PRODUCTION SCHEDULING WITH CAPACITY-LOT SIZE AND SEQUENCE CONSIDERATION

Mr. Rattapon Patikarnmonthon

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วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรดุษฎีบัณฑิต
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By	Mr. Rattapon Patikarnmonthon
Field of Study	Logistics Management
Thesis Advisor	Assistant Professor Manoj Lohatepanont, Sc.D.
Thesis Co-Advisor	Associate Professor Pongsa Pornchaiwiseskul, Ph.D.

Accepted by the Graduate School, Chulalongkorn University in Partial Fulfillment of the Requirements for the Doctoral Degree

....Dean of the Graduate School
(Associate Professor Sunait Chutintaranond, Ph.D.)

THESIS COMMITTEE

....Chairman
(Professor Kamonchanok Suthiwartnarueput, Ph.D.)
....Thesis Advisor
(Assistant Professor Manoj Lohatepanont, Sc.D.)
....Thesis Co-Advisor
(Associate Professor Pongsa Pornchaiwiseskul, Ph.D.)
....Examiner
(Associate Professor Paveena Chaovalitwongse, Ph.D.)
....Examiner
(Assistant Professor Tartat Mokkhamakkul, Ph.D.)
....External Examiner
(Associate Professor Nakorn Indra-payoong, Ph.D.)

รัฐพล ปฏิการมณฑล : การวางแผนการผลิตโดยคำนึงถึง ความสามารถที่จะรับได้ ล็อตการผลิต และลำดับในการผลิต (PRODUCTION SCHEDULING WITH CAPACITY-LOT SIZE AND SEQUENCE CONSIDERATION) อ.ที่ปรึกษาวิทยานิพนธ์หลัก: ผศ. ดร. มาโนช โลหเตปานนท์, อ.ที่ปรึกษาวิทยานิพนธ์ร่วม: รศ. ดร. พงศา พรชัยวิเศษกุล, 76 หน้า.

การวางแผนการผลิตโดยคำนึงถึง ความสามารถที่จะรับได้ ล็อตการผลิต และลำดับในการผลิต (*General Lotsizing and Scheduling Problem* หรือ GLSP) เป็นหนึ่งในกระบวนการสำคัญสำหรับการวางแผนการผลิต โดยเป็นการคำนึงถึงข้อจำกัดหลายๆด้าน เช่น กำลังการผลิต ล๊อตการผลิต และลำดับการผลิต

การศึกษานี้นำเสนอการแบ่ง GLSP ออกเป็นสองกระบวนการ โดยในกระบวนการแรกจะเป็นการสร้างลำดับการผลิต โดยการระบุล๊อตในการผลิตก่อน หลังจากนั้น ลำดับการผลิตที่คำนวนได้จากกระบวนการแรกจะถูกส่งไปยังกระบวนการที่สอง เพื่อทำการคำนวนหาปริมาณการผลิตที่เหมาะสมเพื่อให้ได้ต้นทุนในการผลิตที่ต่ำที่สุด ทั้งนี้ ในการศึกษานี้ยังได้มีการเพิ่ม ซัพพลายจากภายนอกเข้าไปใน แบบจำลอง เพื่อสะท้อนถึงการทำงานในสภาวะของธุรกิจจริงที่มีทรัพยากรจำกัด โดยแบบจำลองที่นำเสนอนั้นจะถูกพิจารณาจากความสามารถในการคำนวน และเวลาที่ใช้ในการคำนวน โดยแบบจำลองจะถูกทดสอบบนสถานการณ์ 8 สถานการณ์ ทั้งนี้ ผลของแบบจำลองพบว่า แบบจำลองที่นำเสนอมีความสามารถในการคำนวนได้ดีกว่า GLSP

สาขาวิชา การจัดการด้านโลจิสติกส์	ลายมือชื่อนิสิต ....
ปีการศึกษา 2559	ลายมือชื่อ อ.ที่ปรึกษาหลัก ....
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RATTAPON PATIKARNMONTHON: PRODUCTION SCHEDULING WITH CAPACITY-LOT SIZE AND SEQUENCE CONSIDERATION. ADVISOR: ASST. PROF. MANOJ LOHATEPANONT, Sc.D., CO-ADVISOR: ASSOC. PROF. PONGSA PORNCHAIWISESKUL, Ph.D., 76 pp.

The *General Lotsizing and Scheduling Problem* (GLSP) is a method of addressing a common problem found in continuous production planning. The problem involves many constraints including machine capacity, production lot-size, and production sequence. This study proposes a re-formulation of the GLSP divided into two phases known as the *General Lotsizing and Scheduling Problem using Two Phases with External Supply* (GLSP-TE). Phase one is the Pattern generation with Specific Batch size and Capacity. Phase two is the Production Allocation using Specified Pattern obtained from the production pattern in Phase One. Additionally, external supplies are included in the formulation to reflect the real situation for businesses faced with limited resources. In this study, the justification of the formulation is based on the ability to solve problems and calculation time. The proposed formulation was tested in eight scenarios.

The results show that the proposed formulation is more tractable and is better at solving problems than the GLSP. The objective value of GLSP-TE showed improvement up to 70% in high fluctuation scenarios compared to the original GLSP with a defined computational time limit.

Field of Study:	Logistics Management	Student's Signature	....
Academic Year:	2016	Advisor's Signature	....
		Co-Advisor's Signature	....

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Chapter 1

Introduction

Manufacturing, operations require several planning levels, including an operational plan, tactical plan, and strategic plan. Strategic planning is the core of the planning process as it has to match the business strategy. Actions resulting from such planning require long term implementation, i.e. building facilities, re-locating facilities and procuring machinery. Tactical planning includes taking into account supply and demand for each product, as well as choosing appropriate raw materials. The benefits received by one's business depend heavily on this level of planning. Operational planning deals with cost considerations, and as such, the main objective of operational planning is to minimize operating costs while still complying with tactical planning goals to pursue the ultimate goal of maximizing margins for the business.

Production scheduling is one of the essential tasks of operational planning. This process must indicate actions required on a daily or hourly basis, together with the types and quantity of the products required for production, according to fluctuation in demand, operational configuration, and production capacity. The inventory carried over the period serves as a buffer for demand that might exceed the production capacity in each period. Cost minimization has to be considered in this planning to ensure that the carrying cost of the inventory is as low as possible, while the demand can still be met. The production scheduling process is a straightforward and effective technique that can be applied to improve cost minimization. This process can be formulated based on a linear programming formulation, which considers demand, inventory carrying cost, and production capacity. Solving this problem is straightforward and effective in real business situations using the linearity assumption of the formulation.

For continuous production, the Changeover Cost is an important variable of the production planning, as converting from production of one product to another product might increase the cost of the operation. Changeover Cost can be defined as the additional cost incurred when a production sequence is altered as the cost for a skipped or reversed sequence is normally higher than maintaining the regular sequence. The production scheduling has to be carefully considered to reduce unnecessary changeover from period to period.

The minimum lot size of the production is another factor in continuous production. The minimum size of production for each product must be determined before changeover to a different product. According to this limitation, the inventory helps to minimize the production cost by carrying over the product that exceeds the current demand to the next period.

Adding lot-size and sequence considerations into production scheduling leads to transformation of calculations from Linear Programming (LP) to Mixed Integer Programming (MILP). The setting up status for each period is defined as the binary variables and also for the min-lot consideration which is cast as the integer variable. Both sets of the discrete variables add complexity into the formulation. The *General Lotsizing and Scheduling Problem* (GLSP), classified as a Non-Deterministic Polynomial-time hard Problem (NP-hard), requires substantial computational time to solve. The exact methodology to solve the problem involves taking into account the fractionality of the binary variables during computation. This fractionality is the cause of a weak bound in branch-and-bound technique that influents the branching technique in an appropriate direction and results in a large number of iterations in the computation. Enormous resources such as memory and computational time are required for finding the solution.

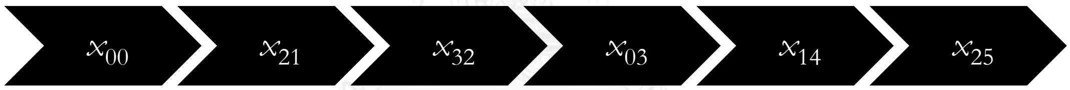

Figure 1-1: Sample of the Production Scheduling

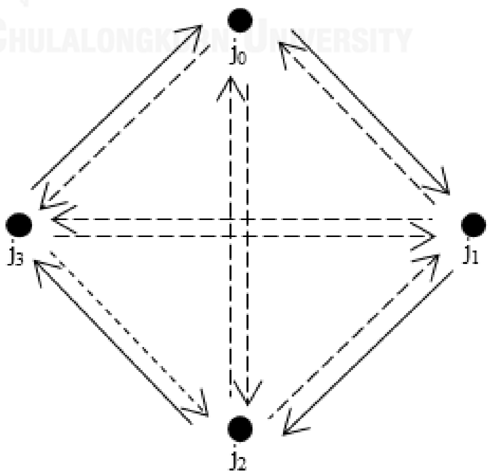

Figure 1 2: Changeover Cost from product i to project (s_{ij})

An example of the Production Schedule is shown in Figure 1.1. The number of production in each period is indicated in x_{js}. In micro-period s_0, the planned production was of product j_0 with the amount of x_{00}. In these 6 periods in the example, the planned production was of product j_0, j_2, j_3, j_0, j_1 and j_2 respectively. The plan shows that the changeover from product i to product j was assigned orderly. The Changeover Cost from product i to product j (s_{ij}) is illustrated in Figure 1.2. The solid line shows the minimum changeover cost from one product to another product. The dashed line shows the more expensive changeover from product to product.

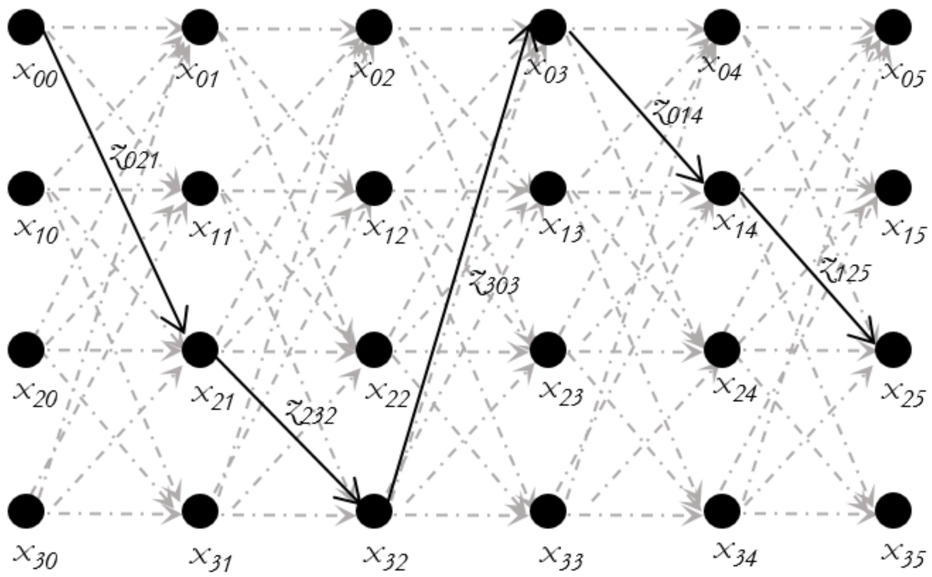

Figure 1-3: Changeover Variable from product i to product j in time s (z_{ijs})

The large number of binary variables is the Changeover variable (z_{ijs}). This binary variable indicates the changeover stage from product *i* to product *j* in time *s*. The number of z_{ijs} is equal to the number of the product squared multiplied by number of micro-period $(|J|^2 \times |S|)$. This set of variables will increase exponentially when the number of the product is increased. The increasing of this variable adds to the complexity of the problem. During the LP relaxation, this set of variables will face fractionality, the part that results in a weak bound in the problem.

This study proposes GLSP improvement by formulating a model by tackling the important part of the formulation and the bound from LP relaxation that is used for determining the solution gap of the incumbent solution. The tighter bound may lead to the calculation of exact methodology to effectively answer this sophisticated problem with less memory usage and computational time.

1.1 Background and Motivation

The production scheduling process influences how much of a product is supplied and how much inventory will be needed due to demand, limited capacities, limited resources or production characteristics. As many constraints are considered in scheduling, the development of the optimal production scheduling is difficult to perform manually. In addition, many binary variables must be considered which adds to the complexity for setting up the computational model.

In the previous studies, this problem is categorized as a NP-hard problem. The NP-hard problem has characteristics that obstruct computation, increasing in the number of parameters, such as time slot or number of product, and generates dramatic changes in the number of both linear variables and binary variables. Also, when some binary variables increase, they can affect the model in both of size and time consumed.

Improvement of the solution methodology for practical implementation can be beneficial for a business due to the optimization of the planning process and efficient management of the time and material consumed.

1.2 Dissertation Objective

This dissertation aims to develop a heuristics methodology for the production scheduling problem that considers the production lot-size, capacity and sequence in the computational model. In previous studies, researchers have introduced an exact methodology for handling the problem; however, this computational model is not appropriate for computing as it is considered a NP-hard problem based model that generates numerous binary variables, resulting in high time consumption and inaccurate calculation.

Current commercial software with the heuristics methodology was used to tackle this problem. If this problem can be overcome by the methodology introduced in this study with an acceptable computing time, this study can be useful for the business planning in real situations with optimum output.

1.3 Dissertation Scope

This dissertation focuses on production scheduling with consideration of the production lot-size, capacity and sequence characterized as:

- single machine
- finite time of production
- limited capacity in given time (K_t)
- setup cost/time from product i to j have constant cost/time for each direction of transition

Data used in this dissertation, including the capacity (K_t) and demand (d_{jt}), were obtained from random generation and were used in the model for computing the results.

1.4 Anticipated Benefit

This dissertation is expected to introduce a modified formulation to address the production scheduling problem that has a tighter bound and is more tractable and solvable to use in practical situations.

Chapter 2

Literature Review

2.1 Formulation

Production scheduling with lot-size and capacity relaxation was introduced by Chen and Thizy (1990). This problem was referred as an NP-hard problem, which determined the magnitude of the operational timing of durable results. Their formulation is shown in formulation 2.1 to 2.4 with following sets and parameters.

Sets:

I : Number of product

T : Number of production period

Parameters:

s_{it} : Production setup cost for product *i* in period *t*

p_{it} : Unit of production cost of product *i* in period *t*

h_{ij} : Inventory cost of one unit of product *i* between periods *t* and *t+1*

c_t : Production capacity in period *t*

a_i : Capacity consume by the production of one unit of product *i*

d_{it} : Demand of product *i* in period *t*

$d_{it\tau}$ $=\sum_{j=t}^{\tau} d'_{ij}$ in which d'_{ij} is the demand for production *i* in period *j* adjusted for initial and final inventories

z_i^0 : The pre-specified initial inventory of product *i*

z_i^T : The pre-specified final inventory of product *i*

Variables:

x_{it} : the amount of product *i* produced in period *t*

z_{it} : the inventory of product *i* carried from period *t* to period *t+1*

$y_{it} \in \{0,1\}$: The variable that has value 1 if $x_{it} > 0$, 0 if $x_{it} = 0$.

Formulation:

$$Min\ z = \sum_{i,t} (p_{it}x_{it} + s_{it}y_{it} + h_{it}z_{it}) \quad (2.1)$$

Subject to:

$$z_{it} = z_{i,t-1} + x_{it} - d_{it} \qquad \forall i \in I, \forall t \in T \quad (2.2)$$

$$\sum_{i} a_i x_{it} \leq c_t \qquad \forall t \in T \quad (2.3)$$

$$x_{it} \leq d_{itT} y_{it} \qquad \forall i \in I, \forall j \in J \quad (2.4)$$

The Objective Function (2.1) is a function that minimizes production and inventory costs which considers demand and inventory carried to the next period in Constraint 2.2, capacity in Constraint 2.3 and production setup in Constraint 2.4. Number of discrete variable is [$I \times T$]. The Chen and Thizy (1990) model does not allow for backlog and production sequences.

Fleischmann and Meyer (1997) studied higher complexity in the production scheduling problem by adding sequence considerations into the formulation, known as the *General Lotsizing and Scheduling Problem* (GLSP). In each setup, changing from one product to other products altered the production cost which depends on the differences between two products. With the sequence consideration included, the discrete variables were introduced into the formulation by defining and setting up the variable between the changing groups. The sets of data, variables and formulation are shown below.

Set:

S_t	: Set of micro-periods s belonging to macro-period t
J	: Set of products
T	: Set of Macro-Period
S	: Set of Micro-Period

Parameters:

K_t	: Capacity (time) available in macro-period t
a_j	: Capacity consumption (time) needed to produce one unit of j
m_j	: Minimum lot-size of product j
h_j	: Holding costs of product j (per unit and per macro-period)
s_{ij}	: Setup costs of changeover from product i to product j
st_{ij}	: Setup time of changeover from product i to product j
d_{jt}	: Demand of product j in macro-period t (units)

I_{j0}	: Initial inventory of product j at the beginning of the planning horizon (units)
y_{j0}	: Equal to 1 of the machine is set up for product j at the beginning of the planning horizon (0 otherwise)

Variables:

$I_{jt} \geq 0$	: Inventory of product j at the end of the planning horizon (units)
$x_{js} \geq 0$	: Quantity of item j produced in micro-period s (units)
$y_{js} \in \{0,1\}$	: Setup state: $y_{js} = 1$, if the machine is set up for product j in micro-period s (0 otherwise)
$z_{ijs} \in \{0,1\}$	: Take on 1, if a changeover from product i to product j takes place at the beginning of micro-period s (units)

Formulation:

$$Min\ z = \sum_{j \in J} \sum_{t \in T} h_j I_{jt} + \sum_{i \in J} \sum_{j \in J} \sum_{s \in S} s_{ij} z_{ijs} \qquad (2.5)$$

Subject to:

$$I_{jt} = I_{j,t-1} + \sum_{s \in S_t} x_{js} - d_{jt} \qquad \forall t \in T, \forall j \in J \qquad (2.6)$$

$$\sum_{j \in J} \sum_{s \in S_t} a_j x_{js} + \sum_{i \in J} \sum_{j \in J} \sum_{s \in S_t} st_{ij} z_{ijs} \leq K_t \qquad \forall t \in T \qquad (2.7)$$

$$x_{js} \leq \frac{K_t}{a_j} y_{js} \qquad \forall t \in T, \forall s \in S_t, \forall j \in J \qquad (2.8)$$

$$x_{js} \geq m_j (y_{js} - y_{j,s-1}) \qquad \forall s \in S, \forall j \in J \qquad (2.9)$$

$$\sum_{j \in J} y_{js} = 1 \qquad \forall s \in S \qquad (2.10)$$

$$z_{ijs} \geq y_{i,s-1} + y_{js} - 1 \qquad \forall s \in S, \forall i \in I, \forall j \in J \qquad (2.11)$$

$$I_{jt} \geq 0 \qquad \forall t \in T, \forall j \in J \qquad (2.12)$$

$$x_{js} \geq 0 \qquad \forall s \in S, \forall j \in J \qquad (2.13)$$

$$y_{js} \in \{0,1\} \qquad \forall s \in S, \forall j \in J \qquad (2.14)$$

$$z_{ijs} \in \{0,1\} \qquad \forall s \in S, \forall i \in J, \forall j \in J \qquad (2.15)$$

The GLSP proposed by Fleischmann and Meyer (1997) contains an Objective Function (2.5) which consists of two parts. The first part is the inventory holding cost of each product in each macro-period. The second part is the setup cost of production changeover from product *i* to product *j* in each micro-period (if needed).

Subject to Constraint 2.6 is the cover demand volume of each product to be fulfilled in each macro-period with the number of inventory to be carried to the next macro-period. Constraint 2.7 is capacity constraint, which covers how much machine time is required in each macro-period and machine time used for production. This constraint calculates how much machine time is needed to produce each product in each macro-period, and how much machine time used in production setup to change from product *i* to product *j*.

Constraint 2.8 is used to determine which product has been set up for product *j* in micro-period *s*. Constraint 2.9 is used to set each production lot needed to produce at least the minimum run for each product. Constraint 2.10 is used to set up only one product in each micro-period. Constraint 2.11 is used to determine when the production changeover from product *i* to product *j* should occur.

With GLSP, the discrete variable required is $[|J|^2 \times |T|]$. This formulation also does not cover backlogging but does cover production sequence.

2.2 Solution Methodology

Production scheduling has been categorized into 5 groups by Drexl and Kimms: (1997) 1) the capacitated lot sizing problem, 2) the discrete lot sizing and scheduling problem, 3) the continuous setup lot sizing problem, 4) the proportional lot sizing and scheduling problem, and 5) the general lot sizing and scheduling problem. They also concluded that complexity can be addressed by casting as multi-level lot sizing and scheduling. Their study noted that the production scheduling problem has limitations such as gaps to approach, more complex setup time, setup with sequence dependent, parallel machines and backlog, and that tackling the scheduling problem can be done using 2 methodologies, the exact and the heuristics methodologies. The Capacitated Lotsizing Problem with sequence dependent Setup Cost (CLSD) was introduced by Haase Knut (1996) and discrete lotsizing problem with sequence dependent setup cost (DLSDSD). The CLSD is quite close to Fleishmann and Meyr's formulation (1997), the General Lotsizing and Scheduling Problem (GLSP) but the setup state can be preserved over idle time for Fleishmann. Haase also used the heuristics methodology to solve his CLSD and DLSDSD with priority rules on local searching in parameter space for lower solution costs. Besides providing an exact methodology, Fleishmann also introduces a heuristics methodology for approaching this problem by using various techniques including: 1) threshold accepting, 2) neighborhood search, and 3) backward oriented lot-sizing for a given setup pattern (Greedy-Sim, Greedy-Mod and Greedy-Cap). The GLSP has been used in many recent studies in which researchers have introduced improvements in both the exact and heuristics approach.

The improvements of the exact methodology were introduced in many aspects for example the Lagrangian Relaxation method was used by Chen and Thizy (1990) on several constraints such as setup, demand and capacity constraints. This method is also involved with the subgradient optimization and column generations in node-arc formations using the shortest path technique. The lower bound improvement by adding cutting plane to the formulation, was introduced by Belvaux and Wholsey (2001). By categorized the startup and changeover into four parts: 1) Small bucket model, 2) one setup per period, 3) two setup per period, and 4) big bucket model with changeovers. In addition, they also introduced the minimum production runs and full-capacity production. However, the drawback of this formulation is the changeover variable that uses a discrete variable that makes the model more complex. The modified branch and bound enumeration method, which was introduced by Haase and Kimms (2000). It stated that in period *T*, perform a branching step by choosing a sequence and doing calculations to choose whether the model needs to move on to period one step by step by doing backtracking in-between if necessary. The multi-level MILP formulation for Medium-Range Production Scheduling of a Multiproduct Batch Plant was introduced by Lin Xiaoxia et al (2002). by decomposition of the entire period into short time horizons using an exact methodology to solve the problem. Multiple intermediate due dates were used in each time horizon to enable the consolidation of the short time horizon in addressing the larger problem.

There are many techniques to approaching the NP-Hard problem. In the survey of Woeginger (2003) it was shown that the researcher used Dynamic Programming, Pruning the Search Tree, Preprocessing the Data and Local Search depending on the characteristics of the problem. The Mixed Integer Dynamic Optimization (MIDO) was used by researchers such as Held, Michael (1962), Bansal Vikrant et al. (2003), Prata, Adrian et al. (2008) and Chu Yunfei (2013). Prata, Oldenburg et al. (2008) was cast the problem as the MIDO and used a validated differential-algebraic model to represent the polymerization behavior. The key idea of implementation was to be the standard solution method for continuous process scheduling which has clear process. The Mixed-Integer Linear Fractional Programming (MILFP) also introduced for the cycle process scheduling problem by You Fengqi (2009). They also used the Dinkelbach's algorithm for solving large-scale MILFP formulation with continuous time Resource-Task Network (RTN). The result of the proposed solution was less computational resources used with greater optimality and efficiency. The Searching over Separator Strategy also was introduced by Hwang R. Z (1993) by dividing the problem into two subproblems in which the results from both subproblems were combined as an optimal solution. Furthermore, Drori Limor (2002) proposed an algorithm recursively partitioned the problem domain and eliminated some branches during calculations. All techniques have been used for tackling the optimization of the complex and time consumed problem.

The heuristics methodology was used by various researchers. Meyr (2000, 2002) also improved his methodology by using the dual network flow to re-optimize the sub-problem. This methodology evaluated the new candidate added back to the current solution to find the better solution using dual price. This methodology also used in both single machine consideration and the multi machines scheduling. Karimi et al. (2003) introduced heuristics approaches such as tabu search, simulated annealing, and other meta-heuristics for solving the capacitated lot-size production scheduling problem. They also added complexity into an exact approach by adding backlogging as well as the setup times and carryover. The three steps of heuristics were published by Gupta and Magnusson (2005) Their formulation considered the capacitated lot-sizing and scheduling problem with sequence-dependent setup cost and time. The flexibility of this approach provides a feasible optimal solution. Their heuristics is divided into three steps: Initialize, Sequence and Improve. The initialize step is used to find initial solutions by determining production quantities without sequence consideration. The sequence step is finding the least-costly production within each period. The last step, the improve step, is to refine production quantities and production sequence in respect to decreasing total cost. The hybrid of the mathematical programming and the local search methods were published by De Araujo, Arenales et al. (2007). This hybrid method is called the relax-and-fix methodology. It divides the problem into two levels: 1) solving some relaxed integer variables and solving relaxed problems, and 2) re-specifying some integer variables and then solving partially fixed problems. The heuristics methodology is used to solve both steps to find feasible solutions. Almada-Lobo and Klabjan (2007) addressed the production lot-size capacity and sequence-dependent problem by adding setup carryover. Five-steps heuristics were introduced to find an appropriate solution for the initial problem using the local search procedure. Their first step is lot-for-lot pass, allocating production volume to each demand period without considering the capacity constraint. The second step is doing a sequencing and amending procedure called the *minmax* algorithm. The third step is to try to improve the quality of the initial solution from first and second steps by backwards pass in time that seeks to avoid the cost and capacity consumption of a setup. Although this step can affect feasibility, fixing feasibility will be recovered at the end. The fourth step is a forward pass that seeks to reduce inventory holding cost by shifting forward a fraction or an entire lot of production which has the possibility to reduce total cost. The last step looks for improvements in the links between adjacent periods in a forward pass. Salomon, Solomon et al. (1997) introduced dynamic programming for solving the discrete lot-sizing scheduling problem with sequence dependent setup cost and time. This methodology was performed by reformulating the problem as a travelling salesman problem with time windows. Solving a reformulated problem using dynamic programming algorithm was introduced by Dumas, Desrosiers et al. (1995). Salomon and Solomon et al found that their approach performance depended on problem dimensions, inventory holding cost, setup time and production capacity utilization. The dynamic programming and heuristics technique that focus on binary variables related to sequences was introduced by Kovács, Brown et al. (2009) while running a pre-processer to determine the items that should appear in an optimal solution. This technique focuses on the binary variables related to the sequences by using heuristics and dynamic programming to give tight LP-relaxation. Kämpf and Köchel (2006) introduced a new idea to approach the capacitated lot-sizing and the scheduling problem. The sequence-dependent setup time and cost were used in this approach with the combination of simulation and optimization. The simulation was used to find the optimal parameters before providing feedback for optimizing and assessing the value from the simulator for the possibility of optimality. The simulation was used to find the optimal parameters before feedback. The decomposition of integrated scheduling for chemical processes by tailoring the decomposition method based on generalized Blenders decomposition was put forth by Chu and You (2013). Dynamic optimization was used in master problem separated by the processing unit by collaboratively optimizing to improve the performance of the batch production from sequential methodology.

To summarize, the exact and heuristics methodologies were used to solve the production scheduling problem. As the problem is defined as an NP-hard problem, the exact methodology is a time-consuming approach due to the large number of the binary variables generated. Therefore, most of the previous studies applied the heuristics methodology to tackle this problem using various technics with more specified applications. Improvement on the GLSP still be the gap. Nowadays the processing power is much more enhancement, some technics can gain benefit from this enhancement. Due to the generalized problem can modify to use in various application, the improvement on GLSP also can accommodate in many applications.

Chapter 3

Methodology

This chapter consists of 3 parts to describe the methodology of this study. The first part is entitled the Dissertation Process, which outlines the steps used in this study. The second part is Data Used. This part describes the data used in testing and analyzing the model including the scenarios in the test. The third part is Tools and Technology Used, which includes the software and hardware used in this study.

3.1 Dissertation process

This dissertation was conducted in 7 steps starting from literature review, implementing the GLSP, analyzing the gap and finding the direction for improvement, formulating and implementing 2-phase formulation, testing & fine tuning the model, verifying and validating, and analyzing results & developing a report as shown in Figure 3-1.

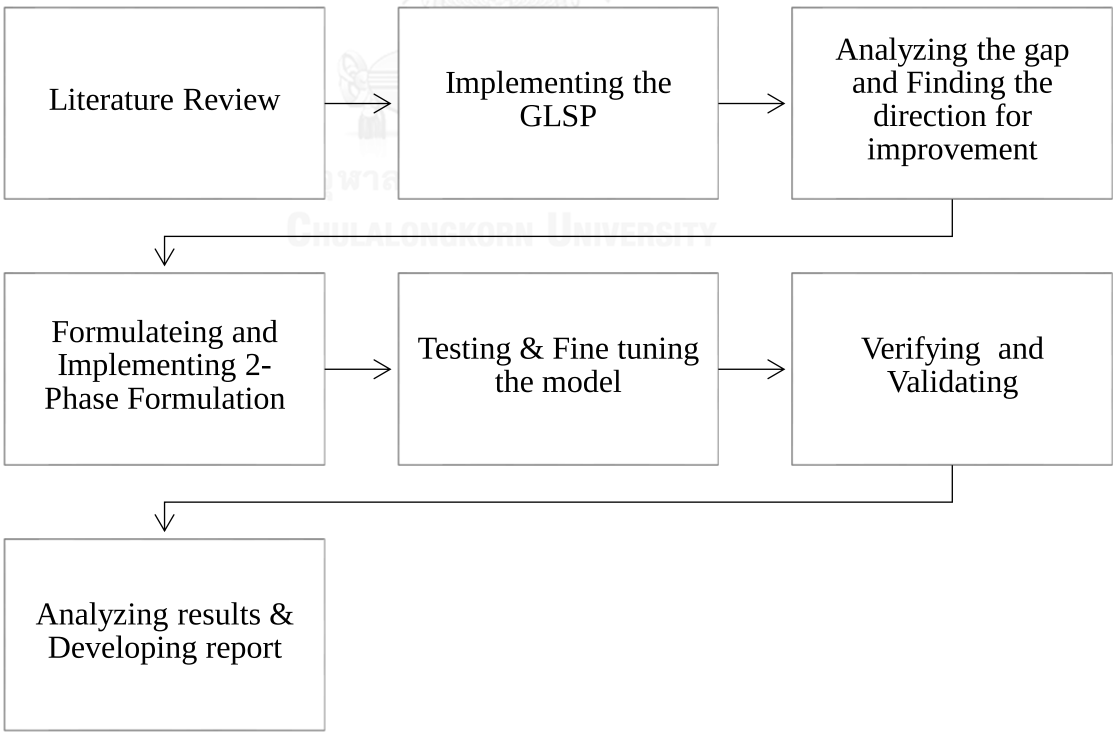

Figure 3-1: Dissertation Process

Literature review

In this step, researching the current and relevant studies related to production scheduling with lot-size, capacity and production sequences was performed, as well as finding a possible research gap. According to the current studies, an exact methodology has not been developed since 2001. The node-arc type formulation obtained from this methodology causes weak bounds when doing LP relaxation in each iteration. This leads to difficulty in finding a solution gap to determine the optimality on each integer solution found. After 2001, the heuristics methodology with various algorithms was used to approach this problem.

Implementing the GLSP

In this step, the GLSP was implemented with C# and CPLEX using concert technology for a connector. The test results were collected and used for gap analysis to find the improvement direction in the next step. The notation and formulation are:

Set:

S_t	: Set of micro-periods s belonging to macro-period t
J	: Set of products
T	: Set of Macro-Period
S	: Set of Micro-Period

Parameters:

K_t	: Capacity (time) available in macro-period t
a_j	: Capacity consumption (time) needed to produce one unit of j
m_j	: Minimum lot-size of product j
h_j	: Holding costs of product j (per unit and per macro-period)
s_{ij}	: Setup costs of changeover from product i to product j
st_{ij}	: Setup time of changeover from product i to product j
d_{jt}	: Demand of product j in macro-period t (units)
I_{j0}	: Initial inventory of product j at the beginning of the planning horizon (units)
y_{j0}	: Equal to 1 of the machine is set up for product j at the beginning of the planning horizon (0 otherwise)

<u>Variables:</u>

$I_{jt}\ \geq 0$: Inventory of product j at the end of the planning horizon (units)

$x_{js}\ \geq 0$: Quantity of item j produced in micro-period s (units)

$y_{js}\ \in \{0,1\}$: Setup state: $y_{js}\ = 1$, if the machine is set up for product j in micro-period s (0 otherwise)

$z_{ijs}\ \geq 0$: Take on 1, if a changeover from product i to product j takes place at the beginning of a micro-period s (units)

<u>Formulation:</u>

$$Min\ z = \sum_{j\in J}\sum_{t\in T} h_j I_{jt} + \sum_{i\in J}\sum_{j\in J}\sum_{s\in S} s_{ij} z_{ijs} \qquad (3.1)$$

Subject to:

$$I_{jt} = I_{j,t-1} + \sum_{s\in S_t} x_{js} - d_{jt} \qquad \forall t \in T, \forall j \in J \quad (3.2)$$

$$\sum_{j\in J}\sum_{s\in S_t} a_j x_{js} + \sum_{i\in J}\sum_{j\in J}\sum_{s\in S_t} st_{ij} z_{ijs} \leq K_t \qquad \forall t \in T \quad (3.3)$$

$$x_{js} \leq \frac{K_t}{a_j} y_{js} \qquad \forall t \in T, \forall s \in S_t, \forall j \in J \quad (3.4)$$

$$x_{js} \geq m_j (y_{js} - y_{j,s-1}) \qquad \forall s \in S, \forall j \in J \quad (3.5)$$

$$\sum_{j\in J} y_{js} = 1 \qquad \forall s \in S \quad (3.6)$$

$$z_{ijs} \geq y_{i,s-1} + y_{js} - 1 \qquad \forall s \in S, \forall i \in I, \forall j \in J \quad (3.7)$$

$$I_{jt} \geq 0 \qquad \forall t \in T, \forall j \in J \quad (3.8)$$

$$x_{js} \geq 0 \qquad \forall s \in S, \forall j \in J \quad (3.9)$$

$$y_{js} \in \{0,1\} \qquad \forall s \in S, \forall j \in J \quad (3.10)$$

$$z_{ijs} \in \{0,1\} \qquad \forall s \in S, \forall i \in J, \forall j \in J \quad (3.11)$$

The GLSP contains an Objective Function (3.1) which consists of two parts. The first part is the inventory holding cost of each product in each macro-period. The second part is the setup cost of production changeover from product i to product j in each micro-period (if needed).

Subject to Constraint 3.2 is the cover demand volume of each product to be fulfilled in each macro-period with the number of inventory carried to next macro-period. Constraint 3.3 is the capacity constraint that covers how much machine time is used in each macro-period and machine time used for production. This constraint calculates the machine time needed to produce each product in each macro-period, and how much machine time is used in the production setup to switch from product i to product j.

Constraint 3.4 is used to determine which product has been set up for product j in micro-period s. Constraint 3.5 is used to set each production lot needed to produce at least a minimum run for each product. Constraint 3.6 is used to set up for only one product in each micro-period.

Constraint 3.7 is used to determine when the production changeover from product i to product j occurs. Constraint 3.8 and 3.9 are for non-negativity on variable I_{jt} and x_{js}. The binary constraint is on Constraint 3.10 and 3.11 on y_{js} and z_{ijs}.

Analyzing the gap and finding the direction for improvement

Based on the previous steps, this model provides a weak bound from binary variables (y_{js}, Z_{ijs}) when the LP relaxation is performed. The binary variables satisfied all constraints and became a fraction. This fraction and sense of formulation lead to the zero-objective value. This causes a weak bound in the most of iterations since initial optimization. The example of a bound that came from LP relaxation with a very large gap in most iterations as shown in Figure 3.2. In this example, the tolerance gap was set to 10% and most early iterations LP relaxation were 0 which caused the tolerance gap to be 100%. After many iterations, LP relaxation resulted in a better bound and an acceptable solution was achieved.

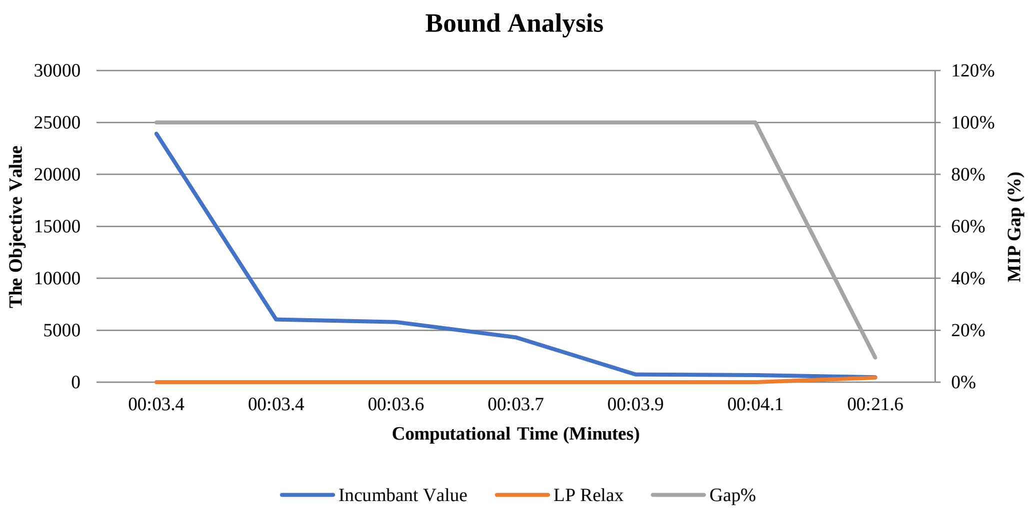

Figure 3-2: The example of bound behavior.

Another point of the problem is that it generates a substantial number of binary variables when we increase micro-periods and number of products (as shown in Figure 3.3). This model contains two sets of binary variables: y_{js} and z_{ijs}. The y_{js} is the number of product multiplied by the number of micro-period ($|j|\times|s|$). The z_{ijs} is the number of product square multiplied by the number of micro-periods ($|j|^2\times|s|$). This increment required significant computational time in order to find a feasible solution in MIP solver.

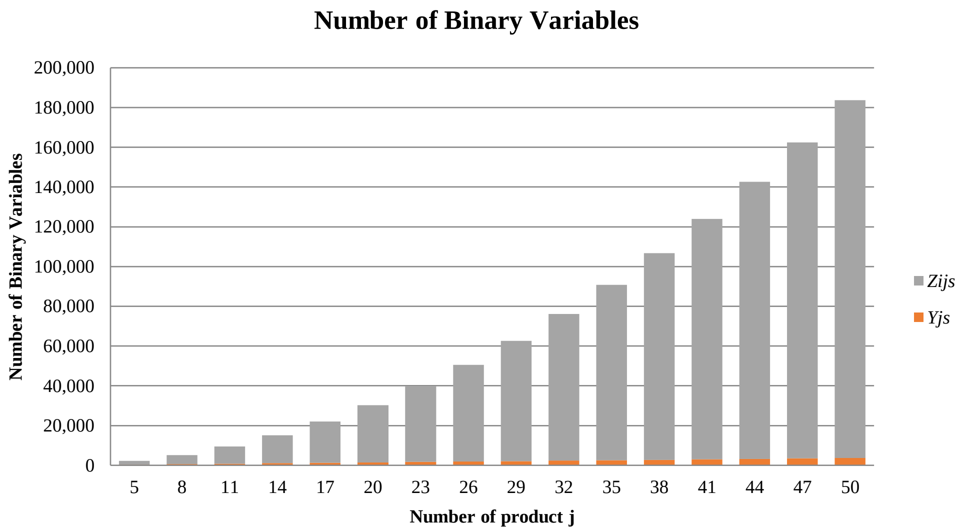

Figure 3-3: The number of binary variables increased from increase production.

A new formulation was proposed to tackle the weak bound, which is caused by fractionality of binary, targeting the set of set-up status (y_{js}) which is the most of fractionality during LP relaxation process by dividing the formulation into 2 parts including pattern generation and production volume calculation.

Another improvement on the proposed formulation is adding external supply to cover the demand that exceeds the capacity and inventory used. External supply will fulfill demand that cannot be satisfied by the inventory and production volume during that period but it will reflect the total cost for the entire solution.

Formulating and Implementing 2-Phase Formulation

The previous formulation has a weak bound on the set of setup binary variables. To tackle this issue, the *General Lotsizing and Scheduling Problem using Two Phases with External Supply* (GLSP-TE) was proposed by separating computation steps into two phases.

First phase of performing approximate optimization was to find a production pattern as shown in Formulation 3.12 to 3.20. Using the following notation to formulate problem:

<u>Set:</u>

S_t	: Set of micro-periods s belonging to macro-period t
J	: Set of products
T	: Set of Macro-Period
S	: Set of Micro-Period

<u>Parameters:</u>

$K_s{}^*$	: Modified Capacity (time) available in micro-period s
a_j	: Capacity consumption (time) needed to produce one unit of j
h_j	: Holding costs of product j (per unit and per macro-period)
C_{jt}	: External supply unit cost of product j in macro-period t
s_{ij}	: Setup costs of changeover from product i to product j
d_{jt}	: Demand of product j in macro-period t (units)
I_{j0}	: Initial inventory of product j at the beginning of the planning horizon (units)
y_{j0}	: Equal to 1 of the machine is set up for product j at the beginning of the planning horizon (0 otherwise)

<u>Variables:</u>

$I_{jt} \geq 0$	: Inventory of product j at the macro-period t (units)
$W_{jt} \geq 0$	: Number of external supply of product j in macro-period t (units)
$x_{js} \geq 0$	: Quantity of item j produced in micro-period s (units)
$y_{js} \in \{0,1\}$	: Setup state: $y_{js} = 1$, if the machine is setup for product j in micro-period s (0 otherwise)
$z_{ijs} \in \{0,1\}$	: Take on 1, if a changeover from product i to product j takes place at the beginning of micro-period s (units)

Phase One : Pattern Generations

$$Min\ z = \sum_{j\in J}\sum_{t\in T} h_j I_{jt} + \sum_{j\in J}\sum_{t\in T} C_j W_{jt} + \sum_{i\in J}\sum_{j\in J}\sum_{s\in S} s_{ij} z_{ijs} \quad (3.12)$$

Subject to:

$$I_{jt} = I_{j,t-1} + \sum_{s} \frac{K_s^*}{a_j} y_{js} + W_{jt} - d_{jt} \quad \forall t \in T, \forall j \in J \quad (3.13)$$

$$\sum_{j\in J} y_{js} = 1 \quad \forall s \in S \quad (3.14)$$

$$z_{ijs} \geq y_{i,s-1} + y_{js} - 1 \quad \forall s \in S, \forall i \in J, \forall j \in J \quad (3.15)$$

$$I_{jt} \geq 0 \quad \forall t \in T, \forall j \in J \quad (3.16)$$

$$W_{jt} \geq 0 \quad \forall t \in T, \forall j \in J \quad (3.17)$$

$$y_{js} \in \{0,1\} \quad \forall s \in S, \forall j \in J \quad (3.18)$$

$$z_{ijs} \in \{0,1\} \quad \forall s \in S, \forall i \in J, \forall j \in J \quad (3.19)$$

The Objective Function (3.12) consists of costs including inventory carrying cost of product j and cost of external supply for product j in macro-period t, and setup cost of change over from product i to product j micro-period s.

The formulation is subject to 3 sets of constraints. First, conservation of flow to determine the inventory of each product j and external supply needed which satisfies demand of product j in macro-period t Constraint 3.13. The $K_s{}^*$ is the modified capacity for each micro-period which is modified to relax real capacity for computing approximate production volume using pre-defined batch size for each product j. The second and third sets are responsible for setup state from product i to product j Constraint 3.14 and Constraint 3.15. For Constraint 3.16 to 3.17 are for non-negativity on variable I_{jt} , W_{jt} The binary constraints are on Constraint 3.18 and Constraint 3.19 on y_{js} and z_{ijs}

After optimizing the first step, the setup state variables (y_{js}) are passed to the second step to be used as a setup state to calculate the amount of production units as in Formulations 3.20 to 3.29, using the following notation to formulate problem:

Set:

S_t	: Set of micro-periods s belonging to macro-period t
J	: Set of products
T	: Set of Macro-Period
S	: Set of Micro-Period

<u>Parameters:</u>

K_t	: Modified Capacity (time) available in macro-period t
a_j	: Capacity consumption (time) needed to produce one unit of j
h_j	: Holding costs of product j (per unit and per macro-period)
C_{jt}	: External supply unit cost of product j in macro-period t
s_{ij}	: Setup costs of changeover from product i to product j
st_{ij}	: Setup time of changeover from product i to product j
d_{jt}	: Demand of product j in macro-period t (units)
I_{j0}	: Initial inventory of product j at the beginning of the planning horizon (units)
y_{j0}	: Equal to 1 of the machine is set up for product j at the beginning of the planning horizon (0 otherwise)

<u>Variables:</u>

$I_{jt} \geq 0$	: Inventory of product j at the macro-period t (units)
$W_{jt} \geq 0$	: Number of external supply of product j in macro-period t (units)
$x_{js} \geq 0$	: Quantity of item j produced in micro-period s (units)
$y_{js} \in \{0,1\}$	: Setup state: $y_{js} = 1$, if the machine is set up for product j in micro-period s (0 otherwise)
$z_{ijs} \in \{0,1\}$	: Take on 1, if a changeover from product i to product j takes place at the beginning of micro-period s (units)

<u>Phase Two: Production Allocation</u>

$$Min\ z = \sum_{j\in J}\sum_{t\in T} h_j I_{jt} + \sum_{j\in J}\sum_{t\in T} C_j W_{jt} + \left(\sum_{i\in J}\sum_{j\in J}\sum_{s\in S} s_{ij} z_{ijs}\right)^{*constant} \quad (3.20)$$

Subject to:

$$I_{jt} = I_{j,t-1} + \sum_{s\in S_t} x_{js} + W_{jt} - d_{jt} \qquad \forall t \in T, \forall j \in J \quad (3.21)$$

$$\sum_{j\in J}\sum_{s\in S_t} a_j x_{js} + \sum_{i\in J}\sum_{j\in J}\sum_{s\in S_t} st_{ij} z_{ijs} \leq K_t \qquad \forall t \in T \quad (3.22)$$

$$z_{ijs} \geq y_{i,s-1} + y_{js} - 1 \qquad \forall s \in S, \forall i \in J, \forall j \in J \quad (3.23)$$

$$I_{jt} \geq 0 \qquad \forall t \in T, \forall j \in J \quad (3.24)$$

$$W_{jt} \geq 0 \qquad \forall t \in T, \forall j \in J \quad (3.25)$$

$$x_{js} \geq 0 \qquad \forall s \in S, \forall j \in J \quad (3.26)$$

The Objective Function in 3.20 considered inventory carrying cost and cost of external supply for product j in each macro-period t, including setup cost for changing product i to product j in micro-period s. The sets of constraints cover demand satisfaction on Constraint 3.21. Capacity consideration takes place on Constraint 3.22 and the switching cost is considered on Constraint 3.23. The minimum lot-size was already considered in the first phase. Constraint 3.24 to Constraint 3.26 are for non-negativity on variable I_{jt} , W_{jt} and x_{js}.

The calculation in each step focuses on different sets of variables. The first phase focuses only the production pattern using the K_s^*, the pre-defined production size. The result from first phase is the blue line in Figure 3-4. The variable that passes to second phase is y_{js} and z_{ijs}. Also, the changeover cost is settled in this phase. After the pattern is calculated in first phase, the second phase determines the production volume x_{js} with inventory carrying cost consideration as shown in green dots in Figure 3-4. The inventory carrying cost is settled in this phase combined with the changeover cost from the first phase which is the total cost consideration in the formulation.

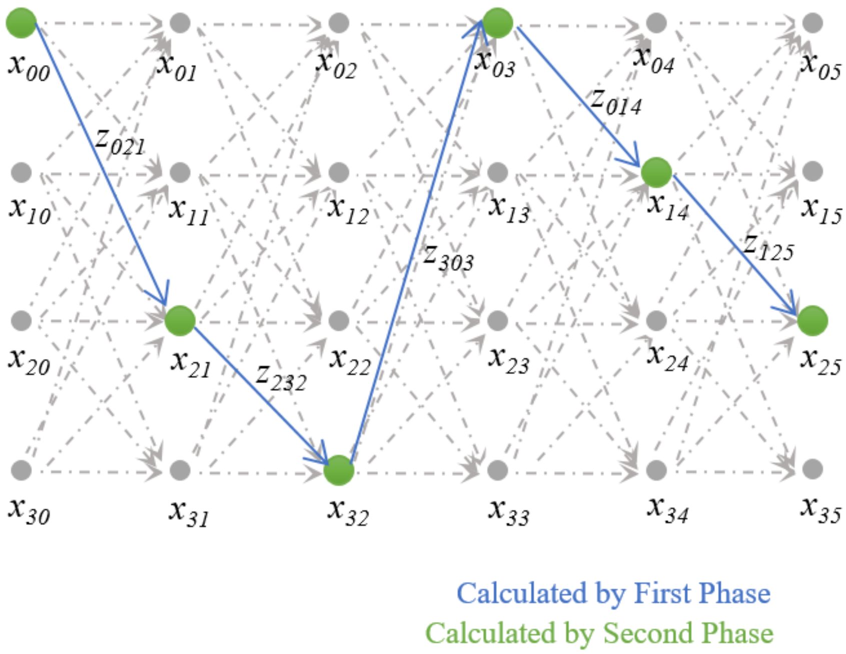

Figure 3-4: Calculations in each phase

Verifying and Validating

Results from the GLSP-TE in step 4 were used in this step to verify and validate the solvability and usability to ensure that GLSP-TE has the appropriate quality for analyzing in next step. The formulation was tested using 8 scenarios on 6 commodities with 720 micro-periods. In the first phase, each scenario was tested on 22 parameters (K_s^*) to adjust for cases including 3 solution gaps.

Analyzing results & Developing report

The last step is the resulting analysis and report development including results on the number of iterations, number of optimal runs, objective function value improvement and computational time.

3.2 Data used

In order to test and analyze the developed model, data used for testing was obtained from random generation including:

- Demand (d_{jt}) as random on normal distribution
- Capacity on s period (K_t) as random on uniform distribution

For constant used in the main problem including;

- Inventory carrying cost for product j (h_j)
- Unit production time for product j (a_j)
- Minimum lot-size of product j (m_j)
- Setup time for changing production from product i to j (st_{ij})

The test scenarios were generated to test the behavior of the GLSP-TE in 8 scenarios grouped into 5 categories.

- <u>Adjacent Demand</u>: The volume of demand in an adjacent period which illustrates that no production is needed in a certain period and build up inventory to satisfy demand in the next period.
    - *Steady*: The demand exists in every period
    - *Interval Demand commodity*: The demand for all commodities is missing in some periods

- <u>Missing Demand</u>: The volume of demand is missing in some periods and some or all commodities which illustrate the skipping of a sequence and build up inventory to satisfy demand in the next period.
    - *No*: No missing demand for all commodities in all periods
    - *Missing Middle demand / Skipped period*: There is missing demand for a commodity in the middle of the sequence and there is a skipped period
    - *One commodity in most periods*: One commodity in the middle of the sequence is missing in most periods
    - *All commodities in the same period*: Missing demand for all commodities in some periods.

- <u>Demand Fluctuation</u>: The fluctuation of demand in all periods which implies the pattern selection can skip a sequence to satisfy the demand when the fluctuation has an effect on the production capacity. Inventory is used to buffer the shortage of capacity in this case. The magnitude of the fluctuation is scaled in 3 levels.
    - *Low*: The ratio of top demand and lowest demand in each period less than 1.5
    - *Moderate*: The ratio of top demand and lowest demand in each period is between 1.6 and 2.2
    - *High*: The ratio of top demand and lowest demand in each period is more than 2.3
    - *Very High*: The ratio of top demand and lowest demand in each period is more than 10

- <u>Demand and Min-Lot:</u> The relation between Demand and Min-Lot which points out the select scheduling pattern that can skip a sequence due to the minimum lot size and inventory carrying is used to satisfy demand in next period. The relation of Demand and Min-Lot can be categorized into:
    - *Above*: All demand in each period will be higher than minimum lot size of each commodity
    - *Under and Above*: All demand in each period can be lower or higher than minimum lot size of each commodity

- <u>Demand and Capacity</u>: The relation between Demand and Production Capacity which signal the buildup of inventory to satisfy demand before the overcapacity demand period. The relation of Demand and Capacity can be categorized into:
    - <u>*Related*</u>: The demand in every single period is under production capacity.
    - <u>*No-Related*</u>: The demand in some periods can be over production capacity.

<u>Scenario 1 (SCN1)</u>

This scenario is the normal scenario in which the demand is steady with no missing demand. The fluctuation of the demand is low, all demand is over min-lot and there is sufficient capacity to satisfy demand. This scenario is the ideal behavior that has everything in control. The expectation of this to show that the GLSP-TE can improve performance in the normal scenario.

Scenario 2 (SCN2)

SCN2 is a scenario that can happen in a real situation. Adding missing demand in the middle sequence and skipped period into the normal scenario (SCN1) can add more complexity into the model. The model needs to make a trade-off between switching cost that has skipped a sequence and inventory carrying cost on production in respect to the sequence and to keep it to satisfy demand in the next period. The production pattern can be shifted to satisfy demand while the skipped demand is not reached by production sequence to avoid the production for storage and switching cost for the skipped sequence.

Scenario 3 (SCN3)

The SCN3 is the more complex than SCN2 due to the skipped demand which occurs in one commodity in most periods. The missing pattern forces the switching cost for the skipped sequence to happen. The model needs to consider the branching between skipping the sequence or production of stock. This is a trade-off between switching cost and inventory carrying cost.

Scenario 4 (SCN4)

The SCN4 is the extreme case. The missing demand for all commodities in the same period is the obvious case but for the formulation that allows to maintain switching stage in idle time which might not impact the complexity of the formulation. The test also adds more fluctuation in this case to add more complexity into the test.

Scenario 5 (SCN5)

The SCN5 is the scenario that tests the GLSP-TE in the fluctuation situation. The level or fluctuation is “high” with the possibility of overcapacity, while the other parameters are still in control. The Adjacent demand is steady, there is no missing demand, and all demand exceeds the minimum lot size. The decision is majority on what commodity should be produced and kept in inventory to satisfy demand in the next period.

Scenario 6 (SCN6)

The SCN6 is the scenario that tests the GLSP-TE in the moderate level of fluctuation. The level or fluctuation is “moderate” with the possibility of overcapacity, while the other parameters are still in control. The Adjacent demand is steady, there is no missing demand, and all demand exceeds the minimum lot size. The decision is which commodity should be produced and kept in inventory to satisfy demand in the next period.

Scenario 7 (SCN7)

The SCN7 is the scenario that tests the GLSP-TE in the high level of fluctuation. The demand can be under the minimum lot size and overcapacity might occur. The level or fluctuation is “high”. The Adjacent demand is steady, there is no missing demand, and some demand can be under the minimum lot size. The decision is which commodity should be produced to be kept in inventory to satisfy demand in the next period and what commodity should be skipped due to the minimum lot size.

Scenario 8 (SCN8)

The SCN8 is the scenario that tests the GLSP-TE in the high level of fluctuation. The demand can be under the minimum lot size and overcapacity might occur. The level or fluctuation is “very high”. The Adjacent demand is steady, there is no missing demand, and some demand can be under the minimum lot size. The decision is which commodity should be produced to be kept in inventory to satisfy demand in the next period and what commodity should be skipped due to the minimum lot size.

3.3 Tools and technology used

This study used the IBM CPLEX Optimizer x64 v.12.4.0 to solve the Mixed Integer Linear Programming (MILP). In the implementation of the model, C# on Visual Studio 2012 with .NET framework 4.0 in a 64 bits environment was used. In the .NET environment, the IBM ILOG Concert Technology was used as the interface for wrapping IBM CPLEX functionality into .NET class in the C# environment. All tests were performed on IBM compatible PC with an intel i7 3770 processer, which has 4 cores with hyper thread technology to perform 8 threads with 3.9GHz maximum frequency. The memory capacity of the machine is 16GB RAM and 1TB Storage to swap the memory. Assessment of the stated hardware and software was done to ensure that the proposed formulation could be performed and be tractable and solvable in practical situations.

Chapter 4

Results

The GLSP was tested using 8 scenarios with 5 angles Adjacent Demand, Missing Demand, Demand Fluctuation, Demand and Min-Lot. Finally, Demand and Capacity were also determined as shown in Table 4-1.

Each scenario was tested with the same parameters. The adjusted K_s^*, the Modified Capacity in Micro-period s, was scaling from min-lot more than two times of the min-lot itself in 22 values to test the solvability and tractability of proposed model.

The K_s^* was initiated as a pre-defined lot-size of each commodity used in the first phase to determine the production pattern and pass the production pattern to second phase to calculate the real production volume in each Micro-period with lot-size consideration.

Table 4-1: Testing Scenarios

Scenario Code	Adjacent Demand	Missing Demand	Demand Fluctuation	Demand and Min-Lot	Demand and Capacity
SCN1	Steady	No	Low	Above	Related
SCN2	Steady	Missing middle demand/ Skipped period	Low	Above	Related
SCN3	Steady	One commodity in almost all periods	Low	Above	Related
SCN4	Interval Demand commodity	All commodity in some periods	Moderate	Above	Related
SCN5	Steady	No	High	Above	Not-related
SCN6	Steady	No	Moderate	Above	Not-related
SCN7	Steady	No	High	Under and Above	Not-related
SCN8	Steady	No	Very High	Under and Above	Not-related

4.1 Model Validity

The GLSP-TE was tested by reducing the size of problem to make sure that GLSP-TE could provide the same optimal quality as GLSP. The reduced size of the problem contains three commodities with three Macro-Periods with a total of nine Micro-Periods. The same objective value was reached by both of GLSP and GLSP-TE, which can validate that GLSP-TE can provide the same optimal quality as GLSP. The Computational time improved 17.65% and the number of iterations improved 17.88% as shown in Figure 4-1.

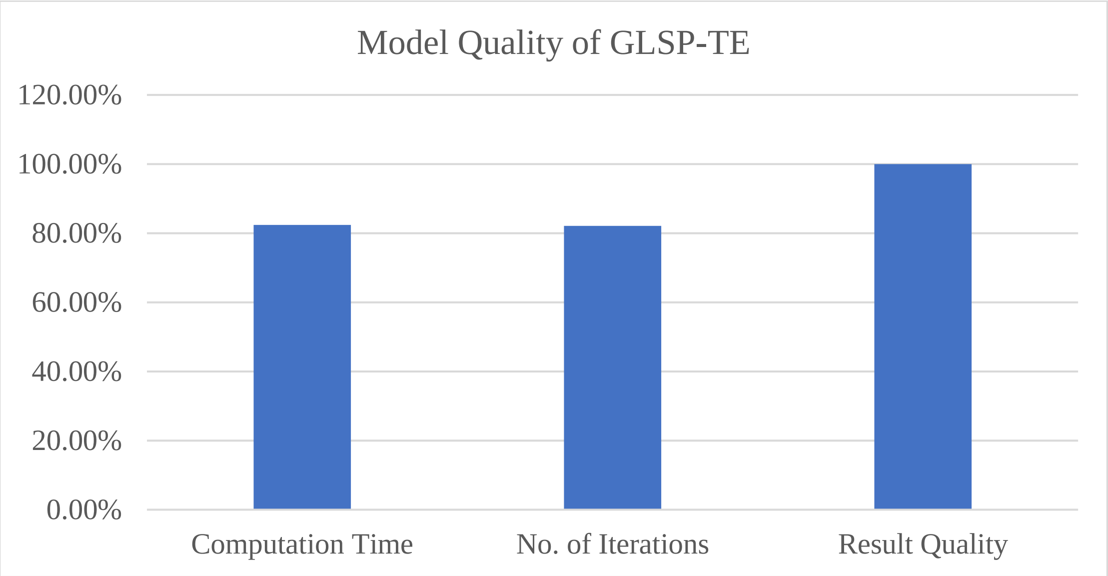

Figure 4-1: Model Quality of GLSP-TE

4.2 Results by Test Scenario

<u>Scenario 1 (SCN1)</u>

In this scenario, the demand is steady with no missing demand. The fluctuation of the demand is low, all demand is over min-lot and there is sufficient capacity to satisfy demand.

The runs on Scenario 1 have a minimum time of 0.06 hours. The first quantile is 0.43 hours, the median is 0.78 hours, the third quantile is 2.01 hours and the maximum time is 2.07 hours as shown in Table 4-2.

The distribution of iterations can be grouped into 2 sets with less time consumption and near timeout set. Most of the runs have less time consumption as shown in Figure 4-2, which means that majority of the test runs found the optimal solution within a 5% gap in a defined timeout. The results also show that 86% of runs reach the optimality as seen in Figure 4-3. Finally, the optimal result improved from GLSP about 40% as shown in Figure 4-18.

Table 4-2: Computational time Result for Scenario 1

	Computational Time
MIN	0.06
Q1	0.43
Median	0.78
Q3	2.01
Max	2.07

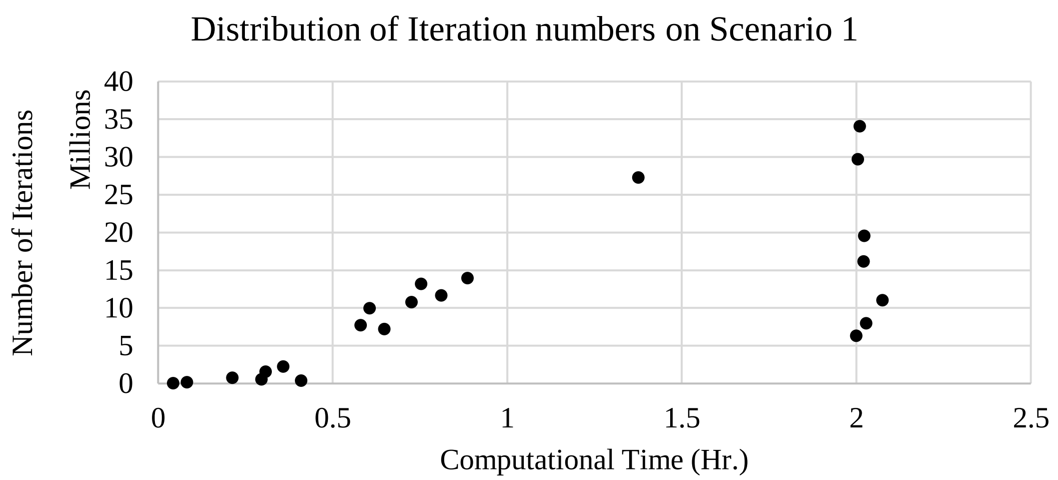

Figure 4-2: Distribution of Iteration numbers on Scenario 1

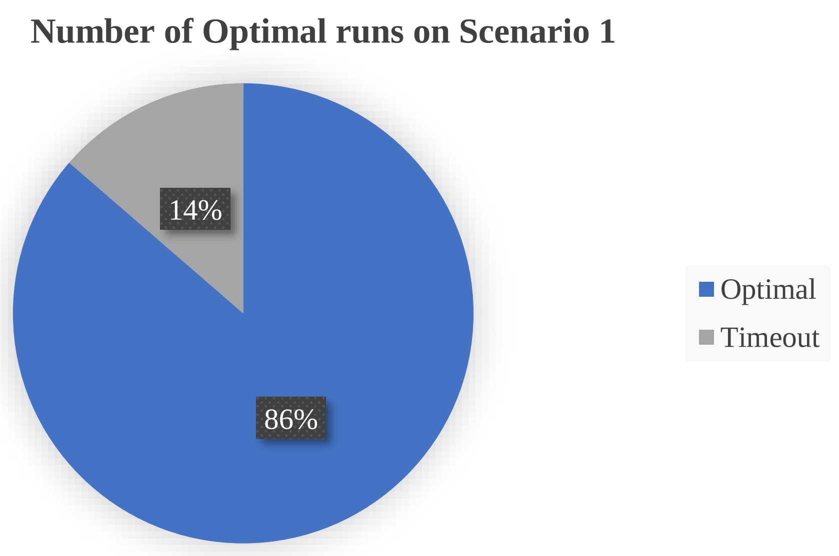

Figure 4-3: Number of Optimal runs on Scenario 1

Scenario2 (SCN2)

For Scenario 2, the missing demand occurred in the middle of a sequence and there is a skipped period.

The runs on Scenario 2 have a minimum time of 0.23 hours, the first quantile is 0.70 hours, the median is 1.12 hours, the third quantile is 2.01 hours and the maximum time is 2.04 hours as shown in Table 4-3.

The distribution of iterations can be grouped into 2 sets with less time consumption and near timeout set. Most of the runs have less time consumption as shown in Figure 4-4, which means that the majority of the test runs found the optimal solution within a 5% gap in a defined timeout. The results also show that 82% of runs reach the optimality as seen in Figure 4-5. Finally, the optimal result improved from GLSP about 35% as shown in Figure 4-18.

Table 4-3: Computational time Result for Scenario 2

	Computational Time
MIN	0.23
Q1	0.70
Median	1.12
Q3	2.01
Max	2.04

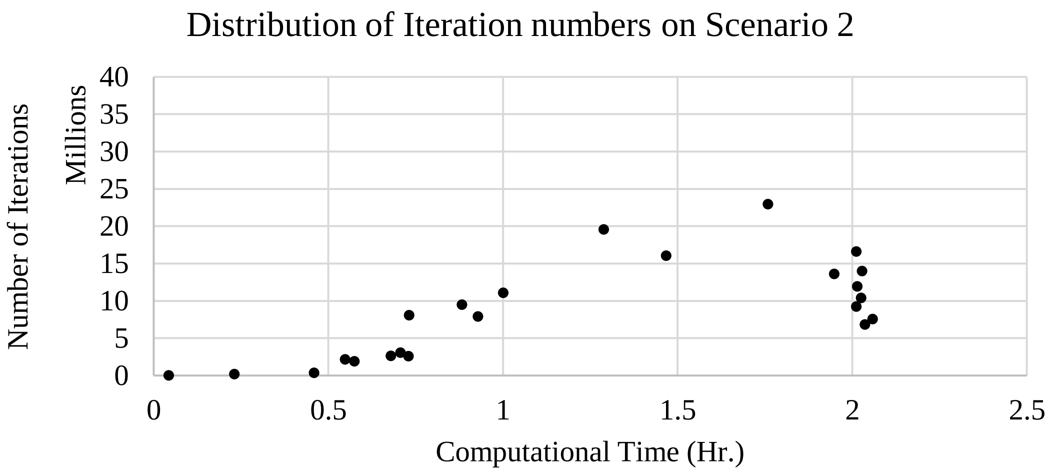

Figure 4-4: Distribution of Iteration numbers on Scenario 2

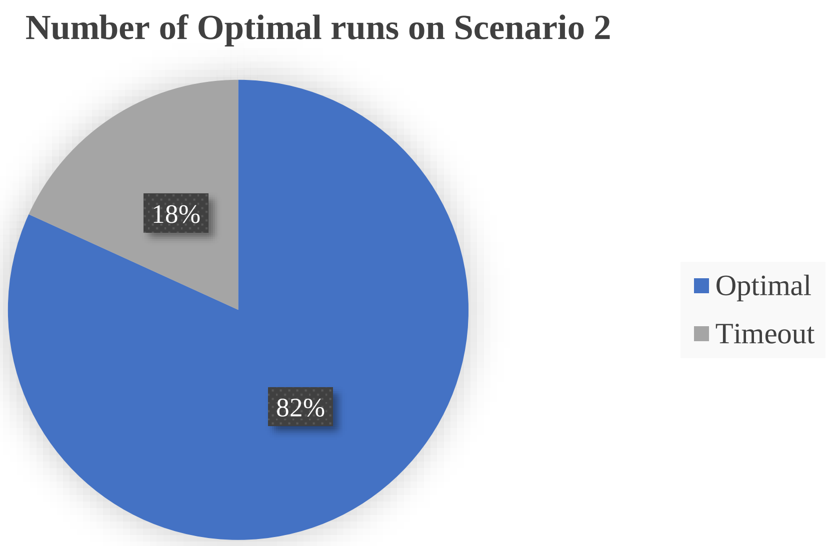

Figure 4-5: Number of Optimal runs on Scenario 2

Scenario3 (SCN3)

In this scenario, the skipped demand occurs in one commodity in most periods. The runs on Scenario 3 have a minimum time of 0.08 hours, the first quantile is 0.63 hours, the median is 1.47 hours, the third quantile is 2.08 hours and the maximum time is 2.18 hours as shown in Table 4-4.

The distribution of iterations can likely be spread along the defined timeout with more runs that reach the timeout as shown in Figure 4-6, which means that the majority of the test runs found the optimal solution within a 5% gap in a defined timeout. The results also show that 68% of runs reach the optimality as seen in Figure 4-7. Finally, the optimal result improved from GLSP about 42% as shown in Figure 4-18.

Table 4-4: Computational time Result for Scenario 3

	Computational Time
MIN	0.08
Q1	0.63
Median	1.47
Q3	2.08
Max	2.18

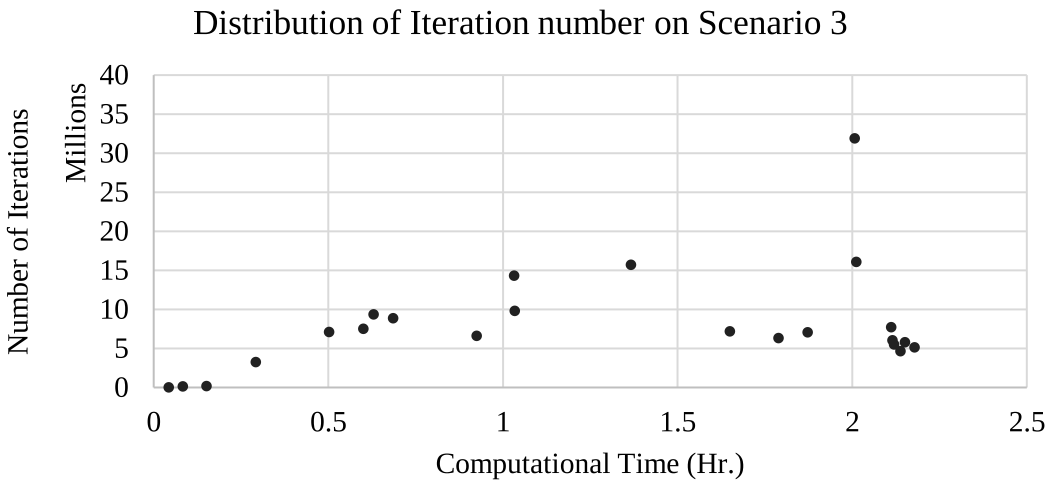

Figure 4-6: Distribution of Iteration on Scenario 3

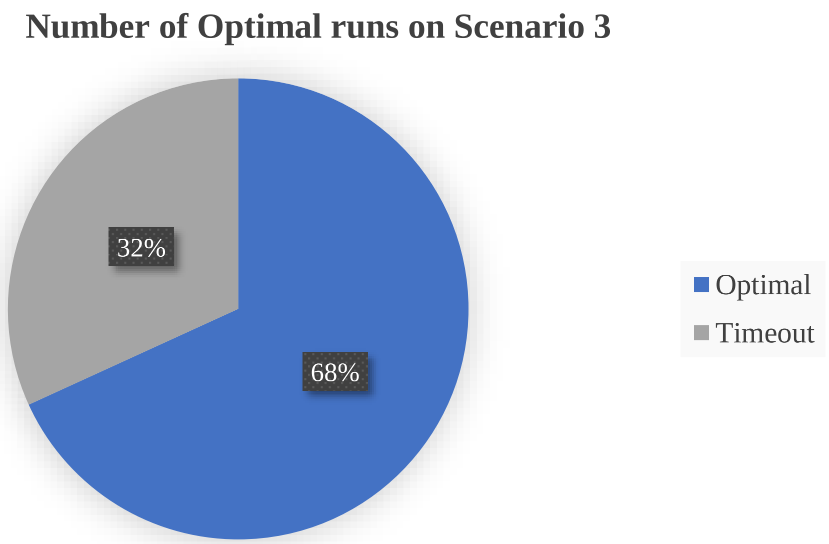

Figure 4-7: Number of Optimal runs on Scenario 3

<u>Scenario4 (SCN4)</u>

In this scenario, the missing demand for all commodities in the same period is the obvious case.

The runs on Scenario 4 have a minimum time of 0.34 hours, the first quantile is 1.05 hours, the median is 1.95 hours, the third quantile is 2.14 hours and the maximum time is 2.20 hours as shown in Table 4-5.

The distribution of iterations can likely be spread along the defined timeout with more runs that reach the timeout as shown in Figure 4-8, which means that the majority of the test runs still found the optimal solution within a 5% gap in a defined timeout. The results also show that 55% of runs reach the optimality as seen in Figure 4-9. Finally, the optimal result improved from GLSP about 18% as shown in Figure 4-18.

Table 4-5: Computational time Result for Scenario 4

	Computational Time
MIN	0.34
Q1	1.05
Median	1.95
Q3	2.14
Max	2.20

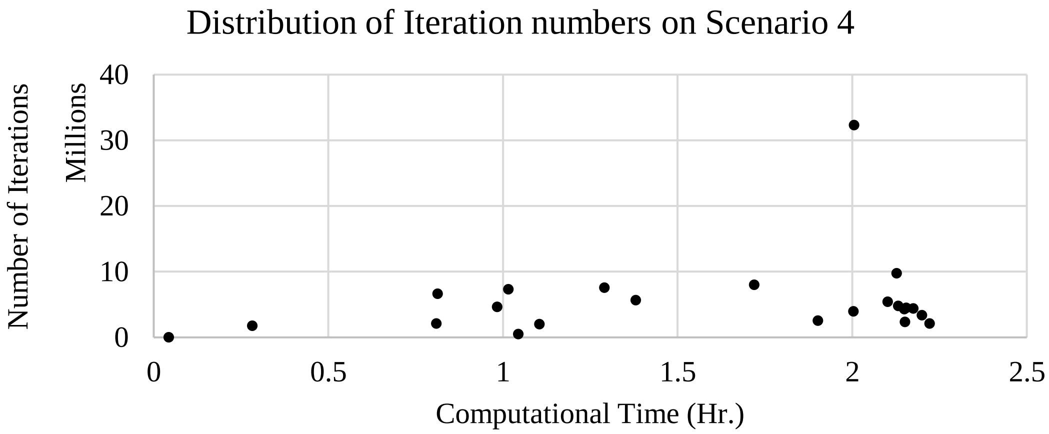

Figure 4-8: Distribution of Iteration numbers on Scenario 4

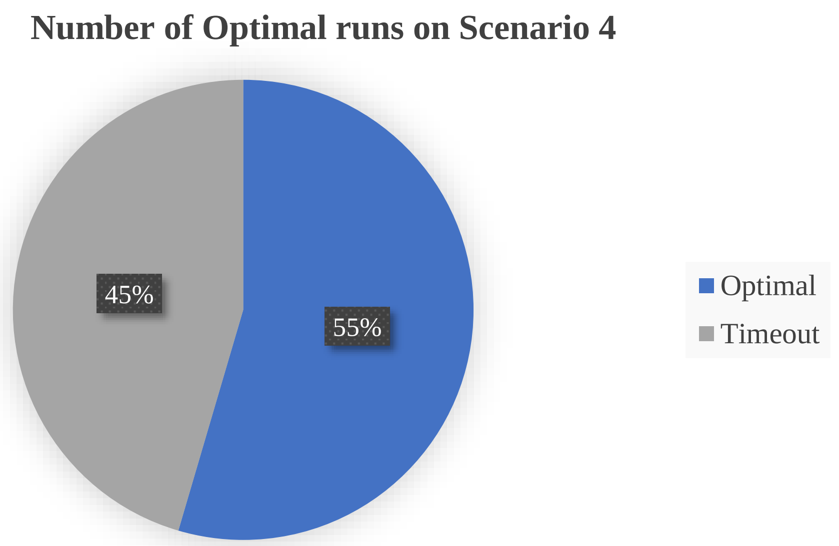

Figure 4-9: Number of Optimal runs on Scenario 4

<u>Scenario5 (SCN5)</u>

In this scenario, the level or fluctuation is “high” with the possibility of overcapacity. The runs on Scenario 5 have a minimum time of 0.15 hours, the first quantile is 1.23 hours, the median is 1.79 hours, the third quantile is 2.14 hours and the maximum time is 2.19 hours as shown in Table 4-6.

The distribution of iterations can be spread along the defined timeout with about the half of runs reaching the timeout as shown in Figure 4-10, which means that about the half of the runs could find the optimal solution within a 5% gap in a defined timeout. The results also show that 50% of runs reach optimality as seen in Figure 4-11. Finally, the optimal result improved from GLSP about 6% as shown in Figure 4-18.

Table 4-6: Computational time Result for Scenario 5

	Computational Time
MIN	0.15
Q1	1.23
Median	1.79
Q3	2.14
Max	2.19

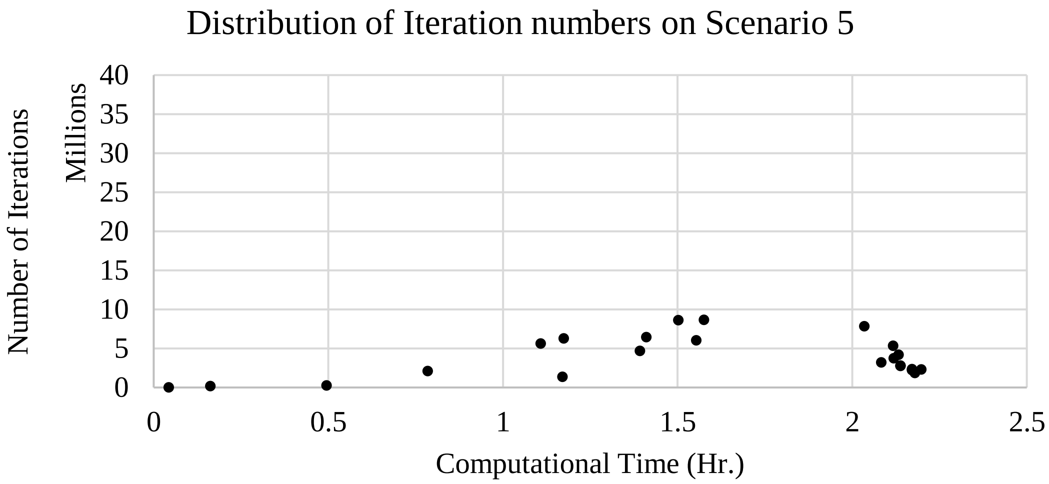

Figure 4-10: Distribution of Iteration numbers on Scenario 5

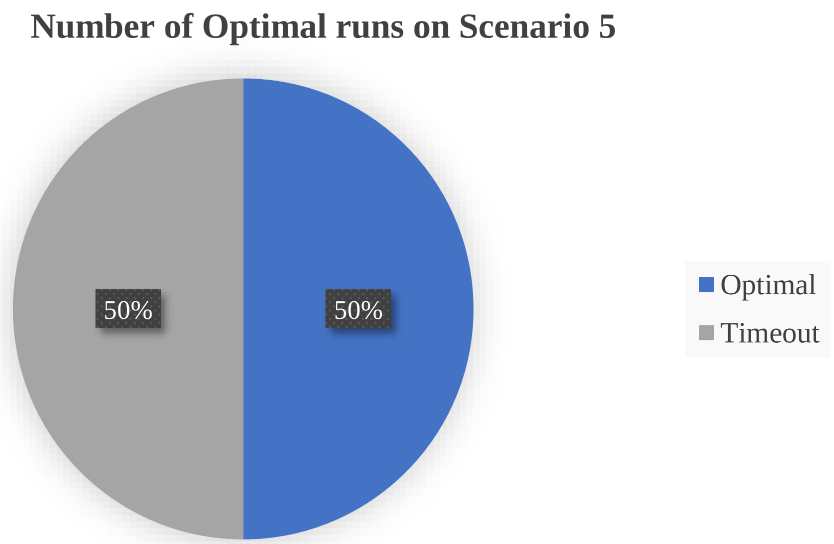

Figure 4-11: Number of Optimal runs on Scenario 5

<u>Scenario6 (SCN6)</u>

Scenario 6 has moderate level of fluctuation with the possibility of overcapacity. The runs on Scenario 6 have a minimum time of 0.16 hours, the first quantile is 1.34 hours, the median is 2.01 hours, the third quantile is 2.14 hours and the maximum time is 2.22 hours as shown in Table 4-7.

The distribution of iterations shows that more runs reached the timeout as shown in Figure 4-12, which means that the majority of the test runs only found a feasible solution in a defined timeout. The results also show that 45% of runs reach optimality as seen in Figure 4-13. Finally, the optimal result did not improve from GLSP as shown in Figure 4-18.

Table 4-7: Computational time Result for Scenario 6

	Computational Time
MIN	0.16
Q1	1.34
Median	2.01
Q3	2.14
Max	2.22

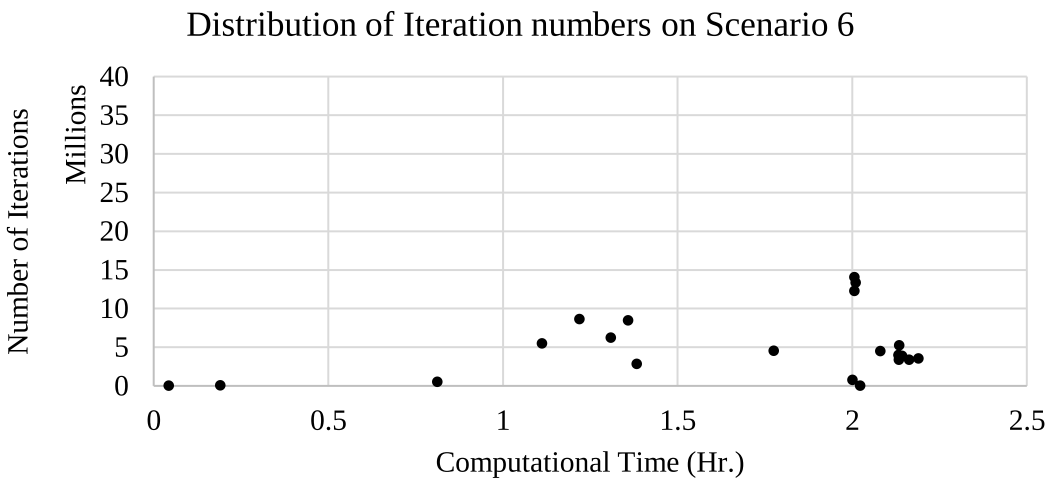

Figure 4-12: Distribution of Iteration numbers on Scenario 6

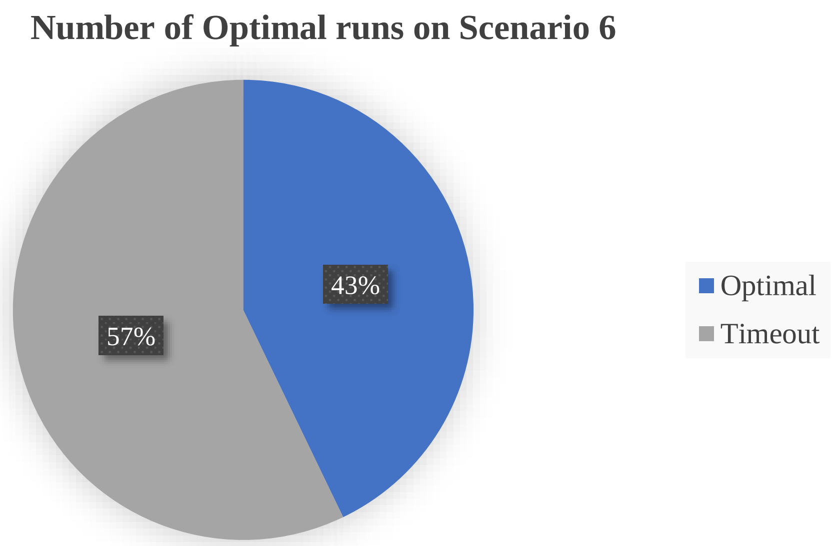

Figure 4-13: Number of Optimal runs on Scenario 6

Scenario7 (SCN7)

In this scenario, which has a high level of fluctuation, the demand can be under the minimum lot size and overcapacity might occur. The runs on Scenario 7 have a minimum time of 0.30 hours, the first quantile is 0.50 hours, the median is 0.85 hours, the third quantile is 1.21 hours and the maximum time is 2.06 hours as shown in Table 4-8.

The distribution of iterations is clustered in less than the defined timeout as shown in Figure 4-14, which means that the majority of the test runs still found the optimal solution within a 5% gap in a defined timeout. The results also show that 95% of runs reach the optimality as seen in Figure 4-15. Finally, the optimal result improved from GLSP about 67% as shown in Figure 4-18.

Table 4-8: Computational time Result for Scenario 7

	Computational Time
MIN	0.30
Q1	0.50
Median	0.85
Q3	1.21
Max	2.06

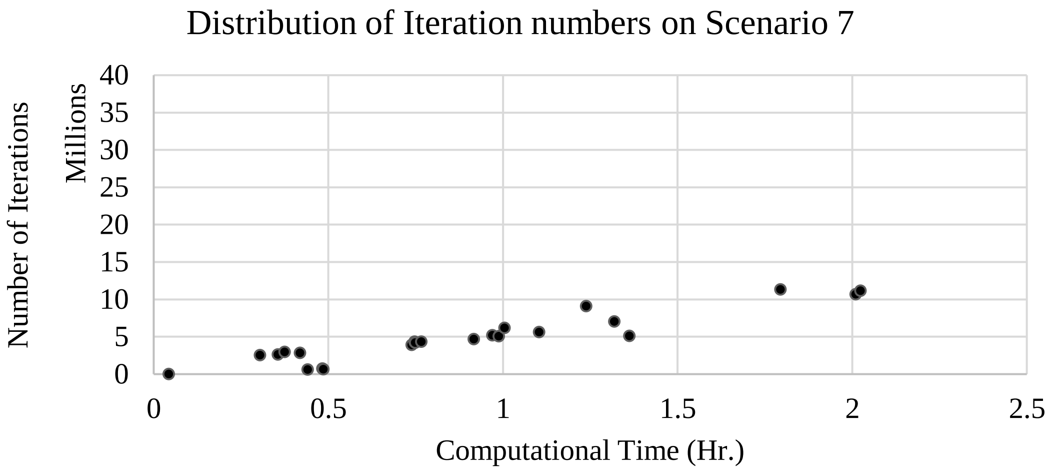

Figure 4-14: Distribution of Iteration numbers on Scenario 7

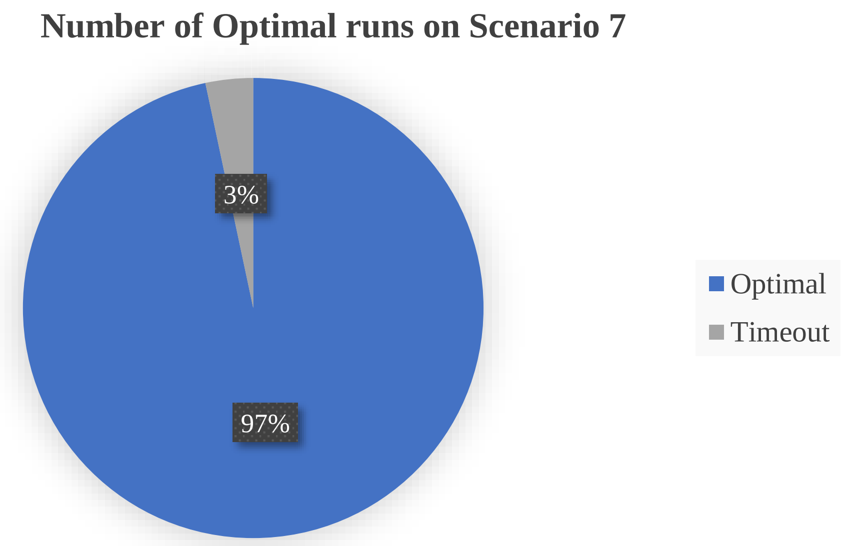

Figure 4-15: Number of Optimal runs on Scenario 7

<u>Scenario8 (SCN8)</u>

In Scenario 8, the level or fluctuation is “high” with some demand under the minimum lot size. The runs on Scenario 8 have a minimum time of 0.09 hours, the first quantile is 0.27 hours, the median is 0.44 hours, the third quantile is 0.97 hours and the maximum time is 2.12 hours as shown in Table 4-9.

The distribution of iterations is clustered in less than the defined timeout as shown in Figure 4-16, which means that the majority of the test runs still found the optimal solution within a 5% gap in a defined timeout. The results also show that 91% of runs reach optimality as seen in Figure 4-17. Finally, the optimal result improved from GLSP about 70% as shown in Figure 4-18.

Table 4-9: Computational time Result for Scenario 8

	Computational Time
MIN	0.09
Q1	0.27
Median	0.44
Q3	0.97
Max	2.12

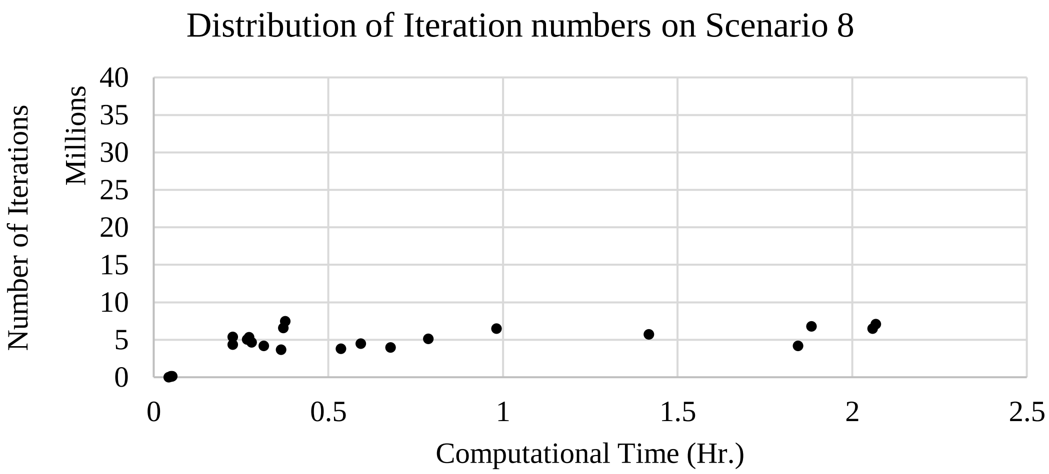

Figure 4-16: Distribution of Iteration numbers on Scenario 8

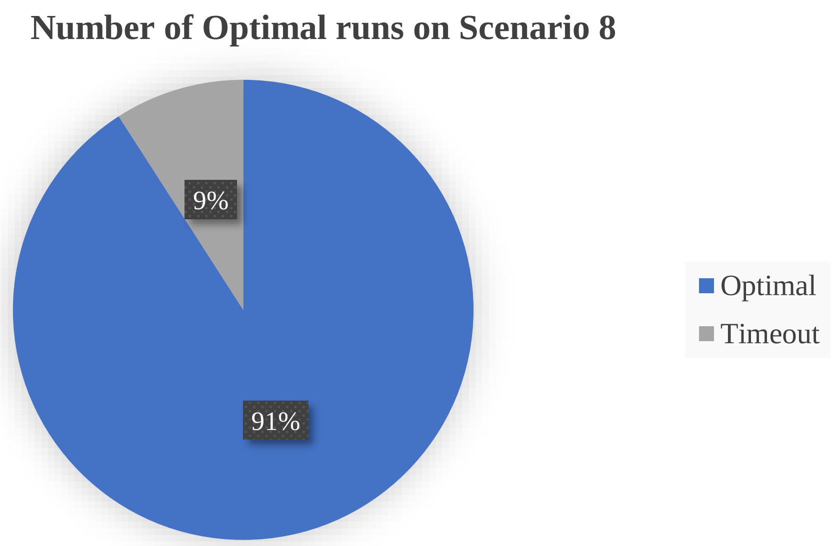

Figure 4-17: Number of Optimal runs on Scenario 8

4.3 Model Results

In this section, the GLSP-TE tested the improvement by running the optimization with 2 hours timeout and a 5% solution gap on the same settings of software and hardware. Phase One was tested by sampling $K_s{}^*$ up to 22 values in each run. The production pattern was passed to Phase Two to do the final calculation, using the average of the objective function value compared with the objective function value of GLSP in each scenario.

Most of the runs of GLSP do not reach optimality before timeout but a feasible solution can be found, except SCN5, in which the optimal solution can be reached. The GLSP-TE improved on SCN SCN1, SCN2, SCN3, SCN4, SCN5, SCN7, and SCN8, which improved to 40%, 36%, 43%, 15%, 5%, 69%, and 72%, respectively, as shown in Fig 4-27. Only SCN6 did not have an improvement of the objective function value.

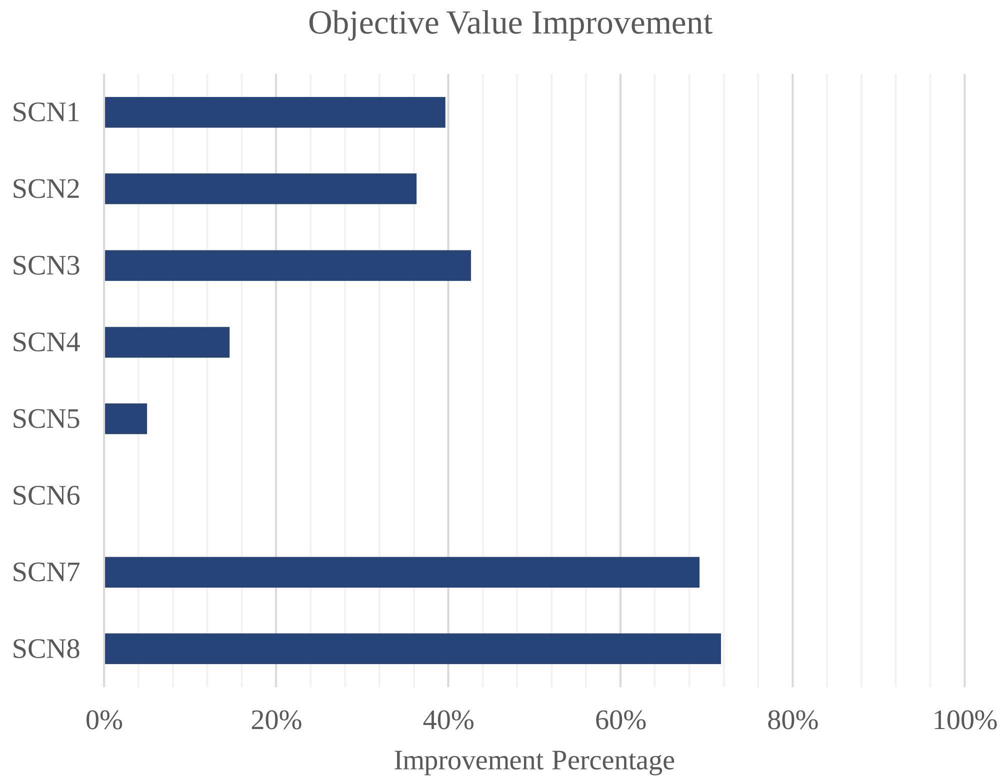

Figure 4-18: Objective Value Improvement

4.4 Model Stress Test

The stress test of the GLSP and GLSP-TE tested the worst and best scenarios, the sixth scenario (SCN6) and the eighth scenario (SCN8). The tests were performed in 2 sets, first, a scaling product from 4 products to 30 products, and second, scaling number of a micro-period from 4 to 24 micro-periods in each macro-period in the scenarios that have 4 products. Both used a 2 hours timeout and 5% solution gap except K_S^*, which has only GLSP-TE which used 10 parameters and the best result for comparison.

The GLSP result in first set shows the timeout with more than a 99% gap for all runs but GLSP-TE can perform most of the runs in optimality in SCN6 and all optimality in SCN8 as shown in Figure 4-19 and Figure 4-20.

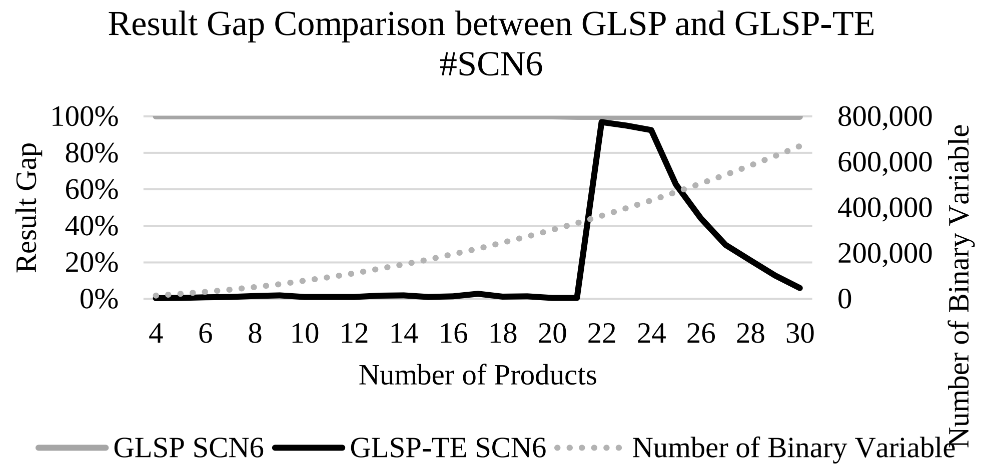

Figure 4-19: Result Gap Comparison between GLSP and GLSP-TE on SCN6

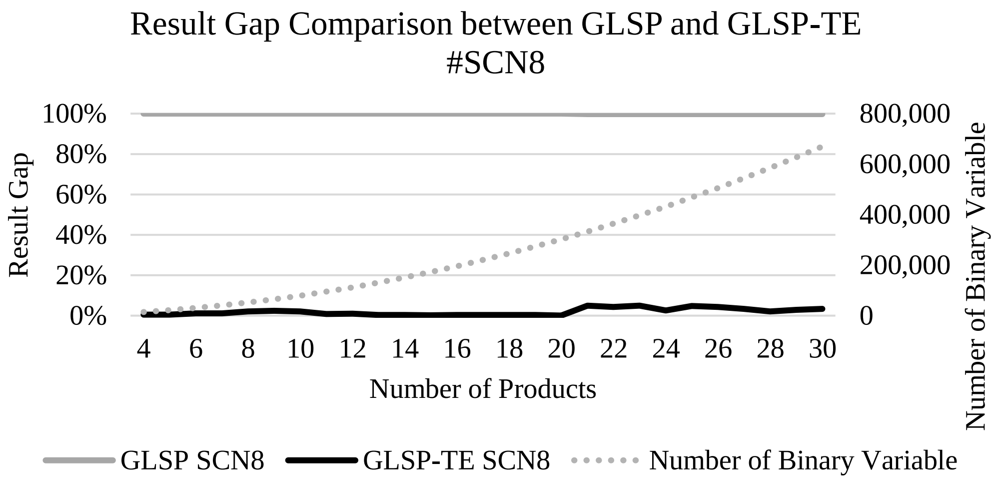

Figure 4-20: Result Gap Comparison between GLSP and GLSP-TE on SCN8

The second set shows that GLSP in SCN6 cannot reach the optimal solution for all runs. For SCN8, the runs that have total binary variable less than 10,000 variables can perform the optimality, but the GLSP-TE can perform all runs up to the optimality stage as shown in Figure 4-21 and Figure 4-22.

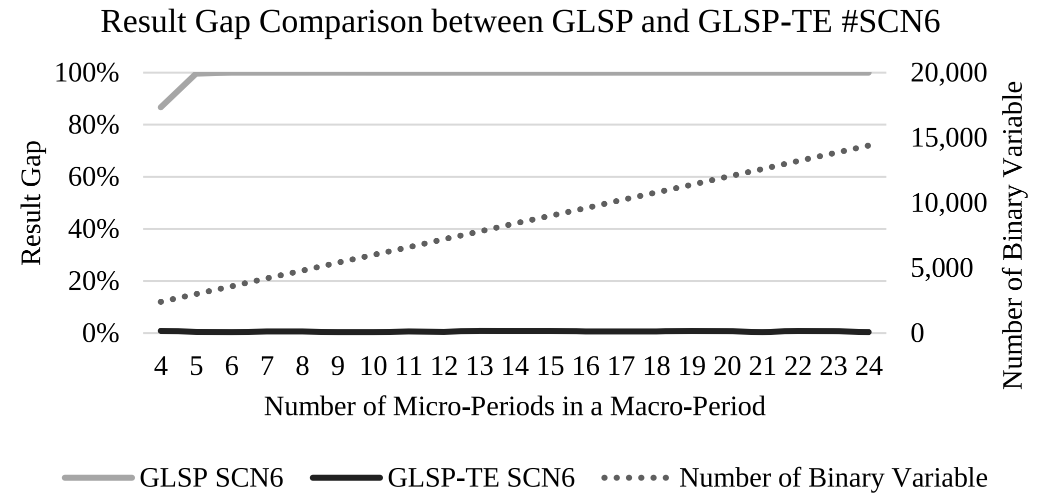

Figure 4-21: Result Gap Comparison between GLSP and GLSP-TE on SCN6

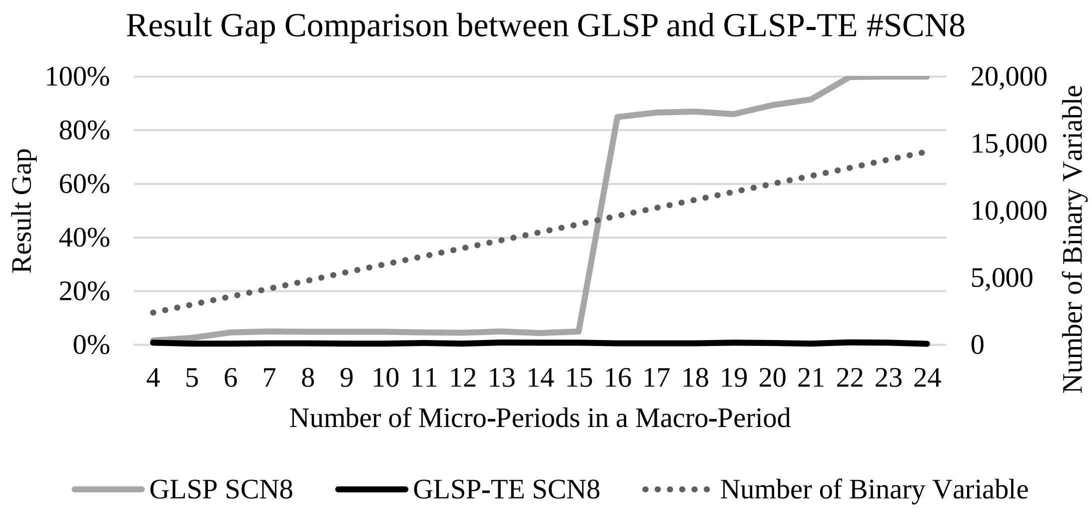

Figure 4-22: Result Gap Comparison between GLSP and GLSP-TE on SCN8

In summary, the GLSP-TE was validated by performing calculations compared with GLSP(Fleischmann & Meyr, 1997) in a reduced problem. The result is GLSP-TE performs with the same optimality result as GLSP(Fleischmann & Meyr, 1997) but uses less computational time and a lower number of iterations. The result from these scenarios also shows that in most of the runs the GLSP-TE can perform better in terms of computational time, percentage of optimality runs and percentage of objective value improvement compared with GLSP(Fleischmann & Meyr, 1997).

Chapter 5

Conclusions

In this chapter, the results by scenario from the previous chapter were used to analyze the results of GLSP-TE compared with GLSP(Fleischmann & Meyr, 1997) to draw conclusions on the proposed formulation (GLSP-TE) in terms of improvement from GLSP, limitations and gaps for further study. This chapter includes 3 parts, Performance categories, Discussion and Gaps for further study.

5.1 Performance categories

The results of all scenarios are shown in 3 categories: Computational Time, Objective function value improvement and Percentage of optimal runs as shown in Table 5-1. The computational time shows brief time consumed in runs with the minimum runtime, the first quantile, the median, the third quantile and the maximum runtime to reflect the behavior of the GLSP-TE.

Table 5-1: Computational Results of all Scenarios

	SCN1	**SCN2**	**SCN3**	**SCN4**	**SCN5**	**SCN6**	**SCN7**	**SCN8**
						Computational Time (Hr.)		
MIN	0.06	0.23	0.08	0.34	0.15	0.16	0.30	0.09
Q1	0.43	0.70	0.63	1.05	1.23	1.34	0.50	0.27
Median	0.78	1.12	1.47	1.95	1.79	2.01	0.85	0.44
Q3	2.01	2.01	2.08	2.14	2.14	2.14	1.21	0.97
Max	2.07	2.04	2.18	2.20	2.19	2.22	2.06	2.12
Objective Function Value							**improvement from GLSP*	
Improvement	40%	36%	43%	15%	5%	0%	69%	72%
Optimality Results							**compared with all runs in scenario*	
% of Optimality	86%	82%	68%	55%	50%	43%	97%	91%

A comparison of the results in each scenario is described in this section. The outcome can be grouped in 3 classes according to the distribution of iteration number, the objective value improvement, the value of the median, the value of the first quantile, the value of the third quantile and the percentage of optimal result, which are shown in Figure 5-1, Figure 5-2, Figure 5-3, Figure 5-4, Figure 5-5 and Figure 5-6, respectively.

The first class, in which GLSP-TE showed its best result, contains SCN7 and SCN8. The model was able to calculate the optimal solution with improvement from GLSP at 69% (SCN7) and 72% (SCN8) as shown in Figure 5-2. The computational time of this class is better than others. The distribution of the iteration and computation time, which is shown in Figure 5-1 annotated as "Green Dot," has low iterations and computational time used in calculation. The percentage optimal results are also low at 97% (SCN7) and 91% (SCN8) as shown in Figure 5-6.

The second class is the class in which GLSP-TE was able to perform with a good result and contains SCN1, SCN2 and SCN3. The model was able to calculate the optimal solution with improvement from GLSP at 40% (SCN1), 36% (SCN2) and 43% (SCN3) as shown in Figure 5-2. The computational time of this class was up to timeout but the median and the first quantile were better than the third class. The distribution of the iteration and computational time, which is shown in Figure 5-1 annotated as "Yellow Rectangle," shows that the distribution of the computational time is spread in the defined timeout range. The percentage of the optimal results are 86% (SCN1) 82% (SCN2) and 68% (SCN3) as shown in Figure 5-6.

The third class is the class, in which GLSP-TE was able to perform with a moderate result, contains SCN4, SCN5 and SCN6. The model improved the optimal result from GLSP at 15% (SCN4), 5% (SCN5) with no improvement on SCN6 as shown in Figure 5-2. The computational times of this class are mostly up to the defined timeout, which is shown in Figure 5-1 annotated as "Red Triangle." Also the median, the first quantile and the third quantile are very high. The percentage of the optimal results is 55% (SCN4), 50% (SCN5) and 43% (SCN6) as shown in Figure 5-6.

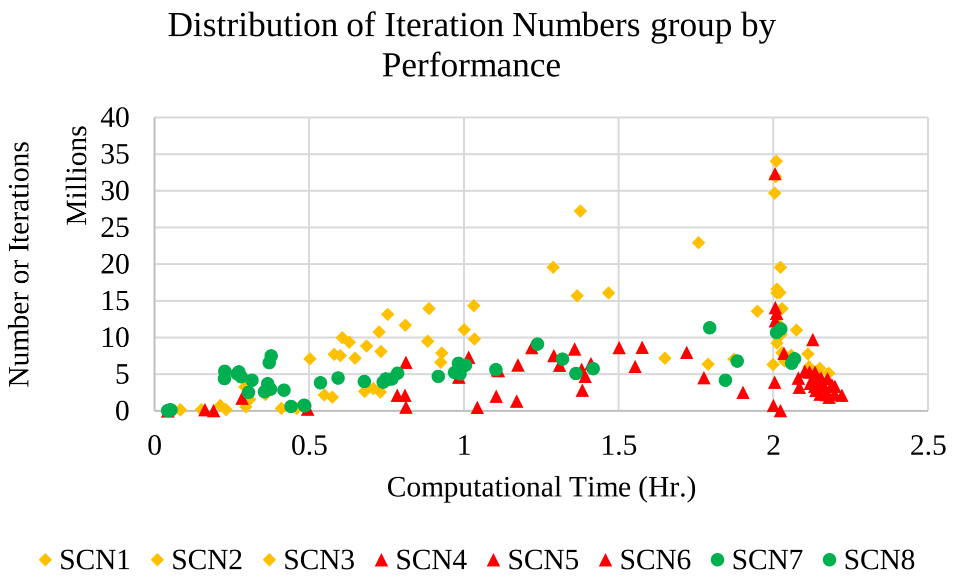

Figure 5-1: Distribution of Iteration Numbers group by Performance

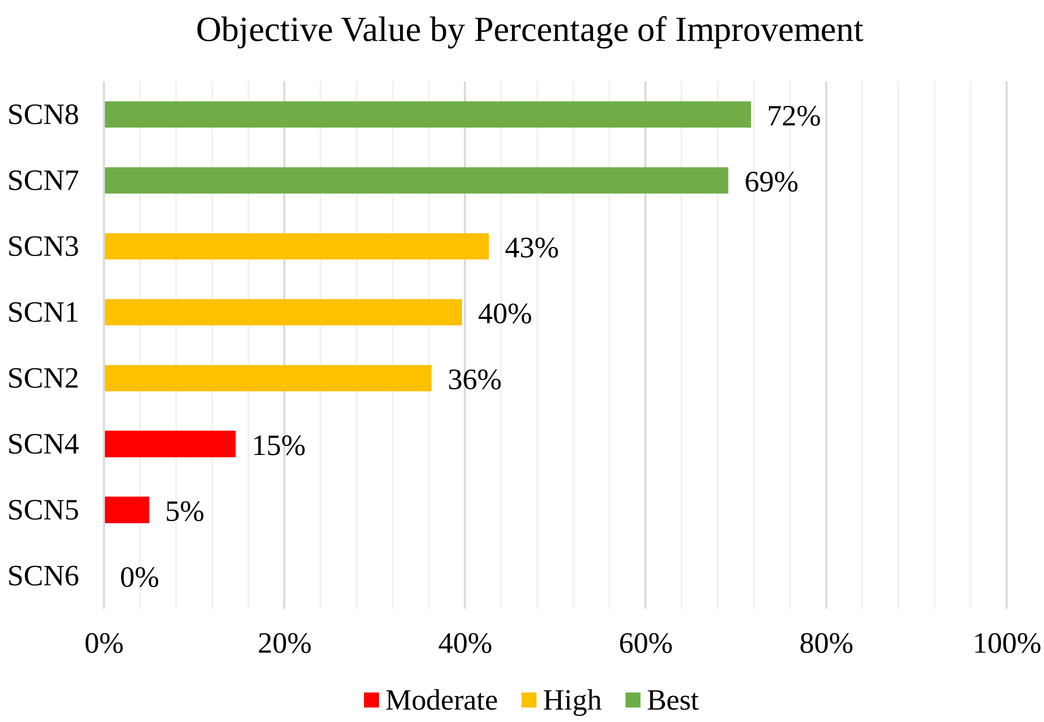

Figure 5-2: Objective Value by Percentage of Improvement

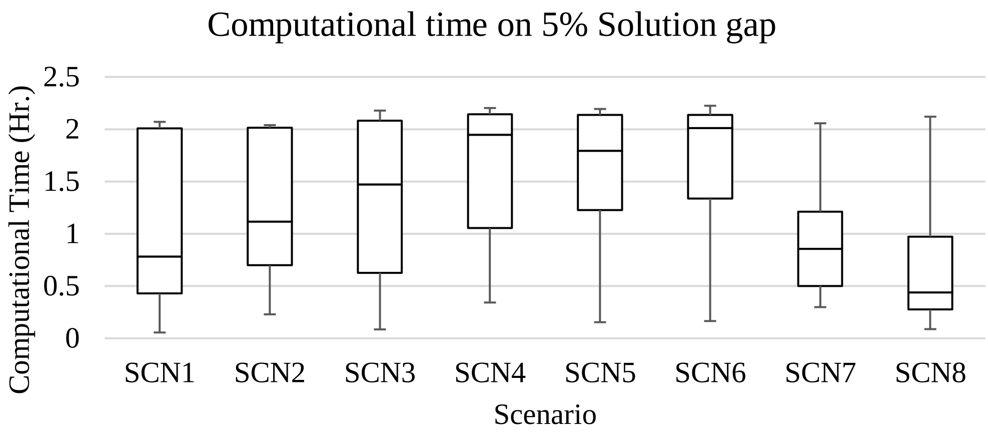

Figure 5-3: Computational time on each scenario using 5% solution gap

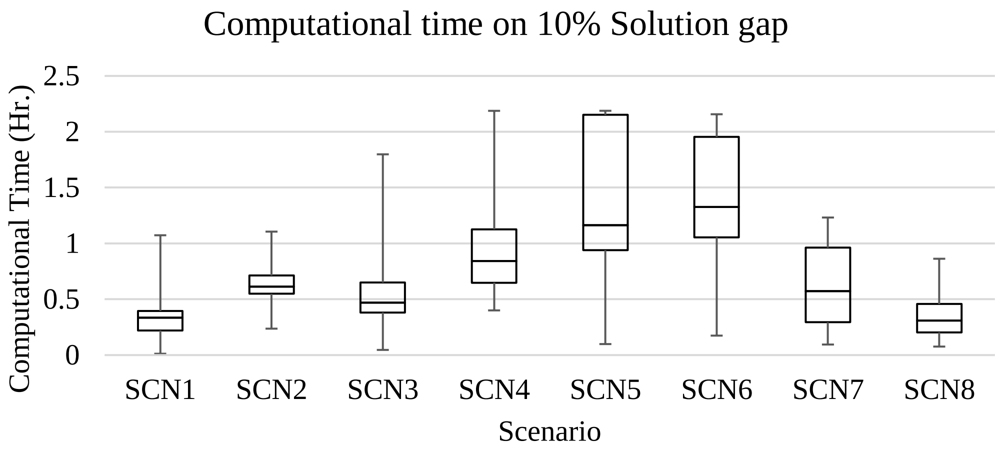

Figure 5-4: Computational time on each scenario using 10% solution gap

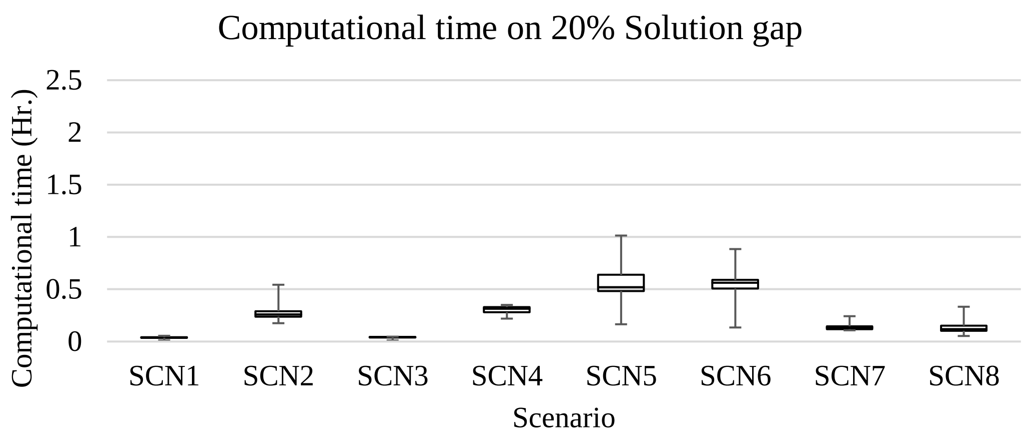

Figure 5-5: Computational time on each scenario using 20% solution gap

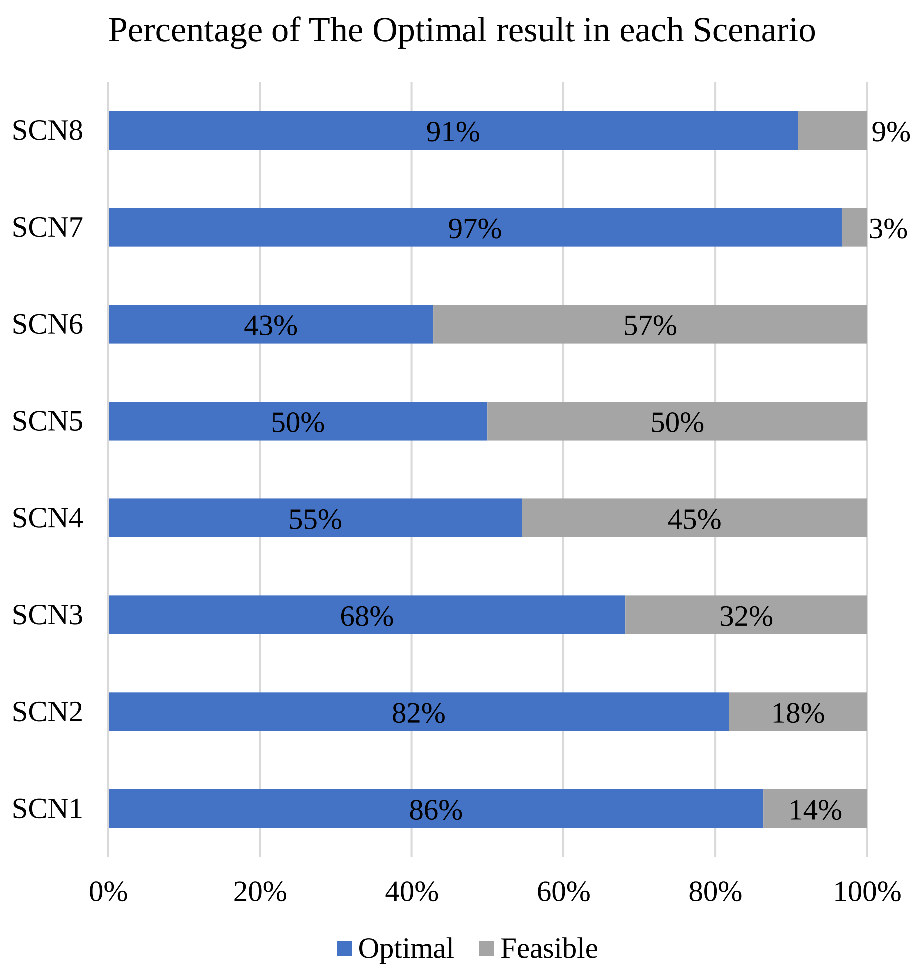

Figure 5-6: Percentage of the Optimal result in each Scenario

5.2 Discussion

This study proposed model with improvement on tractability and solvability by tackle fractionality issue of variable y_{js}. Decomposition technic was used by separating the changeover variables in Phase one, Pattern Generation using a modified capacity (K_S^*) was used in a model to perform an approximate optimization in calculating the production pattern. Since the modified capacity was implemented using this technique, some of the feasible solutions might be removed by pattern generation causing an infeasible solution in Phase Two. For the reason stated, multiple modified capacities were used in the formulation testing in each scenario to ensure the feasible solution was obtained from testing. All the results show the least feasible solutions without any single feasible solution.

In Phase Two, the setup pattern that was calculated in Phase One was used to calculate the production volume with demand, inventory carrying cost and capacity consideration to minimize setup cost and inventory carrying cost in the setup pattern specifically.

The quality of GLSP-TE was tested with a small problem size due to the limitation of the GLSP. The same optimality with less computational time and number of iterations resulted with GLSP-TE: therefore, it can be concluded that the GLSP-TE can provide the optimality level up to GLSP. The GLSP-TE also performed well with a larger problem size. The total computational time of both phases was less than GLSP with better objective function values in most tested scenarios. The objective function value can improve up to 72% compared with GLSP. The percentage of optimality run can be up to 97% of test runs in each scenario.

Based on all tests performed, it can be concluded that the GLSP-TE provides a better optimality level with less computational time than GLSP. The GLSP-TE also provided solution, which is the feasible solution in GLSP with more tractable and solvable. Finally, the GLSP-TE performed better performance in high demand fluctuation with more possibility of switching over.

5.3 Gaps for further study

The GLSP-TE is an exact methodology improvement of the GLSP achieved by separating the calculation into 2 phases. The separation focuses on the most complicated part of the formulation. Production pattern generation was done by using a pre-defined production size and production volume calculation on generated pattern with minimum lot-size and inventory carrying cost consideration.

The most important gap is the pre-defined production size in each micro-period. The K_s^*, in this study did not include the relationship between the size of $K_{s,}^*$ which affects the model behavior. This parameter is very important for the pattern generation procedure, and also affects the changeover cost which is one of the important costs of the problem.

Multiple production lines is also one of the gaps in this study. Due to actual configurations in business, the production lines will involve more than one production. More complicated production planning involves planning across multiple production lines.

In addition, one of the key factors is the allowance of the setup stage in idle time, which means that in idle time the setup stage is maintained with no changeover from one commodity to another commodity. But in some production lines, the idle period is available for the changeover to the next stage. A shutdown or other overhead cost required for the idle period can also be considered a gap in the foundation of the model.

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APPENDIX

APPENDIX I: Data usage

The data used in this study can be categorized in 2 sets

- The fixed parameters
- The scenario based parameters

The fixed parameters are the parameters that fixed for all test scenarios including

- Inventory Handling Cost(h_j)
- Capacity consumption of each production unit (a_j),
- Minimum Lot-size(m_j),
- Cost of External Supply (C_j)

	h_j	a_j	m_j	C_j
Product 1	15%	1	100	200
Product 2	15%	1	100	250
Product 3	15%	0.85	120	230
Product 4	15%	0.85	120	200
Product 5	15%	1.2	90	230
Product 6	15%	1.2	90	250

- Capacity (K_t)

	SCN 1-8	Stress Test
Product 1	2400	15000
Product 2	2700	15000
Product 3	2400	15000
Product 4	2700	15000
Product 5	2400	15000
Product 6	2700	15000
Product 7	N/A	15000
Product 8	N/A	15000
Product 9	N/A	15000
Product 10	N/A	15000
Product 11	N/A	15000
Product 12	N/A	15000

	SCN 1-8	Stress Test
Product 13	N/A	15000
Product 14	N/A	15000
Product 15	N/A	15000
Product 16	N/A	15000
Product 17	N/A	15000
Product 18	N/A	15000
Product 19	N/A	15000
Product 20	N/A	15000
Product 21	N/A	15000
Product 22	N/A	15000
Product 23	N/A	15000
Product 24	N/A	15000

- Switching Cost(s_{ij})

s_{ij}	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5	10	10.5	11	11.5
2	10		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5	10	10.5	11
3	10	10.5		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5	10	10.5
4	10	10.5	11		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5	10
5	10	10.5	11	11.5		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5
6	10	10.5	11	11.5	12		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9
7	10	10.5	11	11.5	12	12.5		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5
8	10	10.5	11	11.5	12	12.5	13		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8
9	10	10.5	11	11.5	12	12.5	13	13.5		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5
10	10	10.5	11	11.5	12	12.5	13	13.5	14		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7
11	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5
12	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6
13	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5
14	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5
15	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16	16.5		0.5	1	1.5	2	2.5	3	3.5	4	4.5
16	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16	16.5	17		0.5	1	1.5	2	2.5	3	3.5	4
17	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16	16.5	17	17.5		0.5	1	1.5	2	2.5	3	3.5
18	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16	16.5	17	17.5	18		0.5	1	1.5	2	2.5	3
19	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16	16.5	17	17.5	18	18.5		0.5	1	1.5	2	2.5
20	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16	16.5	17	17.5	18	18.5	19		0.5	1	1.5	2
21	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16	16.5	17	17.5	18	18.5	19	19.5		0.5	1	1.5
22	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16	16.5	17	17.5	18	18.5	19	19.5	20		0.5	1
23	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16	16.5	17	17.5	18	18.5	19	19.5	20	20.5		0.5
24	10	10.5	11	11.5	12	12.5	13	13.5	14	14.5	15	15.5	16	16.5	17	17.5	18	18.5	19	19.5	20	20.5	21	

- Switching Time(st_{ij})

ST_{ij}	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75	2.96	3.17	3.38	3.59	3.80	4.01	4.22	4.43	4.65	4.86
2	4.22		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75	2.96	3.17	3.38	3.59	3.80	4.01	4.22	4.43	4.65
3	4.22	4.43		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75	2.96	3.17	3.38	3.59	3.80	4.01	4.22	4.43
4	4.22	4.43	4.65		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75	2.96	3.17	3.38	3.59	3.80	4.01	4.22
5	4.22	4.43	4.65	4.86		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75	2.96	3.17	3.38	3.59	3.80	4.01
6	4.22	4.43	4.65	4.86	5.07		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75	2.96	3.17	3.38	3.59	3.80
7	4.22	4.43	4.65	4.86	5.07	5.28		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75	2.96	3.17	3.38	3.59
8	4.22	4.43	4.65	4.86	5.07	5.28	5.49		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75	2.96	3.17	3.38
9	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75	2.96	3.17
10	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75	2.96
11	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53	2.75
12	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32	2.53
13	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11	2.32
14	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90	2.11
15	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76	6.97		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69	1.90
16	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76	6.97	7.18		0.21	0.42	0.63	0.84	1.06	1.27	1.48	1.69
17	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76	6.97	7.18	7.39		0.21	0.42	0.63	0.84	1.06	1.27	1.48
18	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76	6.97	7.18	7.39	7.60		0.21	0.42	0.63	0.84	1.06	1.27
19	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76	6.97	7.18	7.39	7.60	7.81		0.21	0.42	0.63	0.84	1.06
20	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76	6.97	7.18	7.39	7.60	7.81	8.02		0.21	0.42	0.63	0.84
21	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76	6.97	7.18	7.39	7.60	7.81	8.02	8.24		0.21	0.42	0.63
22	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76	6.97	7.18	7.39	7.60	7.81	8.02	8.24	8.45		0.21	0.42
23	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76	6.97	7.18	7.39	7.60	7.81	8.02	8.24	8.45	8.66		0.21
24	4.22	4.43	4.65	4.86	5.07	5.28	5.49	5.70	5.91	6.12	6.33	6.55	6.76	6.97	7.18	7.39	7.60	7.81	8.02	8.24	8.45	8.66	8.87	

The scenario based parameters are the parameter that changed in each scenario, which is demand (d_j)

Demand of Scenario 1 (Demand in Ton)

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 1	455	455	455	455	412	412	412	412	441	441	441	441	397	397	397
Product 2	412	412	441	441	441	441	397	397	397	397	389	389	389	389	445
Product 3	397	397	397	397	389	389	389	389	445	429	390	412	455	455	455
Product 4	389	389	445	429	390	412	455	455	455	455	412	412	412	412	441
Product 5	455	455	455	455	412	412	412	412	441	441	441	441	397	397	397
Product 6	412	412	441	441	441	441	397	397	397	397	389	389	389	389	445

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 1	397	389	389	389	389	445	429	390	412	455	455	455	455	412	412
Product 2	429	390	412	455	455	455	455	412	412	412	412	441	441	441	441
Product 3	455	412	412	412	412	441	441	441	441	397	397	397	397	389	389
Product 4	441	441	441	397	397	397	397	389	389	389	389	445	429	390	412
Product 5	397	389	389	389	389	445	429	390	412	455	455	455	455	412	412
Product 6	429	390	412	455	455	455	455	412	412	412	412	441	441	441	441

Demand of Scenario 2 (Demand in Ton)

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 1	455	455	455	455	412	412	412	412	441	441	441	441	397	397	397
Product 2	412	824	441	882	441	441	397	397	794	397	778	389	389	389	445
Product 3	397	0	397	397	389	778	389	389	0	429	390	412	910	455	455
Product 4	389	389	445	0	390	412	455	455	455	455	0	412	412	412	441
Product 5	455	455	455	455	412	0	412	412	441	441	441	441	0	397	397
Product 6	412	412	441	441	441	441	397	397	397	397	389	389	389	389	445

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 1	397	389	389	389	389	445	429	390	412	455	455	455	455	412	412
Product 2	858	390	824	455	455	455	455	824	412	824	412	441	441	882	441
Product 3	0	412	412	412	824	441	441	0	441	397	397	794	397	0	389
Product 4	441	441	0	397	397	397	397	389	389	0	389	445	429	390	412
Product 5	397	389	389	389	0	445	429	390	412	455	455	0	455	412	412
Product 6	429	390	412	455	455	455	455	412	412	412	412	441	441	441	441

Demand of Scenario 3 (Demand in Ton)

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 1	455	910	455	455	412	412	412	824	441	441	441	882	397	794	397
Product 2	412	412	441	441	441	441	809	397	397	397	389	389	389	389	445
Product 3	852	397	397	852	801	801	389	389	445	429	390	412	852	455	455
Product 4	389	389	445	429	390	412	455	455	455	455	412	412	412	412	441
Product 5	455	0	0	0	0	0	0	0	0	0	0	0	397	0	0
Product 6	412	412	896	441	441	441	397	397	838	838	830	389	389	389	842

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 1	397	389	389	389	389	890	858	390	824	910	910	455	455	412	412
Product 2	429	390	801	455	844	455	455	412	412	412	412	441	441	441	441
Product 3	852	412	412	412	412	441	441	831	441	397	397	852	852	389	801
Product 4	441	441	441	786	397	397	397	389	389	389	389	445	429	802	412
Product 5	0	0	0	0	0	0	0	0	0	0	0	0	0	412	412
Product 6	429	779	412	455	455	455	455	412	412	412	412	441	441	441	441

Demand of Scenario 4 (Demand in Ton)

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 1	455	455			412	412	412		441	441	441		397	397	397
Product 2	412	412			441	441	397		397	397	389		389	389	445
Product 3	397	397			389	389	389		445	429	390		455	455	455
Product 4	389	389			390	412	455		455	455	412		412	412	441
Product 5	455	455			412	412	412		441	441	441		397	397	397
Product 6	412	412			441	441	397		397	397	389		389	389	445

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 1	397		389	389	389		429	390	412	455		455	455	412	412
Product 2	429		412	455	455		455	412	412	412		441	441	441	441
Product 3	455		412	412	412		441	441	441	397		397	397	389	389
Product 4	441		441	397	397		397	389	389	389		445	429	390	412
Product 5	397		389	389	389		429	390	412	455		455	455	412	412
Product 6	429		412	455	455		455	412	412	412		441	441	441	441

Demand of Scenario 5 (Demand in Ton)

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 1	579	411	763	651	216	685	617	707	760	212	636	708	594	343	301
Product 2	516	475	407	751	401	561	246	596	517	386	566	676	592	306	210
Product 3	588	394	551	343	206	672	365	302	203	319	755	706	363	774	797
Product 4	425	485	494	758	758	582	238	745	567	690	312	568	211	209	421
Product 5	249	722	259	265	501	475	493	520	276	582	552	477	217	621	460
Product 6	607	399	551	768	634	415	232	614	676	542	317	682	536	283	284

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 1	425	306	443	399	627	756	268	737	243	324	445	212	609	236	652
Product 2	653	632	699	246	726	234	768	666	426	375	696	709	253	760	377
Product 3	411	707	528	421	313	581	780	646	306	646	524	301	677	266	329
Product 4	726	665	206	672	371	698	249	611	668	415	271	660	263	338	335
Product 5	529	341	736	512	341	374	530	458	413	321	761	651	454	309	726
Product 6	785	482	539	598	738	430	317	659	211	428	593	446	288	724	729

Demand of Scenario 6 (Demand in Ton)

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 1	314	206	285	390	311	305	329	289	262	393	202	207	228	316	267
Product 2	300	210	288	375	211	278	223	213	253	260	334	209	284	322	215
Product 3	342	243	275	395	267	400	388	365	302	226	221	305	351	346	238
Product 4	384	328	343	210	206	364	379	270	297	400	352	232	329	249	298
Product 5	389	343	281	333	267	385	269	273	227	286	312	296	257	317	343
Product 6	350	231	290	366	285	320	344	249	294	368	356	309	226	359	324

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 1	259	366	267	365	289	244	306	234	262	391	399	279	328	274	258
Product 2	208	219	355	309	334	356	399	354	271	205	270	400	276	266	294
Product 3	210	205	340	330	281	288	210	212	378	381	262	373	353	314	209
Product 4	286	291	204	268	370	296	325	357	326	375	231	203	291	254	266
Product 5	332	251	291	349	378	253	397	203	364	378	342	223	333	242	400
Product 6	206	344	254	201	306	332	254	247	359	393	271	336	372	228	285

Demand of Scenario 7 (Demand in Ton)

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 1	190	92	173	373	338	393	196	179	103	36	346	15	355	22	197
Product 2	1	103	149	22	53	133	292	120	211	301	395	291	127	39	168
Product 3	313	66	103	96	200	244	176	49	235	4	320	363	172	383	313
Product 4	95	108	192	103	80	119	105	11	239	400	147	309	378	389	129
Product 5	228	391	279	40	142	70	363	209	226	200	342	347	85	297	204
Product 6	14	194	207	26	143	82	149	77	276	391	125	106	386	183	378

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 1	307	152	353	282	292	82	288	366	322	261	398	386	147	49	281
Product 2	317	348	63	173	246	379	280	359	107	394	56	193	271	117	226
Product 3	383	4	81	236	174	318	144	249	257	226	246	158	116	372	295
Product 4	220	365	90	306	120	62	159	322	336	243	40	309	280	367	201
Product 5	130	289	295	179	49	118	220	48	364	357	144	150	22	336	59
Product 6	48	361	17	352	123	30	121	76	382	257	197	143	375	224	67

Demand of Scenario 8 (Demand in Ton)

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 1	181	412	536	339	567	244	348	180	368	689	487	524	147	416	286
Product 2	374	521	128	495	290	361	72	316	721	440	250	568	530	82	510
Product 3	59	561	133	211	635	337	671	52	793	490	743	734	72	718	538
Product 4	753	517	465	426	503	186	759	718	181	131	34	201	588	634	206
Product 5	77	177	70	403	462	530	698	126	525	27	638	599	119	750	84
Product 6	539	741	492	479	451	674	345	76	639	246	643	640	498	138	1

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 1	505	377	517	281	255	624	776	434	480	762	123	649	316	291	200
Product 2	498	314	4	732	197	12	252	65	756	63	574	109	475	240	48
Product 3	237	754	761	478	198	509	607	724	769	137	234	784	482	698	682
Product 4	208	572	775	216	268	243	771	306	439	694	286	414	107	101	697
Product 5	710	340	140	391	395	4	613	101	194	717	602	582	67	732	230
Product 6	707	456	588	305	574	125	293	561	781	623	748	748	692	674	433

Demand of Scenario 6: Stress Test (Demand in Ton)

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 1	314	206	285	390	311	305	329	289	262	393	202	207	228	316	267
Product 2	300	210	288	375	211	278	223	213	253	260	334	209	284	322	215
Product 3	342	243	275	395	267	400	388	365	302	226	221	305	351	346	238
Product 4	384	328	343	210	206	364	379	270	297	400	352	232	329	249	298
Product 5	389	343	281	333	267	385	269	273	227	286	312	296	257	317	343
Product 6	350	231	290	366	285	320	344	249	294	368	356	309	226	359	324
Product 7	361	311	328	235	309	288	357	347	364	205	236	364	269	303	278
Product 8	351	290	296	203	364	355	328	326	340	256	273	352	271	250	255
Product 9	387	275	393	301	387	334	335	400	261	320	288	204	309	298	353
Product 10	360	376	306	244	258	312	203	338	236	351	354	276	390	396	223
Product 11	273	213	302	300	307	231	348	278	214	352	257	298	400	233	237
Product 12	286	283	316	286	343	339	349	336	296	271	257	210	353	291	330
Product 13	277	266	206	203	232	292	316	375	375	276	387	298	314	336	387
Product 14	214	254	274	358	241	378	249	287	361	349	346	226	223	388	338
Product 15	321	244	370	272	308	297	206	379	333	397	239	329	265	244	262

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 1	314	206	285	390	311	305	329	289	262	393	202	207	228	316	267
Product 2	300	210	288	375	211	278	223	213	253	260	334	209	284	322	215
Product 3	342	243	275	395	267	400	388	365	302	226	221	305	351	346	238
Product 4	384	328	343	210	206	364	379	270	297	400	352	232	329	249	298
Product 5	389	343	281	333	267	385	269	273	227	286	312	296	257	317	343
Product 6	350	231	290	366	285	320	344	249	294	368	356	309	226	359	324
Product 7	290	350	300	277	213	349	247	207	229	220	382	318	302	361	348
Product 8	246	330	279	283	248	353	391	375	314	240	230	329	240	369	371
Product 9	260	240	301	387	267	316	220	395	275	208	394	322	302	208	262
Product 10	264	365	364	291	301	267	312	295	284	273	313	341	211	243	203
Product 11	333	267	325	287	374	395	211	377	339	242	329	349	326	371	322
Product 12	294	232	233	330	287	262	201	279	341	308	367	299	322	352	234
Product 13	260	299	333	297	388	320	368	380	281	370	348	379	304	216	396
Product 14	227	328	398	274	290	220	343	386	320	371	357	341	303	317	372
Product 15	302	359	370	353	400	375	203	258	301	279	301	248	357	277	336

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 16	325	395	296	381	359	360	259	232	347	277	244	250	273	330	374
Product 17	328	397	252	351	240	266	303	225	344	374	390	232	367	331	209
Product 18	358	386	336	392	220	245	399	287	387	375	301	270	223	284	282
Product 19	226	243	236	329	238	258	350	237	341	384	308	381	216	292	328
Product 20	264	368	331	216	311	219	248	344	374	217	215	333	333	247	363
Product 21	286	325	395	301	378	247	292	292	210	253	370	347	233	365	236
Product 22	357	288	394	273	249	277	240	356	230	291	381	252	357	245	243
Product 23	343	366	310	257	213	240	341	228	307	268	324	285	244	331	219
Product 24	342	316	237	301	272	301	268	203	259	247	322	310	370	365	270

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 16	383	245	317	242	215	386	331	349	301	247	229	382	280	264	395
Product 17	356	342	252	399	357	265	322	283	272	244	316	336	276	281	283
Product 18	209	347	246	266	348	240	305	383	238	219	277	391	273	220	244
Product 19	277	237	320	217	294	329	353	302	352	344	240	371	219	246	316
Product 20	245	267	330	362	219	265	274	287	389	295	352	367	319	259	363
Product 21	334	254	327	280	202	274	227	241	289	234	358	247	292	279	309
Product 22	385	286	308	282	271	326	268	226	230	282	383	288	265	256	393
Product 23	365	210	268	224	258	369	395	240	326	224	324	326	217	203	286
Product 24	263	361	308	354	321	204	321	221	215	385	372	318	231	229	232

Demand of Scenario 6: Stress Test (Demand in Ton)

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 1	181	412	536	339	567	244	348	180	368	689	487	524	147	416	286
Product 2	374	521	128	495	290	361	72	316	721	440	250	568	530	82	510
Product 3	59	561	133	211	635	337	671	52	793	490	743	734	72	718	538
Product 4	753	517	465	426	503	186	759	718	181	131	34	201	588	634	206
Product 5	77	177	70	403	462	530	698	126	525	27	638	599	119	750	84
Product 6	539	741	492	479	451	674	345	76	639	246	643	640	498	138	1
Product 7	379	762	520	696	212	89	41	262	567	669	479	234	447	429	680
Product 8	482	722	141	314	631	611	262	607	648	535	101	560	248	211	357
Product 9	366	306	88	391	379	566	396	739	461	728	153	412	405	517	649
Product 10	5	411	257	373	415	378	619	345	446	235	44	723	503	100	468
Product 11	137	697	323	498	398	547	230	604	594	565	352	469	743	380	126
Product 12	610	776	668	123	438	410	607	717	64	646	229	714	734	522	45
Product 13	287	285	98	681	636	112	30	635	522	237	140	304	493	33	512
Product 14	613	663	333	602	90	88	106	279	359	648	372	783	262	195	647
Product 15	37	513	23	361	648	433	486	160	481	89	77	724	218	464	293

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 1	505	377	517	281	255	624	776	434	480	762	123	649	316	291	200
Product 2	498	314	4	732	197	12	252	65	756	63	574	109	475	240	48
Product 3	237	754	761	478	198	509	607	724	769	137	234	784	482	698	682
Product 4	208	572	775	216	268	243	771	306	439	694	286	414	107	101	697
Product 5	710	340	140	391	395	4	613	101	194	717	602	582	67	732	230
Product 6	707	456	588	305	574	125	293	561	781	623	748	748	692	674	433
Product 7	482	277	61	441	419	221	549	184	90	109	386	370	111	776	285
Product 8	5	308	617	364	702	245	9	723	245	73	267	658	712	621	792
Product 9	308	40	49	349	461	76	275	4	762	484	298	278	99	541	126
Product 10	717	371	724	335	580	782	394	360	507	650	465	787	318	269	642
Product 11	320	213	30	277	9	619	715	507	87	103	514	101	278	482	201
Product 12	678	413	629	614	479	291	281	501	643	740	767	72	88	185	482
Product 13	564	733	16	265	613	61	341	732	365	12	726	738	635	106	483
Product 14	127	192	539	701	340	641	423	446	303	571	228	371	22	660	347
Product 15	306	251	475	207	641	199	461	346	32	484	574	495	770	427	229

	Macro-period														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Product 16	457	486	632	266	760	298	393	146	432	491	39	782	591	76	16
Product 17	145	511	271	21	713	308	190	508	300	625	693	325	367	511	545
Product 18	713	492	252	413	740	692	104	71	544	754	351	552	29	296	394
Product 19	85	444	678	680	626	161	404	740	239	642	653	26	669	745	711
Product 20	620	178	215	387	90	143	36	492	1	330	619	125	79	63	544
Product 21	586	25	385	729	44	359	249	525	590	614	779	361	107	632	266
Product 22	592	76	314	571	46	497	611	278	341	69	31	384	564	528	237
Product 23	272	354	75	578	756	403	780	723	169	90	332	96	634	339	135
Product 24	60	214	248	719	279	703	578	641	770	126	45	139	335	441	708

	Macro-period														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Product 16	539	109	233	591	778	743	125	2	637	11	435	751	20	513	752
Product 17	247	76	140	665	737	545	9	580	695	591	68	491	425	528	361
Product 18	104	114	660	330	519	790	82	151	317	244	187	612	93	98	611
Product 19	323	751	154	169	40	705	538	232	388	177	316	23	207	568	345
Product 20	584	513	782	723	329	367	62	84	116	723	394	579	321	636	300
Product 21	769	449	757	652	549	686	38	263	374	163	226	711	614	487	488
Product 22	286	406	104	547	118	491	635	290	550	108	37	137	256	538	590
Product 23	483	572	181	260	630	350	219	779	223	66	572	780	214	572	247
Product 24	428	332	297	529	120	467	441	447	121	226	197	535	382	331	341

VITA

The researcher, Rattapon Patikarnmonthon, was born on 22 May 1981. In 2003, he finished his bachelor's degree in Computer Engineering (B.Eng) from King Mongkut Institute of Technology Ladkrabang, Thailand. In 2009, he earned his Masters of Science degree in Logistics Management (M.Sc.) from Chulalongkorn University, Thailand. Since earning his bachelor's degree, Rattapon has worked in various fields such as Information Technology, Information Systems, Computer Hardware, Software Development, Supply Chain Management, Business Process Improvement, Business Optimization, and Transportation and Business Consulting. He is particularly interested in integrating knowledge across fields to obtain new perspectives and solutions in business and in life.