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MOHD FADZIL FAISAE AB RASHID

Integrated Multi-Objective Optimisation of Assembly Sequence Planning and Assembly Line Balancing using Particle Swarm Optimisation

Supervisor: Professor Ashutosh Tiwari
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ABSTRACT

In assembly optimisation, Assembly Sequence Planning (ASP) and Assembly Line Balancing (ALB) optimisations currently performed in serial, present an opportunity for integration, allowing benefits such as larger search space leading to better solution quality, reduced error rate in planning and fast time-to-market for a product. The literature survey highlights the research gaps, where the existing integrated ASP and ALB optimisation is limited to a Genetic Algorithm (GA) based approach, while Particle Swarm Optimisation (PSO) demonstrates better performance in individual ASP and ALB optimisation compared to GA. In addition, the existing works are limited to simple assembly line problems which run a homogeneous model on an assembly line. The aim of this research is to establish a methodology and algorithm for integrating ASP and ALB optimisation using Particle Swarm Optimisation. This research extends the problem type to integrated mixed-model ASP and ALB in order to generalise the problem. This research proposes Multi-Objective Discrete Particle Swarm Optimisation (MODPSO), to optimise integrated ASP and ALB. The MODPSO uses the Pareto-based approach to deal with the multi-objective problem and adopts a discrete procedure instead of standard mathematical operators to update its position and velocity. The MODPSO algorithm is tested with a wide range of problem difficulties for integrated single-model and mixed-model ASP and ALB problems. In order to supply sufficient test problems that cover a range of problem difficulties, a tuneable test problem generator is developed. Statistical tests on the algorithms' performance indicates that the proposed MODPSO algorithm presents significant improvement in terms of larger non-dominated solution numbers in Pareto optimal, compared to comparable algorithms including GA based algorithms in both single-model and mixed-model ASP and ALB problems. The performance of the MODPSO algorithm is finally validated using artificial problems from the literature and real-world problems from assembly products.

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LIST OF COMMONLY USED ABBREVIATIONS

ACO	Ant Colony Optimisation
ALB	Assembly Line Balancing
ASP	Assembly Sequence Planning
ct	Cycle time
ct_{max}	Maximum cycle time
D	Assembly direction
DPSO	Discrete Particle Swarm Optimisation
ER	Error ratio
FR	Frequency ratio
GA	Genetic Algorithm
GALBP	Generalised Assembly Line Balancing Problem
GD	Generational distance
HGA	Hybrid Genetic Algorithm
HSD	Honestly Significant Different
M	Assembly time
MMALB	Mixed-Model Assembly Line Balancing
MODPSO	Multi-Objective Discrete Particle Swarm Optimisation
MOGA	Multi-Objective Genetic Algorithm
MOPSO	Multi-Objective Particle Swarm Optimisation
n	Number of assembly task
NSGA-II	Elitist Non-Dominated Sorting Genetic Algorithm
nws	Number of workstation
OS	Order Strength
PSO	Particle Swarm Optimisation
pt	Processing time
SA	Simulated Annealing
SALBP	Simple Assembly Line Balancing Problem
$Spread_{max}$	Maximum spread
T	Assembly tool
TPG	Test problem generator
TV	Time variability ratio
v	Workload variation
ws	Workstation
$\tilde{\eta}$	Number of non-dominated solution in Pareto optimal

CHAPTER 1

INTRODUCTION

The current global market continuously puts pressure on manufacturers to compete with competitors from all over the world. In order to ensure that their products remain competitive, manufacturers need to speed up the time-to-market and at the same time minimise manufacturing cost (Padrón et al., 2009). In addition, manufacturers also need to utilise all the resources at an optimum level (Amin and Karim, 2013).

Assembly is considered as one of the important processes in manufacturing. It consumes up to 50% of total production time and accounts for more than 20% of total manufacturing cost (Pan, 2005). Assembly is a sub-system of the manufacturing system and involves bringing and joining parts and/or sub-assemblies together (Marian, 2003). Regarding the challenge of remaining competitive in the global market, assembly optimisation activities are necessary to optimise the assembly resources. The concurrent assembly optimisation reduces the time-to-market for a product. This research details the integrated multi-objective optimisation of two assembly optimisation activities (i.e. Assembly Sequence Planning and Assembly Line Balancing) using Particle Swarm Optimisation algorithm.

1.1 Introduction to Assembly Optimisation

Assembly optimisation involves bringing and joining parts and/or sub-assemblies to make the process as efficient as possible (Rashid et al., 2012a). There exists a substantial amount of recent work on assembly optimisation. This work employs a variety of optimisation approaches. The research in assembly optimisation is classified according to the three stages of product development and production, as shown in Figure 1.1 (Marian, 2003).

The main assembly issue in Product Conception and Design stage is to apply Design for Assembly (DFA) methodology to reduce the number of parts and complexity in assembly. Besides reducing cost, DFA also brings additional benefits in terms of increased quality, reliability and shorter manufacturing time. The approach shortens the product cycle and ensures a smoother transition from prototype to production (Corallo et al., 2010). In general, any optimisation activities which involve the design of products are categorised as Product Conception and Design family.

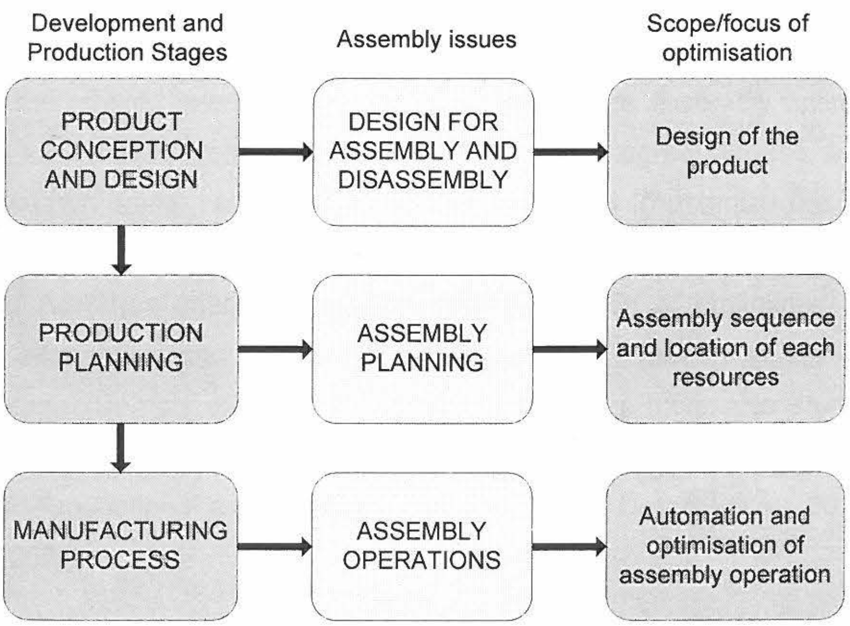

Figure 1.1: Assembly related issues in different product development stages (Marian, 2003)

Assembly optimisation in the Production Planning stage deals with the determination of optimum assembly sequence and the determination of optimum location of each resource. The best known optimisation activity in this stage is Assembly Sequence Planning (ASP), which has been studied since the 1980s. Solving the ASP problem is crucial because it determines many assembly aspects, including tool changes, fixture design and assembly freedom. Assembly sequence also influences overall productivity because it determines how efficiently and accurately the product is assembled.

During the Manufacturing Process stage, assembly optimisation focuses on two major activities. The first activity is determining the optimum automation level in assembly. The purpose of this activity is to apply the appropriate automation level in assembly in order to balance the investment in automation and the output. The second activity in this stage is assigning the assembly tasks into workstations, so that the workstations have equal or almost equal load (Marian, 2003). This activity is usually known as Assembly Line Balancing (ALB). In this stage, research in assembly optimisation focuses more on ALB problems rather than optimisation of automation levels. This can be observed through the number of publications as presented in Section 2.7.

Besides the straight-forward approach of optimising the assembly optimisation activities sequentially, researchers have considered integrating these activities. Many research works have been conducted designed to optimise the product design and ASP concurrently. For example, an integrated framework combining DFA and ASP has enabled the concurrent generation of preliminary design solution information and the assembly sequence information at the product design stage (Demoly et al., 2011). Many other works have also studied the integration of assembly optimisation within the Product Conception and Design stage and Production Planning stage (Pan et al., 2006; Demoly et al., 2012; Zha and Du, 2001).

However, research works studying the integration of assembly optimisation between the Production Planning stage and Manufacturing Process stage remain limited, as presented in Section 2.7.1. This research therefore focuses on integrated optimisation of ASP and ALB activities which are classified in the Production Planning and Manufacturing Process stages respectively. In general, both ASP and ALB share important similarities, especially when focusing on increasing production with maximum resource utilisation. Both activities also share similar concepts such as assembly time and precedence constraint. ASP and ALB are both categorised as NP-hard problems where the solution space is increased excessively when the number of tasks are increased (Goldwasser and Motwani, 1997; Wee and Magazine, 1982). It makes the selection of appropriate optimisation algorithm crucial.

1.2 ASP and ALB

Assembly Sequence Planning (ASP) refers to a task for which planners, on the basis of their particular heuristics in assembling all the components of a product, arrange a specific assembly sequence according to the product design description (Tseng and Tang, 2006). Usually, the ASP research objective is to optimise the assembly sequence in terms of assembly time, assembly direction, tool changes and assembly stability (Hui et al., 2009; Gao et al., 2010; Wang and Liu, 2010). Figure 1.2 shows a common assembly representation using a Directed Acyclic Graph (DAG).

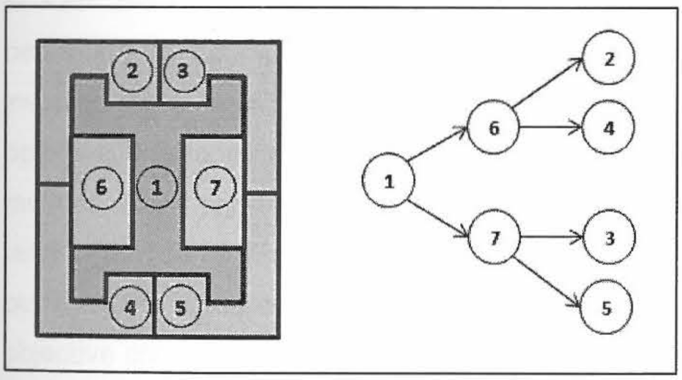

Figure 1.2: Assembly representation using Directed Acyclic Graph

From this graph, numerous feasible assembly sequences can be generated such as {1 6 7 2 4 3 5}, {1 7 3 6 5 4 2} or {1 6 2 7 4 3 5}. Based on this example it can be seen that ASP is about determining the optimum sequence to assemble a product from all feasible assembly sequences.

An assembly line task involves the establishment of stations and products to be assembled (Tseng and Tang, 2006). According to researchers, Assembly Line Balancing (ALB) means the decision problem of optimally partitioning the assembly work among the stations with respect to particular objectives (Becker and Scholl, 2006).

For example in Figure 1.2, let the optimum assembly sequence from ASP be {1 6 2 7 4 3 5} and this assembly job will be assigned to three workstations. There are many possible assembly job assignment combinations, such as {(1 6), (2 7 4), (3 5)} or {(1 6 2), (7 4), (3 5)} or {(1 6 2 7), (4 3), (5)}. ALB determines the best assembly job combinations which feature equal or almost equal workload between workstations. In ALB, some of the optimisation objectives are to minimise the number of workstations, minimise the workload variance, minimise the idle time and maximise the line efficiency (Suwannarongsri and Puangdownreong, 2008).

1.3 Multi-objective PSO

In ASP and ALB optimisation literature, several objectives have been used to determine the optimum solution for the problem. When an optimisation problem involves more than one objective, this problem is known as a multi-objective optimisation problem (Deb, 2001). Traditionally, the simplest way to optimise a multi-objective problem is to bundle all the objectives into a single evaluation term using some kind of weighted assignment.This approach requires high-quality prior knowledge and experience regarding the importance of one objective compared to others.

Instead of focusing on one single optimum point, the researchers might be interested in all the best options available. There are many ways of defining a set of best options, but there is one predominant way, i.e. the Pareto optimal solutions (Luke, 2010).In order to establish the set of "best option" solutions for multi-objective optimisation problem, the algorithm selection is critical.

The growth of heuristic algorithms has attracted many researchers to explore and apply these algorithms for multi-objective optimisation. One of the heuristic algorithms that have attracted researchers is Particle Swarm Optimisation (PSO). PSO is a population-based stochastic optimisation technique, developed by Kennedy and Eberhart in 1995. It was inspired by the social behaviour of bird-flocking or fish-schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA).

The system is initialised with a population of random solutions and searches for optimum solutions by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles (Kennedy and Eberhart, 1995). This is done by updating the particle position and velocity towards the current optimum solution.

The major advantage of PSO over the basic Evolutionary Algorithms (EAs), as highlighted by many researchers, is the simplicity of the algorithm (Shinzawa et al., 2007; Lu et al., 2010; Premalatha and Natarajan, 2009). The GA for example, requires 3 operations to converge, i.e. selection, crossover and mutation, while the PSO relies on velocity calculation to update the particle position (Rahmat-Samii, 2003). It reduces the computational time, as well as the memory usage.

Another PSO advantage is that it maintains the best solution history for an individual particle and also among the particles. Each particle remembers its previous velocity and the previous best position and uses them in its movement (Pasupuleti and Battiti, 2006). These features enable the PSO to maintain a balance between exploration and exploitation in the swarm and achieve fast convergence (Jeong et al., 2009).

In addition, the PSO algorithm is converged on the basis of "constructive cooperation" rather than "survival of the fittest" as in EAs (Shayeghi et al., 2010; Zeng and Jiang, 2010). This character ensures that all the particles in the initial population reach the final iteration (Sinha and Purkayastha, 2004). Therefore, by using PSO, better final solution variety can be achieved at the end of the optimisation process.

In addition to the advantages of PSO as discussed above, the PSO algorithm also proved to perform better than GA in ASP and ALB optimisations. In the majority of the ASP and ALB optimisations which compared the performance of GA and PSO, it was concluded that PSO has better overall performance than GA. The detail of the performance comparison between GA and PSO for ASP and ALB optimisation is presented in Section 2.4.5. Based on this fact, PSO is more promising to be used for ASP and ALB optimisation.

1.4 Research Problem and Motivation

Research works in individual ASP and ALB optimisation have seen rapid growth with hundreds of publications since the 1960s. However, only a limited amount of the research optimises both activities together. From the literature review in Section 2.7.1, only Genetic Algorithms have been used to optimise the integrated ASP and ALB, despite the fact that the PSO algorithm offers a good prospect based on its advantages and track record in individual ASP and ALB optimisation.

The assembly sequence plays an important role in the assembly plan. Many aspects of the assembly process, such as assembly line layout, assembly resource utilisation, etc., are designed and arranged by referring to the assembly sequence. In addition, good assembly sequences tend to improve the assembly efficiency and reduce the assembly cost (Wang and Liu, 2010). On the other hand, ALB also plays a vital function in assembly. The installation of an assembly line is a long-term decision and usually requires large capital investments. Therefore, it is important that such a system is designed and balanced so that it works as efficiently as possible (Becker and Scholl, 2006).

In current practice, the ASP and ALB optimisation are performed sequentially. Normally the ASP is optimised before the ALB because it belongs to different product development stages. This practice causes a few problems since the ASP and ALB are interlinked. One such problem is that the sequential optimisation causes sub-optimal assembly operations, which means that the final solutions only fully satisfy one party (normally ASP). This problem occurs because of different search space sizes between ASP and ALB, as shown in Figure 1.3. In comparison with ASP search space, the search space of the ALB (a subsequent activity) is reduced because it is formed by the output of ASP optimisation.

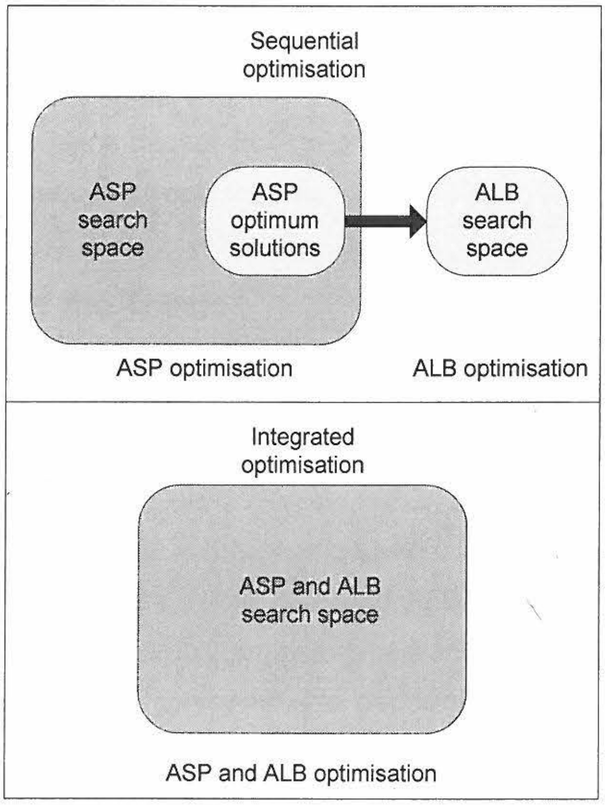

Figure 1.3: Search space different between sequential and integrated optimisation

Another problem which is caused by reduction of search space from ASP to ALB is the loss of possible optimum solutions. Since the solution space of ALB is filtered according to ASP objectives, there exists the possibility of losing the optimum solutions which fulfil the criteria for both activities. In this case, a better solution for ASP and ALB might be one of the solutions filtered away during ASP optimisation. This can be avoided by performing the integrated optimisation for ASP and ALB.

The integrated ASP and ALB problem is more challenging compared to individual ASP or ALB one, due to the complexity of the problem. The ASP and ALB problems individually are categorised as NP-hard combinatorial problems, where the solution spaces are excessively increased when the number of tasks increases (Goldwasser and Motwani, 1997; Wee and Magazine, 1982). When the optimisation of both activities is performed together, the problem difficulties are increased and require proper optimisation set-up including the algorithm selection. However, the integrated ASP and ALB is expected to create a better quality of assembly plans because of the provision of a larger search space for ALB compared to sequential optimisation.

1.5 Structure of the Thesis

This thesis is structured into nine chapters, as presented in Figure 1.4.

Chapter 1 gives an introduction to the research. It also presents the research problem and motivation.

Chapter 2 reviews literature in the ASP and ALB optimisation, including the individual optimisation, assembly problem types and optimisation algorithm. In this chapter, the literature survey is also performed to identify the research trends and research gaps in the area.

Chapter 3 outlines the research aim, objectives and scope. In addition, this chapter also presents the research methodology to present the overview of how this research is conducted.

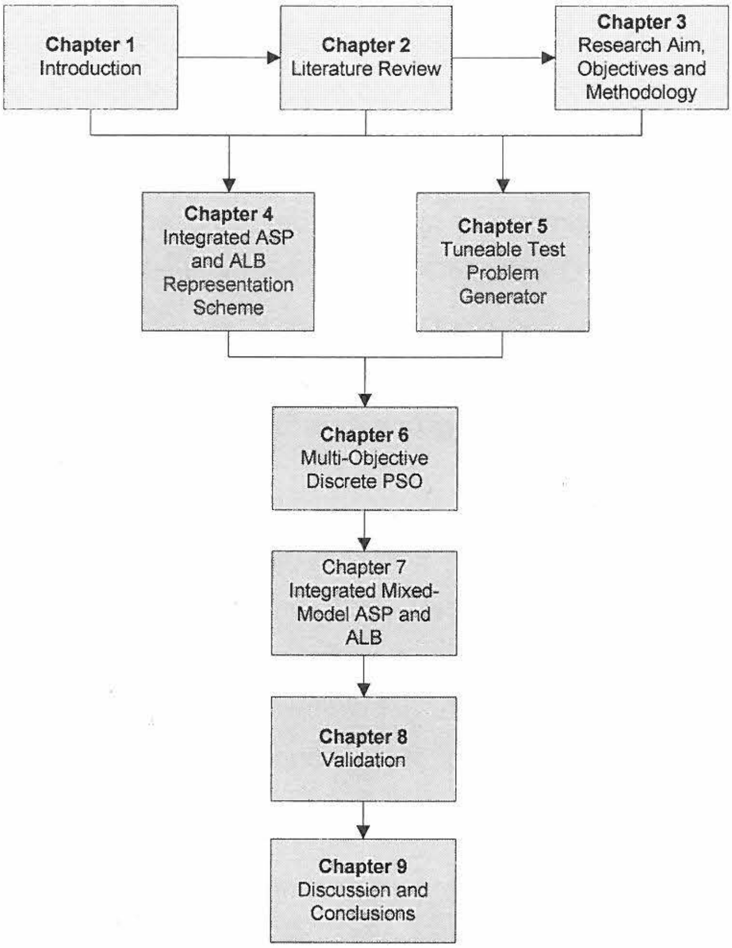

Figure 1.4: Thesis structure

Chapters 4 to 8 describe the main research activities and explain how research objectives are met. From Chapters 5 to 8, each chapter has its own numerical experiment and results to ensure validity, which form the basis for the following chapter.

Chapter 4 presents the representation scheme used to represent the integrated ASP and ALB problem. The proposed integrated representation will be the basis for optimisation in this research. In this chapter, an example based on assembly product is presented to show how the representation is established from a real product.

Chapter 5 proposes a tuneable test problem generator for integrated ASP and ALB with the purpose of generating sufficient test problems to cover a range of problem difficulties. This is important to overcome the limitation of test problems and also to ensure that the proposed algorithm is tested with a wide range of problem difficulties.

Chapter 6 presents the proposed algorithm to optimise integrated ASP and ALB problems. The algorithm called Multi-Objective Discrete Particle Swarm Optimisation (MODPSO) is specifically developed to deal with discrete problems as in ASP and ALB. The performance of the proposed MODPSO algorithm is then tested with the problems generated from the tuneable test problem generator.

Chapter 7 extends the application of the proposed MODPSO to optimise integrated mixed-model ASP and ALB. This assembly line is important to enhance the product variety using minimum investment cost. In this chapter, the formulation of integrated mixed-model ASP and ALB is explained. Comprehensive testing is also conducted to identify the ability of MODPSO to optimise this problem.

Chapter 8 validates the performance of the proposed MODPSO algorithm using problems from the literature. The optimisation results using the proposed MODPSO are compared with results presented in the literature. The MODPSO's performance is validated using real-world problems. Following that, a numerical comparison between integrated and sequential optimisation approaches is presented.

Chapter 9 discusses and concludes the contribution of the research findings to the knowledge and the limitations of this research. Finally, this chapter discusses the future direction of the research.

1.6 Chapter Summary

In summary, this chapter addresses the following points:

- The research in assembly optimisation, including Assembly Sequence Planning and Assembly Line Balancing has been introduced.
- Multi-objective optimisation and Particle Swarm Optimisation has been introduced.
- The research problem, motivation and challenge of the integrated ASP and ALB optimisation have been presented.
- The structure of this thesis has been explained.