AN ENHANCED ARTIFICIAL IMMUNE SYSTEM APPROACH FOR ASSEMBLY LINE BALANCING PROBLEM THROUGH SHIFTING BOTTLENECK IDENTIFICATION

MOHD NOR AKMAL KHALID

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by

MOHD NOR AKMAL KHALID

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

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PENDEKATAN SISTEM IMUN BUATAN YANG DIPERTINGKATKAN UNTUK MASALAH MENGIMBANGI BARISAN PEMASANGAN MELALUI PENGENALPASTIAN KESESAKAN PERALIHAN

ABSTRAK

Industri perkilangan telah berkembang pesat dalam beberapa tahun kebelakangan ini, disebabkan oleh ekonomi berdaya saing global, tuntutan pasaran yang berkualiti tinggi, dan produk yang disesuaikan dengan kos yang paling rendah. Ini boleh dicapai dengan memisahkan beban kerja di antara sumber yang ada untuk mendapatkan jumlah beban kerja yang sama dalam sistem barisan pemasangan, yang mentakrifkan masalah barisan pemasangan (ALB). Masalah ALB yang paling menonjol adalah masalah barisan pemasangan mudah (SALB) yang yang telah digunakan selama beberapa dekad untuk menyediakan asas untuk menguji pendekatan yang berbeza. Walaupun pelbagai teknik komputasi telah menangani masalah ALB, yang boleh dikategorikan sebagai pendekatan tepat, heuristik, dan meta-heuristik, sedikit kerja telah dilakukan terhadap masalah SALB-E kerana kesukaran mendapatkan penyelesaian yang optimum. Di samping itu, kesesakan masih boleh berlaku semasa operasi pemasangan yang menjejaskan kualiti pengeluaran dan mendorong kos yang tidak perlu. Mengenal pasti dan mengoptimumkan mesin dengan kemungkinan kesesakan operasi seterusnya jarang ditangani dalam barisan pemasangan terutamanya apabila ia beralih dari satu mesin ke mesin yang lain (dipanggil kesesakan peralihan). Kajian ini mencadangkan pendekatan komputasi yang berkesan untuk menangani masalah SALB-E melalui pengenalpastian kesesakan peralihan. Pendekatan berasaskan biologi telah sering digunakan untuk mengendalikan masalah pengoptimuman kompleks dan gabungan melalui cara yang mudah namun berkesan.

Oleh itu, kaedah komputasi, dikenali sebagai pendekatan sistem imun buatan (AIS), telah dicadangkan. Tiga variasi pendekatan AIS dicadangkan, iaitu AIS yang berjangkit (CAST), AIS berjangkit dengan simulasi kesesakan berasingan (CASTOR) dan rangkaian imun berjangkit dengan matrik penunjuk kesesakan (COMET). Ketiga-tiga pendekatan ini telah diuji pada 24 set data SALB-E dunia sebenar dengan 242 contoh. Keputusan eksperimen menunjukkan bahawa pendekatan CAST, CASTOR, dan COMET yang dicadangkan telah berjaya menyelesaikan sehingga 34.30%, 66.12%, dan 100% contoh set data masing-masing. Selain itu, kajian komparatif terhadap pendekatan dari kesusasteraan dijalankan di mana hasil statistik yang ketara sehingga 99.5% selang keyakinan ($p < 0.00001$) telah disimpulkan. Kajian ini menyimpulkan bahawa perwakilan masalah, pengurangan kerumitan, dan penggunaan kesesakan peralihan membantu untuk membimbing penambahbaikan penyelesaian. Dengan menangani kesesakan peralihan yang dikenal pasti, kerumitan pengiraan dikurangkan dengan menggunakan maklumat khusus masalah apabila pendekatan yang dicadangkan menghadapi masalah SALB-E yang sukar.

AN ENHANCED ARTIFICIAL IMMUNE SYSTEM APPROACH FOR ASSEMBLY LINE BALANCING PROBLEM THROUGH SHIFTING BOTTLENECK IDENTIFICATION

ABSTRACT

The manufacturing industry has evolved rapidly in the past few years, due to the global competitive economy, high-quality market demands, and customized products with the lowest possible costs. This is achieved by partitioning the workloads among the available resource to obtain an equal amount of workloads in the assembly line system, which defines the assembly line balancing (ALB) problem. The most prominent ALB problem is the simple assembly line balancing (SALB) problem which has been utilized for decades to provide a basis for testing different approaches. Despite varieties of computational techniques have addressed the ALB problem, which can be categorized as exact, heuristic, and meta-heuristic approaches, little work had been done on SALB-E problem due to its difficulty of obtaining the optimal solutions. Additionally, bottlenecks can still occur during the assembly operations that affect the production quality and induce unnecessary costs. Identifying and optimizing machines with the likelihood of the next operation bottleneck had been rarely addressed in the assembly line especially when it shifts from one machine to another (called shifting bottleneck). This study propose an effective computational approach to address the SALB-E problem through the shifting bottleneck identification. A bio-inspired approach had been frequently adopted for handling complex and combinatorial optimization problem through a simple yet effective manner. As such, a computational method, known as artificial immune system (AIS) approach, had been proposed. Three variants of the AIS approaches were proposed, namely the contagious AIS (CAST), contagious AIS with discrete bottleneck simulator (CASTOR) and contagious immune network with bottleneck indicator matrix (COMET). These three approaches were tested on 24 real-world SALB-E data sets with 242 instances. The experimental results showed that the proposed CAST, CASTOR, and COMET approaches have solved up to 34.30%, 66.12%, and 100% instances of the data sets, respectively. Additionally, comparative study against approaches from the literature was conducted where statistically significant results up to 99.5% confidence interval ($p < 0.00001$) were deduced. This study concludes that problem representation, complexity reduction, and utilizing the shifting bottleneck helps to guide solution improvement. By addressing the identified shifting bottleneck, the computational complexity is mitigated by utilizing the problem-specific information when the proposed approaches are faced with difficult SALB-E problems.

CHAPTER 1

INTRODUCTION

1.1 Problem Background

The manufacturing industry has gone through considerable changes in the past few years, relatively from the local economy to a highly competitive global economy. These circumstances invoke demand for high quality customizable products at the lowest possible cost with the shortest life cycles (Leitao, 2009). In manufacturing, one of the core production activities is the product assembly; it encompasses both the production time and cost (Li *et al.*, 2017). Consequently, the product assembly is accountable between 20% to 50% for both cost and lead-time of a product; it can also reach up to 90% in newly emerged areas of micro-technologies and electronics (Marian *et al.*, 2006). As such, balancing the resources (machines or workers) in terms of both utilization and performance during product assembly is crucial.

Production system variations from internal and/or external sources often disrupt the performance of the production line. This could potentially cause workload imbalances (machine overloading and/or idling) (Zhengcai *et al.*, 2012). This situation causes the expected production goal (i.e., expected cycle time) to be affected. Usually, these issues are handled by either forecasting, buffering, or smoothing. Forecasting causes inaccuracy in the anticipated input and internal processes of the production while lot buffering in production would impose significant costs (Hamzeh *et al.*, 2012). Meanwhile, smoothing the production, which involves balancing the workload among the resources (machines) or assembly line balancing problem, is the most adopted method for handling workload imbalances among the resources.

Over the past half-century, assembly line balancing (ALB) problems have been the subject of a great deal of research due to their practical relevance and the difficulty in finding optimal solutions (Kara *et al.*, 2010; Chiang *et al.*, 2012; Kucukkoc *et al.*, 2015). The ALB problem considers the assignment of processes with different durations to a sets of machines with specific machinery and pre-configured settings (Bukchin and Rabinowitch, 2006), in such a manner that all machines have an approximately equal amount of work (Avikal *et al.*, 2013). Additional constraints may also be considered depending on the shop floor configuration, assumptions used, and its performance; thus, it can be associated with a high running cost and utilization rate (Boysen *et al.*, 2007; Sivasankaran and Shahabudeen, 2014; Ogan and Azizoglu, 2015). The importance of the current subject in production research can be seen by the vast number of studies conducted to solve the ALB problem in a wide-range of applications, including the automotive industry, consumer electronics, and household items (Battaïa and Dolgui, 2013; Morrison *et al.*, 2014; Hudson *et al.*, 2015).

Balancing the assembly line helps to improve the productivity and efficiency of the production line, which elicits a steady production rate and minimal works-in-process (WIP) (Hudson *et al.*, 2015); thus, meeting organizational requirements and satisfying certain measures of performance (Kucukkoc *et al.*, 2015). However, in certain situations, allocation of limited machines efficiently, rather than evenly, would enable finer production line optimization and control. A production line's performance is usually indicated by their production rate (often referred to as throughput). Occasionally, one or more machines can potentially constrain the throughput of the production system (Subramaniyan *et al.*, 2016b). These machines are referred to as “bottleneck” machines (Zhang and Wu, 2012).

The bottleneck machine is one of the main impediments that hurt productivity and system performance in the strongest manner (Li *et al.*, 2007; Betterton and Silver, 2012; Wedel *et al.*, 2016). In addition, bottleneck machines negatively impact a system by impeding manufacturing resources, system throughput, and possibly the total cost of production (Li *et al.*, 2007; Li and Ni, 2009; Betterton and Silver, 2012). A bottleneck may lead to either of the following situations: (1) An upstream machine has finished processing items, but cannot deliver them to a downstream machine because that machine is still busy, or (2) a downstream machine is idle and waiting for items to be delivered from an upstream machine, which is still processing. These bottleneck machines lead to two major problems in a production process (Glock and Jaber, 2013). Firstly, the company may lose on both sales and customer reputation if the capacity of the production system is not sufficient to fulfill customers’ demands. Secondly, additional costs can be incurred if excess work-in-progress (WIP) items accumulate in front of bottleneck machines.

Bottlenecks can be classified as either primary or secondary based on the level of impact on the system (Lemessi *et al.*, 2012). In addition, bottlenecks can also be differentiated by the time of their occurrences (Lima *et al.*, 2008; Lemessi *et al.*, 2012). A bottleneck that normally occurs at the time of the current operation of an assembly line is known as a *static* bottleneck, while a bottleneck that occurs in the next and subsequent operations is called a *dynamic* bottleneck. The static bottleneck occurrence can be easily determined by observing a direct machine parameter (such as the total processing time). However, more than a direct method is required to determine the occurrence of a dynamic bottleneck since it may also change from one machine to another; commonly known as the “shifting” bottleneck. Therefore, identifying the bottleneck machines that occur dynamically in the assembly line is very important, especially when those machines are limited (Li *et al.*, 2011; Subramaniyan *et al.*, 2016b).

Throughout this thesis, the term assembly line balancing and shifting bottleneck will be used extensively to describe the balancing of the workload and the next operation bottleneck or dynamic bottleneck, respectively.

1.2 Challenges Of The Assembly Line Balancing Problem Through Bottleneck Identification

The ALB problem involves the assembly work tasks which are grouped and distributed among the machines; satisfying both precedence and cycle time constraints, and optimizing some objective(s) (Al-Hawari *et al.*, 2015). The most prominent ALB problem is the simple assembly line balancing (SALB) problem which has been utilized for decades to provide a basis for testing different approaches.

One of the crucial parts of designing a new assembly line or optimizing an existing one is determining the objective measures of the SALB problem. Since an assembly line represents both a long-term and significant investment, maximizing the assembly line objective measure is crucial (Becker and Scholl, 2006; Venkatesh and Dabade, 2008). Four primary objective measures of the SALB problem are the minimization of machine number (Type-1), minimization of cycle time (Type-2), maximization of assembly line efficiency (Type-E), and determining the available feasible solution for a given number of stations and cycle time (Type-F). However, the Type-E objective is scarcely adopted and more difficult to deal with due to its non-linear form (increase in machine number decreases the required cycle time, and vice versa) (Boysen *et al.*, 2007; Battaïa and Dolgui, 2013; Sivasankaran and Shahabudeen, 2014). Additionally, the Type-E objective cannot be directly solved since neither the machine number and cycle time of an SALB solution is fixed.

From another perspective, variation and inconsistency due to imbalances and bottlenecks may affect the performance of the production system, which ultimately affect throughput and efficiency (Zhengcai *et al.*, 2012). The bottleneck is typically identified through the manipulation of machine parameters, enabling the introduction of different types of bottleneck identification methods (Gu *et al.*, 2015; Guner *et al.*, 2016). Identifying bottlenecks that are relevant to the immediate performance of the assembly line would be beneficial to the present goal of the production system, but may not be relevant over time as the bottlenecks may shift from one machine to another (a concept identified as shifting bottlenecks) (Roser *et al.*, 2002; Lima *et al.*, 2008). Most bottleneck methodologies focus on bottleneck identification which detects the constraining machine(s) in the current operation, but these poorly perform when handling shifting bottleneck (Lima *et al.*, 2008; Lemessi *et al.*, 2012).

In essence, the primary issue of concern for the ALB problem is how to determine the optimum productive portion of the production system which is relatively computed through the simultaneous improvement of the machine number and its capacity; thus, relating it to the computational methods of improving the assembly line efficiency (Battaïa and Dolgui, 2013). Meanwhile, the primary issue in bottleneck identification involves determining the improvement method when the primary bottleneck is identified (Ng *et al.*, 2014). The main problem concerning this study was the scarcity of research addressing these two issues, especially when expanding the ALB problem to jointly solve the shifting bottleneck identification.

Figure 1.1 depicts the joint problems of the SALB-E and the shifting bottleneck identification in this study. The diagram depicts an example tracking of a bicycle product being assembled in the manufacturing where the problem is being generally addressed. The (A) procedure involves translating the real world problem into a precedence graph structure in order to be represented as a feasible solution. Then, (B) involves evaluating the presented solutions based on the objective measure of SALB-E while (C) involves identifying the bottlenecks by simulating two product horizon. Finally, (D) re-examines and re-evaluate for solution improvement based on the bottleneck information.

1.3 Problem Statement

The SALB problems are known to be NP-hard problem where J tasks with R ordering constraints would produce $J!/2^R$ of possible task sequences (Mozdgir *et al.*, 2013). Even for a small SALB problem containing 5, 7 and 10 tasks each with 0.01 ordering constraints (meaning the ordering of tasks are least constrained; or formally known as order strength (Scholl, 1999)), the number of possible task arrangements become about 119, 5005 and 3,603,734, respectively. With such a vast search space, it

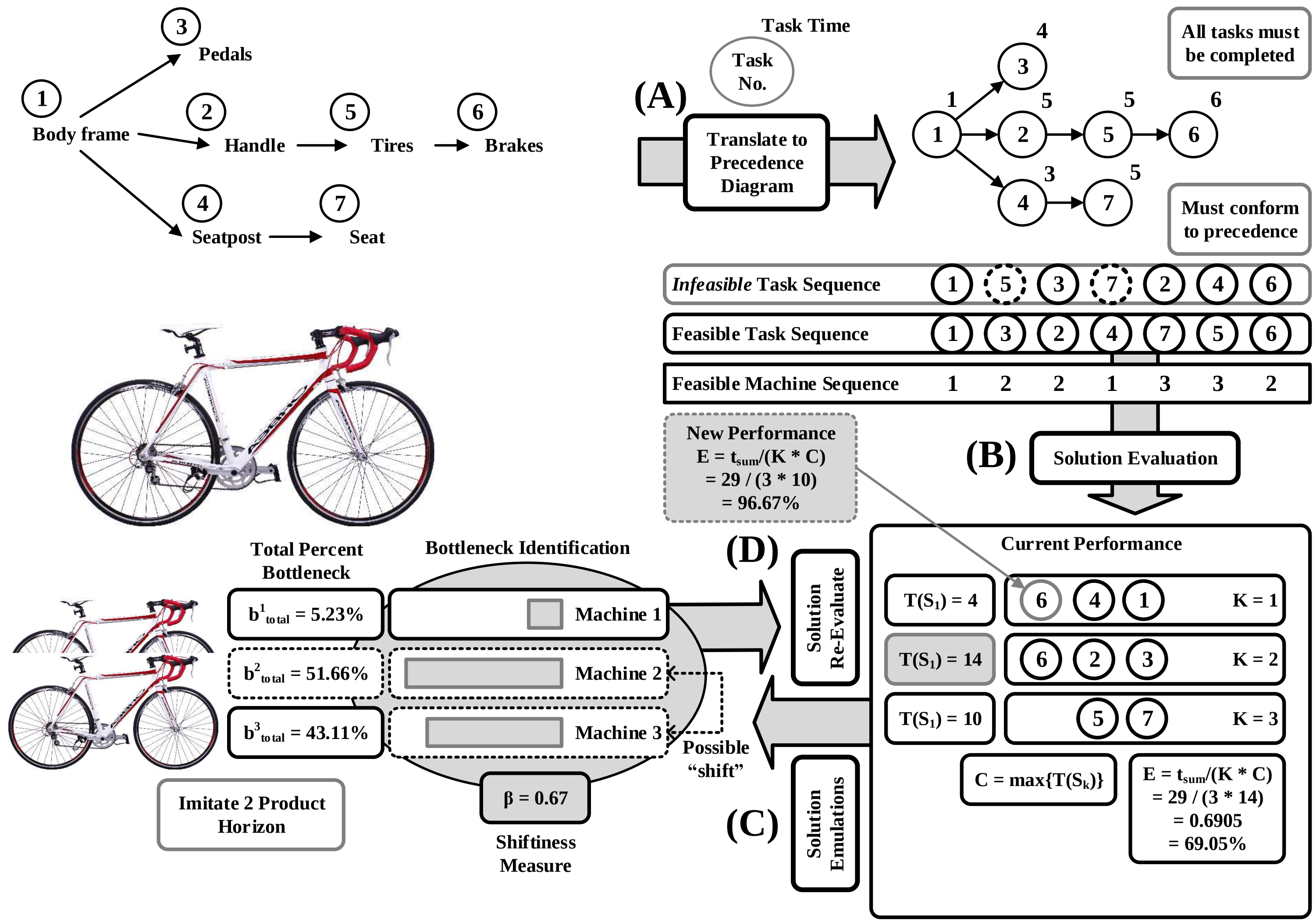

Figure 1.1: A demonstration of the assembly line balancing and the bottleneck identification scenario on the assembly line of the manufacturing system

is nearly impossible to obtain an optimal solution using exact approaches. These demonstrates the SALB problem requires more than conventional computational method in order to address them within reasonable computational time (Talbi, 2009).

The Type-E SALB problem also increases the complexity of the problem further. A general combinatorial optimization problem mainly consists of a finite ground set $U = \{1, 2, , n\}$, a subset of feasible solutions $F \subseteq U$ and a cost function f computing the cost of feasible solutions (Ji *et al.*, 2017). The goal of combinatorial optimization is to find the optimal solution in all feasible solutions which has the minimum cost. By considering combinations (canonical to the U) of different number of machines $K \in \{K_{\text{min}}, K_{\text{max}}\}$ and all possible number of cycle times $C \in \{C_{\text{min}}, C_{\text{max}}\}$ that induces the highest efficiency measures E (canonical to the f) of an assembly line, the possible solutions would be $K \times C$ where the SALB-E problem becomes a complex NP-hard combinatorial optimization problems (Scholl and Becker, 2006; Talbi, 2009; Juan *et al.*, 2015).

By considering the SALB-E problem alone, finding the best (or near optimal) solution of the problem requires exponential time complexity which can grows rapidly even for 10 tasks with 0.01 order strength with only two combinations of K and C ($\approx$14,414,936 of possible solutions). In addition, representing the problem itself is challenging because evaluation of these possible solutions in a practical amount of time may not be a feasible option (Hossain, 2016). On this basis alone, reducing the “scope” of the search for the best (or near optimal) solution out of all possible solutions is achieved by incorporating additional criteria of evaluation. In order to address the difficulty of the SALB-E problem, two research directions are necessary. On one hand, improvement on the optimization approach itself is important since an efficient search mechanism would increase the likelihood of finding optimal solutions. On the other hand, the utilization of problem-specific information will enhance the capabilities of those optimization approaches. In other words, if the utilization of the problem-specific information can be incorporated into the searching process of some optimization approach, the final solution quality is expected to be improved (near-optimal).

This is achievable by incorporating a problem-specific information known as the bottleneck identification which can potentially reduces the size of possible solutions. One interesting study conducted by Pastor *et al.* (2012) involves utilizing bottleneck criteria (called machine "criticality") to identify optimal solution, called lexicographic bottleneck assembly line balancing (LB-ALB) problem. Although the modelled ALB problem by Pastor *et al.* (2012) provides good grounds for bottleneck identification, their work lacks two items. Firstly, some machine may perform inconsistently over time (caused by learning (Glock and Jaber, 2013) or downtime (Roser *et al.*, 2002)), making some processing stages have unequal production rate; thus, causing bottleneck to "shift" over time (Lima *et al.*, 2008; Lemessi *et al.*, 2012). Secondly, most bottleneck identification methods have identified bottlenecks without emphasizing the action needed to improve it afterward (Ng *et al.*, 2014). Correspondingly, incorporating this information would also add another layer of complexity to an already complex SALB-E problem in terms of finding the optimal solution. Therefore, trade-offs between an efficient optimization approach and a high-quality solution are to be expected.

To this end, the main research question of this study is as follows:

"How to minimize the complexity of SALB-E problem while maximizing its objective measure using the shifting bottleneck identification as the problem-specific information without losses in solution's quality?"

1.4 Goal and Objectives of The Study

To recapitulate, Figure 1.2(a) represents the primary issues that determine the optimum assembly line balancing and determine the improvement method for the primary bottleneck identification. These issues lead to (b) the joint resolution of the problem which addresses the identified bottleneck improvement effectively, and presents an effective and efficient balancing method, with respect to the dependency between the aforementioned problems. Thus, these problems lead to (c) the goal of this study.

The goal of this study is to determine an effective computational method that jointly addresses the SALB-E problem and the bottleneck identification problem. This includes the development of an appropriate encoding solution as well as an improvisation scheme that could represent and optimize the SALB-E problem through the shifting bottleneck identification. In addition, the computational method should be able to provide an optimal solution with respect to the maximization of Type-E SALB problem in order to be effective. Likewise, the optimization of the solution with respect to the identified shifting bottleneck machines should be able to mitigate the computational complexity imposed by the underlying problem.

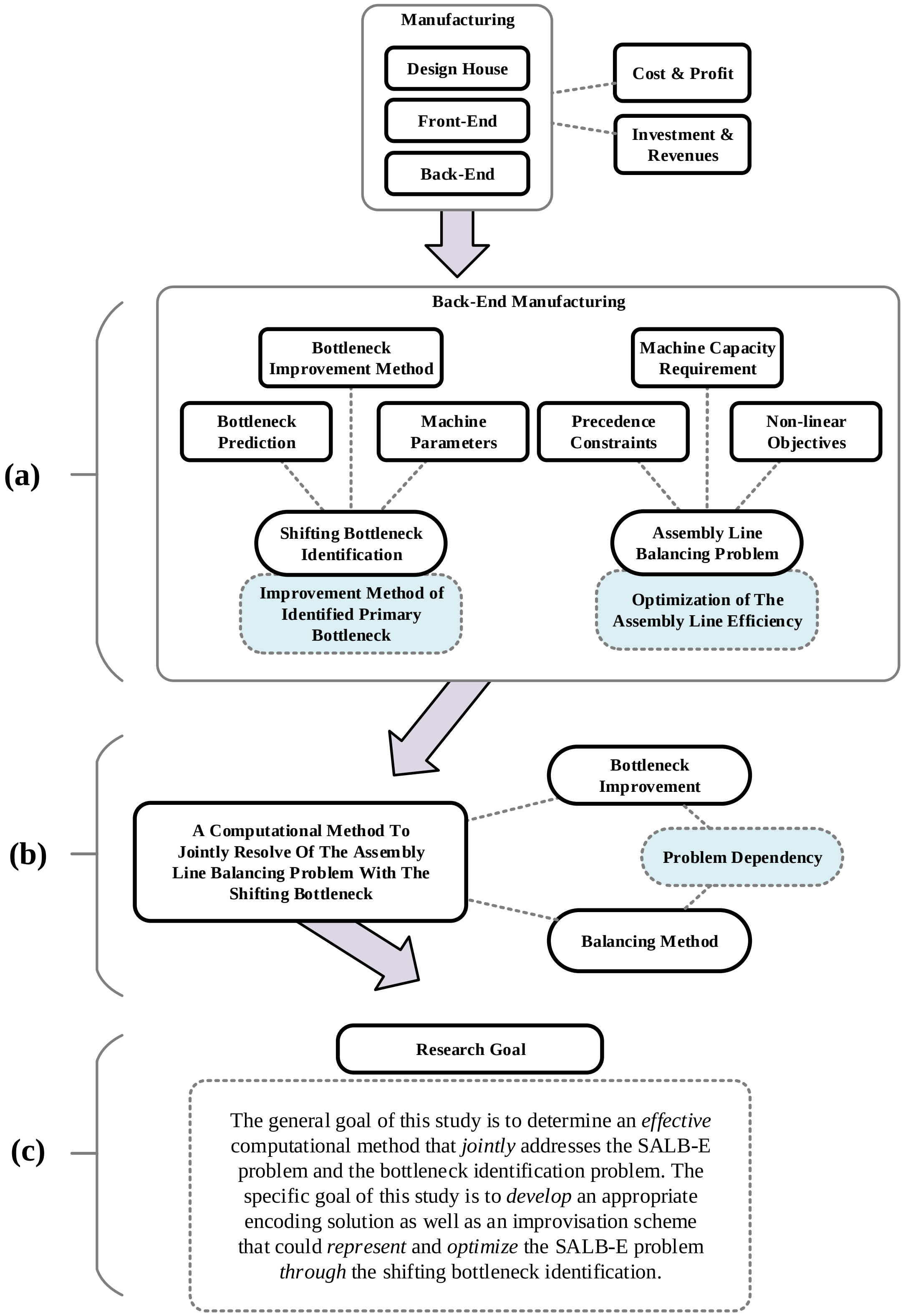

Figure 1.2: Scenarios of the assembly line balancing problem and the shifting bottleneck identification in the assembly line of the manufacturing system

The general objective would be to design and evaluate an artificial immune approach that can effectively solve the SALB-E problem by considering the bottleneck identification. Specifically, the research objectives are:

(i) To develop and evaluate an artificial immune system approach to maximize the efficiency measure of the assembly line balancing problem.

(ii) To develop and evaluate the artificial immune system approach that incorporates the shifting bottleneck identification method.

(iii) To develop and evaluate the enhancement of the proposed artificial immune system approach to improve the efficiency measure of the assembly line balancing problem with an integrated shifting bottleneck identification method.

1.5 Study Scope and Significance

The ALB problem involves various organizational and technological requirements which pose a challenge in solving the respective problem. As such, some scopes and limitations have to be made in order to make the study much more manageable. The scopes and limitations of this study are given as follows:

(i) This study considers only the back-end production of the manufacturing system, specifically the simple or straight assembly line system where production process is referred to an indivisible work element or task.

(ii) This study assumes that each task has precedence or orders of the process that are fixed and known beforehand.

(iii) The production resources; implying the workstations are multi-purpose and identical, where processing time for a specific task is deterministic and provided in advance. Also, the workstation is essentially regarded as a placement or positioning of machinery or worker, thus it may be referred to as a machine or work center or station (in which the terms are used interchangeably).

(iv) This study assumes no task splitting. This implies that if a process of a task is assigned to a machine, all requirements of that operation should be processed on the same machine and no splitting among machines.

(v) This research does not consider the determination of process parameters, setup time, tooling, material handling and the transportation system. It is assumed that the transportation system and all required materials are always available; the tools and material handling system during tasks processing are always available; while the setup times and transportation time required for each machine to receive a new task and release the processed task to the successive machine is negligible;

The manufacturing industry is the key driver for an export-driven economy emergence in Malaysia (Dogan *et al.*, 2013). With an efficient and well-balanced utilization of resources in the assembly line, the productivity can be improved and the manufacturing industry in various developed countries will be able to move up the value-chain by having the capability of producing highly customized products in relatively high volumes. This will help the manufacturing industry broaden the manufacturing base and act as enablers for other industries, as well as maintain the competitive edge of the domestic-owned manufacturing enterprises. Many developing countries like Malaysia can also embellish on the increased economy from the improved performance of manufacturing enterprises. Therefore, immediate implications such as cultivation of the manufacturing industry growth and increases in employment opportunities (Dogan *et al.*, 2013; Rasiah, 2017), act as key drivers for any developing country to also become a developed nation and encourage domestic manufacturing firms of any developed country to participate as one of the leading industries of the world.

1.6 Outline of the Thesis

This thesis is organized into seven chapters. Brief descriptions of the content of each chapters are given as follows:

(i) Chapter 2 outlines the state-of-the-art and current advances in the domain of assembly line balancing problem and bottleneck detection problem. This chapter also provides some insight of the theoretical background of the focused domain problems, trends, and directions that motivate the pursuit of this study.

(ii) Chapter 3 describes the research methodology employed in this research including the research framework, data sources, instrumentation, problem description, performance measures, and experimental design and analysis conducted in the research study.

(iii) Chapter 4 elaborates on the motivation and design of artificial immune system (AIS) approach, namely the contagious artificial immune system (CAST) approach. The CAST was designed in accordance to the SALB-E problems.

(iv) Chapter 5 discusses the proposal of incorporating the shifting bottleneck identification problem with the proposed CAIS approach, namely the contagious artificial immune system with discrete bottleneck simulator (CASTOR). The CASTOR approach is designed to incorporate the shifting bottleneck through a discrete bottleneck simulator engine with respect to the SALB-E problem.

(v) Chapter 6 discusses the enhancement proposal of the proposed AIS approach based on the result findings of the previous two approaches, namely the contagious artificial immune network with bottleneck indicator matrix (COMET) approach. The COMET approach is designed to enhance the basic structure of the CAST approach while implicitly integrating the shifting bottleneck identification, unavailable to the CASTOR approach, to improve the objective measure of the SALB-E problem.

(vi) Chapter 7 focuses on the evaluation of the proposed three AIS approaches, which involves conducting comparative studies over the SALB-E data sets. The collective behaviors of the CAST, CASTOR and COMET approaches are also observed and analyzed. In addition, the potential impact(s) and implication(s) of the proposed approaches are also formalized and discussed.

(vii) Finally, Chapter 8 provides the concluding remark regarding the overall findings and contributions, potential future work, and the outcome of the research in detail.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter will review related works in the area of the ALB problem. Throughout this chapter, the motivation and inspiration of adopting the domain problem as well as the chosen methodology for the research study will be emphasized. Additionally, the potential trend and direction derived from the review are discussed within the scope of this research study. The organization of this chapter is given in Figure 2.1.

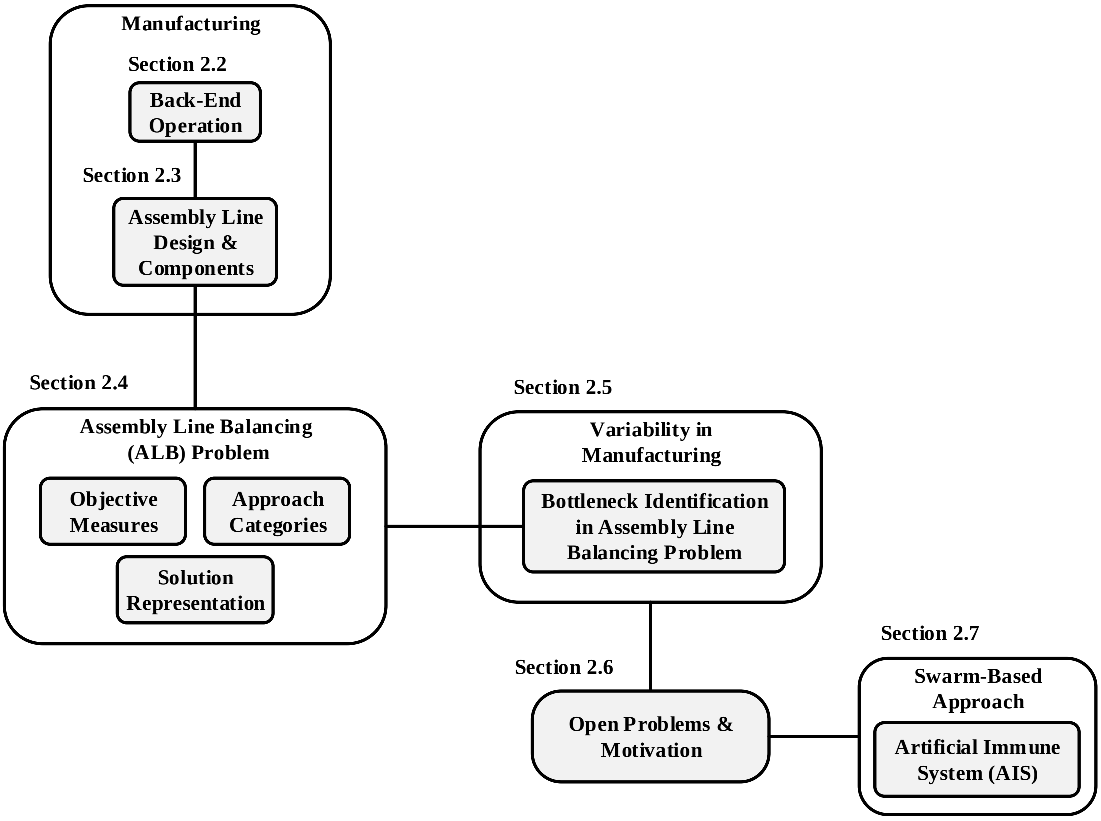

Figure 2.1: The content structure of Chapter 2

2.2 Manufacturing Operations

The manufacturing industry was originally very integrated which is associated with complex processes along with their life-cycle from designing to re-engineering. In the recent decade, the manufacturing industry has been decentralized because of the technological differences, core business focus, and cost scale (Lin *et al.*, 2013). The manufacturing industry is divided into three major operations; design house, front-end, and back-end. The design-house and front-end operations involve meeting customer demands through product definitions and product design, respectively (Jiao *et al.*, 2007). Meanwhile, the back-end operations involve process design and supply chain design. Consequently, the manufacturing industry is highly susceptible to uncertainty and the entrusted capital investment is vulnerable to risk. This is true, especially the back-end operations where the assembly line alone contributes up to 20% to 50% on both cost and lead-time of a product, and sometimes even more (approaching 90% in specific areas of micro-technologies and electronics) (Marian *et al.*, 2006).

In the manufacturing back-end operation, materials will undergo some or all of the processes on the shop floor, which typically consists of 20–40 processes (depending on the type of manufacturing industry), before they are transformed into end products (Tang *et al.*, 2003). Generally, the process flow or routing logic for each product is provided or predetermined, which acts as a guideline for management and production personnel. Different products have different designs in terms of specification (e.g. size and shape), demand volume (e.g. quantity and due date), and processing requirements (e.g. machine requirement, process precedence, and processing time). Therefore, process flows are different from one product to another which makes any decisions pertaining to increasing the efficiency of manufacturing operation, crucial (Rane *et al.*, 2015).

Typically, the lead time of the front-end operation is relatively longer than that of the back-end. This prompts the customers to request back-end assembly to provide a short but robust lead time service to absorb inventory fluctuation and avoid physical inventory (Lin *et al.*, 2013). Manufacturers also have to consider other initiatives to improve their market responsiveness through cycle time reduction and improvement of the timely delivery and utilization in order to handle excess global capacity, intense competition, and supply chain management drives. Therefore, back-end assembly, specifically the assembly line[1], is associated with complex decision-making problems and resource management issues.

A manufacturing assembly line is a flow line system composed of a number of workstations, arranged in series and in parallel. Product parts are added to a semifinished product as it moves from one workstation to another with the help of a transportation system (such as a conveyor or moving belt), whose mission is to supply materials to the main flow and to move the production items from one workstation to the next (Kucukkoc *et al.*, 2015; Roshani and Giglio, 2015). Operators, robots, or machines handle semi-finished products (known as operations or tasks) when passing the workstations in a sequential manner, where the time taken to complete a task at each operation is known as the process time (Rane *et al.*, 2015; Roshani and Giglio, 2015).

[1]the term assembly line, production line, and production system are used interchangeably

The assembly line deals with a high volume of products where each requires route specifications, resulting in a substantially large number of process flows or routings (Low *et al.*, 2005). In a typical back-end assembly, the cycle-time of the assembly operation usually falls in the range of 3 to 6 days. In addition, the assembly line also embodies the complexity of the production system, involving different levels of managerial decisions, where time, costs, and performances are significantly affected (Maurizio Faccio *et al.*, 2015). As a consequence, optimization problems such as the process planning, facility layout, workload or assembly balancing, resource allocation, equipment selection, and component management have to be considered for designing a new line or reconfiguring existing lines for a new product.

2.2.1 Assembly Line Design and Components

Designing a new assembly line or optimizing an existing one is crucial since the assembly line involves significant investments (Becker and Scholl, 2006; Venkatesh and Dabade, 2008). This is because extra costs in the future stages of the manufacturing, such as the material selection and equipment selection, can be avoided (Mohebalizadehgashti, 2016). Additionally, the main concern of the manufacturer is to exploit its available resources, such as workers, space, machines, and money, to better serve the demand of their customer. The basic data required for any assembly line design involves the precedence relationship between operations, required processing time of the operation, and the capacity of the production (i.e. number of machine) (Sivasankaran and Shahabudeen, 2014).

The assembly line is also composed of interrelated components that may be dependent and interdependent between each other based on the considered assembly line design. According to (Mohebalizadehgashti, 2016), the major components of the assembly line are, but not limited to, work elements, sub-assemblies, operators, operations, precedence graphs, workstations, equipment, material handling, buffers, feeder lines, pallets, fixtures, line layout, and inspection. The aforementioned components of the assembly line are addressed in order to represent a minimum working example of a practical assembly line system.

A *work element* is a basic term (or canonical term such as workpieces, tasks, process; depending on the manufacturing industry) used to describe an unfinished product, which is made up of different pieces of components where various processing requirements are conducted to form the final product (Torenli, 2009; Mohebalizadehgashti, 2016). Meanwhile, complex parts that add to the main work element in the assembly line are called *sub-assemblies*, where the part is assembled with different components Torenli (2009).

The operators, operations, and workstations can work in tandem with each other, where *operator* is the one that is responsible for performing different *operations* on the work element on the *workstations*. Different factor may relates to the operators such as the capacity of the operators (Aase *et al.*, 2004), skill levels (Corominas *et al.*, 2008), task learning (Toksarı *et al.*, 2010), and ergonomics (Battini *et al.*, 2015). Also, an *operation* typically requires a deterministic time, while other practical options would consider fuzzy task time (Zacharia and Nearchou, 2012) and stochastic task time (Zhang *et al.*, 2017). In addition, operations are directly related to the *precedence graph*, where basic information like operation names, operation times, and forward and backward paths are provided (Boysen *et al.*, 2007). Different workstation factors may include parallelling (Ege *et al.*, 2009; Kara *et al.*, 2010), positional constraints (Tuncel and Topaloglu, 2013), and resource-constrained requirements (Quyen *et al.*, 2017).

Some operations may require special *equipment* to perform the installation of the work elements, which translates to an additional investment cost on the assembly line. Operations that shared similar equipment may mitigate the cost involved due to reduced installation requirement (Becker and Scholl, 2006; Boysen *et al.*, 2007; Mohebalizadehgashti, 2016). Material handling is a factor that may not add any value to the final product, but crucial to mitigate waste (i.e. delay time) and moving work elements from one place to another (Mohebalizadehgashti, 2016). On the other hand, the feeder line, which generally is present in a multi-line assembly system provides sub-assemblies to the main assembly line.

According to Groover (2016), the buffer, pallet, and fixtures relate to both operation and workstation. A *buffers* provide temporary space to store work elements between workstations. Meanwhile, a *pallet* is utilized to move multiple items (materials) between places and works in tandem with the material handling system, and a *fixture* provides support for holding work elements during operations (typically required for heavy industries, such as automotive). The concerns related to buffer and pallet are capacity and size, respectively.

Other components such as the *inspection* and *line layout* involve the integration of other properties of the assembly line. Inspection is typically adapted to the work elements, either periodically, constantly, or implicitly, throughout the assembly line (Carcano and Portioli-Staudacher, 2006). This component will ensure the quality and minimize the faults, thus mitigating the costs that may follow. Likewise, the line layout also plays an important role in determining the overall flow of the assembly line which involves a different component arrangement of the assembly line. The layout can be divided based on the flow rate (i.e. paced (Boysen *et al.*, 2007) and un-paced assembly line (Quyen *et al.*, 2017)) and the structure of the layout (i.e. straight, U-shaped, multi-line, or crossover lines (Lusa, 2008)).

2.3 Assembly Line Balancing (ALB) Problem

Design considerations and the intricacy of multiple components involved in the assembly line can cause complications in mitigating demand variations. There are two main methods adopted in order to cope with demand variation; workload balancing and capacity adjustment (Li and Gao, 2014). The workload balancing or assembly line balancing (ALB) problem aims to find a line configuration that can meet demand variation without further adjustments. In contrast, capacity adjustment meets changing demands by minor adaption of the manufacturing operations. In addition, the capacity adjustment problem is a long-term planning problem where improvement is conducted in between the period of one to 10 years, while the ALB problem is a medium-term planning problem where the expected improvement is within weeks or months (Pearce, 2015). As such, addressing the ALB problem is important in order to cope with immediate demand variation of an assembly system.

The ALB problem was introduced by Salveson (1995) and this problem has been addressed through various methods under different situations in order to make better decisions in real-life situations. The ALB problem is one of the paramount issues that has been the subject of a large body of the literature and is a well-studied problem with a wide-range of applications, including the automotive industry, consumer electronics, and household items (Morrison *et al.*, 2014; Hudson *et al.*, 2015). When manufacturing high-demand products, the ALB problem arises when a firm introduces a new assembly line or redesigns an existing one. The new balanced system is expected to save capital expenditure and reduce cycle time into a value (actual cycle time) that is less than that predefined by management (also called theoretical cycle time) which is usually determined based on the desired production rates.

Depending on the number of product models considered in the manufacturing production (Yang and Gao, 2016), the ALB problem can be further classified into single-model, mixed-model, and multi-model ALB problems. The most popular ALB problem is called the single-model or simple assembly line balancing (SALB) problem. The mixed-model ALB problem deals with several models simultaneously with negligible setup cost, while the SALB problem is characterized by mass production of the single standardized product. Meanwhile, a multi-model ALB problem involves different items which are performed in small batches, where division of labour, specialization, and standardization are still being benefited (Pereira, 2018). Compared to the single-model ALB problem, the mixed-model and multi-model ALB problems are generally focused on specialized markets and tend to be application-based. Meanwhile, the SALB problem has been utilized for decades to provide a basis for testing different approaches to varying characteristics of the problem with respect to the known optimality. As such, this motivates the adoption of the SALB problem as the main focus area of this study.

The SALB problem is based on the assumption that most components in the assembly line are always available or simplified (Morrison *et al.*, 2014), which exhibits the following characteristics (Boysen *et al.*, 2007; Scholl *et al.*, 2010):

(i) A mass-production of one homogeneous product; given production process;

(ii) A paced line with fixed cycle time C_t;

(iii) A deterministic (and integral) operation time t_j;

(iv) No assignment restrictions other than the precedence constraints;

(v) A serial line layout with k stations;

(vi) All stations are equally equipped with respect to machines and workers;

The SALB problem is formally defined as the assembly work tasks $j = 1,2,...,J$ which are usually accomplished by a set of workers or stations, grouped and distributed among the workstations while satisfying both precedence and cycle time constraints as well as optimizing some objective(s) (Al-Hawari *et al.*, 2015). Even the SALB problems are known to be NP-hard, where j tasks and r ordering constraints result in a $j!/2^r$ number of possible task sequences (Mozdgir *et al.*, 2013). At each machine, certain operations are repeatedly performed with respect to the *cycle time C* (maximum or average time available for each workcycle) of the machine (Becker and Scholl, 2006). Each task requires a certain amount of time to be completed when it is assigned to a workstation. This is called task time or task processing time t_j.

Due to some technological or organizational restrictions (called precedence relationship constraint), some tasks need to be completed before initializing some other tasks and this must be satisfied for all tasks in order to obtain feasible and balanced solutions. Another essential constraint is that every task must be assigned to exactly one workstation, which means that tasks cannot be split between workstations. The sum of processing times cannot exceed the capacity of that workstation, designated by the cycle time which also determines the production rate or throughput rate (Kucukkoc *et al.*, 2015). The cycle time is determined by means of the demand rate of the product(s) in a planning horizon (Kara *et al.*, 2010) or utilization of effective time out of the available production shifts (Sivasankaran and Shahabudeen, 2014). The set S_{jk} of tasks assigned to a station k $(1, \ldots, K)$ constitutes its station load where the cumulated task time $t(S_{jk}) = \sum_{j}^{S_{jk}} t_{jk}$ is called station time. When a fixed common cycle time C_t is given, a line balance is feasible only if the station time of neither station exceeds C_t. In case of $t(S_{jk})$, the station k has an idle time of $C_t - t(S_{jk})$ time units in each cycle, which represents a repetitive unproductive time span (Scholl *et al.*, 2010).

2.3.1 Bottleneck Identification

In production resources, bottleneck has many definitions. Some defined the bottleneck as one of the main reasons that impede productivity and system performance in the strongest manner as well as having a negative impact on a system (Li *et al.*, 2007; Betterton and Silver, 2012; Wedel *et al.*, 2016). With respect to the context of this study, bottleneck can be referred to as the resource that constrained the performance of the production system. To improve the utilization of limited