zeros(total_parts,machines*(bggst+1),pop_size);
for c = 1 : pop_size
   for a = 1 : total_parts
```

```
        for b = 1:cycle(a,:,c)
            traveling_time( a , machines*(b-1) + 1 : machines*(b), c)=transport_time;
        end
    end
end

% Original
reeentrant_post = zeros(total_parts, max(number_of_operations) + 1,  pop_size);
for c = 1 : pop_size
    for a = 1 : total_parts
        cic = 1;
        reeentrant_post( a, 1, c) = cic;
        for b=2 : max(number_of_operations)
            if initial_habitat(a,b,c) < initial_habitat(a,b-1,c) && initial_habitat(a,b,c)~=0
                cic = cic + 1;
                reeentrant_post( a, b, c) = cic;
            else
                reeentrant_post( a, b, c) = cic;
            end
        end
    end
end
part_routes=initial_habitat;
for c = 1 : pop_size
    part_routes( : , max(number_of_operations) + 1,c) = zeros( total_parts, 1);
end
for c = 1 : pop_size
    for a = 1: total_parts
        for b=2 : max(number_of_operations)
            if part_routes( a, b, c) < part_routes( a, b-1, c) && part_routes( a, b, c)~=0
                part_routes( a, b, c) = part_routes(a,b,c) + machines*(reeentrant_post(a,b,c)-1);
            else
                part_routes(a,b,c)=part_routes(a,b,c);
            end
        end
    end
end
proc_timess=zeros(total_parts,machines*(bggst+1), pop_size);
for c=1 : pop_size
    for a=1 : total_parts
        for b=1:machines * bggst
            for d=1:max(number_of_operations);
                if part_routes(a,d,c) == b
                    proc_timess(a,b,c) = proc_time(a,d);
                end
            end
        end
    end
end
% same machine adjustment (check the machine duplicate)
reeentrant_post2 = zeros(total_parts,max(number_of_operations)+1,pop_size);
initial_habitats=initial_habitat;
for c=1:pop_size
    initial_habitats(:,max(number_of_operations)+1,c)=zeros(total_parts,1);
end
we_are_the_same=zeros(size(initial_habitats));
for c=1:pop_size
    for a=1:total_parts
```

```
      for b=2:max(number_of_operations)+1
        if initial_habitats(a,b,c) == initial_habitats(a,b-1,c) && initial_habitats(a,b,c) ~= 0

initial_habitats(a,b:max(number_of_operations),c)=initial_habitats(a,b+1:max(number_of_operations)+1,c);
          we_are_the_same(a,b-1,c)=1;
        end
      end
    end
  end
  for c=1:pop_size
    for a=1:total_parts
      cic=1;
      reeentrant_post2(a,1,c) = cic;
      for b=2:max(number_of_operations)
        if initial_habitats(a,b,c) < initial_habitats(a,b-1,c) && initial_habitats(a,b,c)~=0
          cic=cic+1;
          reeentrant_post2(a,b,c) = cic;
        else
          reeentrant_post2(a,b,c) = cic;
        end
      end
    end
  end
  part_route=initial_habitats;
  for c=1:pop_size
    part_route(:,max(number_of_operations)+1,c)=zeros(total_parts,1);
  end
  for c=1:pop_size
    for a=1:total_parts
      for b=2:max(number_of_operations)
        if part_route(a,b,c)<part_route(a,b-1,c) && part_route(a,b,c)~=0
          part_route(a,b,c)=part_route(a,b,c)+machines*(reeentrant_post2(a,b,c)-1);
        else
          part_route(a,b,c)=part_route(a,b,c);
        end
      end
    end
  end
  proc_times=zeros(total_parts, machines*(bggst+1), pop_size);
  for c=1:pop_size
    for a=1:total_parts
      for b=1:machines*bggst
        for d=1:max(number_of_operations);
          if part_routes(a,d,c)==b
            proc_times(a,b,c)=proc_times(a,b,c)+proc_time(a,d);
          end
        end
      end
    end
  end
  % time calculatio
  for c=1:pop_size
  arrive_on_machine_const_final=zeros(total_parts, exs);
  out_from_machine_const_final=zeros(total_parts, exs);
  queue_time_final=zeros(total_parts, exs);
  best_krom_forever=load_time;
  shortcut_route=zeros(max(cycle( : , : , 1))+5,total_parts);
  shortcut_position=zeros(2,2);
```

```
time=2;
final_solution=[];
final_solution(1:total_parts, 1)=zeros(total_parts, 1);
for i=1:total_parts
    start_position(i)=1;
    machine_post(i)=0;
    step_post(i)=0;
    if 1<best_krom_forever(i)
        final_solution(i,1)=98;
    elseif 1==best_krom_forever(i)
        final_solution(i,1)=50;
    end
end
while any(final_solution(:,time-1)~=99);
    for i=1:total_parts
        if start_position(i)==best_krom_forever(i)
            arrive_on_machine_const_final(i,1)=time;
            if time<start_position(i) + transport_time_loading(1)
                final_solution(i,time)=50;
            elseif time==start_position(i) + transport_time_loading(1)
                step_post(i)=1;
                machine_post(i)=1;
                out_from_machine_const_final(i,1)=time;
                start_position(i)=time;
            end
        end
        n(i)=ceil(machine_post(i)/machines);
        m(i)=machine_post(i)-(machines*(n(i)-1));
        if final_solution(i,time-1)==99
            final_solution(i,time)=99;
        elseif time<best_krom_forever(i)
            final_solution(i,time)=98;
        elseif time==best_krom_forever(i)
            final_solution(i,time)=50;
            start_position(i)=time;
        else
            if step_post(i)==0
                final_solution(i,time)=final_solution(i,time);
            elseif m(i)==initial_habitats(i,step_post(i),c)
                bob=max(queue_time_final(:,initial_habitats(i,step_post(i),c)));
                rob=find(final_solution(:,time-1)==initial_habitats(i,step_post(i),c));
                if final_solution(i,time-1)==initial_habitats(i,step_post(i),c)
                    if time<(start_position(i)+proc_times(i,part_route(i,step_post(i),c),c))
                        final_solution(i,time)=initial_habitats(i,step_post(i),c);
                        out_from_machine_const_final(i,
machine_post(i))=(start_position(i)+proc_times(i,part_route(i,step_post(i),c),c));
                    elseif time==out_from_machine_const_final(i,machine_post(i))
                        final_solution(i,time)=50;
                        start_position(i)=time;
                        step_post(i)=step_post(i)+1;
                        out_from_machine_const_final(i,machine_post(i))=time;
                    end
                else
                    if all(final_solution( : , time-1) ~= initial_habitats( i, step_post(i), c)) && final_solution( i,
time-1)~=100
                        if i==1
                            final_solution(i,time) = initial_habitats( I , step_post(i), c);
                            start_position(i) = time;
```

```
                queue_time_final(i , initial_habitats(i,step_post(i), c))=0;
            else
                if all(final_solution(1: (i-1), time) ~= initial_habitats(i, step_post(i), c))
                    final_solution(i,time) = initial_habitats(i, step_post(i), c);
                    start_position(i)=time;
                    queue_time_final( i, initial_habitats(i,step_post(i), c))=0;
                else
                    final_solution(i,time)=100;
                    start_position(i)=time;

queue_time_final(i,initial_habitats(i,step_post(i),c))=queue_time_final(i,initial_habitats(i,step_post(i),c))+1;
                end
            end
        elseif numel(rob)==1 && time==out_from_machine_const_final(rob,machine_post(rob))
            if queue_time_final(i,initial_habitats(i,step_post(i),c))==bob
                if i==1
                    final_solution(i,time)=initial_habitats(i,step_post(i),c);
                    start_position(i)=time;
                    queue_time_final(i,initial_habitats(i,step_post(i),c))=0;
                else
                    if all(final_solution(1:(i-1),time)~=initial_habitats(i,step_post(i),c))
                        final_solution(i,time)=initial_habitats(i,step_post(i),c);
                        start_position(i)=time;
                        queue_time_final(i,initial_habitats(i,step_post(i),c))=0;
                    else
                        final_solution(i,time)=100;
                        start_position(i)=time;

queue_time_final(i,initial_habitats(i,step_post(i),c))=queue_time_final(i,initial_habitats(i,step_post(i),c))+1;
                    end
                end
            else
                final_solution( i, time) =100;
                start_position(i)=time;

queue_time_final(i,initial_habitats(i,step_post(i),c))=queue_time_final(i,initial_habitats(i,step_post(i),c))+1;
            end
        else
            final_solution(i, time)=100;
            start_position(i)=time;

queue_time_final(i,initial_habitats(i,step_post(i),c))=queue_time_final(i,initial_habitats(i,step_post(i),c))+1;
        end
    end
else
    if shortcut_route(n(i),i)~=0
        if m(i)==shortcut_position(1,shortcut_route(n(i),i))
            if time<start_position(i)+traveling_time(i, machine_post(i),c)-1
                final_solution(i,time)=50;
            elseif time==start_position(i)+traveling_time(i, machine_post(i),c)-1
                final_solution(i, time)=50;
                start_position(i)=time+1;
                if shortcut_type(1,shortcut_route(n(i),i))==1
                    machine_post(i)=shortcut_position(2,shortcut_route(n(i),i))+(length(machine)*(n(i)-
1));
                else
                    machine_post(i)=shortcut_position(2,shortcut_route(n(i),i))+(length(machine)*n(i));
                end
```

```
                    arrive_on_machine_const_final(i, machine_post(i))=start_position(i);
                    out_from_machine_const_final(i, machine_post(i))=start_position(i);
                end
            else
                if time < start_position(i) + traveling_time(i, machine_post(i), c)-1
                    final_solution( i, time)=50;
                elseif time==start_position(i)+traveling_time(i, machine_post(i), c)-1
                    final_solution(i, time)=50;
                    start_position(i) = time+1;
                    machine_post(i) = machine_post(i)+1;
                    arrive_on_machine_const_final(i,machine_post(i))=start_position(i);
                    out_from_machine_const_final(i,machine_post(i))=start_position(i);
                end
            end
        else
            if time<start_position(i)+traveling_time(i,machine_post(i),c)-1
                final_solution(i,time)=50;
            elseif time==start_position(i)+traveling_time(i,machine_post(i),c)-1
                final_solution(i,time)=50;
                start_position(i)=time+1;
                machine_post(i)=machine_post(i)+1;
                arrive_on_machine_const_final(i,machine_post(i))=start_position(i);
                out_from_machine_const_final(i,machine_post(i))=start_position(i);
            end
        end
    end
  end
  n_out(i)=ceil((machine_post(i)-1)/machines);
  m_out(i)=(machine_post(i)-1)-(machines*(n_out(i)-1));
  if m_out(i)==4 && n_out(i)==cycle(i,:,c)
     out_from_system_point(i)=start_position(i)-traveling_time(i,machine_post(i),c)-
traveling_time(i,machine_post(i)-1,c)+transport_time_unloading;
     final_solution(i,out_from_system_point(i):time)=99;
     out_from_machine_const_final(i,machine_post(i))=out_from_system_point(i);
  end
 end
 time=time+1;
end
out_of_all(c,:)=out_from_system_point;
end
%• fitness calculation
procc_time=reshape(processing_time',[1,numero_uno]);
ind_facc=find(procc_time==0);
procc_time(ind_facc)=[];
numero_duo=length(initial_habitat(1,:,1))*length(initial_habitat(:,1,1));
for a=1:pop_size
   habitots=reshape(initial_habitat(:,:,a)',[1,numero_duo]);
   ind_facc=find(habitots==0);
   habitots(ind_facc)=[];
   all_habitots(a,:)=habitots;
end
%• system unbalance
for a=1:pop_size
   for b=1:machines
      ind_macc=find(all_habitots(a,:)==b);
      fowl=sum(procc_time(ind_macc));
      sys_u_m(b)=abs(H-fowl);
   end
```

```
        system_unbalance(a)=sum(sys_u_m);
        each_machines_record(a,:)=sys_u_m;
        square_sys_u(a)=(system_unbalance(a))^2;
    end
    for a=1:pop_size
        normal_system_unbalance(a)=system_unbalance(a)/(sqrt(sum(square_sys_u)));
    end
    %• makespan
    for a=1:pop_size
        makespan(a)=max(out_of_all(a,:));
        square_makespan(a)=(makespan(a))^2;
    end
    for a=1:pop_size
        normal_makespan(a)=makespan(a)/(sqrt(sum(square_makespan)));
    end
    %• total flow time
    for a=1:pop_size
        total_flow_time(a)=sum(out_of_all(a,:));
        square_total_flow_time(a)=(total_flow_time(a))^2;
    end
    for a=1:pop_size
        normal_total_flow_time(a)=total_flow_time(a)/(sqrt(sum(square_total_flow_time)));
    end
    •% total fitness
    for a=1:pop_size
        fitness(a,:)=[system_unbalance(a) makespan(a) total_flow_time(a)];
        total_fitness(a)=system_unbalance(a)+makespan(a)+total_flow_time(a);
        normal_fitness(a,:)=[normal_system_unbalance(a) normal_makespan(a) normal_total_flow_time(a)];

total_normal_fitness(a)=normal_system_unbalance(a)+normal_makespan(a)+normal_total_flow_time(a);
    end
    u_r=[all_habitots fitness each_machines_record total_fitness' normal_fitness total_normal_fitness'
zeros(pop_size,1)];
    u_r=sortrows(u_r,length(u_r(1,:))-1);
    best_habitats_ever=u_r(1,:);
    bank_solutions=best_habitats_ever;
    bank_solutions(length(u_r(1,:)))=[];
    %• Iteration process
    while Iteration~=1000
    %immigration/emigration ratex_x=1:pop_size;
    habitats=[all_habitots total_normal_fitness' x_x'];
    habitats=sortrows(habitats,-(length(all_habitots(1,:))+1));
    for a=1:pop_size
        emigration_rate(a)=E*(a/pop_size);                    % miu values
        immigration_rate(a)=1-emigration_rate(a);             % lamda values
    end
    total_emig_rate=sum(emigration_rate);
    cum_emig_rate(1)=emigration_rate(1);
    for a=2:pop_size
        cum_emig_rate(a)=cum_emig_rate(a-1)+emigration_rate(a);
    end
    emig_rate=cum_emig_rate/total_emig_rate;
    habitats(:,length(all_habitots(1,:))+1:length(habitats(1,:)))=[];
    habitats_mig=habitats;
    %%migration procedure
    for a=1:pop_size
        if rand<=immigration_rate(a)
            em_rand=rand;
```

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```
        for b=1:pop_size
            if em_rand<=emig_rate(b)
                changer=habitats_mig(b,:);
                break;
            end
        end
        SIV_no=randi(length(all_habitots(1,:)),1,1);
        SIV_pos=randi(length(all_habitots(1,:)),1,SIV_no);
        habitats_mig(a,SIV_pos)=changer(SIV_pos);
    end
end
% mutation values
    mut_rate=[];
    habitats=[all_habitots total_normal_fitness' x_x'];
    habitats=sortrows(habitats,-(length(all_habitots(1, :)) + 1));
    for a=1:ceil((pop_size+1)/2)
        vi_ai(a)=factorial(pop_size)/(factorial(pop_size-1-a)*factorial(a-1));
    end
    for a=ceil((pop_size+1)/2)+1:pop_size
        vi_ai(a)=vi_ai(pop_size+2-a);
    end
    total_vi_ai=sum(vi_ai);
    for a=1:pop_size
        Pi(a)=vi_ai(a)/total_vi_ai;
    end
    Pmax=max(Pi);
    for a=1:pop_size
        mut_rate(a)=0.01*((1-Pi(a))/Pmax);
    end
    prob_mut=mut_rate;
%mutation procedure
habitats_mut=habitats_mig;
for a=1:pop_size
    for d=1:length(habitats_mut(1,:))
        randall_borg(d)=rand;
    end
    position=find(randall_borg<prob_mut(a));
    if all(randall_borg>prob_mut(a))
        position=randi(length(habitats_mut(a)-2),1,1);
    end

    for c=1:length(position)
        for b=1:parts
            if position(c)<=cum_all_num_ope(b) && b~=1
                xox=rem((position(c)-cum_all_num_ope(b-1)),number_of_operation(b));
                if xox==0
                    xox=number_of_operation(b);
                end
                rand_part_ope=[b,xox];
                break
            elseif position(c)<=cum_all_num_ope(b) && b==1
                xox=rem(position(c),number_of_operation(b));
                if xox==0
                    xox=number_of_operation(b);
                end
                rand_part_ope=[b,xox];
                break
            end
```

```
            end

habitats_mut(a,position(c))=machine(rand_part_ope(2),randi(number_of_available_machine(rand_part_ope(1
),rand_part_ope(2))),rand_part_ope(1));
         end
     end
     %unification of habitat
     habitats(:,length(habitats_mut(1,:))+1:length(habitats_mut(1,:))+2)=[];
     allhabitats=[habitats;habitats_mut];
     %converting
     a=length(initial_habitats(:,1,1));
     b=length(initial_habitats(1,:,1))-1;
     c=pop_size*2;
     initial_habitat=zeros(a,b,c);

     for a=1:pop_size*2
         initial_habitat(1,1:number_of_operation(1),a)=allhabitats(a,1:number_of_operation(1));
         parts_posi=0;
         start_hab_posi=1;
         end_hab_posi=number_of_operation(1);
         for b=1:parts
             for c=1:batch_size(b)
                 parts_posi=parts_posi+1;
                 if parts_posi~=1
                     start_hab_posi=end_hab_posi+1;
                     end_hab_posi=start_hab_posi+number_of_operation(b)-1;

initial_habitat(parts_posi,1:number_of_operation(b),a)=allhabitats(a,start_hab_posi:end_hab_posi);
                 end
             end
         end
     end
     %Constraint adjustment
     %cycle
     all_pop_size=pop_size*2;
     for c=1:all_pop_size
         for a=1:total_parts
             cyc=1;
             for b=2:max(number_of_operation)
                 if initial_habitat( a, b, c) < initial_habitat(a,b-1,c) && initial_habitat(a,b,c) ~= 0
                     cyc = cyc + 1;
                 end
             end
             cycle(a,:,c) = cyc;
         end
     end
     bigg=max(cycle);
     bggst=max(bigg);
     traveling_time=zeros(total_parts,machines*(bggst+1),all_pop_size);
     for c=1:all_pop_size
         for a=1:total_parts
             for b=1:cycle(a,:,c)
                 traveling_time(a,machines*(b-1)+1:machines*(b),c)=transport_time;
             end
         end
     end
     %original
     reeentrant_post=zeros(total_parts,max(number_of_operations)+1,all_pop_size);
```

```
for c=1:all_pop_size
   for a=1:total_parts
      cic=1;
      reeentrant_post(a,1,c)=cic;
      for b=2:max(number_of_operations)
         if initial_habitat(a,b,c)<initial_habitat(a,b-1,c) && initial_habitat(a,b,c)~=0
            cic=cic+1;
            reeentrant_post(a,b,c)=cic;
         else
            reeentrant_post(a,b,c)=cic;
         end
      end
   end
end
part_routes=initial_habitat;
for c=1:all_pop_size
   part_routes(:,max(number_of_operations)+1,c)=zeros(total_parts,1);
end
for c=1:all_pop_size
   for a=1:total_parts
      for b=2:max(number_of_operations)
         if part_routes(a,b,c)<part_routes(a,b-1,c) && part_routes(a,b,c)~=0
            part_routes(a,b,c)=part_routes(a,b,c)+machines*(reeentrant_post(a,b,c)-1);
         else
            part_routes(a,b,c)=part_routes(a,b,c);
         end
      end
   end
end
proc_timess=zeros(total_parts,machines*(bggst+1),all_pop_size);
for c=1:all_pop_size
   for a=1:total_parts
      for b=1:machines*bggst
         for d=1:max(number_of_operations);
            if part_routes(a,d,c)==b
               proc_timess(a,b,c)=proc_time(a,d);
            end
         end
      end
   end
end
%------------------------same machine adjustment---------------------------
reeentrant_post2=zeros(total_parts,max(number_of_operations)+1,all_pop_size);
initial_habitats=initial_habitat;
for c=1:all_pop_size
   initial_habitats(:,max(number_of_operations)+1,c)=zeros(total_parts,1);
end
we_are_the_same=zeros(size(initial_habitats));
for c=1:all_pop_size
   for a=1:total_parts
      for b=2:max(number_of_operations)+1
         if initial_habitats(a,b,c)==initial_habitats(a,b-1,c) && initial_habitats(a,b,c)~=0
initial_habitats(a,b:max(number_of_operations),c)=initial_habitats(a,b+1:max(number_of_operations)+1,c);
            we_are_the_same(a,b-1,c)=1;
         end
      end
   end
end
```

```
for c=1:all_pop_size
   for a=1:total_parts
      cic=1;
      reeentrant_post2(a,1,c)=cic;
      for b=2:max(number_of_operations)
         if initial_habitats(a,b,c)<initial_habitats(a,b-1,c) && initial_habitats(a,b,c)~=0
            cic=cic+1;
            reeentrant_post2(a,b,c)=cic;
         else
            reeentrant_post2(a,b,c)=cic;
         end
      end
   end
end
part_route=initial_habitats;
for c=1:all_pop_size
   part_route(:,max(number_of_operations)+1,c)=zeros(total_parts,1);
end
for c=1:all_pop_size
   for a=1:total_parts
      for b=2:max(number_of_operations)
         if part_route(a,b,c)<part_route(a,b-1,c) && part_route(a,b,c)~=0
            part_route(a,b,c)=part_route(a,b,c)+machines*(reeentrant_post2(a,b,c)-1);
         else
            part_route(a,b,c)=part_route(a,b,c);
         end
      end
   end
end
proc_times=zeros(total_parts,machines*(bggst+1),all_pop_size);
for c=1:all_pop_size
   for a=1:total_parts
      for b=1:machines*bggst
         for d=1:max(number_of_operations);
            if part_routes(a,d,c)==b
               proc_times(a,b,c)=proc_times(a,b,c)+proc_time(a,d);
            end
         end
      end
   end
end
arrive_on_machine_const_final=zeros(total_parts,exs);
out_from_machine_const_final=zeros(total_parts,exs);
queue_time_final=zeros(total_parts,exs);
best_krom_forever=load_time;
shortcut_route=zeros(max(cycle(:,:,1))+1,total_parts);
shortcut_position=zeros(2,2);
time=2;
final_solution=[];
final_solution(1:total_parts,1)=zeros(total_parts,1);
for i=1:total_parts
   start_position(i)=1;
   machine_post(i)=0;
   step_post(i)=0;
   if 1<best_krom_forever(i)
      final_solution(i,1)=98;
   elseif 1==best_krom_forever(i)
```

```
            final_solution(i,1)=50;
        end
    end
    while any(final_solution(:,time-1)~=99);
        for i=1:total_parts
            if start_position(i)==best_krom_forever(i)
                arrive_on_machine_const_final(i,1)=time;
                if time<start_position(i)+transport_time_loading(1)
                    final_solution(i,time)=50;
                elseif time==start_position(i)+transport_time_loading(1)
                    step_post(i)=1;
                    machine_post(i)=1;
                    out_from_machine_const_final(i,1)=time;
                    start_position(i)=time;
                end
            end
            n(i)=ceil(machine_post(i)/machines);
            m(i)=machine_post(i)-(machines*(n(i)-1));
            if final_solution(i,time-1)==99
                final_solution(i,time)=99;
            elseif time<best_krom_forever(i)
                final_solution(i,time)=98;
            elseif time==best_krom_forever(i)
                final_solution(i,time)=50;
                start_position(i)=time;
            else
                if step_post(i)==0
                    final_solution(i,time)=final_solution(i,time);
                elseif m(i)==initial_habitats(i,step_post(i),c)
                    bob=max(queue_time_final(:,initial_habitats(i,step_post(i),c)));
                    rob=find(final_solution(:,time-1)==initial_habitats(i,step_post(i),c));
                    if final_solution(i,time-1)==initial_habitats(i,step_post(i),c)
                        if time<(start_position(i)+proc_times(i,part_route(i,step_post(i),c),c))
                            final_solution(i,time)=initial_habitats(i,step_post(i),c);

out_from_machine_const_final(i,machine_post(i))=(start_position(i)+proc_times(i,part_route(i,step_post(i),c)
,c));
                        elseif time==out_from_machine_const_final(i,machine_post(i))
                            final_solution(i,time)=50;
                            start_position(i)=time;
                            step_post(i)=step_post(i)+1;
                            out_from_machine_const_final(i,machine_post(i))=time;
                        end
                    else
                        if   all(final_solution(:,time-1)~=initial_habitats(i,step_post(i),c))   &&   final_solution(i,time-
1)~=100
                            if i==1
                                final_solution(i,time)=initial_habitats(i,step_post(i),c);
                                start_position(i)=time;
                                queue_time_final(i,initial_habitats(i,step_post(i),c))=0;
                            else
                                if all(final_solution(1:(i-1),time)~=initial_habitats(i,step_post(i),c))
                                    final_solution(i,time)=initial_habitats(i,step_post(i),c);
                                    start_position(i)=time;
                                    queue_time_final(i,initial_habitats(i,step_post(i),c))=0;
                                else
                                    final_solution(i,time)=100;
                                    start_position(i)=time;
```


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```
queue_time_final(i,initial_habitats(i,step_post(i),c))=queue_time_final(i,initial_habitats(i,step_post(i),c))+1;
                        end
                    end
                elseif numel(rob)==1 && time==out_from_machine_const_final(rob,machine_post(rob))
                    if queue_time_final(i,initial_habitats(i,step_post(i),c))==bob
                        if i==1
                            final_solution(i,time)=initial_habitats(i,step_post(i),c);
                            start_position(i)=time;
                            queue_time_final(i,initial_habitats(i,step_post(i),c))=0;
                        else
                            if all(final_solution(1:(i-1),time)~=initial_habitats(i,step_post(i),c))
                                final_solution(i,time)=initial_habitats(i,step_post(i),c);
                                start_position(i)=time;
                                queue_time_final(i,initial_habitats(i,step_post(i),c))=0;
                            else
                                final_solution(i,time)=100;
                                start_position(i)=time;

queue_time_final(i,initial_habitats(i,step_post(i),c))=queue_time_final(i,initial_habitats(i,step_post(i),c))+1;
                            end
                        end
                    else
                        final_solution(i,time)=100;
                        start_position(i)=time;

queue_time_final(i,initial_habitats(i,step_post(i),c))=queue_time_final(i,initial_habitats(i,step_post(i),c))+1;
                    end
                else
                    final_solution(i,time)=100;
                    start_position(i)=time;

queue_time_final(i,initial_habitats(i,step_post(i),c))=queue_time_final(i,initial_habitats(i,step_post(i),c))+1;
                end
            end
        else
            if shortcut_route(n(i),i)~=0
                if m(i)==shortcut_position(1,shortcut_route(n(i),i))
                    if time<start_position(i)+traveling_time(i,machine_post(i),c)-1
                        final_solution(i,time)=50;
                    elseif time==start_position(i)+traveling_time(i,machine_post(i),c)-1
                        final_solution(i,time)=50;
                        start_position(i)=time+1;
                        if shortcut_type(1,shortcut_route(n(i),i))==1
                            machine_post(i)=shortcut_position(2,shortcut_route(n(i),i))+(length(machine)*(n(i)-
1));

                        else
                            machine_post(i)=shortcut_position(2,shortcut_route(n(i),i))+(length(machine)*n(i));
                        end
                        arrive_on_machine_const_final(i,machine_post(i))=start_position(i);
                        out_from_machine_const_final(i,machine_post(i))=start_position(i);
                    end
                else
                    if time<start_position(i)+traveling_time(i,machine_post(i),c)-1
                        final_solution(i,time)=50;
                    elseif time==start_position(i)+traveling_time(i,machine_post(i),c)-1
                        final_solution(i,time)=50;
                        start_position(i)=time+1;
```

```
                machine_post(i)=machine_post(i)+1;
                arrive_on_machine_const_final(i,machine_post(i))=start_position(i);
                out_from_machine_const_final(i,machine_post(i))=start_position(i);
              end
            end
          else
            if time<start_position(i)+traveling_time(i,machine_post(i),c)-1
              final_solution(i,time)=50;
            elseif time==start_position(i)+traveling_time(i,machine_post(i),c)-1
              final_solution(i,time)=50;
              start_position(i)=time+1;
              machine_post(i)=machine_post(i)+1;
              arrive_on_machine_const_final(i,machine_post(i))=start_position(i);
              out_from_machine_const_final(i,machine_post(i))=start_position(i);
            end
          end
        end
      end
      n_out(i)=ceil((machine_post(i)-1)/machines);
      m_out(i)=(machine_post(i)-1)-(machines*(n_out(i)-1));
      if m_out(i)==4 && n_out(i)==cycle(i,:,c)
        out_from_system_point(i)=start_position(i)-traveling_time(i,machine_post(i),c)-
traveling_time(i,machine_post(i)-1,c)+transport_time_unloading;
        final_solution(i,out_from_system_point(i):time)=99;
        out_from_machine_const_final(i,machine_post(i))=out_from_system_point(i);
      end
    end
    time=time+1;
  end
  out_of_all(c,:)=out_from_system_point;
  end

  %---------------------------fitness calculation----------------------------
  procc_time=reshape(processing_time',[1,numero_uno]);
  ind_facc=find(procc_time==0);
  procc_time(ind_facc)=[];

  numero_duo=length(initial_habitat(1,:,1))*length(initial_habitat(:,1,1));
  for a=1:all_pop_size
    habitots=reshape(initial_habitat(:,:,a)',[1,numero_duo]);
    ind_facc=find(habitots==0);
    habitots(ind_facc)=[];
    all_habitots(a,:)=habitots;
  end


  % system unbalance
  for a=1:all_pop_size
    for b=1:machines
      ind_macc=find(all_habitots(a,:)==b);
      fowl=sum(procc_time(ind_macc));
      sys_u_m(b)=abs(H-fowl);
    end
    system_unbalance(a)=sum(sys_u_m);
    each_machines_record(a,:)=sys_u_m;
    square_sys_u(a)=(system_unbalance(a))^2;
  end
  for a=1:all_pop_size
```

```
    normal_system_unbalance(a)=system_unbalance(a)/(sqrt(sum(square_sys_u)));
  end

  % makespan
  for a=1:all_pop_size
    makespan(a)=max(out_of_all(a,:));
    square_makespan(a)=(makespan(a))^2;
  end
  for a=1:all_pop_size
    normal_makespan(a)=makespan(a)/(sqrt(sum(square_makespan)));
  end

  % total flow time
  for a=1:all_pop_size
    total_flow_time(a)=sum(out_of_all(a,:));
    square_total_flow_time(a)=(total_flow_time(a))^2;
  end
  for a=1:all_pop_size
    normal_total_flow_time(a)=total_flow_time(a)/(sqrt(sum(square_total_flow_time)));
  end

  % total fitness
  for a=1:all_pop_size
    fitness(a,:)=[system_unbalance(a) makespan(a) total_flow_time(a)];
    total_fitness(a)=system_unbalance(a)+makespan(a)+total_flow_time(a);
    normal_fitness(a,:)=[normal_system_unbalance(a) normal_makespan(a) normal_total_flow_time(a)];

total_normal_fitness(a)=normal_system_unbalance(a)+normal_makespan(a)+normal_total_flow_time(a);
  end

  % non-dominated sorting procedure
  no_of_dominating=zeros(1, 2*pop_size);
  for a=1 : 2 * pop_size
    for b=1 : 2* pop_size
      if a~=b && system_unbalance(a) == system_unbalance(b) && makespan(a)==makespan(b) &&
total_flow_time(a)==total_flow_time(b)
        no_of_dominating(a)=no_of_dominating(a);
      elseif a ~= b && system_unbalance(b) <= system_unbalance(a) && makespan(b)<=makespan(a)
&& total_flow_time(b)<=total_flow_time(a)
        no_of_dominating(a)=no_of_dominating(a)+1;
      else
        no_of_dominating(a)=no_of_dominating(a);
      end
    end
  end
  mix_all=[all_habitots fitness each_machines_record total_fitness' normal_fitness total_normal_fitness'
no_of_dominating'];
  mix_all=sortrows(mix_all,[length(mix_all(1,:)) length(all_habitots(1,:))+4+machines]);

  %replacement
  best_habitats(Iteration,:)=mix_all(1,:);
  if
best_habitats_ever(length(all_habitots(1,:))+4+machines)>best_habitats(Iteration,length(all_habitots(1,:))+4+
machines)
    best_habitats_ever=best_habitats(Iteration,:);
  end
  data_of_generation=mix_all(1:pop_size,:);
  all_habitots=data_of_generation(:,1:length(habitots));
```

```
fitness=data_of_generation(:,length(habitots)+1:length(habitots)+3);
best_record_machs=data_of_generation(length(habitots)+4:length(habitots)+3+machines);
total_fitness=data_of_generation(:,length(habitots)+4+machines)';
normal_fitness=data_of_generation(length(habitots)+5+machines:length(habitots)+5+machines+2);
total_normal_fitness=data_of_generation(:,length(mix_all(1,:))-1)';
data_for_bank=unique(mix_all,'rows');
data_for_bank(:,length(data_for_bank(1,:)))=[];
bank_solutions=[bank_solutions; data_for_bank];
Iteration=Iteration+1
end
%record best solution
best_habitat=best_habitats_ever(1:length(habitots));
fitnesss=best_habitats_ever(length(habitots)+1:length(habitots)+3);
best_record_mach=best_habitats_ever(length(habitots)+4:length(habitots)+3+machines);
total_fitnesss=best_habitats_ever(length(habitots)+4+machines);
normal_fitnesss=best_habitats_ever(length(habitots)+5+machines:length(habitots)+5+machines+2);
total_normal_fitnesss=best_habitats_ever(length(best_habitats_ever)-1);
solute=bank_solutions(:,1:length(habitots));
fitness_bank=bank_solutions(:,length(habitots)+1:length(habitots)+3);
record_bank=bank_solutions(:,length(habitots)+4:length(habitots)+3+machines);
total_fitnesss_bank=bank_solutions(:,length(habitots)+4+machines);
normal_fitness_bank=bank_solutions(:,length(habitots)+5+machines:length(habitots)+5+machines+2);
total_normal_fitnesss_bank=bank_solutions(:,length(mix_all(1,:))-1);


allen_solution=[solute fitness_bank record_bank total_fitnesss_bank];
for a=1:length(allen_solution(:,1))
   square_sys_un(a)=(allen_solution(a,length(habitots)+1))^2;
   square_makes(a)=(allen_solution(a,length(habitots)+2))^2;
   square_tot_flo(a)=(allen_solution(a,length(habitots)+3))^2;
end
for a=1:length(allen_solution(:,1))
   normal_sys_un(a)=(allen_solution(a,length(habitots)+1))/(sqrt(sum(square_sys_un)));
   normal_makes(a)=(allen_solution(a,length(habitots)+2))/(sqrt(sum(square_makes)));
   normal_tot_flo(a)=(allen_solution(a,length(habitots)+3))/(sqrt(sum(square_tot_flo)));
   normal_tot_fitness(a)=normal_sys_un(a)+normal_makes(a)+normal_tot_flo(a);
end
allen_solution=[allen_solution normal_sys_un' normal_makes' normal_tot_flo' normal_tot_fitness'];
allen_solution=sortrows(allen_solution,(length(allen_solution(1,:))));
%record best solution
best_habitat_normal=allen_solution(1,1:length(habitots));
fitnesss_normal=allen_solution(1,length(habitots)+1:length(habitots)+3);
best_record_mach_normal=allen_solution(1,length(habitots)+4:length(habitots)+3+machines);
total_fitnesss_normal=allen_solution(1,length(habitots)+4+machines);
normal_fitnesss_normal=allen_solution(1,length(habitots)+5+machines:length(habitots)+5+machines+2);
total_normal_fitnesss_normal=allen_solution(1,length(allen_solution(1,:)));
%-all solutions record
solute_normal=allen_solution(:,1:length(habitots));                    %-----all solutions
fitness_bank_normal=allen_solution(:,length(habitots)+1:length(habitots)+3);    %-----all fitness value
%all machine unbalance
record_bank_normal=allen_solution(:,length(habitots)+4:length(habitots)+3+machinestotal_fitnesss_bank
_normal=allen_solution(:,length(habitots)+4+machines);                    %-----all total fitness
normal_fitness_bank_normal=allen_solution(:,length(habitots)+5+machines:length(habitots)+5+machines
+2) %all normalized fitness
total_normal_fitnesss_bank_normal=allen_solution(:,length(allen_solution(1,:)));%all normalized total
fitness
%converting
a=length(initial_habitats(:,1,1));
```

```
    b=length(initial_habitats(1,:,1))-1;
    c=length(allen_solution(:,1));
    final_habitat=zeros(a,b,c);
    for a=1:length(allen_solution(:,1))
      final_habitat(1,1:number_of_operation(1),a)=solute_normal(a,1:number_of_operation(1));
      parts_posi=0;
      start_hab_posi=1;
      end_hab_posi=number_of_operation(1);
      for b=1:parts
        for c=1:batch_size(b)
          parts_posi=parts_posi+1;
          if parts_posi~=1
            start_hab_posi=end_hab_posi+1;
            end_hab_posi=start_hab_posi+number_of_operation(b)-1;
final_habitat(parts_posi,1:number_of_operation(b),a)=solute_normal(a,start_hab_posi:end_hab_posi);
          end
        end
      end
    end
    best_habitatss(1,:)=best_habitat_normal(1:number_of_operation(1));
    parts_posi=0;
    start_hab_posi=1;
    end_hab_posi=number_of_operation(1);
    for b=1:parts
      for c=1:batch_size(b)
        parts_posi=parts_posi+1;
        if parts_posi~=1
          start_hab_posi=end_hab_posi+1;
          end_hab_posi=start_hab_posi+number_of_operation(b)-1;

best_habitatss(parts_posi,1:number_of_operation(b))=best_habitat_normal(start_hab_posi:end_hab_posi);
        end
      end
    end
    disp('best habitat')
    disp(best_habitatss)   % the best solution
    disp('fitness')
    disp(fitnesss_normal)      % for determining the values of best solution: SU, MK, TFT
    disp('total fitness')
    disp(total_fitnesss_normal)
    disp('system unbalance for each machine')
    disp(best_record_mach_normal)     % SU for each machine
    disp('normalization fitness')
    disp(normal_fitnesss_normal)
    disp('total normalization fitness')
    disp(total_normal_fitnesss_normal)
    %figure visualization of graphics
    scatter3(fitness_bank_normal(:,1),fitness_bank_normal(:,2),fitness_bank_normal(:,3),30,'fill')
    a=min(fitness_bank_normal(:,1))-(max(fitness_bank_normal(:,1))-min(fitness_bank_normal(:,1)))*0.1;
    b=max(fitness_bank_normal(:,1))+(max(fitness_bank_normal(:,1))-min(fitness_bank_normal(:,1)))*0.1;
    c=min(fitness_bank_normal(:,2))-(max(fitness_bank_normal(:,2))-min(fitness_bank_normal(:,2)))*0.1;
    d=max(fitness_bank_normal(:,2))+(max(fitness_bank_normal(:,2))-min(fitness_bank_normal(:,2)))*0.1;
    e=min(fitness_bank_normal(:,3))-(max(fitness_bank_normal(:,3))-min(fitness_bank_normal(:,3)))*0.1;
    f=max(fitness_bank_normal(:,3))+(max(fitness_bank_normal(:,3))-min(fitness_bank_normal(:,3)))*0.1;
    axis([(a-0.1*a) (b+0.1*b) c d e f])
    xlabel('system unbalance')
    ylabel('makespan')
    zlabel('total flow time')
```

```
view(20,20)
figure('Name','system unbalance vs makespan','NumberTitle','off');
scatter(fitness_bank_normal(:,1),fitness_bank_normal(:,2),30,'fill')
axis([(a-0.1*a) (b+0.1*b) c d])
xlabel('system unbalance')
ylabel('makespan')
figure('Name','system unbalance vs total flow time','NumberTitle','off');
scatter(fitness_bank_normal(:,1),fitness_bank_normal(:,3),30,'fill')
axis([(a-0.1*a) (b+0.1*b) e f])
xlabel('system unbalance')
ylabel('total flow time')
figure('Name','makespan vs total flow time','NumberTitle','off');
scatter(fitness_bank_normal(:,2),fitness_bank_normal(:,3),30,'fill')
axis([c d e f])
xlabel('makespan')
ylabel('total flow time')
save historyresultdata_casestudy2_machineloadingproblem.mat
```

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