BIO-INSPIRED AND MUSICAL-HARMONY APPROACHES FOR MACHINE ALLOCATION OPTIMIZATION IN FLEXIBLE MANUFACTURING SYSTEM

UMI KALSOM BINTI YUSOF

UNIVERSITI TEKNOLOGI MALAYSIA

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UMI KALSOM BINTI YUSOF

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Dengan Nama Allah yang Maha Pemurah dan Maha Penyayang

Khas buat ayah dan bonda
Teristimewa buat suami tercinta
Untuk anak-anak penyejuk mata dan penawar hati

Ya Allah! Sesungguhnya aku memohon kepadaMu
ilmu yang bermanfaat,
rezeki yang halal
dan amal yang diterima.

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”In the name of Allah, most Gracious, most Compassionate”

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ABSTRACT

Manufacturing industries need to constantly adjust to the rapid pace of change in the market. Many of the manufactured products often have a very short life cycle. These scenarios imply the need to improve the efficiency of capacity planning, an important aspect of machine allocation plan that is known for its complexity. Two common approaches to solve the machine allocation problem include optimization-based methods and heuristic oriented methods. Although optimization-based methods are robust in their applicability, they tend to become impractical when the problem size increases, while heuristic approaches are mainly dependent on rules and constraints of an individual problem. Due to this, heuristic approaches always face difficulties to estimate results in a changed environment. The use of new and innovative meta-heuristic searching techniques of population-based algorithms in this research can overcome these limitations. The objectives of this research are to minimize the system unbalance and machine makespan utilization, and to increase throughput taking into consideration of the technological constraints. Population-based algorithms that consist of constraint-chromosome genetic algorithm (CCGA), constraint-vector harmony search (CVHS) and hybrid of constraint-chromosome genetic algorithm and harmony search (H-CCGaHs) were adopted. To ensure the feasibility of the results and to promote for a faster convergence, the right mapping chromosome or harmony memory representation was applied to the domain problem in all the three algorithms. Genetic algorithm is known for its exploitative ability, whereas harmony search is recognized for its explorative capability. H-CCGaHs combines these strengths to produce a more effective algorithm where both aspects will be optimized and helps avoid getting trapped in local minima. These three algorithms (CCGA, CVHS and H-CCGaHs) were tested on both benchmark data (10 datasets) and industrial data (5 datasets). The results indicated that the proposed H-CCGaHs achieves better results, with faster convergence and a reasonable time to run the algorithm.

ABSTRAK

Syarikat pengeluar sentiasa memerlukan adaptasi untuk menghadapi perubahan pasaran. Kebanyakan daripada produk pengeluar mempunyai kitaran jangka hayat yang pendek. Senario ini membawa kepada keperluan untuk memperbaiki kelicinan perancangan kapasiti, satu aspek penting yang mana perancangan pengagihan mesin yang terkenal dengan kekompleksan. Dua pendekatan lazim untuk menyelesaikan masalah pengagihan mesin termasuklah kaedah berdasarkan optimum dan kaedah berorientasikan heuristik. Walaupun kaedah-kaedah berdasarkan optimum adalah teguh dalam aplikasinya, ia berkecenderungan menjadi tidak praktikal apabila saiz masalah bertambah, sementara pendekatan heuristik bergantung kepada peraturan dan kekangan bagi setiap masalah. Oleh sebab itu, pendekatan heuristik selalu berdepan dengan masalah untuk menganggarkan hasilan apabila persekitaran berubah. Keterbatasan ini boleh diatasi dengan penggunaan teknik algoritma carian meta-heuristik berdasarkan populasi yang baru dan berinovasi dalam kajian terkini. Objektif kajian ini adalah untuk meminimakan ketidakseimbangan sistem dan penggunaan rentang buatan (*makespan*) mesin, dan untuk meningkatkan pengeluaran sambil mengambilkira kekangan teknologi. Algoritma berdasarkan-populasi yang mengandungi algoritma genetik berkekangan-kromosom (CCGA), algoritma carian harmoni berkekangan-vektor (CVHS) dan hibrid algoritma genetik berkekangan-kromosom dan algoritma carian harmoni (H-CCGaHs) diadaptasikan. Untuk memastikan kelaksanaan hasilan dan untuk mempromosikan pertembungan yang lebih cepat, perwakilan pemantauan kromosom atau ingatan harmoni yang betul diterapkan pada masalah domain dalam ketiga-tiga algoritma tersebut. Algoritma genetik terkenal dengan kebolehan ekplotatif, manakala carian harmoni terkenal dengan kebolehan eksploratif. H-CCGaHs menggabungkan kekuatan-kekuatan ini untuk menghasilkan algoritma yang lebih efektif yang mana kedua-dua aspek tersebut akan dioptimakan dan membantu untuk mengelakkan daripada terperangkap dalam minima lokal. Ketiga-tiga algoritma (CCGA, CVHS and H-CCGaHs) telah diuji ke atas data tanda aras (10 set data) dan data industri (5 set data). Keputusan menunjukkan bahawa H-CCGaHs mampu mencapai hasilan yang lebih baik dan pertembungan yang lebih cepat, juga mengambil masa yang munasabah untuk menjana algoritma.

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LIST OF ABBREVIATIONS

ACO	–	Ant Colony Optimization
CCGA	–	Constraint-chromosome Genetic Algorithm
COF	–	Combined Objective Function
CR	–	Crossover Rate
CVHS	–	Constraint-vector Harmony Search
FMS	–	Flexible Manufacturing System
GA	–	Genetic Algorithm
HS	–	Harmony Search
HMS	–	Harmony Memory Size
HMCR	–	Harmony Memory Consideration Rate
H-CCGaHs	–	Hybrid of Constraint-chromosome Genetic Algorithm and Harmony Search
MS	–	Makespan
MR	–	Mutation Rate
NI	–	Number of improvisation
PAR	–	Pitch Adjustment Rate
PSO	–	Particle Swarm Optimization
SU	–	System Unbalance
TH	–	Throughput
TPT	–	Throughput Time
WIP	–	Work-in-process
	–	

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CHAPTER 1

INTRODUCTION

1.1 Problem Background

In manufacturing industry, many critical decisions are based on demand forecast (Cakanyildirim, 2002). The demand forecast which is usually projected on 6-months rolling forecast, nevertheless, is always subjected to error when it comes to a actual demand. Due to the various factors, the actual demand from the customers which is within 2 - 4 months lead-time, is always different from the demand forecast. Since most of the important and risky decisions such as machines or tools purchases are made based on this unreliable forecast, it is always a goal for the manufacturing industries to find a method to reduce this risk.

In spite of demand market volatility, manufacturing companies need to adapt a strategy that makes them able to meet the expected demand. One of the approaches is to keep their resources as lean as possible and put the emphasis on producing products based on customer's order (make-to-order). As a result of this growing requirement of customized production environment, many companies are adopting the Flexible Manufacturing System (FMS) to effectively and efficiently optimize available capacity resources through machine allocation with the objective of producing high quality products with a shorter leadtime.

FMS is a manufacturing system in which there is some amount of flexibility that allows the system to react to any changes (Chunwei and Zhiming, 2001). It can be classified as static or dynamic based on how the orders from the customers are being handled, allocated and released to the production floor (Saravanan, 2006). In a static machine allocation environment, the parts that were allocated are known beforehand; while in a dynamic environment, which is the real manufacturing environment, the allocation of the resources has to consider resource unavailability (machine) over time, such as machine break down or the unexpected demand that can adversely affect the utilization level and efficiency of FMS.

Demand forecast is rarely accurate. Therefore, capacity planning with a good strategy plays a very important role in sizing the company in order to meet the current and future demand from the customers (Olhager *et al.*, 2001). The strategy may include setting up new facilities, new equipment purchases or optimizing the current available resources in the facility. It may also include machine upgrading and adjusting the resources to overcome the constraints due to product varieties.

Machine allocation in an advanced manufacturing system such as FMS is considered dynamic. Machines break down constantly especially when they are aged. When this occurs, decision needs to be made either to wait for the machine to be repaired or move to another machine. Typical in a hard down situation, the affected part type will be moved to another machine to meet to the customer's requirement date. Frequent machine breakdowns may result in shop floor nervousness due to inability and lack of continuity in the current shop floor plan because the allocation is exposed to frequent and huge amounts of deviation (Wang *et al.*, 2007). In addition, machine breakdown is one of the major undesirable inputs as it can cause additional maintenance cost. Therefore, the ability to quickly reallocate the unfinished part types to another machine without jerking or causing interruption to the shop floor is the most desirable goal of any companies. At the same time, it can minimize the adverse impact of the failures on the objective measures of the machine allocation problem, so the production goals can be achieved (Mandal *et al.*, 2010).

The productivity is crucial especially when costly equipments and materials are involved in the production because any deviation from the original plan may increase the production costs. The 'pain' will be even felt greater in advanced manufacturing plant where the cost of initial investment is huge, the yearly machines and tools procurement shoot up to several millions due to high technology equipment base and fast product turn-over. Therefore, it is important to increase the productivity through maximizing the overall throughput as well as to balance the works-in-process (WIP) where the resources are highly utilized. In the meantime, to improve the efficiency, it aims on minimizing the system unbalance, makespan and machine hours during the part allocation. System unbalance is a summation of remaining time (idle time) on all available machines. By minimizing system unbalance, utilization level of machines can be increased. Meanwhile, makespan can be defined as the maximum value of working time over cumulative processing time of machines in the given planning horizon. This objective will balance the work-load among machines. Machine hours denotes the number of hours allocated to process the parts for given operations, with the consideration of the machine technological constraints. This scenario is depicted in Figure 1.1.

The machine allocation problems have been extensively researched over the years, and many findings and contributions have been reported. Nevertheless hitherto, all the studies on machine allocation problem are performed based on the assumption of deterministic environment, where the theories have been a little used in real manufacturing environment. In the real world, FMS operates in a dynamic environment where interruptions such as machine breakdown and reallocation of part types can adversely affect the utilization level and efficiency of FMS. There are a lot more to offer from research done on the machine allocation to manufacturing industries, but more work is needed to address the gap between theories and practice in machine allocation.

One of the common assumptions on machine allocation theories, which is unlikely to take place in practice is that the machine allocation environment is static. Most of the machine allocation or loading researches have been focused on providing a good loading plan from deterministic requirements. Very few studies are done on machine allocation problem that deals with machine's interruption and control policies; which imitates the real environment of FMS. Recently, Mandal *et al.* (2010) proposed to include the machine breakdowns on machine allocation model in an effort to minimize the effect of the breakdowns so that profitability can be boosted. Consequently, dynamic machine allocation process is vital in order to improve the performance of the allocation plan due to the dynamic problem that is inherited by the aforementioned factors.

In the real industrial practice, dynamic machine allocation problem is handled manually by human schedulers who observe the potential problems and revise the allocation based on their knowledge and experiences. However, the combinatorial complexity of the machine allocation problem tends to overburden them and leads to poor allocation performances. Mandal *et al.* (2010) proposed a model that combines the online monitoring scheme, where the machines are continuously monitored to measure the failure potential and the actions are determined beforehand to avoid a potential breakdown. In addition, manual monitoring ensures the action is taken as soon as possible to minimize the impact due to the sudden breakdown.

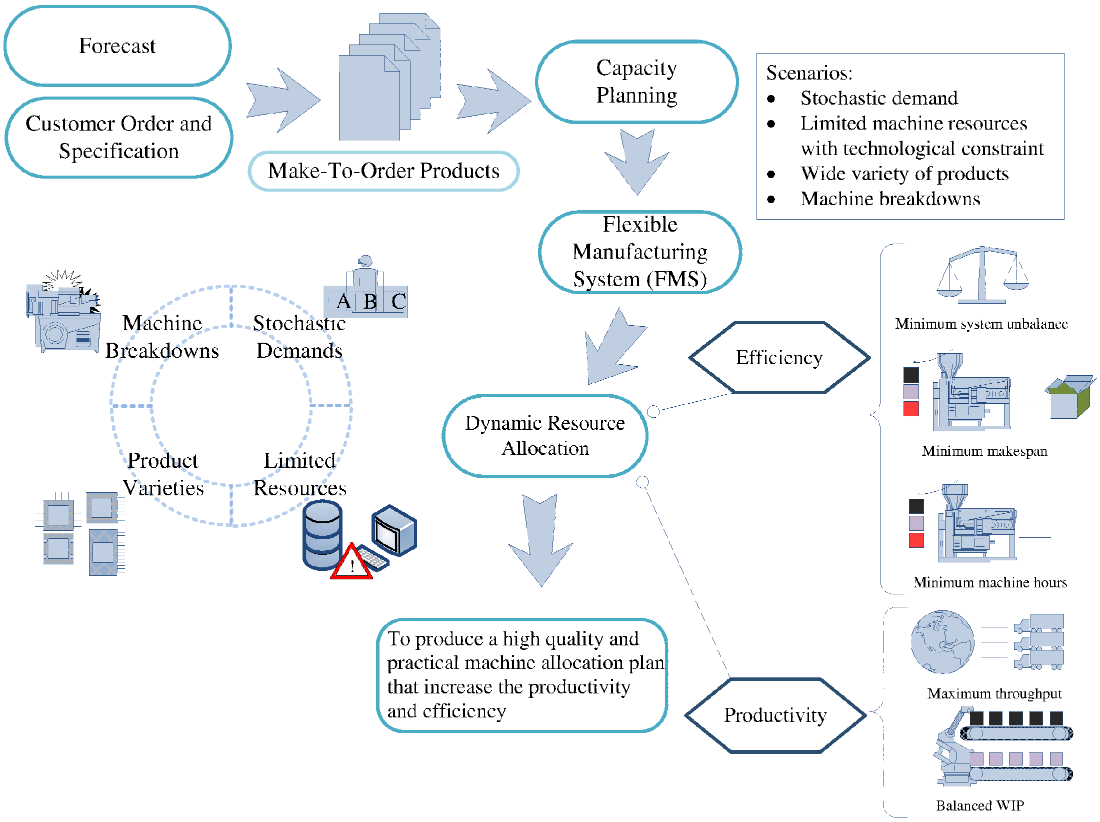

Figure 1.1: A lean manufacturing machine allocation scenario

1.2 Challenges of the Flexible Manufacturing System Dynamic Machine Allocation Problem

Most of manufacturing industries make a practice of preparing the demand forecast planning for every five to ten years ahead. This is important to project the company's growth, to prepare for any facilities expansion or to procure additional machines and tools with better capabilities. The plan is constantly reviewed and adjusted, usually on quarterly or half yearly basis.

In any manufacturing industry, there always is a bottle neck area that the management would need to review. They have to decide either to expand the capacity or replace the older machines with newer technology so that the company can continue to grow. The machines and tools delivery leadtime typically range from 6-12 months. Hence, machine procurement plan need to be based on at least a year demand forecast (Cakanyildirim, 2002) which is hardly accurate. It will be more difficult to plan or to set up capacity requirement for a new product line that involves new machines portfolio.

Balancing capital investment against the customer demands in a volatile environment has always been a challenge for any industry. Machines are purchased well in advance but the actual production build will start only when orders are received. With rapidly changing technology, many companies are adopting build-to-order concept. In other word, there is no product built ahead for inventory, waiting for the customers' order. This scenario is very much apparent especially in high-technology industries.

Resource allocation and capacity adjustment is another obstacle faced by the manufacturing industries. Most of the time, the orders from customers are different from the demand forecasted earlier. Some orders are totally in a different product mix. Product mix changes can have a big impact on capacity. This requires the plant to adjust the machines allocation, raw materials and manpower in order to meet this constantly changing customers demand.

On top of it, each product has its own unique requirements and may require a different set of technological processes. It is common in a big manufacturing plant to have a mix between the old and new machines, with different capabilities. Newer machines have better capabilities and are faster as compared to the older machines. It will be a challenge to a planner to schedule and allocate machines that suit to the requirements of the products that need to be built. It may in the process, create bottleneck areas in one process and idling stations in another process, thus hindering the plant from optimizing the throughput and profit.

Unexpected events may occur while processing or running products. Customer's pull-in the orders or machine breakdowns are common occurrence in any manufacturing plant and this requires the planner to make adjustments on the allocation of the available resources. These constraints require that the manufacturing plants are be able to maximize the machine resources when there are machine breakdowns or machines scheduled for preventive maintenance. The inability to adjust to suit to the actual demand may put the company into loss of business opportunities and may have direct impact on the bottom-line performance (profit and loss) of a company. In short, a company with the ability to allocate resources to meet to the actual demand would not only survive but also thrive in this competitive market.

The challenges create a dynamic machine allocation scenario that is more complex and difficult than the conventional machine allocation, as signified in Figure 1.2. The complexities intensify as versatile machine configuration makes the machine

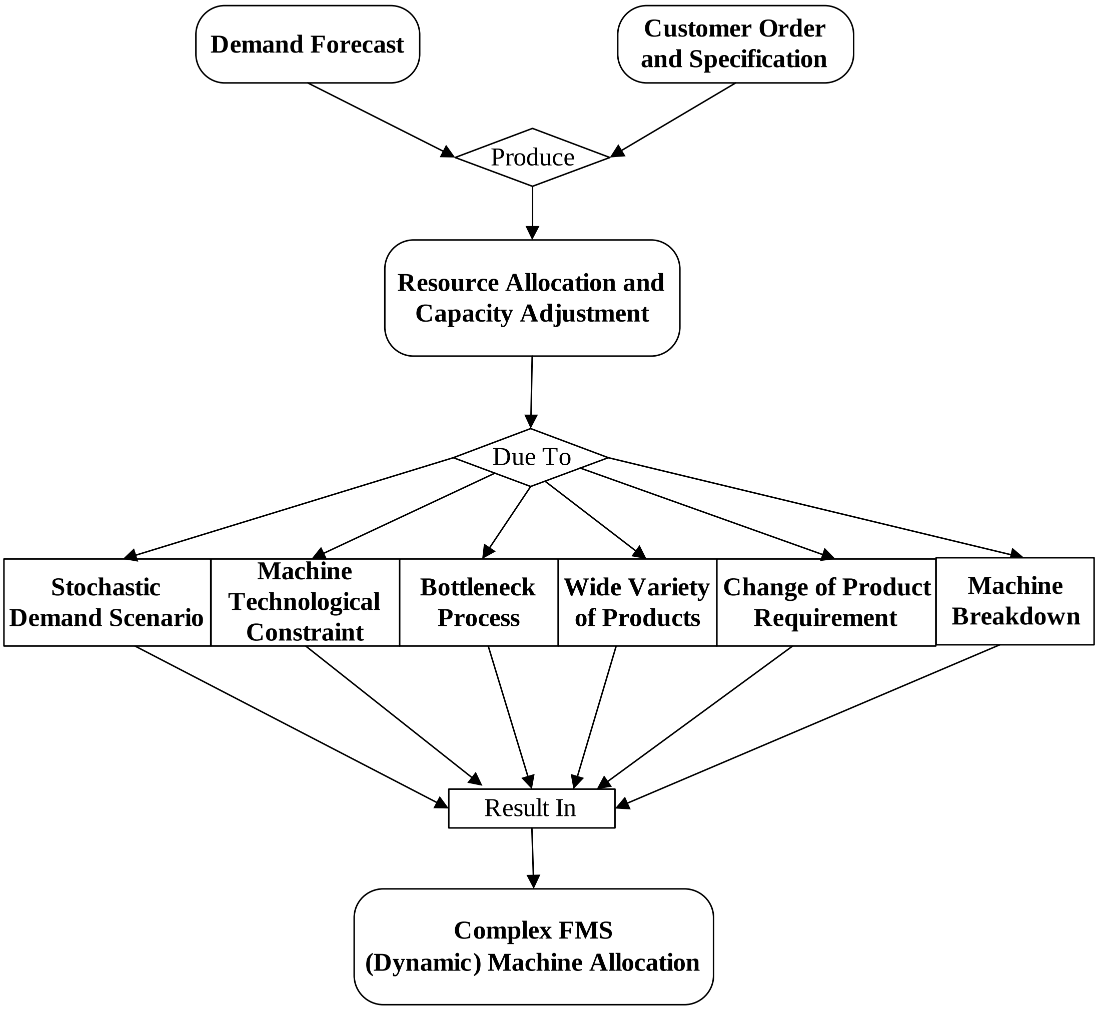

Figure 1.2: Factors leading to the complex Flexible Manufacturing System (FMS) machine allocation problem

flexible to perform different operations; hence rendering many allocation options. This scenario creates a large scale of number of machines with a variety of products that increase the combinatorial complexity; added with the variability of parameters (batch size, processing times, unit per hour of the machine (UPH), etc.) and constraints (machine, resources capabilities).

In addition, widely studied intelligent methods such as genetic algorithm (GA) can be used to solve the machine allocation problem. GA has been researched for many years and it is one of the most common methods reported in the literature, mainly due to its ability to provide good performance solutions. It has the capability of mimic the whole problem to be solved, and easily adjusts the variability of FMS parameters and constraints that are faced in the real manufacturing problem. In addition, a new intelligent method, harmony search (HS), is also among the promising meta-heuristic algorithms. Although it is not yet performed on machine allocation domain area, the results that have been shown in many literatures in other domain areas promise a good comparative result.

1.3 Problem Statement

In order for the manufacturing industries to response effectively to the challenges in a volatile manufacturing environment, an effective and practical approach is needed to address the real FMS machine allocation problem. The approach should be able to optimize the current available resources in considering change of customers requirements and machine breakdowns.

Thus, the main research question of this study is:

How to practically and effectively optimize the machine resources due to the change of customers' requirements and machine breakdowns in optimizing the productivity and efficiency of the machine allocation in FMS?

1.4 Research Goal and Objectives

The goal of this research is a practical and effective dynamic machine allocation approach for FMS. In order to be practical, it has to consider the real FMS environment as well as the desired manufacturing objectives so as to provide an acceptable solution with satisfactory performance. Likewise, it also have to provide high quality solutions not only with respect to the efficiency that improves quality and reduces the production time and makespan, but also maximize the resource utilization and throughput.

The general objectives would be to design and evaluate population-based algorithms to maximise throughput, and minimize the system unbalance and makespan. More specifically, the objectives of the study are:

(i) To design and evaluate two population-based algorithms, i.e. constraint-chromosome genetic algorithm (CCGA) and constraint-vector harmony search (CVHS) for maximizing throughput and minimizing system unbalance.

(ii) To design and evaluate a hybrid of the population-based algorithms, ie H-CCGaHs for further improvement of the system in terms of throughput (maximized) and system unbalance (minimized).

(iii) To design and evaluate machine allocation model that in incorporating with and without machine breakdowns in actual manufacturing industry and evaluate the performance by using population-based algorithms (CCGA, CVHS and H-CCGaHs).

Figure 1.3 summarizes the scenarios leading to the problem and the goal of this study. There are three main issues that contribute to the dynamic machine allocation problem. The first one is the gap between forecasted demand and actual demand of the customer; second is the change of customer requirement and specification; and third is the disruption of the machine resources due to machine breakdown.

1.5 Research Scopes and Significance

As the FMS machine allocation involves some level of flexibilities, various parameters, constraints and uncertainties that further complicate the problem; some scopes and limitations have been made in order to make it tractable. The scopes and limitations of this research are as follows:

(i) This study considers only discrete manufacturing system and therefore, production is referred to as parts production;

(ii) Non-splitting of part type - this implies that a part type undertaken for processing is to be completed for all its operations before considering a new part type; Production requirements of part types cannot be split among the machines. This means, if an operation of a part type is assigned to a machine, all requirements of that part should be processed on the same machine.

(iii) Unique part type routing - although flexibility exists in the selection of a machine for optional operation, the operation must be completed on the same machine once a machine is selected.

(iv) Sharing of tool slots is not considered.

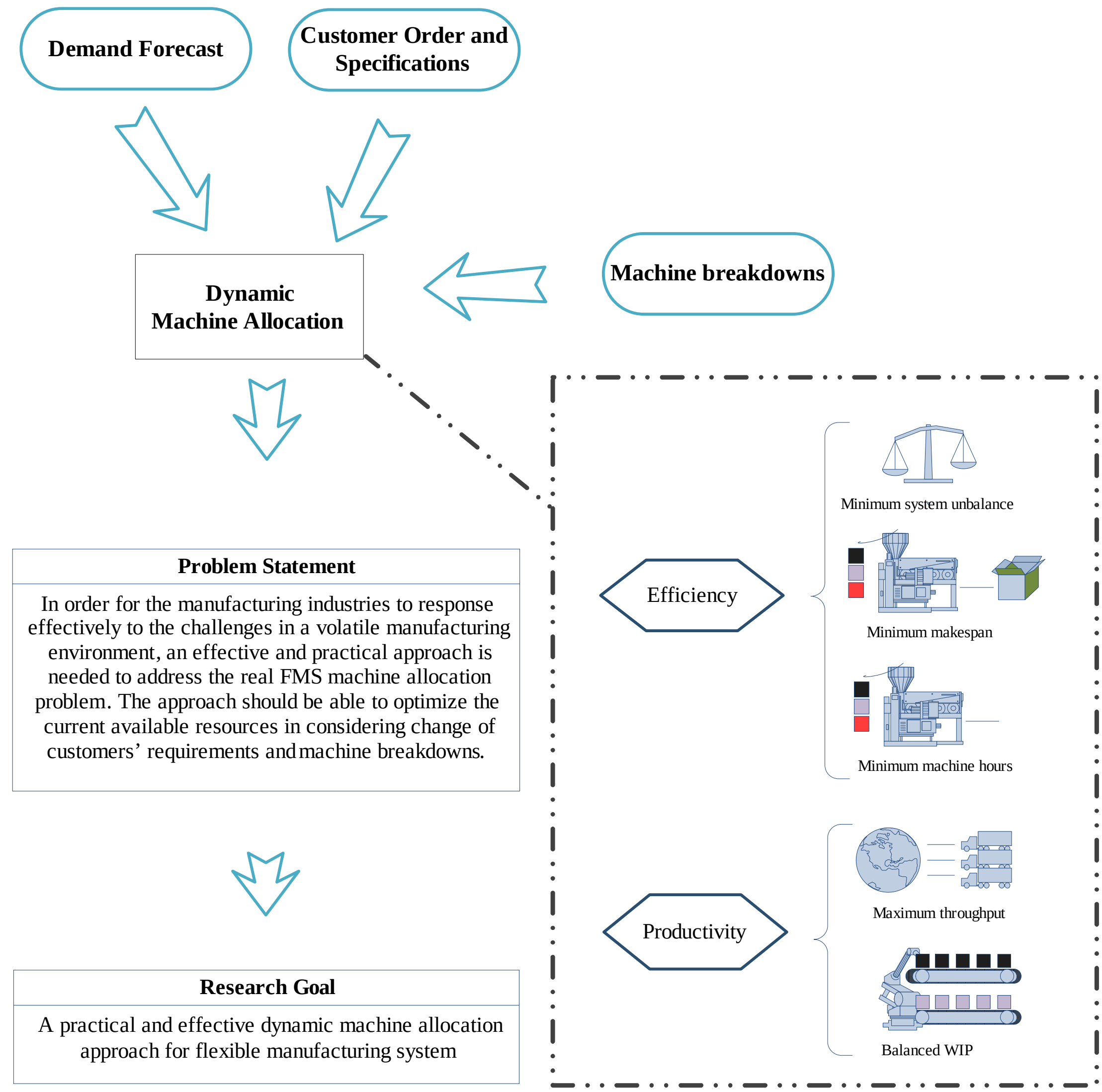

Figure 1.3: Scenario of the problem and research goal

(v) Parts are readily available. The resources such as pallets, fixtures, etc., used in the system are sufficient and readily available.

(vi) Material handling time between machines is negligible.

(vii) Machines required for an operation are determined.

(viii) The number of machines slots needed for each type is given.

(ix) Processing times are deterministic and given in advance.

(x) Machine life and the number of available copies for each machine type are given in advance.

(xi) Dedicated machines for certain part types are determined in advance.

(xii) The real FMS data used in this study are provided by the industrial collaborator.

This research is considered significant as it tends to solve (dynamic) machine allocation problems due to the constraint of the resources (machines) as well as due to machine breakdown(s) that commonly happens in all lean manufacturing companies. The proposed algorithms; constraint-based genetic algorithm (CCGA), harmony search (HS) and a hybrid of these two algorithms will provide an alternative to the decision makers to achieve near optimal solutions with less computation cost and time. In addition, the proposed dynamic machine allocation strategy will accommodate the remaining part types with a minimum number of deviations to the current loading, thus providing a promising approach to the decision makers to cater to shop floor nervousness.

The performance measures considered in this research are concerned about the productivity of the short-term planning and work-in-process (WIP), and the customer satisfaction. This is in tandem with one of the aims of lean manufacturing to improve the quality, and reduce the production time and cost. Therefore, the success of this research will support the betterment of the lean manufacturing performance. The improvement can be achieved through the maximization of throughput, minimization of system unbalance, and minimization of machine make span utilized while satisfying the technological constraints such as machine time availability and tool slots. Furthermore, this research will also suggest the manufacturing approach on machine allocation strategy.

1.6 Structure of the Thesis

This thesis is organized into eight chapters. Figure 1.4 shows the structure of the thesis.

Brief descriptions of the contents of each chapter are given as follows:

(i) The thesis begins with discussions on some problem background, goal, objectives, scopes and significance of this research as featured in Chapter 1.

(ii) Chapter 2 reviews some related works in the area as well as related domains that would help in understanding the rest of the thesis.

(iii) Chapter 3 describes the research methodology employed in this research including the research framework, data sources, instrumentation, problem

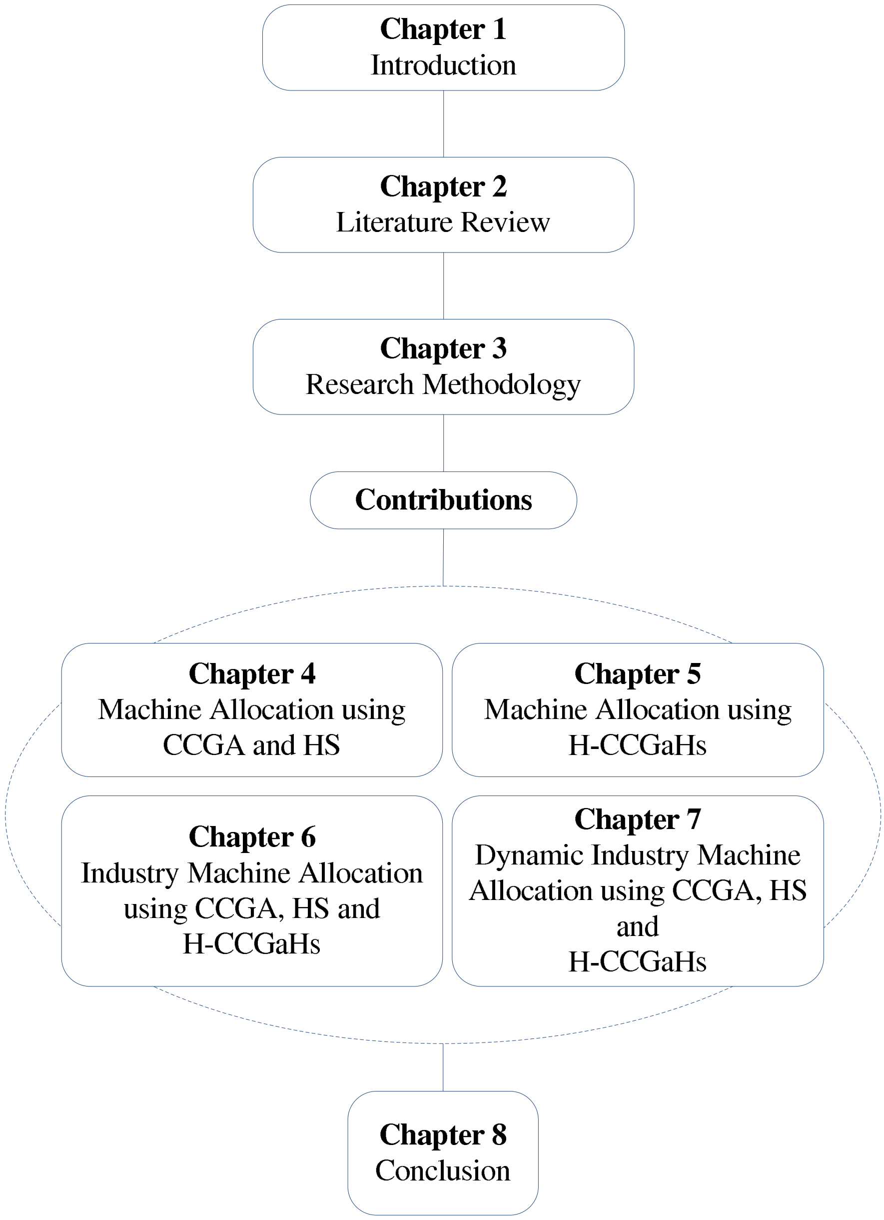

Figure 1.4: Structure of the thesis

description, performance measures, experiment and analysis used in the thesis.

(iv) Then, Chapter 4 discusses on how the machine allocation is being handled in the machine allocation problem using two population algorithms; constraint-chromosome genetic algorithm (CCGA) and harmony search (HS). It also compares the performance of proposed algorithms with current literatures as well as discusses on the strength of these algorithms;

(v) Chapter 5 discusses on the development of hybrid of constraint-chromosome genetic algorithm and harmony search called H-CCGaHs and evaluated against the current literatures and the two-algorithms previously developed.

(vi) Then, Chapter 6 discusses on the applications of the three algorithms (CCGA, HS and H-CCGaHs) on industry problem datasets, taking into consideration the product specification and machine resource technological constraints. The results from three algorithms are compared.

(vii) Further on, Chapter 7 discusses the design of the dynamic machine allocation framework and approach in real industrial data taking into consideration the machine breakdowns. The performance of the proposed approach is evaluated using CCGA, HS and H-CCGaHs.

(viii) Finally, Chapter 8 concludes the findings, contributions and potential future research to be conducted as derived from this study.

REFERENCES

Al-Betar, M. and Khader, A. (2012). A harmony search algorithm for university course timetabling. *Annals of Operations Research*. 194(1), 3–31.

Alia, O., Mandava, R. and Aziz, M. (2010). A hybrid Harmony Search algorithm to MRI brain segmentation. In *9th IEEE International Conference on Cognitive Informatics (ICCI)*. July. 712–721.

Ammons, J. C., Lofgren, C. B. and McGinnis, L. F. (1985). A large scale machine loading problem in flexible assembly. *Annals of Operations Research*. 3(7), 317–332.

Ayten, T., Selim, A. and Storer, R. (2007). Due date and cost-based FMS loading, scheduling and tool management. *International Journal of Production Research*. 45(5), 1183–1213.

Azimi, Z. N. (2004). Comparison of Metaheuristic Algorithms for Examination Timetabling Problem. *Applied Mathematics and Computation*. 16(1), 337–354.

Benavides, D., Duley, J. and Johnson, B. (1999). As good as it gets: optimal fab design and deployment. *IEEE Transactions on Semiconductor Manufacturing*. 12(3), 281–287.

Berrada, M. and Stecke, K. E. (1986). A branch and bound approach for machine load balancing in flexible manufacturing systems. *Management Science*. 32(10), 1316–1335.

Bimal, K. M. and Shanker, K. (1994). Models and solution approaches for part movement minimization and load balancing in FMS with machine, tool and process plan flexibilities. *International Journal of Production Research*. 33(7), 1791–1816.

Bloomfield, M. W., Herencia, J. E. and Weaver, P. M. (2010). Analysis and benchmarking of meta-heuristic techniques for lay-up optimization. *Computers and Structures*. 88(5-6), 272 – 282.

Bretthauer, K. and Venkataramanan, M. (1990). Machine loading and alternate routing in a flexible manufacturing system. *Computers and Industrial Engineering*. 18(3), 341–350.

Cakanyildirim, R. O. R. (1999). Demand Forecasting and Capacity Planning in the semicondubor Industry. *Technical Report 119, SORIE. Cornell University, NY*.

Cakanyildirim, R. R., M. (2002). SeDFAM: Semiconductor demand forecast accuracy model. *IIE Transactions*. 34(5), 449–465.

Caramia, M. and Dell'Olmo, P. (2006). *Effective Resource Management in Manufacturing Systems: Optimization Algorithms for Production Planning*. Springer Series in Advanced Manufacturing.

Catay, E. S. V. A., B. (2003). Tool capacity planning in semiconductor manufacturing. *Computers and Operations Research*. 30(9), 1349–1366.

Chan, F. and Swarnkar, R. (2006). Ant colony optimization approach to a fuzzy goal programming model for a machine tool selection and operation allocation problem in an FMS. *Robotics and Computer-Integrated Manufacturing*. 22(4), 353–362.

Chan, F. T. S., Swarnkar, R. and Tiwari, M. K. (2005). Fuzzy goal-programming model with an artificial immune system (AIS) approach for a machine tool selection and operation allocation problem in a flexible manufacturing system. *International Journal of Production Research*. 43(19), 4147–4163.

Che, Z.-H. (2010). Using Hybrid Genetic Algorithms for Multi-Period Product Configuration Change Planning. *International Journal of Innovative Computing, Information and Control*. 6(6), 2761–2785.

Chen, S.-H., Chang, P.-C., Zhang, Q. and Wang, C.-B. (2009). A Guided Memetic Algorithm with Probabilistic Models. *International Journal of Innovative Computing, Information and Control*. 5(12), 1–12.

Chen-Fang, T. and Kuo-Ming, C. (2007). An Effective Chromosome Representation for Optimising Product Quality. In *11th International Conference on Computer Supported Cooperative Work in Design, CSCWD 2007*. 1032–1037.

Chou, Y. C. (2007). Managing Dynamic Demand Events in Semiconductor Manufacturing Chains by Optimal Control Modelling. *Springer Series in Advanced Manufacturing*, 335–363.

Chou, Y. C., Cheng, C. T., Yang, F. C. and Liang, Y. Y. (2007). Evaluating alternative capacity strategies in semiconductor manufacturing under uncertain demand and price scenarios. *International Journal of Production Economics*. 105(2), 591–606.

Choudhary, A., Tiwari, M. and J.A, H. (2006). Part selection and operation-machine assignment in FMS environment: A genetic algorithm with chromosome differentiation based methodology. Proceedings of the Institution of Mechanical Engineers. *Journal of Engineering Manufacture*. 220(5), 677–694.

Chunwei, Z. and Zhiming, W. (2001). A Genetic Algorithm Approach to the Scheduling of FMS with Multiple Routes. *International Journal of Flexible Manufacturing Systems*. 13(1), 71–88.

Co, H., Biermann, J. and Chen, S. (1990). A methodical approach to the flexible manufacturing system batching, loading, and tool configuration problems. *International Journal of Production Research*. 28(12), 2171–2186.

Cormen, T. H., Eliserson, C. E., Rivest, R. L. and Stein, C. (2008). *Introduction to Algorithms*. Prentice-Hall, Inc.

Cormier, D., O'Grady, P. and Sanii, E. (1998). A constraint-based genetic algorithm for concurrent engineering. *International Journal of Production Research*. 36(6), 1679 – 1697.

Davis, L. (1991). *Handbook of Genetic Algorithms*. Van Nostrand Reinhold, New York.

Deris, S., Omatu, S., Ohta, H., Kutar, S. and Samat, P. (1999b). Ship Maintenance Scheduling by Genetic Algorithm and Constraint-Based Reasoning. *European Journal of Operational Research*. 112(3), 489–502.

Deris, S., Omatu, S., Ohta, H. and Saad, P. (1999). Incorporating Constraint Propagation in Genetic Algorithm for University Timetable Planning. *Journal of the Engineering Application of Artificial Intelligence*. 12(3), 241–253.

Ferreira, C. (2006). *Gene Expression Programming: Mathematical Modeling by an Artificial Intelligence (Studies in Computational Intelligence)*. Springer.

Fordyce, K. and Sullivan, G. (1994). A dynamically generated rapid response capacity planning model for semiconductor fabrication facilities. *Impact of emerging technologies on computer science and operations research. Dordrecht: Kluwer*, 103–127.

Geary, S., Disney, S. and Towill, D. (2006). On bullwhip in supply chains-historical review, present practice and expected future impact. *International Journal of Production Economics*. 101(1), 2–18.

Geem, Z. (2006). *Improved Harmony Search from Ensemble of Music Players*. *Lecture Notes in Computer Science*, vol. 4251. Springer Berlin / Heidelberg.

Geem, Z. W. (2005). School bus routing using harmony search. In *Genetic and Evolutionary Computation Conference (GECCO) 2005*. 1–6.

Geem, Z. W. (2007a). Harmony Search Algorithm for Solving Sudoku. In *Knowledge-Based Intelligent Information and Engineering Systems*. (pp. 371–378). vol. 4692. Springer Berlin.

Geem, Z. W. (2007b). Optimal Scheduling of Multiple Dam System Using Harmony Search Algorithm. In *Computational and Ambient Intelligence*. (pp. 316–323). vol. 4507. Springer Berlin.

Geem, Z. W. and Choi, J. Y. (2007). *Music composition using harmony search algorithm.* In M. Giacobini (Ed.), Lecture notes in computer science: Vol. 4448. EvoWorkshops 2007. Heidelberg: Springer.

Geem, Z. W., Kim, J. H. and Loganathan, G. (2001). A New Heuristic Optimization Algorithm: Harmony Search. *SIMULATION*. 76(2), 60–68.

Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley Longman Publishing Co., Inc.

Goswami, M. and Tiwari, M. K. (2006). A reallocation-based heuristic to solve a machine loading problem with material handling constraint in a flexible manufacturing system. *International Journal of Production Research*. 44(3), 569–588.

Guerro, F., Lozano, K. T., S and J., L. (1999). Machine loading and part type selection in flexible manufacturing systems. *International Journal of Production Research*. 37(6), 1303–1317.

Guo, Z. X., Wong, W. K., Leung, S. Y. S., Fan, J. T. and Chan, S. F. (2008). A Genetic-Algorithm-Based Optimization Model for Scheduling Flexible Assembly Lines. *The International Journal of Advanced Manufacturing Technology*. 36(1), 156–168.

Ho, N. B. and Tay, J. C. (2004). GENACE: an efficient cultural algorithm for solving the flexible job-shop problem. In *Congress on Evolutionary Computation, CEC2004*, vol. 2. 1759–1766.

Hood, S. J., Bermon, S. and Barahona, F. (2003). Capacity Planning Under Demand Uncertainty for Semiconductor Manufacturing. *IEEE Transactions on Semiconductor Manufacturing*. 16(2), 273–280.

Huang, D., Yan, J. and Qiao, F. (2004). Modeling With Hierarchical Petri Net of Semiconductor Manufacturing System. *8th International Conference on Control, Automation, Robotics and Vision*. 3, 2217–2222.

Huh, R. R. O., W. T. and Cakanyildirim, M. (2006). A general strategic capacity planning model under demand uncertainty. *Naval Research Logistics (NRL)*. 53(2), 137–150.

Ip, W. H., Li, Y., Man, K. F. and Tang, K. S. (2000). Multi-product planning and scheduling using genetic algorithm approach. *Computers and Industrial Engineering*. 38(2), 283–296.

Kallrath, J. and Maindl, T. I. (2006). Planning in Semiconductor Manufacturing. In *Real Optimization with SAP APO*. (pp. 105–118). Springer Berlin Heidelberg. ISBN 978-3-540-34624-1.

Kameshwaran, R., Rai, S. and Tiwari, M. (2002). Machine-tool Selection and operation allocation in FMS: solving a fuzzy goal-programming model using genetic algorithm. *International Journal of Production Research*. 40(3), 641– 665.

Karabuk, S. (2001). *Coordinating capacity decisions for the supply chain in high-tech industry.* Ph.D. Thesis. Lehigh University.

Keung, K., IP, W. and Lee, T. (2001). A Genetic algorithm approach to the multiple machine tool selection problem. *Journal of Intelligent Manufacturing*. 12(4), 331–342.

Kim, H., Kim, J. and Yu, J. (2010). Loading algorithms for flexible manufacturing systems with partially grouped unrelated machines and tooling constraints. *International Symposium on Computer Communication Control and Automation (3CA)*, 326–329.

Kim, H. S. and Kim, D. H. (2010). Genetic Algorithm-based Dynamic Channel Allocation to Minimize the Inter-Cell Interference in Downlink Wireless Communication Systems. *International Journal of Innovative Computing, Information and Control*. 6(11), 5179–5190.

Kim, J. and Kim, Y. (2005). Multileveled Symbiotic Evolutionary Algorithm: Application to FMS Loading Problems. *Applied Intelligence*. 22(3), 233–249.

Kim, Y. D. and Yano, C. A. (1997). Impact of throughput-based objectives and machine grouping decisions on the short-term performance of flexible manufacturing systems. *International Journal of Production Research*. 35(12), 3303–3322.

Kotcher, R. and Chance, F. (1999). Capacity planning in the face of product-mix uncertainty. In *IEEE international symposium on semiconductor manufacturing conference proceedings, USA: Santa Clara, CA*. 73-76.

Kuhn, H. (1995). A heuristic algorithm for the loading problem in flexible manufacturing systems. *International Journal of Flexible Manufacturing Systems*. 7(3), 229–254.

Kumar, A., Prakash, Tiwari, M. K., Shankar, R. and Baveja, A. (2006). Solving machine-loading problem of a flexible manufacturing system with constraint-based genetic algorithm. *European Journal of Operational Research*. 175(2), 1043–1069.

Kumar, N. and Shanker, K. (2000). A genetic algorithm for FMS part type selection and machine loading. *International Journal of Production Research*. 38(16), 3861–3887.

Kumar, R., Amarjit, K. S. and Tiwari, M. (2004). A fuzzy based algorithm to solve the machine-loading problems of a-FMS and its neurofuzzy Petri net model. *International Journal of Advanced Manufacturing Technology*. 23(5), 318–341.

Lashkari, R., Dutta, S. and Padhye, A. (1987). A new formulation of operation allocation problem in flexible manufacturing systems: mathematical modeling and computational experience. *International Journal of Production Research*. 25(9), 1267–1283.

Lee, D. and Kim, Y. (2000). Loading algorithms for flexible manufacturing systems with partially grouped machines. *IIE Transactions*. 32(1), 33–47.

Lee, K., Geem, Z., Lee, S. and Bae, K. (2005). The harmony search heuristic algorithm for discrete structural optimization. *Engineering Optimization*. 37(7), 663–684.

Lee, K. S. and Geem, Z. W. (2004). A new structural optimization method based on the harmony search algorithm. *Computers Structures*. 82(9-10), 781 – 798.

Lee, S. and Jung, H. (1989). A multi-objective production planning model in a flexible manufacturing environment. *International Journal of Production Research*. 27(11), 1981–1992.

Leu, G., Simion, S. and Serbanescu, A. (2004). Mems Optimization using genetic algorithms. In *Semiconductor Conference, 2004. CAS 2004*. 475–478.

Li, L. P. and Wang, L. (2009). Hybrid algorithms based on harmony search and differential evolution for global optimization. In *Proceedings of the first ACM/SIGEVO Summit on Genetic and Evolutionary Computation*. GEC '09. New York, NY, USA: ACM, 271–278.

Li, Y., Ip, W. and Wang, D. (1998). Genetic algorithm approach to earliness and tardiness production scheduling and planning problem. *International Journal of Production Economics*. 54(1), 65–76.

Liaw, C. (2000). A hybrid genetic algorithm for the open shop scheduling problem. *European Journal of Operational Research*. 124(1), 28–42.

Lin, F.-T. (2010). Simulating Fuzzy Numbers for Solving Fuzzy Equations with Constraints using Genetic Algorithms. *International Journal of Innovative Computing, Information and Control*. 6(1), 239–253.

Lin, F.-T. and Tsai, T.-R. (2009). A Two-stage Genetic Algorithm for Solving the Transportation Problem with Fuzzy Demands and Fuzzy Supplies. *International Journal of Innovative Computing, Information and Control*. 5(12(B)), 4775–4785.

Maeda, Y. and Li, Q. (2005). Parallel Genetic Algorithm with Adaptive Genetic Parameters Tuned by Fuzzy Reasoning. *International Journal of Innovative Computing, Information and Control*. 1(1), 95–107.

Man, K., Tang, K. and Kwong, S. (1996). Genetic Algorithms; concepts and applications. *IEEE Transactions on Industrial Electronics*. 43(5), 519–532.

Mandal, S. K., Pandey, M. K. and Tiwari, M. K. (2010). Incorporating dynamism in traditional machine loading problem: an AI-based optimisation approach. *International Journal of Production Research*. 48(12), 3535–3559.

Mesghouni, K., Hammadi, S. and Borne, P. (1996). Production Job-Shop Scheduling Using Genetic Algorithms. In *IEEE International Conference on Systems, Man and Cybernetics.*, vol. 2. 1519–1524.

Mgwatu, M. I., Opiyo, E. Z. and Victor, M. A. M. (2009). Integrated Decision Model for Interrelated Sub-Problems of Part Design or Selection, Machine Loading and Machining Optimization. *ASME 2009 International Design Engineering Technical Conference Computers and Information in Engineering Conference, Proceedings*, 3–12.

Michalewicz, Z. and Nazhiyath, G. (1995). Genocop III: a co-evolutionary algorithm for numerical optimization problems with nonlinear constraints. In *IEEE International Conference on Evolutionary Computation*, vol. 2. 647–651.

Mohamed, Z. M., Kumar, A. and Motwani, J. (1999). An improved part grouping model for minimizing makespan in FMS. *European Journal of Operational Research*. 116(1), 171–182.

Mukhopadhyay, A., Roy, A., Das, S. and Abraham, A. (2008). Population-variance and explorative power of Harmony Search: An analysis. In *Third International Conference on Digital Information Management, 2008. ICDIM 2008.* 775 –781.

Mukhopadhyay, S. K., Midha, S. and Krishna, V. M. (1992). A heuristic procedure for loading problems in flexible manufacturing systems. *International Journal of Production Research*. 30(9), 2213–2228.

Mukhopadhyay, S. K., Singh, M. K. and Srivastava, R. (1998). FMS machine loading: a simulated annealing approach. *International Journal of Production Research*. 36(6), 1529–1547.

Nagarjuna, N., Mahesh, O. and Rajagopal, K. (2006). A heuristic based on multi-stage programming approach for machine-loading problem in a flexible manufacturing system. *Robotics and Computer-Integrated Manufacturing*. 22(4), 342–352.

Nanvala, H. B. and Awari, G. K. (2011). Approaches for solving machine loading problem in FMS: A Review. *International Journal of Engineering and Technology*. 3(2), 64–73.

Nayak, G. K. and Acharya, D. (1998). Part type selection, machine loading and part type volume determination problems in FMS planning. *International Journal of Production Research*. 36(7), 1801–1824.

Nazzala, D., Mollaghasemib, M. and Anderson, D. (2006). A simulation-based evaluation of the cost of cycle time reduction in Agere Systems wafer fabrication facilitya case study. *International Journal of Production Economics*. 100(2), 300–313.

Okuhara, K., Shibata, J. and Ishii, H. (2007). Adaptive Worker's Arrangement and Workload Control for Project Management by Genetic Algorithm. *International Journal of Innovative Computing, Information and Control*. 3(1), 175–188.

Olhager, J., Rudberg, M. and Wikner, J. (2001). Long-term capacity management: Linking the perspectives from manufacturing strategy and sales and operations planning. *International Journal of Production Economics*. 69(2), 215–225.

Omran, M. G. and Mahdavi, M. (2008). Global-best harmony search. *Applied Mathematics and Computation*. 198(2), 643–656.

Ono, S., Hirotani, Y. and Nakayama, S. (2009). A Memetic Algorithm for Robust Optimal Solution Search - Hybridization of Multi-objective Genetic Algorithm and Quasi-Newton Method. *International Journal of Innovative Computing, Information and Control*. 5(12(B)), 5011–5019.

Osman, I. and Laporte, G. (1996). Metaheuristics: A bibliography. *Annals of Operations Research*. 63(5), 511–623.

Petrovic, S. and Fayad, C. (2005). A Genetic Algorithm for Job Shop Scheduling with Load Balancing. *In Zhang, S. and Jarvis, R. (Eds.). Advances in Artificial Intelligence, Lecture Notes in Artificial Intelligence, 3809. Springer.*, 339–348.

Pongcharoen, P., Hicks, C. and Braiden, P. M. (2004). The development of genetic algorithms for the finite capacity scheduling of complex products, with multiple levels of product structure. *European journal of Operational Research*. 152(1), 215–225.

Ponnambalam, S. and Low, S. K. (2008). Solving Machine Loading Problem in Flexible Manufacturing Systems Using Particle Swarm Optimization. *World Academy of Science, Engineering and Technology*. 39, 14–19.

Prakash, A., Khilwani, N., Tiwari, M. and Cohen, Y. (2008). Modified immune algorithm for job selection and operation allocation problem in flexible manufacturing systems. *Advances in Engineering Software*. 39(3), 219–232.

Prakash, A., M.K, T. and Shankar, R. (2004). Optimal job sequence determination and operation machine allocation in flexible manufacturing systems: an approach using adaptive hierarchical ant colony algorithm. *Journal of Intelligent Manufacturing*. 19(2), 161–173.

Reddy, K. R. B., Xie, N. and Subramaniam, V. (2004). Dynamic Scheduling of Flexible Manufacturing Systems. *Innovation in Manufacturing Systems and Technology*. 1(1), 1–9.

Reeves, C. R. (1993). *Modern heuristic techniques for combinatorial problems*. New York, NY, USA: John Wiley & Sons, Inc. ISBN 0-470-22079-1.

Sandhyarani, B. and Mahapatra, S. (2008). Modified particle swarm optimization for solving machine-loading problems in flexible manufacturing systems. *The International Journal of Advanced Manufacturing Technology*. 39(9), 931–942.

Sandhyarani, B. and Mahapatra, S. (2009). An improved metaheuristic approach for solving the machine loading problem in flexible manufacturing systems. *International Journal of Services and Operations Management*. 5(1), 76–93.

Saravanan, R. (2006). *Manufacturing Optimization through Intelligent Techniques*. New York: CRC Press.

Sarin, S. and Chen, C. (1987). The machine loading and tool allocation problem in a flexible manufacturing system. *International Journal of Production Research*. 25(7), 1081–1094.

Sarma, U. B. S., Kant, S., Rai, R. and Tiwari, M. (2002). Modelling the machine loading problem of FMSs and its solution using a tabu-search-based heuristic. *International Journal of Computer Integrated Manufacturing*. 15(4), 285–295.

Sawik, T. (1995). Dispatching scheduling of machines and vehicles in a flexible manufacturing system. In *Proceedings of 1995 INRIA/IEEE Symposium on Emerging Technologies and Factory Automation*. 3–13.

Shanker, K. and Srinivasulu, A. (1989). Some solution methodologies for loading problems in a flexible manufacturing system. *International Journal of Production Research*. 27(6), 1019–1034.

Shanker, K. and Tzen, Y.-J. J. (1985). A loading and dispatching problem in a random flexible manufacturing system. *International Journal of Production Research*. 23(3), 579–595.

Sheu, C. and Krajewski, L. (1994). A decision model for corrective maintenance management. *International Journal of Production Research*. 32(6), 1365–1382.

Srinivas, Tiwari, M. K. and Allada, V. (2004). Solving the machine-loading problem in a flexible manufacturing system using a combinatorial auction-based approach. *International Journal of Production Research*. 42(9), 1879–1893.

Srivastava, B. and Chen, W.-H. (1996). Heuristic solutions for loading in flexible manufacturing systems. *IEEE Transactions on Robotics and Automation*. 12(6), 858–868.

Stecke, K. E. (1983a). Formulation and solution of nonlinear integer production planning problem for flexible manufacturing systems. *Management Science*. 26, 273–288.

Stecke, K. E. (1983b). Formulation and Solution of Nonlinear Integer Production Planning Problems for Flexible Manufacturing Systems. *Management Science*. 29(3), 273–288.

Suryoatmojo, H., Elbaset, A. A., Syafaruddin and Hiyama, T. (2010). Genetic Algorithm Based Optimal Sizing of PV-Diesel-Battery System considering CO2 Emission and Reliability. *International Journal of Innovative Computing, Information and Control*. 6(10), 4631–4649.

Swaminathan, J. M. (2000). Tool capacity planning for semiconductor fabrication facilities under demand uncertainty. *European Journal of Operational Research*. 120(3), 545–558.

Swarnkar, R. and Tiwari, M. K. (2004). Modeling machine loading problem of FMSs and its solution methodology using a hybrid tabu search and simulated annealing-based heuristic approach. *Robotics and Computer-Integrated Manufacturing*. 20(3), 199–209.

Tan, T.-H., Huang, Y.-F. and Liu, F.-T. (2010). Multi-User Detection in DS-CDMA Systems using a Genetic Algorithm with Redundancy Saving Strategy. *International Journal of Innovative Computing, Information and Control*. 6(8), 3347–3364.

Tiwari, M., Kumar, S., Kumar, S., Prakash and Shankar, R. (2006). Solving Part-Type Selection and Operation Allocation Problems in an FMS: An Approach Using Constraints-Based Fast Simulated Annealing Algorithm. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*. 36(6), 1170–1184.

Tiwari, M., Saha, J. and Mukhopadhyay, S. (2007). Heuristic solution approaches for combined-job sequencing and machine loading problem in flexible manufacturing systems. *The International Journal of Advanced Manufacturing Technology*. 31(7), 716–730.

Tiwari, M. K., Hazarika, B., Vidyarthi, N. K., Jaggi, P. and Mukhopadhyay, S. K. (1997). A heuristic solution approach to the machine loading problem of an FMS and its Petri net model. *International Journal of Production Research*. 35(8), 2269–2284.

Tiwari, M. K., Saha, J. and Mukhopadhyay, S. K. (2008). Part-selection and machine-loading problems in a flexible manufacturing system environment: a heuristic approach based on reallocation paradigm. *International Journal of Computer Applications in Technology*. 32(2), 142–157.

Tiwari, M. K. and Vidyarthi, N. K. (2000). Solving machine loading problems in a flexible manufacturing system using a genetic algorithm based heuristic approach. *International Journal of Production Research*. 38(14), 3357–3384.

Tsai, C.-F. and Chao, K.-M. (2007). An Effective Chromosome Representation for Optimising Product Quality. In *11th International Conference on Computer Supported Cooperative Work in Design, 2007. CSCWD 2007*. 1032–1037.

Vidyarthi, N. and Tiwari, M. (2001). Machine loading problem of FMS: a fuzzy-based heuristic approach. *International Journal of Production Research*. 39(5), 953–979.

Viraj, T. and Ajai, J. (2008). Assessing the effectiveness of flexible process plans for loading and part type selection in FMS. *Advances in Production Engineering & Management*. 3(1), 27–44.

Vrajitoru, D. (2000). Large population or many generations for genetic algorithms? Implications in information retrieval. *Soft computing in information retrieval: techniques and applications*. 50, 199–222.

Wang, K. J., Lee, S. J., Yeh, C. F. and Huang, T. C. (2007). Operating an effective resource allocation for wire bonders in the semiconductor assembly industry. *Production Planning and Control: The Management of Operations*. 18(3), 226–238.

Wang, L., Pan, Q.-K. and Tasgetiren, M. F. (2011). A hybrid harmony search algorithm for the blocking permutation flow shop scheduling problem. *Computers & Industrial Engineering*. 61(1), 76–83.

Wardar, G. E. S. F. J. W., C. (2007). A framework for evaluating remote diagnostics investment decisions for semiconductor equipment suppliers. *European Journal of Operational Research*. 180(3), 1411–1426.

Yang, H. and Wu, Z. (2002). GA-based integrated approach to FMS Part type selection, machine loading problem. *International Journal of Production Research*. 40(16), 4093–4110.

Yang, X.-S. (2009). *Harmony Search as a Metaheuristic Algorithm, in: Music-Inspired Harmony Search Algorithm: Theory and Applications Studies in Computational*

Intelligence. vol. 191. Springer Berlin.

Yogeswaran, M., Ponnambalam, S. G. and Tiwari, M. K. (2009). An efficient hybrid evolutionary heuristic using genetic algorithm and simulated annealing algorithm to solve machine loading problem in FMS. *International Journal of Production Research*. 47(19), 5421–5448.

Zeballos, L. J., Quiroga, O. D. and Henning, G. P. (2010). A constraint programming model for the scheduling of flexible manufacturing systems with machine and tool limitations. *Journal Engineering Applications of Artificial Intelligence*. 23(2), 229–248.

Zhang, M. T., Fu, J. and Zhu, E. (2005). Dynamic capacity modeling with multiple re-entrant workflows in semiconductor assembly manufacturing. In *Proceedings of the 2005 IEEE International Conference on Automation Science and Engineering, Edmonton, Canada*. 160–165.