STOCHASTIC PROGRAMMING MODEL FOR SUPPLY CHAIN DESIGN WITH SHORT RESPONSE TIME AND HEURISTIC

BY

THANATORN SINPHATSIRIKUL

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING (LOGISTICS AND SUPPLY CHAIN SYSTEMS ENGINEERING)

SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY

THAMMASAT UNIVERSITY

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A Thesis Presented

By

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Abstract

STOCHASTIC PROGRAMMING MODEL FOR SUPPLY CHAIN DESIGN WITH SHORT RESPONSE TIME AND HEURISTIC

by

THANATORN SINPHATSIRIKUL

[Engineering Management: Bachelor, Sirindhorn International Institute of Technology, 2013]

This research studies the impact of demand uncertainty to the supply chain design by using a stochastic programming approach. Each potential location has two modes of supply: long response time used before the demand is realized and short response lead time mode (with higher cost) used after the demand is realized. The capacity of each model will be optimally determined from the model. This means that each location allow the manufacturer to install machines to produce in a large quantity at low cost (due to economy of scale) and keep in the internal warehouse or to install flexible rapid response machines to produce with short lead time at high cost after the demand shortage is expected. Moreover, the model allows different production cost functions which the unit cost could be different when production quantity is different using piecewise function. A stochastic programming model is developed to handle the situation explained. We have conducted 4 experiments to test the model in different perspective; (1) Sampling test – to test the effect of the sample size to the result, (2) Parameter variation – to test how each variable affect the results, (3) Cost function testing – to reveal the property of different cost function and (4) Pair-T test to prove how short LT response facility could improve certain situation and mitigate the effect of demand uncertainty. Furthermore, for heuristic part, we applied linear relaxation and decomposition method on two binary variables to separate the model into two phases; (1) Location decision and (2) Segmentation decision. For the result, heuristic model affords to contribute the optimal result for about 26 out of 32 instances or 81.25% of the total number of computable instances deriving from every cost function. The average overall total profit gap is 0.32%. The average computational time reduction is 71.65%. Moreover, our heuristics model is able to solve big size problems which the optimal model failed to do within acceptable time.

Keywords: Facility and location, Stochastic programming, Piecewise function, Short lead time response, Heuristic

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Chapter 1
Introduction

Every company relies on one of the most important factor which is the demand of product to create income and survive in the world of business. In reality, demand happens to be uncertain along the whole supply chain for most of the time. As demand is very sensitive, every company needs to thoughtfully plan for serving topmost demand in order to acquire the highest revenue, minimized the cost and maximizes the profit. In the other hand, overlooking demand may cause unacceptable shortage or overflow overage of products which conceives excessive cost and eventually leads to loss of profit. Uncertainty of demand has crucial impact not only for the single company, but for the whole stream of supply chain. Some researchers have statistically proven that divergence between demand and supply is very vital. Hendricks et al. (2005) informed that a company may lose up to 30% of its typical income due to the mismatch of its supply against customer's demand. In an example case from Nagali et al. (2008), Hewlett-Packard, 425 billion dollars is save aggregately by developing treatment for handling the uncertainty. Hau L. lee, (1997) b informed that bullwhip effect is also one of the major problems obviously affected by the demand uncertainty. Bullwhip effect is the distortion of demand upstream and creates the massive deviation of order along the supply chain stream.

According to the problem, short lead time response (also known as quick response and accurate response) of production is highlighted as one of the methods for handling the uncertainty of demand. Fisher & Raman (1994) were two of the researchers who pioneer the short response to mitigate the effect of uncertainty. They prove that short response helps reducing relative cost and comparatively increasing profits by 60%. Short response increases rate of production, so the company can rapidly serve the received order within short period of time. On the other hand, it technically costs more on many directions to afford the specialized technology for flexible production. Moreover, theoretically, to ensure the effectiveness of quick response production, they also need to improve the cohesiveness of data transferring along the supply chain for legitimate demand information.

Hence, we introduce our research on for the according problem in two parts. For the first part, we diagnoses and control the uncertainty of demand by developing stochastic programming model. The model is two echelons supply chain with single-commodity, multi-facilities and multi-retailers. In addition, we have implanted short lead time response facilities in order to handle the demand fluctuation more effectively. Moreover, the model also focuses on different production cost function which different in price when purchase in different amount by developing the piecewise function to handle various cost curve segmentation. Furthermore, for the second part, we proposes two phases heuristic model of stochastic programming model for supply chain design with short response time by re-engineering the original model with linear relaxation and decomposition concept.

1.1 Problem Statement

This research mainly focuses on 4 problems; facility and location problem, production with demand uncertainty, piecewise cost function and heuristic. First, for the facility location problem, the main purpose is to allocate the location of facility while minimizing the total cost of opening facility and transportation cost. Second, demand uncertainty is the major problem of our research. We try to analyze how short response lead time facility can help lessen the effect uncertainty. Demand is randomly assume in each considering scenarios. Third, for the cost of production, we encounter with 3 kinds of piecewise production cost function which are s-shaped, convex and concave cost function. We try to study the decisive nature of each cost function as they all have distinct characteristics. Fourth, we develop heuristic model to proof that there is better process of solving the problem as we refine our model and its usage. We test the justification based on the gap of objective result and time efficiency.

1.2 Objectives of Research

- To find the model and heuristics that help the manufacturer and supply chain member on operational decisions for facility location problem with short lead time response facility featuring various cost function.
- To show the benefit of short response lead time facility.
- To test the efficiency of heuristic for various cost function and problem size.

1.3 Overview of Research

This thesis report is organized as follows. Chapter 2 informs review of literatures. Chapter 3 describes problem description and mathematical model. Chapter 4 presents numerical experiment and results. And lastly, Chapter 5 is the conclusion of our thesis.

Chapter 2
Literature Review

We have reviewed some literatures on 3 main bases: (1) Facility location models with supply chain context (2) Stochastic programming (with demand uncertainty) and (3) Piecewise function and (4) Heuristics. These 4 contents are the main contribution of our research.

2.1 Facility and Location

Thanh et al. (2007) proposed a mixed integer linear programming of multi-level, multi-period, multi-commodity of production and distribution with deterministic demand. The decisions are to decide whether to close, open or enlarge the existing network facility. They also applied the model to handle the increasing of demand.

Melo et al. (2004) presented dynamic multi-commodity capacitated facility location problem which figure the relocation, reduction and expansion of initial facilities that originally operated over the planning horizon. Moreover, the paper also concern about fluctuation of seasonal demand.

Jouzdani et al. (2012), fuzzy linear programming is developed which focuses on dynamic dairy facility location and supply chain planning of dairy products. Triangular Fuzzy concept is utilized to model the uncertainty of the problem. In addition, non-linear mixed integer programming is implemented on traffic congestion.

Amin et al. (2012) considered mixed integer linear programming for closed-loop supply chain network. The model also regarded on environmental factors by implementing e-constraint and weighted sums methods. For considering the uncertainty of some parameters, they developed scenario-based analysis on stochastic programming with probability function. As the results from sensitivity analysis, they informed that stochastic model obviously costs more comparing with deterministic model at the same disposal fraction value.

2.2 Stochastic Programming

Kaki et al. (2014) proposed stochastic problem applying newsvendor concept with distribution function, cumulative function and expected value. They focused on the affected of interdependent supply and demand uncertainty. They implemented scenarios based on copula functions which valid to handle linear and nonlinear dependences. Also, capacity reservation contract was used to compromise the uncertainty of demand and supply.

Xu and Zhang (2013) introduced mixed-integer bi-level programming model and employs the iterative-optimization method. The bi-level programming divided into 2 parts: (1) the upper model is the logistics network design (LND). (2) The lower model is the order quantity determination (OQD). For stochastic demand, they utilized probability distributions to handle the uncertainty.

Chouinard et al. (2007) presented two-stage stochastic model for supply loops design. Linear regression and normal distribution are utilized to represent the uncertainty of demand. Furthermore, they extent heuristics on sample average approximation (SAA) featuring the Monte Carlo sampling methods. They used SAA to fix the network configuration across the fixed number of scenarios for approximating the expected value acquired from previous model optimization. Monte Carlo method was used to generate the scenarios regardless the optimization procedure.

Goh et al. (2007) proposed multi-stage stochastic convex programming applying probability for demand uncertainty. The uncertainty data is represented by set of distinction realizations. Moreover, they also used Moreua-Yoshida regularization and designed algorithm for interpreting of multi-stage global supply chain network problem.

2.3 Piecewise Function and Cost Function

Da Lu (2010) proposed non-linear mixed integer programming on facility location problem with economies of scale and congestion and also proposes the Lagrangian solution approach. In addition, this paper interpret capacitated facility location problem applying various type of cost functions which i.e. convex cost function, concave cost function and s-shaped cost function.

Diabat and Theodorou (2014) presented mixed integer non-linear programming for single-warehouse multi-retailer inventory problem. They utilized piecewise function to convert non-linear to linear term by transforming non-convex problem into discrete convex problem. They also compare the result with other proposed Lagrangian relaxation results regardless any extraordinary algorithms.

Chan et al. (2002) introduced linear programming based algorithm for effective zero inventory ordering policies for single warehourse, multi-retalier problem with inventory and transportation strategies on satisfying demand variation. Piecewise linear function is utilized for expressing quantity discount function, incentive of volume based pricing and conceptual economies of scale.

2.4 Heuristics: Stochastic Programming, Mixed Integer Programming, Facility Location and Supply Chain.

First, Ramezanian and Saidi-Mebrabad (2012) proposed hybrid model of simulated annealing and mixed integer programming based heuristics for multi-phase stochastic scheduling and lot-sizing problem. They applied probability distribution (density function) and chance-constrained programming (CCP) to transform the stochastic problem into deterministic. Moreover, two MIP-based heuristics are mentioned to solve the problem. The first heuristic is developed based on the original model and the second heuristic is based on permutation/non-permutation heuristic technique.

Melo and Wolsey (2012) presented mixed integer programming and heuristics for two-level production and transportation problems. They developed a hybrid heuristic with variable fixing to restrict the qualified formulation. They prove that the heuristic provide optimal results with remarkable less computational time.

Absi et al. (2012) presented heuristic for multi-item capacitated lot-sizing problem. The model is decomposed and adapt dynamic programming algorithm to specify the sub-problems. They utilized non-myopic heuristic base with probing strategy to acquire the feasible solution. They applied Lagrangian relaxation to acquire commendable lower bound and upper bound.

Miranda and Garrido (2006) proposed a facility location and inventory control model with stochastic capacity constraints. For the stochastic demand, they used mean and variance to represent the fluctuation of demand. They suggested that in order to numerically analyze stochastic results, it needs a deterministic benchmark. However, to analyze the deterministic approach when it is stochastic in practical, it particularly assumes a probability of 0.5 according to symmetric distribution (ex. Normal distribution).

Coelho et al. (2014) proposed heuristics for dynamic and stochastic inventory routing. They used forecasting to manipulate the stochastic data in planning process. They separate the solution policy into two bases; reactive and proactive. For reactive, they anticipate the real information to optimally deciding the next decision. For proactive, they attempted to forecast the information before making decisions. They prove that, with the stochastic solution, it practically gives out better solution than using static setting.

Guastaroba and Speranza (2014) presented heuristic for binary integer linear programming of single source capacitated facility location problem. They also applied Kernel search heuristics framework to the problem. They used the decision variables to restrict the problem into sequence sub-problems as the subset of decision variables are constructed from linear relaxation entity. By developing the heuristic, they could remarkably contributed optimal solution from 165 out of 170 instances with overall average gap of 0.64%.

Smith and Penuel (2008) introduced two-phase facility location problem with second-phase activation costs. They offered scenario-based stochastic facility problem when the facility is located in the first period, then the second period becomes the sub-problem activating the located facility among the chosen site from the first period. They developed mixed integer programming with binary variables of facility location allocation. They applied relaxation method on the first phase model and lower bounding restriction on second phase model.

Lastly, Boujelben et al. (2014) proposed heuristics for mixed integer programming formulation of automotive industry distribution network design problem. They utilized linear relaxations to develop various heuristics of mixed integer programming formulation. They offered clustering-based location-routing approach to group the close customer into clusters for delivery. They also developed two-phase heuristic method based on two essential binary variables; (1) location decisions and (2) assignment decisions. This two phase heuristic part of this research paper is authentic enough to be studied for our heuristics approach application to our model. They introduced Lagrangian relaxation and sub-gradient method for heuristic to solve the non-linear terms which considered being a NP-hard problem.

Chapter 3
Problem Description and Mathematical Model

The detailed problem description is simplified in section 3.1 to expose the situation of the problem, entity and limitations of the supply chain. Also the base case mapping is illustrated to further clarify the situation. In section 3.2, we informed the mixed integer programming model, parameter a notation, variable notation and model description.

3.1 Problem Description

For this research, we have created a scenario of two echelons supply chain with 3 representative sites of facility serving product A to 20 dispersed customers. Each location has potential to construct 2 types of facility (1 for each type) which are short lead time response facility and long lead time response facility. In fact, the short lead time response facility produce the same exact product as the long lead time, but it has much shorter lead time and able to response more effectively during critical time. Moreover, as it has more sophisticated technology and machines to perform the according specialty, it also cost more to build one. Both type of facility has its own production cost function represented in term of piecewise function with 3 segments. In accordance to the piecewise function, the 2nd and the 3rd segment can be opened only if their previous segment is opened. Next, we divide the production schedule into 2 periods. For the first period, only long lead time response facility is opened for advanced production before receiving the real demand data, which will not take part on the fluctuation of future demand. This is scheduled as the stand by product. Then, for the second period, Short lead time response facility will chase the fluctuation of the demand of every simulated scenario in order to make the most neutralized decisions for overall production, minimizing overage and shortage amount to avoid supplemental cost from mismatched production. Ultimately, as the facilities are determined, the customer's demand will be served based on the decision made previously allocating which customer will be serving by which facility.

3.2 Mathematical Model

Indexes:

$i = demand\ node$

$j = facility\ node\ (JL: Long,\ JS: short)$

$k = segment\ k\ of\ production\ cost$

$s = scenario\ of\ second\ stage$

Parameters:

$c_{ij} = transportation\ cost\ from\ j\ to\ i$

$l_{jk} = production\ cost\ (slope)\ per\ unit\ using\ line\ segment\ k\ at\ location\ j$

$ac_{jk} = marginal\ fixed\ cost\ to\ construct\ faciliy\ of\ size\ k\ at\ location\ j$

$(additional\ cost\ in\ expand\ capacity\ from\ size\ k-1\ to\ size\ k)$

$fc_{jk} = fixed\ cost\ to\ construct\ faciliy\ at\ location\ j$

$p = probability\ of\ scenarios$

$Sh = Shortage\ cost\ per\ unit$

$Ov = Overage\ (holding)\ cost\ per\ unit$

$D_{is} = Demand\ of\ product\ at\ location\ i\ under\ scenario\ s$

$L_{jk} = Length\ of\ segment\ k\ of\ production\ cost\ at\ location\ j\ or$

$(Additional\ capacity\ if\ size\ k\ is\ selected\ over\ size\ k-1\ at\ location\ j)$

$UP = Unit\ selling\ price$

Decision Variables:

First stage:

$x_{ij} = quantity\ shipped\ from\ j\ to\ i\ using\ long\ lead\ time\ facility$

$\delta^x_{jk} = quantity\ produced\ at\ location\ j\ using\ long\ lead\ time\ under\ segment\ k\ of\ production\ cost$

$w_{jk} = 1\ if\ quantity\ produced\ is\ at\ upperbound\ k\ (full\ capacity\ of\ segment\ k)\ of\ production\ cost$

$(\delta^x_{jk} = L_{jk}\ or\ \delta^y_{jk} = L_{jk}),\ 0\ otherwise$

$OPEN_j = 1\ if\ a\ facility\ is\ open\ at\ location\ j,\ 0\ otherwise$

Second stage:

$y_{ijs} = quantity\ shipped\ from\ j\ to\ i\ using\ short\ lead\ time\ facility\ under\ scenario\ s$

$\delta^y_{jks} = quantity\ produced\ at\ location\ j\ using\ short\ lead\ time\ under\ segment\ k\ of\ production\ cost$

$SQ_{is} = shortage\ quantity\ at\ location\ i\ under\ scenario\ s$

$OQ_{is} = overage\ quantity\ at\ location\ i\ under\ scenario\ s$

Two Stages Stochastic Programming Model

$1st\ \ stage\ \ stochastic:$

$$Minimize \qquad Up\left(\sum_i \sum_j^{JL} x_{ij} - \sum_i OQ_i\right) -$$

$$\left(\begin{array}{l}\sum_i \sum_j c_{ij} x_{ij} + \sum_j^{JL} \sum_k l_{jk} \delta_{jk}^x + \sum_j \sum_k w_{jk} ac_{jk} + \sum_j OPEN_j fc_j + \\ \sum_i SQ_i Sh + \sum_i OQ_i Ov\end{array}\right)$$

$Subject\ to$

$$ct\,1:\ \sum_j x_{ij} + SQ_i - OQ_i = D_i, \forall i$$

$$ct\,2:\ \sum_i x_{ij} = \sum_{k=1}^{K} \delta_{jk}^x, \forall j \in JL$$

$$ct\,3:\ \sum_i x_{ij} \le OPEN_j M, \forall j \in JL$$

$$ct\,4:\ L_{j1} w_{j1} \le \delta_{j1}^x \le L_{j1}, \forall j \in JL$$

$$ct\,5:\ L_k w_{jk} \le \delta_{jk}^x \le L_{jk} w_{j,k-1}, \forall j \in JL, \forall k \in \{2,3,\ldots,K-1\}$$

$$ct\,6:\ 0 \le \delta_{jK}^x \le L_{jK} w_{j,K-1}, \forall j \in JL$$

$2nd\ \ stage\ \ stochastic:$

$$Minimize \qquad Up\left(\sum_s p \sum_i \sum_j^{JS} y_{ijs} - \sum_s p \sum_i OQ_{is}\right) -$$

$$\sum_s p_s \left(\sum_i \sum_j c_{ij} y_{ijs} + \sum_j^{JS} \sum_k l_{jk} \delta_{jks}^y + \sum_i SQ_{is} Sh + \sum_i OQ_{is} Ov\right)$$

Subject to

$$ct1:\ \sum_j y_{ijs} + SQ_{is} - OQ_{is} = D_{is},\ \forall i, s$$

$$ct2:\ \sum_i y_{ijs} = \sum_{k=1}^{K} \delta^{y}_{jks},\ \forall j \in JS, s$$

$$ct3:\ \sum_i y_{ijs} \le OPEN_j M,\ \forall j \in JS, s$$

$$ct4:\ L_{j1} w_{j1} \le \delta^{x}_{j1} \le L_{j1},\ \forall j \in JL$$

$$ct5:\ L_{j1} w_{j1} \le \delta^{y}_{j1s} \le L_{j1},\ \forall j \in JS, s$$

$$ct6:\ L_k w_{jk} \le \delta^{y}_{jks} \le L_{jk} w_{j,k-1},\ \forall j \in JS, \forall k \in \{2,3,\ldots,K-1\}, s$$

$$ct7:\ 0 \le \delta^{y}_{jKs} \le L_{jK} w_{j,K-1},\ \forall j \in JS, s$$

Entire Mode (Combine 1st and 2nd stage)l:

$$\text{Minimize}\qquad Up\left(\sum_i \sum_j^{JL} x_{ij} + \sum_s p \sum_i \sum_j^{JS} y_{ijs} - \sum_s p \sum_i OQ_{is}\right) -$$

$$\left(\begin{array}{l} \displaystyle\sum_i \sum_j c_{ij} x_{ij} + \sum_j^{JL} \sum_k l_{jk} \delta^{x}_{jk} + \sum_j \sum_k w_{jk} ac_{jk} + \sum_j OPEN_j fc_j + \\ \displaystyle\sum_s p_s \left(\sum_i \sum_j c_{ij} y_{ijs} + \sum_j^{JS} \sum_k l_{jk} \delta^{y}_{jks} + \sum_i SQ_{is} Sh + \sum_i OQ_{is} Ov\right) \end{array}\right)$$

Subject to

$$ct1: \sum_j x_{ij} + \sum_j y_{ijs} + SQ_{is} - OQ_{is} = D_{is},\ \forall i, s$$

$$ct2: \sum_i x_{ij} = \sum_{k=1}^{K} \delta^{x}_{jk},\ \forall j \in JL$$

$$ct3: \sum_i y_{ijs} = \sum_{k=1}^{K} \delta^{y}_{jks},\ \forall j \in JS, s$$

$$ct4: \sum_i x_{ij} \le OPEN_j M, \forall j \in JL$$

$$ct5: \sum_i y_{ijs} \le OPEN_j M, \forall j \in JS, s$$

$$ct6: L_{j1} w_{j1} \le \delta^x_{j1} \le L_{j1}, \forall j \in JL$$

$$ct7: L_k w_{jk} \le \delta^x_{jk} \le L_{jk} w_{j,k-1}, \forall j \in JL, \forall k \in \{2,3,...,K-1\}$$

$$ct8: 0 \le \delta^x_{jK} \le L_{jK} w_{j,K-1}, \forall j \in JL$$

$$ct8: L_{j1} w_{j1} \le \delta^y_{j1s} \le L_{j1}, \forall j \in JS, s$$

$$ct9: L_k w_{jk} \le \delta^y_{jks} \le L_{jk} w_{j,k-1}, \forall j \in JS, \forall k \in \{2,3,...,K-1\}, s$$

$$ct10: 0 \le \delta^y_{jKs} \le L_{jK} w_{j,K-1}, \forall j \in JS, s$$

$$ct11: x_{ij}, y_{ij}, \delta^x_{jk}, \delta^y_{jks}, SQ_{is}, OQ_{is} \ge 0$$

$$ct12: w_{jk}, OPEN_j \in \{0,1\}$$

The objective function of the model is to maximize the profit from sales of product from short lead time response and long lead time response (excluding the overage amount) and deduct by various cost of long lead time response and short lead time response i.e. transportation cost (long lead time), production cost (long lead time), capacity additional cost, facility fixed cost, and with the probability distribution for transportation cost (short lead time), production cost (short lead time), shortage cost and overage cost. Constraint (1) represents the demand satisfaction. Constraint (2) determines total production and delivery from all of the long lead time response facility. Constraint (3) determines total production and delivery from all of the short lead time response facility. Constraint (4) locates the long lead time response facility. Constraint (5) locates the short lead time response facility. Constraint (6, 7, and 8) represents the piecewise function of long lead time response facility’s production capacity. Constraint (9, 10, and 11) represents the piecewise function of short lead time response facility’s production capacity. Constraint (12) determines the non-negativity variables. Lastly, Constraint (13) determines the binary variable.

Chapter 4
Numerical Experiment and Results

In this chapter, we interpret the numerical experiment and the results in detail. We delicately analyze the result base on our insight understanding. This part is divided into two parts; PART 1 and PART 2. For PART 1, we developed some experiments to test the contribution of the model on the situation. We mainly focus on the limitation, adaptation and feature of the model. For PART 2, we developed heuristic with our model to extend the limitation and improve our model toward certain ways.

Part 1

4.1 Numerical Experiment

Table 1 reveals all of the input data that implemented in the model for solving the model which is utilized in all of the experiment of PART 1. We utilize IBM ILOG CPLEX 12.1 for programming and solving.

Table 1:
Input data of the base case

Type	*Facility fixed cost*	*Capacity additional cost*	*Selling price per unit*	*Transportaion cost per unit (Random)*		*Demand Distribution*	
				min	*max*	*mean*	*SD*
Long	5M	1M	38,000	45	140	70	10
Short	7M	1M					

Overage Cost per unit	*Shortage Cost per unit*	*Transportaion cost per unit (Random)*		*Demand Distribution*		Average transportation cost (sites to customers)		
		min	*max*	*Mean*	*SD*	Site A	Site B	Site C
6,000	0	45	140	70	10	98	102	95

Figure 1 and Table 2 shows the result of base case scenario. It shows all the significance decisions and distribution mapping of the whole situation. Site A opens a long response lead time facility with 2 segments production capacity. Site B is not chosen to open any facility. Site C opens both long and short response lead time facility with full capacity of 3 segments. For more detail, this decision is made based on the average distance between representative sites and customers. Site C (95) has the least average distances to customers so opening full capacity at C will save the most transportation cost, following by site A (98). Thus, site B (102) with the most average distance is ignored as it costs more transportation cost.

Table 2:
Results of the base case

Type	*Location*									*Production amount*		*Average Shortage amount*	*Average overage amount*	*Total Profit*
	A			*B*			*C*							
	Segmentation									*Individual*	*Total*			
	1	*2*	*3*	*1*	*2*	*3*	*1*	*2*	*3*					
Long	■	■	□	□	□	□	■	■	■	850	1339.07	50.94	3.72	10,604,193
Short	□	□	□	□	□	□	■	■	■	489.07				

For the experiment part, this research introduces 4 separated experiments: (1) Sampling test, (2) Parameter variation, (3) Cost function testing and (4) Pair-T test. For these experiments, data variation is mainly applied to conduct those experiments. This part visualizes how each of input data influentially affects certain situation. Moreover, some experiments are developed by constructing some statistical analysis to obtain concrete and reliable results.

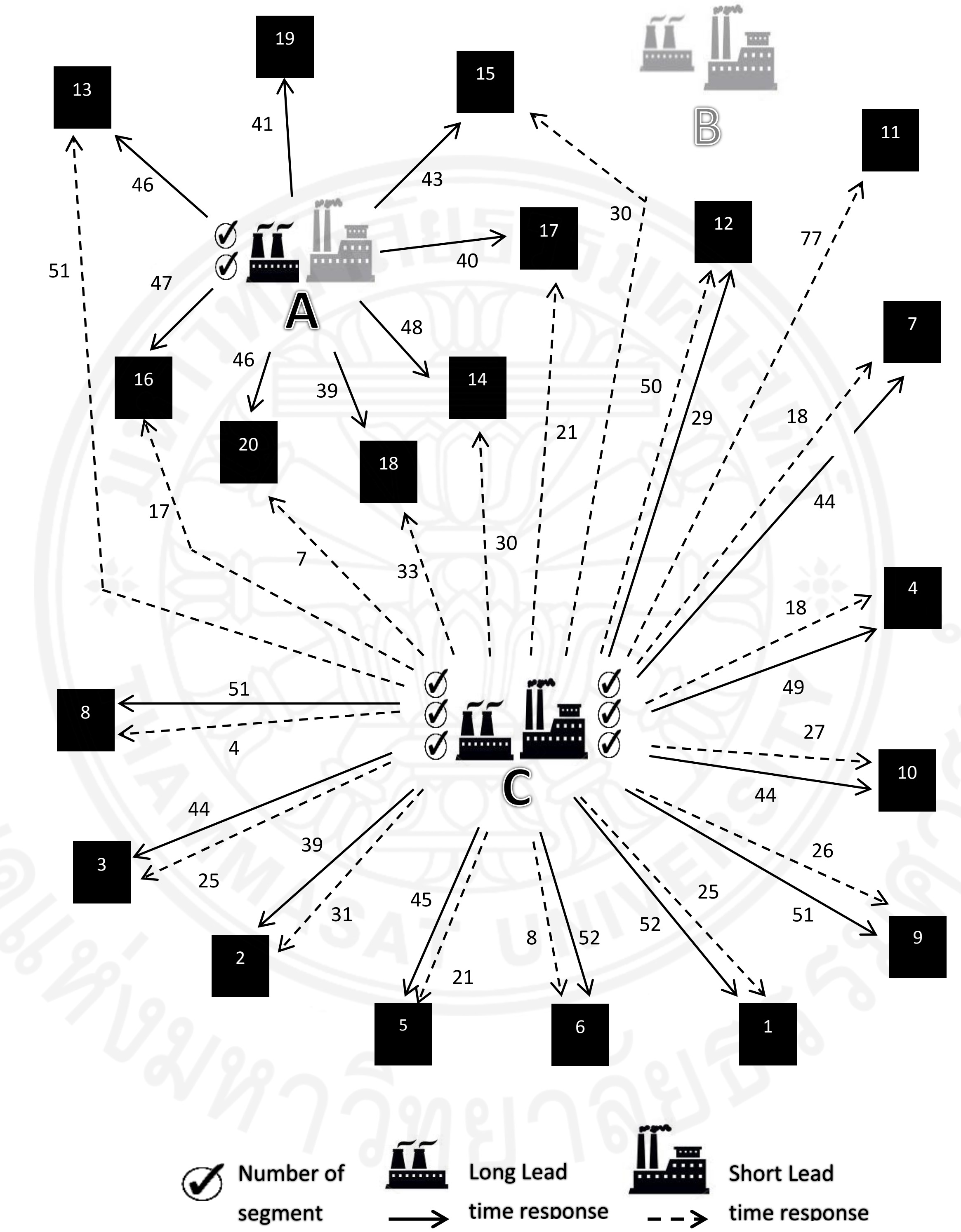


Figure 1: Base case scenario's result

- **Sampling test**

Theoretically, larger samples increases the chances of exposing specific mean difference because they are more reliably reflecting the population mean. This experiment is conducted to test how the size of sampling consequently contributed the results. We test to see that the sample size is bigger, the deviation would be smaller. Distribution of customer's demand in each scenario considered to be the sample size of the problem. Every scenario is created based on the same distribution (mean and standard deviation).

- **Parameter variation**

In this experiment, we vary various parameters of the model to acquire quantitative and qualitative difference of the results. For the quantitative difference, the comparison can obviously be shown by the numerical differences of major quantitative decisions i.e. total profit, amount of production, shortage amount and overage amount. Then, for the qualitative difference, we try to test how the physical decisions are changed according to the variation of parameter i.e. location of facilities and segmentation of facilities.

- **Cost function testing**

In this part, we develop a test to analyze the changes of the quantitative and qualitative results when different distribution of production cost function is implemented. We simulate 4 different characteristics of cumulative cost function i.e. (1) Convex cost function (2) Concave cost function (3) S-shaped cost function and (4) Stable cost function. Each cost curve is divided into 3 segments which each segment is refined according to the type of certain function.

- **Pair-T test**

For the last experiment, this experiment evaluates a significant contribution of this research which is the short LT response facility. We construct Pair-T test to prove how short LT response facility could improve certain situation and mitigate the effect of demand uncertainty, we compare the total profit among 3 cases which are (1) Only short LT response facility (2) Only long LT response facility and (3) Long and short LT response facility.

4.2 Results and analysis

This part is devoted to reveal the result of according experiments. We analyze the results in term of both quantitative and qualitative resolution. As we mentioned, quantitative analysis is focusing on profit and production and qualitative is targeting on facility location and segmentation allocation.

4.2.1 Sampling test

The experiment uses data of the base case. Each number of scenarios is retrieved from average of 5 replications.

From Table 3 and Figure 2, we focus on the change of standard deviation. We can obviously illustrate that as the size of the sample increase, standard deviation decline. The standard deviation is descending from 25,106.82 to 3,573.61 as the number of sample ascending from 100 to 400 respectively. Moreover, Figure 2 obviously shows that as the number of scenarios increases, the fluctuation rate of profit graph is decreased. For average profit, there is no relationship or trend among the scenarios, they are all rely on the random distribution of demand which is unnecessary to be concerned in this part. Hence, it is statistically consistent with the sampling theory, so we can support that bigger sample size could produce more refined and precise results. In the other hand, for bigger sample size, it reasonably requires much longer computational time.

Table 3:
Sampling test illustrating the change in deviation

Number of S		*Cost*	*Avg cost*	*SD*	*time*	
	100(1)	10,895,847.15			1.37	mins
	100(2)	10,922,218.58			1.35	mins
100	100(3)	10,861,803.73	10,894,615.79	25,106.82	1.31	mins
	100(4)	10,914,954.62			1.44	mins
	100(5)	10,878,254.85			1.41	mins
	200(1)	10,857,082.45			7.08	mins
	200(2)	10,903,527.42			5.36	mins
200	200(3)	10,870,304.00	10,879,163.00	21,308.97	6.02	mins
	200(4)	10,864,631.82			7.13	mins
	200(5)	10,900,269.31			8.33	mins
	300(1)	10,889,839.32			19.39	mins
	300(2)	10,870,616.34			15.42	mins
300	300(3)	10,878,082.69	10,883,290.84	8,740.92	18.56	mins
	300(4)	10,891,274.46			24.82	mins
	300(5)	10,886,641.38			27.24	mins
	400(1)	10,886,558.30			52.23	mins
	400(2)	10,884,037.59			50.00	mins
400	400(3)	10,887,485.63	10,883,616.65	3,573.61	55.14	mins
	400(4)	10,879,247.36			57.55	mins
	400(5)	10,880,754.38			53.22	mins

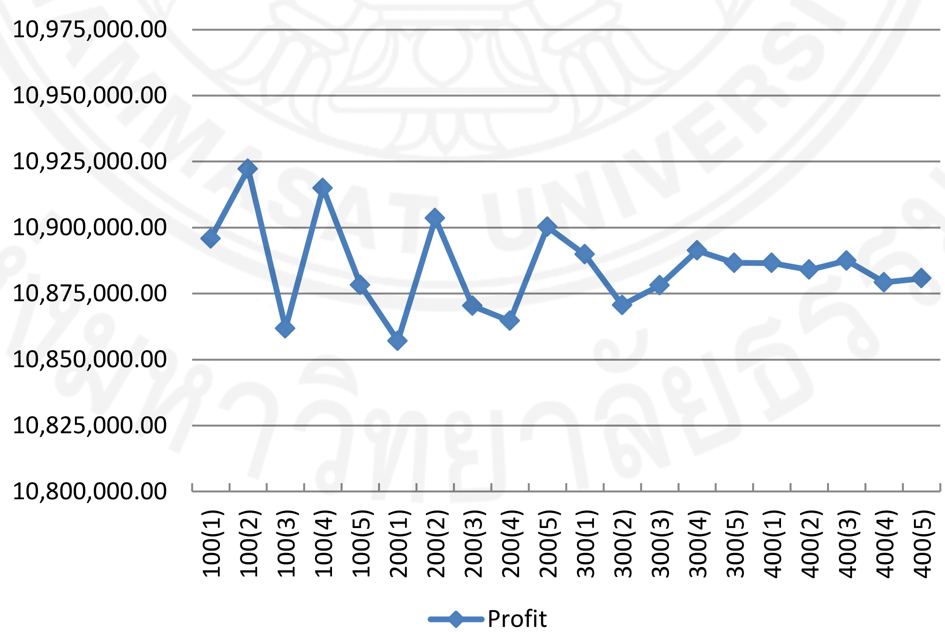


Figure 2: Sample size testing results

4.2.2 Parameter variation

For some of the parameter, the results are reasonably deviate according to general relationship of the parameter which are direct and inverse relationship. Hence, we decide to capture some parameter of this experiment that highlight the significance modification of the result. We also develop a simple sensitivity analysis to find the degree of effect on the total profit by variation of the parameters.

4.2.2.1 Unit Selling Price

From Table 4, for the first unit price, 30,000 baht, there are two long response LT facilities on location A and C, the production is 399 units short for satisfying demand and the profit is comparatively small at 1,454,690 baht. Hence, as the unit price decrease from 38,000 (base case) to 30,000 baht, it decides to opened just two long LT response facility to produce 1,000 units. In addition, it chooses to be short in production because in order to invest in opening one more facility, it may eventually turn the situation from gaining small amount of profit into loss. In particular, selling 399 units would not overcome the cost that they have to take to produce them.

For the second unit price, 46,000 baht, the profit is relatively increases as the selling price increases. According to table 4, as the unit price is higher, the long response facility in location A decide to add more capacity by opening the 3rd segment to sell more product for logical profit. The additional sale technically overcomes the cost of adding production capacity for all of the facility. Hence, the according unit price increases the production (comparing with the base case) from 1,339.07 to 1,394.19 and earns profit of 21,358,848 baht.

Table 4:
Results of unit price variation

Unit Price	*Type*	*Location*									*Production amount*		*Averaage Shortage amount*	*Average Overage amount*	*Total Profit*
		A			*B*			*C*							
		Segmentation													
		1	*2*	*3*	*1*	*2*	*3*	*1*	*2*	*3*	*Individual*	*Total*			
30,000	Long	■	■	■				■	■	■	1000	1000	399	12.71	1,454,690
	Short										0				
38,000*	Long	■	■					■	■	■	850	1339.07	50.94	3.72	10,604,193
	Short							■	■	■	489.07				
46,000	Long	■	■	■				■	■	■	965	1394.19	4.045	11.95	21,358,848
	Short							■	■	■	429.19				

***Base case**

4.2.2.2 Facility fixed cost

According to Table 5, first, for [3M, 5M] facility fixed cost, we can obviously see the inverse relationship between facility fixed cost and total profit, as the fixed cost decreases from [5M, 7M], the profit increase from 10,604,192 to 13,808,329 baht. More importantly, this variation has highlighted the significance part of the decision, as the facility cost decreases, more facilities with smaller capacity are opened comparing with the base case. More importantly, all of the short response facilities are open even that they are more expensive. This case has proven that even the short LT facility has more fixed cost but it could overcome the cost to effectively handle the demand uncertainty.

Second, for [6M, 8M] facility fixed cost, as the fixed cost raises for 1 million baht for both type of facility, total profit drop from 10,604,192 to 7,893,976 baht. In this case, all of the decisions are the same as the base case, just the difference between the facility costs that cause the decline in profit.

Table 5:
Results of facility fixed cost variation

Type	***Facility fixed cost***	*Location*									*Production amount*		*Average Shortage amount*	*Average Overage amount*	*Total Profit*
		A			*B*			*C*							
		Segmentation									*Individual*	*Total*			
		1	*2*	*3*	*1*	*2*	*3*	*1*	*2*	*3*					
Long	3M	■	■								1050	1377.97	26.645	18.32	13,808,329
Short	5M	■	■		■	■		■	■		327.97				
Long	5M*	■	■					■	■	■	850	1339.07	50.94	3.72	10,604,192
Short	7M*							■	■	■	489.07				
Long	6M	■	■					■	■	■	850	1339.07	50.94	3.72	7,893,976
Short	8M							■	■	■	489.07				

***Base case**

4.2.2.3 Capacity additional cost

From Table 6, first, for 500K capacity additional cost, one significant thing that has changed from the base case is that the long LT response facility of the 500K cost has opened the 3rd segment as the cost of expansion is halved. According from the total production amount, as the 3rd segment is opened, the production from 500K cost is slightly higher than the 1M cost with 50 units. As a matter of fact, opening the 3rd segment reinforces 150 units more production capacity, but in this case, only about 50 units from potential of 150 units are produced which is surprisingly unexpected. Hence, the model made this decision because selling those 50 more units has overcome the cost of additional segment even that the leftover capacity is considerably abandoned. Ultimately, the profit of 500K facility cost is 13,304,165 baht.

Second, for 2.5M capacity additional cost, as the cost raises for 1 million baht, short LT response facility which has higher fixed cost are ignored to compensate the raise in capacity additional cost. From the base case to certain case, the short LT response facility in location C is closed and decides to open one more long LT response facility at location B to persuade the level of production. In addition, only at location A could afford to open three segments, the other two locations decided to open just 2 segments and result in 1,200 units in production which is about 100 units short. Therefore, as the capacity additional cost enhanced from 1M to 2M, the total profit reduces from 10,604,193 to 6,329,765 baht

Table 6:
Results of capacity additional cost variation

Type	***Capacity addition al cost***	*Location*									*Production amount*		*Average Shortage amount*	*Average Overage amount*	*Total Profit*
		A			*B*			*C*							
		Segmentation									*Individual*	*Total*			
		1	*2*	*3*	*1*	*2*	*3*	*1*	*2*	*3*					
Long	500K	■	■	■	□	□	□	■	■	■	957	1391.77	5.335	10.815	13,304,165
Short	500K	□	□	□	□	□	□	■	■	■	434.77				
Long	1M*	■	■	□	□	□	□	■	■	■	850	1339.07	50.94	3.72	10,604,193
Short	1M*	□	□	□	□	□	□	■	■	■	489.07				
Long	2.5M	■	■	□	■	■	□	■	■	□	1050	1050	354.45	18.16	3,906,800
Short	2.5M	□	□	□	□	□	□	□	□	□	0				

***Base case**

4.2.2.4 Demand distribution

From Table 7, first thing that is needed to be explain is that, it is practical that as the demand decline from mean of 70 units to 60 units, the total profit is reasonably decline as well. The less of incoming demand, the less of sales occurred.

Second, by focusing on each mean of demand, for the mean of 70 units, we can obviously see that as the standard deviation (S.D.) raise from 5 to 10 then to 15, total profit is decreased from 11,945,595 to 10,908,190 then to 10,613,078 baht respectively. As well as for the mean of 60 units, as the S.D. raise from 5 to 10 then to 15, total profits are decreased from 9,868,849 to 9,146,386 then to 8,254,120 respectively. Hence, we can say that the less standard deviation of demand, the more profit could be performed.

Third, as we have proposed that short LT response facility helps handling the uncertainty of demand. The more standard deviation represents more degree of demand fluctuation or the level of uncertainty. In this part, for the mean of 70 units, as the S.D. reduce from 10 (base case) to 5, the short LT response facility is eliminated due to the cutback in level of uncertainty. In the other hand, for the mean of 60 units, as the S.D. enhance to 15, the short LT response facility is opened at maximum potential with 3 segments. Moreover, it pulls the production from the long LT response facility to itself to minimize the error from the fluctuation more effectively.

Table 7:
Results of demand variation

Demand Distribution		*Type*	*Location*									*Production amount*		*Avg. Shortage amount*	*Avg. Overage amount*	*Total Profit*
			A			*B*			*C*							
			Segmentation													
Mean	*SD*		*1*	*2*	*3*	*1*	*2*	*3*	*1*	*2*	*3*	*Individual*	*Total*			
70	5	Long	■	■	■	■	■	□	■	■	■	1350	1350	64.14	23.49	11,945,595
		Short	□	□	□	□	□	□	□	□	□	0				
70	10	Long	■	■	□	□	□	□	■	■	■	850	1346.4	46.7	0	10,908,190
		Short	□	□	□	□	□	□	■	■	■	496.38				
70	15	Long	■	■	□	□	□	□	■	■	■	850	1338.1	52.26	3.9	10,613,078
		Short	□	□	□	□	□	□	■	■	■	488.14				
60	5	Long	■	■	□	□	□	□	■	■	□	1000	1000	191.3	0.92	9,868,849
		Short	□	□	□	□	□	□	□	□	□	0				
60	10	Long	■	■	□	□	□	□	■	■	□	1000	1000	207.8	17.33	9,146,386
		Short	□	□	□	□	□	□	□	□	□	0				
60	15	Long	■	■	□	□	□	□	■	■	□	700	1170.5	23.73	6.09	8,254,120
		Short	□	□	□	□	□	□	■	■	■	470.5				

***Base case**

4.2.2.5 Sensitivity Analysis

This sensitivity analysis reveals the change of output when 1% of the input parameter is changed. The sign of sensitivity value indicates the type relationship between the parameter and output. If the sensitivity value is negative, that parameter has direct relationship with the total profit. However, if the sensitivity value is positive, that parameter has inverse relationship with the total profit. According to Table 8, we can summarize that unit price has direct relationship to the total profit. Moreover, unit price is the most sensitive parameter comparing among the others. If the unit selling price increases for 1%, the total profit will increase for 409.84%. On the other hand, if the unit selling price decreases for 1%, the total profit will increase for 481.74%.

Table 8:
Sensitivity analysis

Variable	*Parameter Change (direction)*	*Parameter change (%)*	*Output Change (%)*	*Sensitivity*
Unit selling price	Decrease	-0.21	-86.28	409.84
	Increase	0.21	101.42	481.74
Fixed cost	Decrease	-0.33	30.22	-90.65
	Increase	0.17	-25.56	-153.35
Capacity additional cost	Decrease	-50.00	25.46	-0.51
	Increase	150.00	-63.16	-0.42
Demand (SD)	Decrease	-50.00	9.51	-0.19
	Increase	50.00	-2.71	-0.05

4.2.3 Cost function testing

The costs are representing in a form of a cumulative function. The slope indicates the cost in each segment. If the slope of the line is steep, the cost is more expensive, and vice versa. More importantly, the first segment has the capacity of 200 unit and 150 units each for the next 2 segments, so, each facility has the maximum possible capacity at 500 units. All of the 4 functions have weight average cost of 14,000 baht.

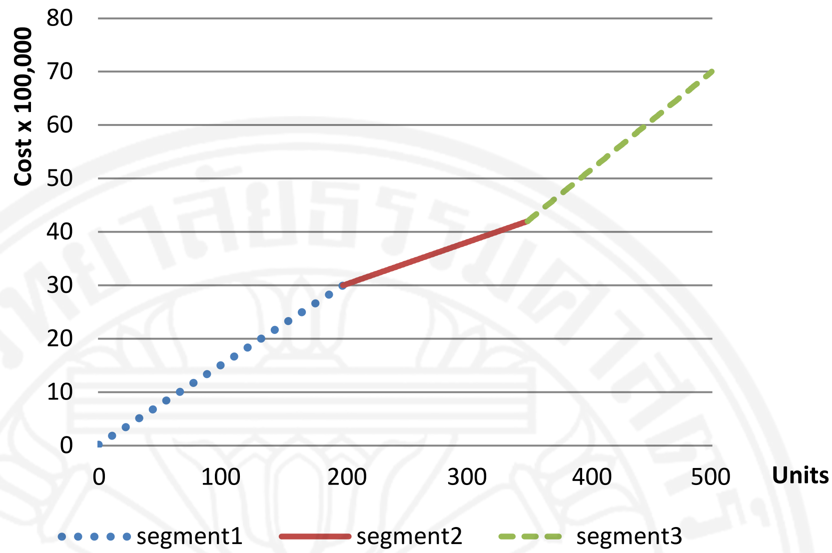
From Table 9, first, for the s-shaped cost function (Figure 3), two segments for location A and three segments for location C of long LT response facility are opened. For short LT response, only facility from location C is opened with three segments. So in this case, location C is literally the critical location for minimizing the transportation cost in this framework as both long and short response facility are both opened at the same location. Besides, there are 850 units for long LT response facility and 496.16 units for short LT response which results in 1,346.15 units in total. Consequently, this cost function produces 10,903,814 baht for the profit.

Second, convex cost function (Figure 4) achieves 15,552,714 baht profit which is comparatively higher than the s-shaped cost function. The first point to be focused is the nature of the function which the first 350 units from the first and second segment hold the cheap production cost and formidably increase for the last segment. Under those circumstances, from table 9, we obviously observe that the third segment is avoided in every opened facility. The results were decided not to operate in the expensive cost segment and wisely chose to open one more facility at location B instead of keep up the level of production to serve demand. Ultimately, this function particularly makes more remarkable profit because as only first two segments are determined on each facility, the average cost has decently drop and overcome the cost of opening additional long LT response facility at location B.

Third, concave cost function (Figure 5) announces the profit of 9,827,047 baht which is somewhat less than the s-shaped function. We observe that the facilities are opened at location A and C; both of them are all opened for all of the 3 segments for 500 units maximum. According to the property of the cost function, the cost for first segment is very high comparing with the upcoming segments. The function itself undertakes the economies of scale role, as the higher quantity to be produced, the lower the average cost it is. In practical, economies of scale is the advantage for the supply chain member which they can acquire less average cost per unit as the inverse relationship between quantity and cost occur. Nevertheless, this situation arises differently, as total of 1,000 units are produced in long response facility, but it is still about 386.4 units short according to the demand. We accept that in this case, if any facility is opening, they all have to be fully capacitated to ensure the reasonable average cost. In the other hand, if one more facility is fully opening to satisfy the left over demand, it will create lots of overage unit and their penalty. Moreover, if one more facility is opening for one or two segments, the cost of production would no longer be suitable, leads to less margin and could not overcome the cost of opening the additional facility.

Lastly, the stable cost function (Figure 6), the result is apparently close to S-shaped cost function in many ways, the location and segmentation is the same, production and shortage are slightly different and has 743,394 baht less profit, so we could announce that s-shaped function is the most similar to linear average cost function which are casually implement in practical.

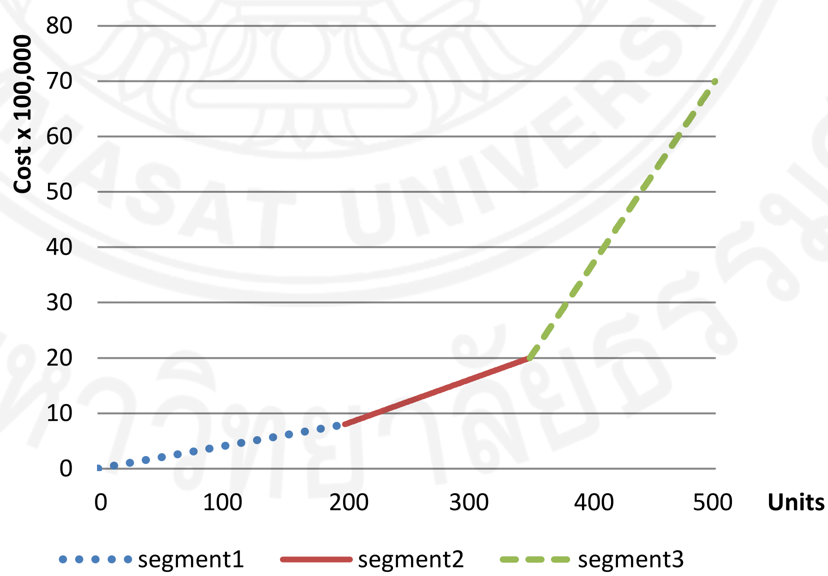
4.2.3.1 S-Shaped cost function



Cost: *15,000* *8,000* *18,666.67*

Figure 3: S-shaped cost function

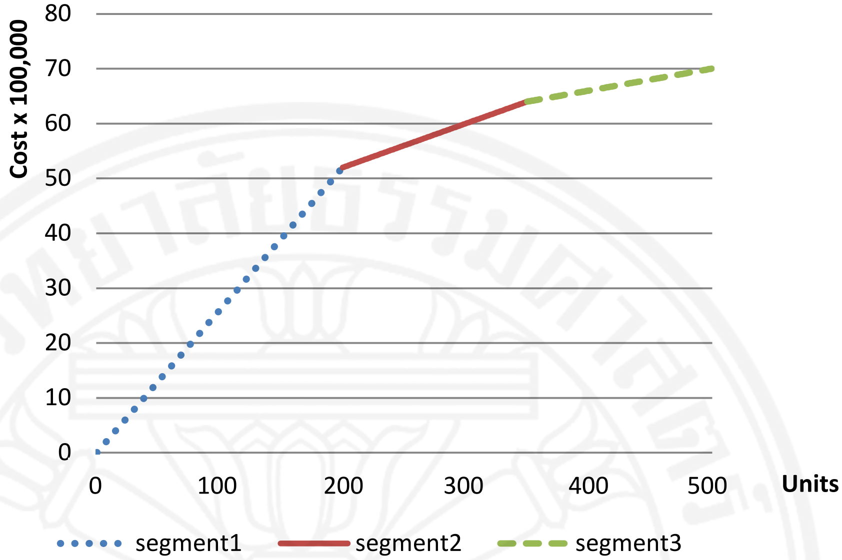
4.2.3.2 Convex cost function



Cost: *4,000* *8,000* *33,333.33*

Figure 4: Convex cost function

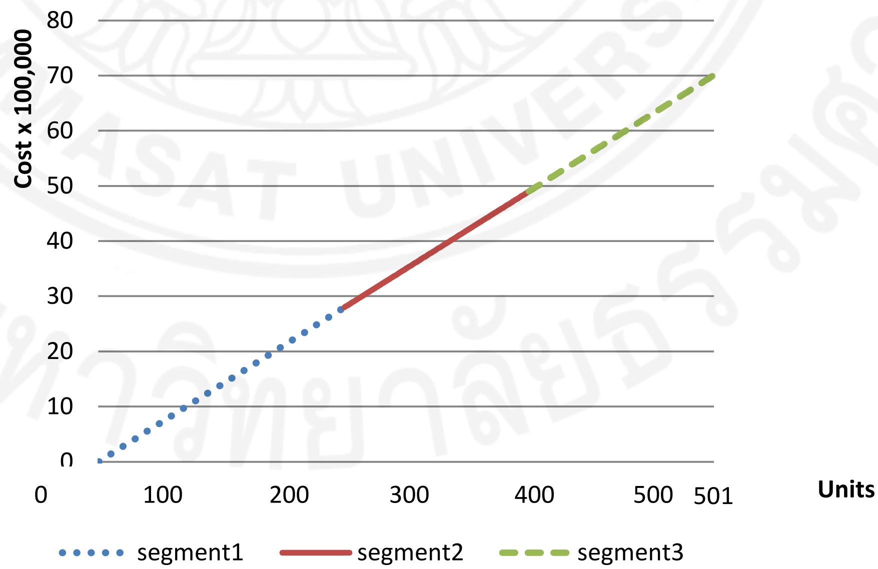
4.2.3.3 Concave cost function



Cost: *26,000* *8,000* *4,000*

Figure 5: Concave cost function

4.2.3.4 Stable cost function



Cost: *14,000* *14,000* *14,000*

Figure 6: Stable/average cost function

Table 9:
Results of 4 different cost function

Cost fn.	*Type*	*Location*									*Production amount*		*Avg. Shortage amount*	*Avg. Overage amount*	*Total Profit*
		A			*B*			*C*							
		Segmentation									*Individual*	*Total*			
		1	*2*	*3*	*1*	*2*	*3*	*1*	*2*	*3*					
S-shaped	Long	■	■					■	■	■	850	1346.16	41.275	0	10,903,814
	Short							■	■	■	496.16				
Convex	Long	■	■		■	■		■	■		1050	1379.15	11.575	3.29	15,552,714
	Short							■	■		329.15				
Concave	Long	■	■	■				■	■	■	1000	1000	386.42	1.86	9,827,047
	Short										0				
Stable	Long	■	■					■	■	■	850	1345.09	19.735	0	10,160,420
	Short							■	■	■	495.09				

4.2.1 Pair-T test

The purpose of this test is to do the hypothesis testing between short response lead time and long response lead time in order to proof that which kind of facility perform more efficiently under certain situation. This test is created based on 200 observations (scenarios), 95% confidence interval and 0.1 degree of freedom.

From Table 10 and 11 and 12, firstly, we can literally prove that combining short LT response and long LT response facilities perform better than each single one of them itself. With short and long LT response, profit maximize to 10,911,015 which is 553,089 higher than with long LT response only and 3,993,218 higher than short LT response only. Moreover, we have developed the pair-t test to statistically test the difference between the mean of each comparison. As the results, short and long together has more profit mean than either short LT response only or long LT response only, as the p-value for both of them is less than 0.05 and reject the null hypothesis that their mean are not the same.

Table 10:
Pair-t test comparing the profit among 3 cases

	Total Profit				
	1. Short only	*2.Long only*	*3. Short + Long*	*3-1*	*3-2*
1	6,979,683	9,948,947	10,977,188	3,997,505	1,028,241
2	6,980,396	9,948,947	10,977,807	3,997,411	1,028,860
3	6,825,646	9,156,947	10,823,164	3,997,518	1,666,217
4	6,978,874	10,388,947	10,976,390	3,997,516	587,443
.					
.					
.					
198	6,981,452	10,828,947	10,978,862	3,997,410	149,915
199	6,979,782	10,080,947	10,977,427	3,997,645	896,480
200	6,980,673	10,960,947	10,978,693	3,998,020	17,746

	Total Profit				
	1. Short only	*2.Long only*	*3. Short + Long*	*3-1*	*3-2*
Average	6,917,798	10,357,927	10,911,016	3,993,218	553,089
SD	226,300	538,740	243,130		

4.2.1.1 Short / Short and Long

$$H_0 : \mu_1 = \mu_3$$
$$H_A : \mu_1 \neq \mu_3$$

Table 11:
Pair-T test: paired two sample for means (Short / Long and Short)

	Variable 3 (Short + Long)	*Variable 1 (Short only)*
Mean	10,911,015.74	6,917,799.00
Variance	59,112,171,183.37	51,211,728,788.14
Observations	200.00	200.00
Pearson Correlation	0.99	
Hypothesized Mean Difference	0.00	
df	199.00	
t Stat	1,311.12	
P(T<=t) one-tail	0.00	

t Critical one-tail	1.65
P(T<=t) two-tail	0.00
t Critical two-tail	1.97

4.2.1.2 Long / Short and Long

$$H_0 : \mu_1 = \mu_3$$

$$H_A : \mu_1 \neq \mu_3$$

Table 12:
Pair-T test: paired two sample for means (Long / Long and Short)

	Variable 3 (Short + Long)	*Variable 2 (Long only)*
Mean	10,911,015.74	10,357,927.00
Variance	59,112,171,183.37	290,240,401,608.04
Observations	200.00	200.00
Pearson Correlation	0.53	
Hypothesized Mean Difference	0.00	
df	199.00	
t Stat	17.09	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.65	
P(T<=t) two-tail	0.00	
t Critical two-tail	1.97	

4.2.1.3 Short / Long

$$H_0 : \mu_1 = \mu_2$$

$$H_A : \mu_1 \neq \mu_2$$

Secondly, according to table 13, as p-value is less than 0.05, so the null hypothesis is rejected. We compare the profit between individual long and short LT response only, the long LT response give out more profit than another. As we proposed earlier, the advantage of short LT response facility of this model does help to manipulate the demand uncertainty. But in this case, minimization of loss demand does not overcome the cost of affording specialized facilities. So, ultimately, it costs more and results in less profit.

Table 13:
Pair-T test: paired two sample for means (Short / Long)

	Variable 1 (Short only)	*Variable 2 (Long only)*
Mean	10,357,927.00	6,917,799.00
Variance	290,240,401,608.04	51,211,728,788.14
Observations	200.00	200.00
Pearson Correlation	0.51	
Hypothesized Mean Difference	0.00	
df	199.00	
t Stat	104.27	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.29	
P(T<=t) two-tail	0.00	
t Critical two-tail	1.65	

PART 2
HEURISTIC

4.3 Heuristic approach

Our proposed model has proven that it can solve the according supply chain situation, but the problem size is considerably small and not convincing to be used in real life situation. In practical, manager has to deal with bigger problem size with more number of sites and customers. As the problem is considered as NP-hard, more number of location and customer cause substantial increase in computational time. Hence, we decide to further develop heuristic model to overcome the computational time problem.

The heuristic model is grabbed from the main model with supplemental refinement i.e. the upper bound (UB) and lower bound (LB) value which will be highlighted and interpreted further in the different cost function. We develop the linear relaxation and decomposition method by manipulating two binary variable; $OPEN_j$ and w_j and separating them into two phases.

4.3.1 1st phase: Location decision

This part focuses on the location allocation ($OPEN_j$) for both long and short LT response facility and the preliminary amount of production to ensure that the according number of opening facility is adequate to serve the demand. We use the weight average cost from each cost function as the cost for certain preliminary production.

4.3.1.1 Production upper bound (UB) and lower bound (LB) setting

From previous experiment, we have discovered the decisive nature of each distinct cost functions. Each cost function has different natural property which influentially affects the decision on determining the size of the facility capacity (segmentation) and leads to the number of opening facility under the according demand circumstances. Hence, we have to set the upper bound and lower bound to manipulate preliminary production decision for the first phase base on each type of cost function.

4.3.1.1.1 S-shaped cost function bounding

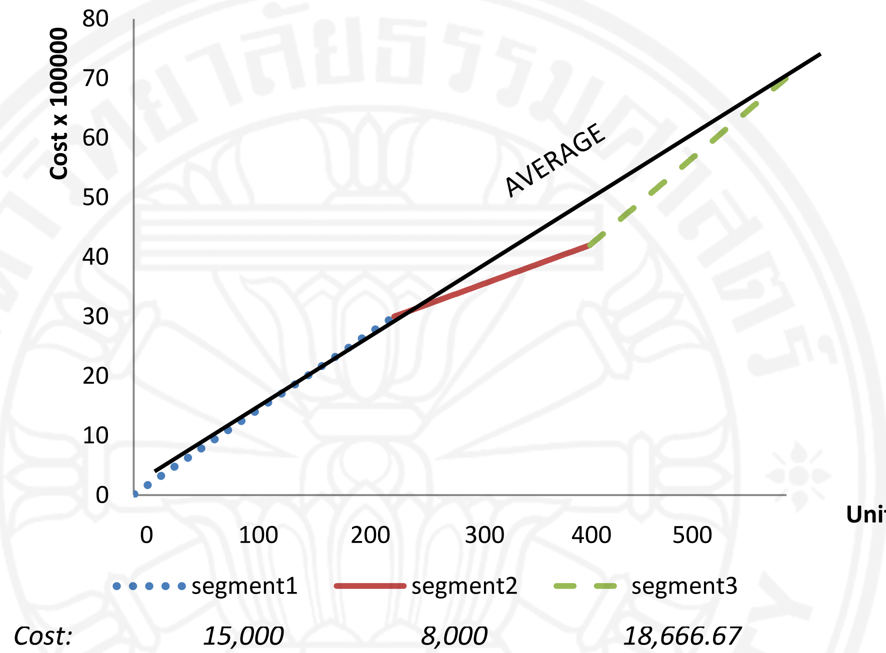
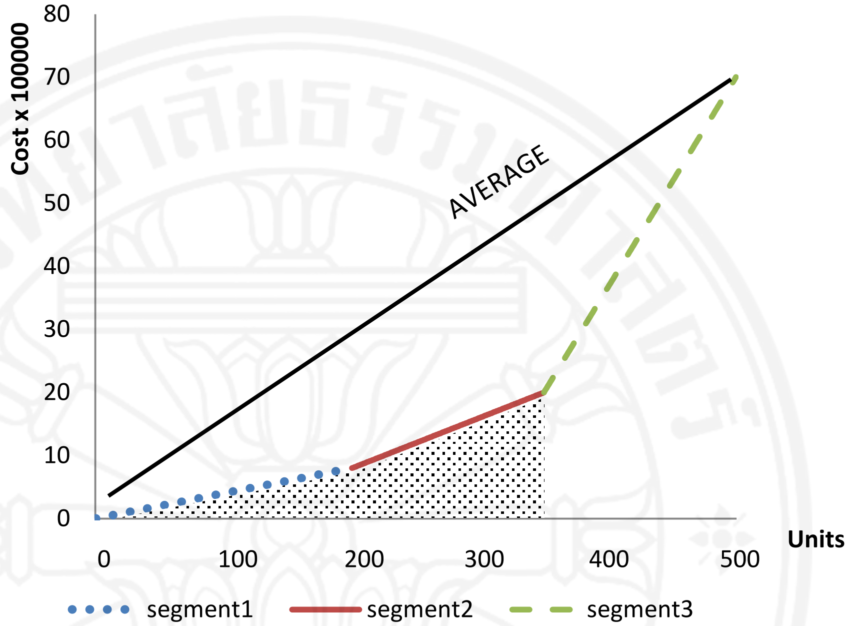


Figure 7: S-shaped cost function bounding

- *LB: 0 , UB: none*

S-shaped cost function is considerably familiar with average cost, so no upper bound and lower bound needed be set.

4.3.1.1.2 Convex cost function bounding



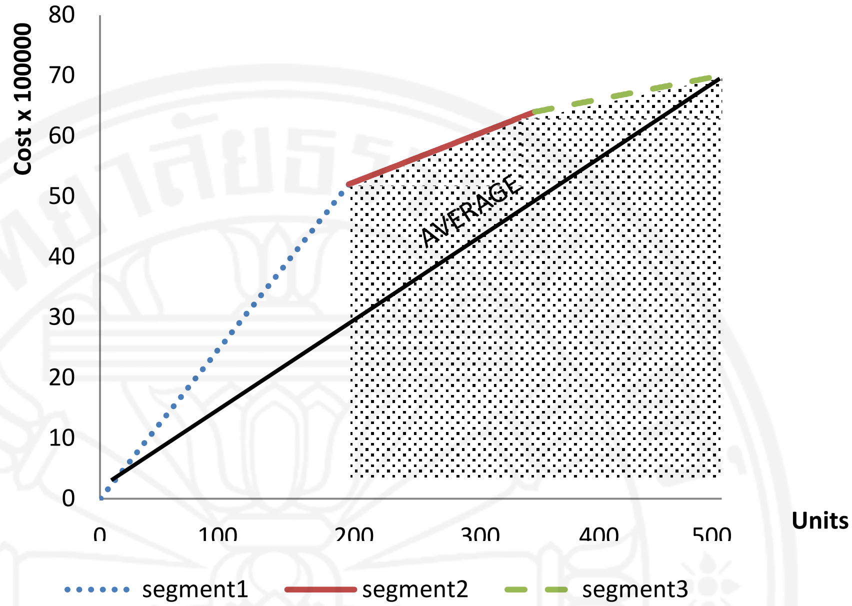
Cost: *4,000* *8,000* *33,333.33*

Figure 8: Convex cost function bounding

- *LB: 0 , UB: 350*

For convex cost function, upper bound is set at 350 to restrict the production from the expensive cost of the 3rd segment. This function has been proof that it is worth to open more small facility instead of opening the 3rd segment.

4.3.1.1.3 Concave cost function bounding



Cost: *26,000* *8,000* *4,000*

Figure 9: Concave cost function bounding

- *LB: 200 , UB: 500*

For concave cost function, as the 1st segment offering high cost, so the lower bound is set at 200 to ensure that the facility is opening beyond the 1st segment in order to alleviate the overall average cost of production from the lower production cost of 2nd and 3rd segment.

4.3.2 2nd phase: Segmentation decision

After deciding the location, the decision (*OPENj*) will be substituted as input data in the 2nd phase model or *original model* (available in PART 1) for further segmentation decisions (w_j) and product assignment allocation.

4.4 Heuristics model: Two phases heuristic model

Indexes:

$i = demand\ node$

$j = facility\ node\ (JL: Long,\ JS: short)$

$k = segment\ k\ of\ production\ cost$

$s = scenario\ of\ second\ stage$

Parameters:

$c_{ij} = transportation\ cost\ from\ j\ to\ i$

$l_{jk} = production\ cost\ (slope)\ per\ unit\ using\ line\ segment\ k\ at\ location\ j$

$l = weight\ average\ \cos t\ per\ unit$

$ac_{jk} = marginal\ fixed\ cost\ to\ construct\ faciliy\ of\ size\ k\ at\ location\ j$

$(additional\ cost\ in\ expand\ capacity\ from\ size\ k-1\ to\ size\ k)$

$fc_{jk} = fixed\ cost\ to\ construct\ faciliy\ at\ location\ j$

$p = probability\ of\ scenarios$

$Sh = Shortage\ cost\ per\ unit$

$Ov = Overage\ (holding)\ cost\ per\ unit$

$D_{is} = Demand\ of\ product\ at\ location\ i\ under\ scenario\ s$

$L_{jk} = Length\ of\ segment\ k\ of\ production\ cost\ at\ location\ j\ or$

$(Additional\ capacity\ if\ size\ k\ is\ selected\ over\ size\ k-1\ at\ location\ j)$

$UB = upper\ bound\ of\ production$

$LB = lower\ bound\ of\ production$

$UP = Unit\ selling\ price$

$MC = Maximun\ capacity$

Decision Variables:

First stage:

$x_{ij} = quantity\ shipped\ from\ j\ to\ i\ using\ long\ lead\ time\ facility$

$\delta_j^x / \delta_{jk}^x = quantity\ produced\ at\ location\ j\ using\ long\ lead\ time\ under\ segment\ k\ of\ production\ cost$

$w_{jk} = 1\ if\ quantity\ produced\ is\ at\ upperbound\ k\ (full\ capacity\ of\ segment\ k)\ of\ production\ cost$

$(\delta_{jk}^x = L_{jk}\ or\ \delta_{jk}^y = L_{jk}),\ 0\ otherwise$

$OPEN_j = 1\ if\ a\ facility\ is\ open\ at\ location\ j,\ 0\ otherwise$

$Second\ stage:$

y_{ijs} = quantity shipped from j to i using short lead time facility under scenario s

$\delta^{y}_{js} / \delta^{y}_{jks}$ = quantity produced at location j using short lead time under segment k of production cost

SQ_{is} = shortage quantity at location i under scenario s

OQ_{is} = overage quantity at location i under scenario s

1st phase heuristic model (Location decision)

$$Minimize\quad Up\left(\sum_i\sum_j^{JL} x_{ij} + \sum_s p\sum_i\sum_j^{JS} y_{ijs} - \sum_s p\sum_i OQ_{is}\right) -$$

$$\left(\begin{array}{l}\sum_i\sum_j c_{ij}x_{ij} + l\sum_j^{JL}\sum_k \delta^x_j + \sum_j\sum_k w_{jk}ac_{jk} + \sum_j OPEN_j fc_j + \\ \sum_s p_s\left(\sum_i\sum_j c_{ij}y_{ijs} + l\sum_j^{JS}\sum_k \delta^y_{js} + \sum_i SQ_{is}Sh + \sum_i OQ_{is}Ov\right)\end{array}\right)$$

Subject to

$$ct1: \sum_j x_{ij} + \sum_j y_{ijs} + SQ_{is} - OQ_{is} = D_{is},\ \ \forall i, s$$

$$ct2: \sum_i x_{ij} = \sum_{k=1}^{K} \delta^x_{jk},\ \forall j \in JL$$

$$ct3: \sum_i y_{ijs} = \sum_{k=1}^{K} \delta^y_{jks},\ \forall j \in JS, s$$

$$ct4: OPEN^x_j\, LB \ \le \ \sum_i x_{ij} \ \le \ OPEN^x_j\, UB,\ \ \forall j \in JL$$

$$ct5: OPEN^y_j\, LB \ \le \ \sum_i y_{ijs} \ \le \ OPEN^y_j\, UB,\ \ \forall j \in JS, s$$

$$ct6: \ \delta^x_j \le MC,\ \ \forall j \in J$$

$$ct7: \ \delta^y_{js} \le MC,\ \ \forall j \in J, s$$

$$ct8: x_{ij}, y_{ij}, \delta^x_{jk}, \delta^y_{jks}, SQ_{is}, OQ_{is} \ge 0$$

$$ct9: w_{jk}, OPEN_j \ \in \{0,1\}$$

Model interpretation (1st phase)

The objective function of the model is to maximize the profit from sales of product from short LT response and long LT response (excluding the overage amount) and deduct by various cost of long LT response and short LT response i.e. transportation cost (long LT), production cost (long LT), capacity additional cost, facility fixed cost, and with the probability distribution for transportation cost (short LT), production cost (short LT), shortage cost and overage cost. Constraint (1) represents the demand satisfaction. Constraint (2) determines total production and delivery from all of the long LT response facility. Constraint (3) determines total production and delivery from all of the short LT response facility. Constraint (4) bounds the production of each single long LT facility to be within the lower bound and upper bound. Constraint (5) bounds the production of each single short LT facility to be within the lower bound and upper bound. Constraint (6), Constraint (7) limits the maximum production of each facility (long and short) at 500 units. Constraint (8) determines the non-negativity variables. Lastly, Constraint (9) determines the binary variable.

4.5 Heuristic: Numerical experiment

As mentioned earlier, we develop the heuristic by breaking down the model into two phases. The first phase decides the location to open short LT response facilities or long LT response facilities among the determined location candidates. Next, second phase utilizes the acquired location decision from the first phase as additional input data to allocate the production schedule and segmentation for according decided facilities.

The experiments interpret the strength of heuristic comparing to the original model in terms of time efficiency and profit efficiency. We separate the analysis into three parts according to three types of cost function i.e. s-shaped (Figure 2), concave (Figure 3) and convex (Figure 4). Each cost function has different property which leads to give out distinctive decisions. In addition, each cost function employs identical input data set as shown in table 14 for the solving model. We generate three problem sizes for more complexity which each instance is differentiated by the mean and standard deviation of demand. Table 15 shows the input data utilized for the whole experiments which the data are all identical for every experiment.

Table 14:
Input data for each instance

Exp. no.	*Int.*	*Number of sites*			*No. of customers*	*Shortage cost*	*Overage cost*	*Unit Price*	*Transportation cost (Random range)*		*Demand (distribution)*	
		Long res.	*Short res.*	*Total*					*Min*	*Max*	*Mean*	*SD*
1 (small)	1A	5	5	10	20	400	6000	38000	60	190	115	12
	2A	5	5	10	20	400	6000	38000	60	190	115	23
	3A	5	5	10	20	400	6000	38000	60	190	120	35
2 (medium)	2A	8	8	16	20	400	6000	38000	60	190	180	19
	2B	8	8	16	20	400	6000	38000	60	190	180	38
	2C	8	8	16	20	400	6000	38000	60	190	190	50
3 (large)	3A	10	10	20	30	400	6000	38000	60	190	150	16
	3B	10	10	20	30	400	6000	38000	60	190	150	32
	3C	10	10	20	30	400	6000	38000	60	190	160	48
4 (very large)	4A	15	15	30	50	400	6000	38000	60	190	135	14
	4B	15	15	30	50	400	6000	38000	60	190	135	27
	4C	15	15	30	50	400	6000	38000	60	190	145	40

Abbreviation: Exp. = experiment, no. = number, Int. = Instance, res. = response

Table 15:
Common input data for testing heuristic

Type	*Facility fixed cost*	*Capacity additional cost*	*Selling price per unit*	*Overage cost per unit*	*Shortage cost per unit*	*Transportaion cost per unit (Random)*	
						min	*max*
Long	5M	1M	38,000	6,000	400	70	220
Short	7M	1M					

4.6 Heuristic: Results and Analysis

In this part, we examine the results of the four experiment sizes (small, medium, large and very large) from three types of the cost function which shown in detail in Table 16, 17, and 18. We focus on two attentions from the results table; total profit gap percentage and computational time reduction.

4.6.1 S-Shaped cost function

According to the result of testing s-shaped cost function in Table 16, first, for experiment set 1, the heuristics has given the same profit as the optimal result for instance 1A, 1B and 1C. The computational time for both optimal model and heuristic model are less than 1 minute, so the time gap is not significantly needed to be concerned.

For experiment 2, the heuristic has given the same profit as the optimal result for instance 2A and 2B. For instance 2C, the heuristic has acceptable gap of 0.75% comparing to optimal. The average computational time reduction is 79.82%.

For experiment 3, the heuristic has given the same profit as the optimal result for instance 3A, 3B and 3C. The average computational time reduction is 84.05%.

For experiment 4, the heuristic has given the same profit as the optimal result for instance 4A. For instance 4B and 4C, the optimal model failed solve the problem as the memory ran out, but heuristics were able to solve the problem in within decent time. So, we can say that the average computational time reduction is 86.67%

Table 16:
Optimal and heuristics results comparison for S-shaped cost function

Experi-ment no.	*Int.*	*Heu. Test #*	*Avg. overage*	*Avg. shortage*	*Total Long res. (X)*	*Total Short res. (Y)*	*Total Profit*	*% gap*	*Time (mins)*	*% Time red.*	*Avg. % gap (time)*
1 (small)	1A	Optimal	6.96	183.2	1500	499.62	17,419,948.48	0.00	1	0.00	0.00
		Heuristic	6.96	183.2	1500	499.62	17,419,948.48		1		
	1B	Optimal	36.76	224.48	1500	499.56	16,094,086.83	0.00	1	0.00	
		Heuristic	36.76	224.48	1500	499.56	16,094,086.83		1		
	1C	Optimal	27.62	222.06	1000	984.12	14,199,460.30	0.00	1	0.00	
		Heuristic	27.62	222.06	1000	984.12	14,199,460.30		1		
2 (medium)	2A	Optimal	7.36	106.48	3000	494.16	32,243,657.39	0.00	10	90.00	79.82
		Heuristic	7.36	106.48	3000	494.16	32,243,657.39		1		
	2B	Optimal	40.74	155.62	2000	1468.1	26,253,633.06	0.00	5	60.00	
		Heuristic	40.74	155.62	2000	1468.1	26,253,633.06		2		
	2C	Optimal	44.24	290.72	2500	993.6	31,909,880.02	0.75	19	89.47	
		Heuristic	40.74	155.62	2000	1468.1	31,670,695.03		2		
3 (large)	3A	Optimal	28.58	45.06	4000	483.86	41,073,734.70	0.00	20	85.00	84.05
		Heuristic	28.58	45.06	4000	483.86	41,073,734.70		3		
	3B	Optimal	62.62	85.9	3500	969.72	37,286,488.04	0.00	40	97.50	
		Heuristic	62.62	85.9	3500	969.72	37,286,488.04		1		
	3C	Optimal	61.72	69.02	3350	1414.8	37,352,887.36	0.00	402	69.65	
		Heuristic	61.72	69.02	3350	1414.8	37,352,887.36		122		
4 (very large)	4A	Optimal	0.6	78.26	5250	1385.2	54,401,655.19	0.00	75	86.67	-
		Heuristic	0.6	78.26	5250	1385.2	54,401,655.19		10		
	4B	Optimal	-	-	-	-	-	-	out.	-	
		Heuristic	31.1	71.48	4500	1446.3	51,078,739.12		30		
	4C	Optimal	-	-	-	-	-	-	out.	-	
		Heuristic	72.78	99.48	4000	1932.7	46,972,276.41		100		

Abbreviation: Exp. = experiment, Int. = Instance, Out. = out of memory, res. = response, red. = reduction Avg. = average

4.6.2 Convex cost function

According to the result of testing convex cost function in table 17, first, for experiment set 1, the heuristics produce the same profit as the optimal result for instance 1A, 1B and 1C. The computational time for both optimal model and heuristic model are less than 1 minute, so the time gap is not significantly needed to be concerned.

For experiment 2, the heuristic has given the same profit as the optimal result for instance 2A and 2B. For instance 2C, the heuristic has acceptable gap of 1.6%

comparing to optimal. The computational time for both optimal model and heuristic model are still very short, so it is not needed to be concerned.

For experiment 3, the heuristic has given the same optimal result for instance 3A and 3B. For instance 3C, the heuristic has acceptable gap of 0.72% comparing to optimal. The average computational time reduction is 50%.

For experiment 4, the heuristic has given the same optimal result for instance 4A and 4B and 4C. The average computational time reduction is 60.88%.

Table 17:
Optimal and heuristics results comparison for convex cost function

Exp. no.	*Int.*	*Model*	*Avg. overage*	*Avg. shortage*	*Total Long res. (X)*	*Total Short res. (Y)*	*Total Profit*	*% gap*	*Time (mins)*	*% Time red.*	*Avg. % gap (time)*
1 (small)	1A	Optimal	31.58	111	1750	346.44	28,062,274.30	0.00	1	0.00	0.00
		Heuristic	31.58	111	1750	346.44	28,062,274.30		1		
	1B	Optimal	26.16	124.22	1400	689.22	26,082,233.90	0.00	1	0.00	
		Heuristic	26.16	124.22	1400	689.22	26,082,233.90		1		
	1C	Optimal	76.26	169.86	1400	684.96	23,733,558.04	0.00	1	0.00	
		Heuristic	76.26	169.86	1400	684.96	23,733,558.04		1		
2 (medium)	2A	Optimal	1.08	103.2	2800	691.16	48,376,372.96	0.00	1	0.00	22.22
		Heuristic	1.08	103.2	2800	691.16	48,376,372.96		1		
	2B	Optimal	98.86	194.96	2450	1036.9	41,911,401.98	0.00	1.2	16.67	
		Heuristic	98.86	194.96	2450	1036.9	41,911,401.98		1		
	2C	Optimal	90.1	67.06	2800	963.12	45,413,231.46	1.60	2	50.00	
		Heuristic	39.24	286.14	2450	1043.2	44,687,937.32		1		
3 (large)	3A	Optimal	0	12.36	3500	987.98	60,703,142.90	0.00	1	0.00	50.00
		Heuristic	0	12.36	3500	987.98	60,703,142.90		1		
	3B	Optimal	63.44	57.08	3500	999.36	58,234,539.58	0.00	4	75.00	
		Heuristic	63.44	57.08	3500	999.36	58,234,539.58		1		
	3C	Optimal	80.6	52.6	3500	1300.1	59,283,081.86	0.72	28	75.00	
		Heuristic	78.76	304.94	3500	1045.9	58,858,582.20		7		
4 (very large)	4A	Optimal	0	29.62	4200	1712.4	78,471,732.64	0.00	32	68.75	60.88
		Heuristic	0	29.62	4200	1712.4	78,471,732.64		10		
	4B	Optimal	13.76	92.86	4200	1707.5	77,709,179.88	0.00	12	58.33	
		Heuristic	13.76	92.86	4200	1707.5	77,709,179.88		5		
	4C	Optimal	97.26	140.72	4200	1716.4	74,265,134.50	0.00	18	55.56	
		Heuristic	97.26	140.72	4200	1716.4	74,265,134.50		8		

Abbreviation: Exp. = experiment, Int. = Instance, out. = out of memory, res. = response, Avg. = average

4.6.3 Concave cost function

According to the result of testing concave cost function in table 18, first, experiment set 1, the heuristics has given the same profit as the optimal result for instance 1A and 1B and 1C. Next, the computational time of this size is about 1 minute for both heuristic and optimal.

For experiment 2, the heuristic has given the optimal result for instance 2A and 2B. For instance 2C, the heuristic has acceptable gap of 4.63% comparing to optimal. The average computational time reduction is 81.87%.

For experiment 3, the heuristic has given the same optimal result for the instance 3A and 3B. For instance 3C, the heuristic has acceptable gap of 3.4% comparing to optimal. The average computational time reduction is 86.09%.

For experiment 4, For instance 4A and 4C, the optimal model failed solve the problem as the memory ran out, but heuristics were able to solve the problem in within decent time. For instance 4B, the heuristic has acceptable gap of 0.35% comparing to optimal. The average computational time reduction is 93.25%.

Table 18:
Optimal and heuristics results comparison for concave cost function

Exp. no.	*Int.*	*Model*	*Avg. overage*	*Avg. shortage*	*Total Long res. (X)*	*Total Short res. (Y)*	*Total Profit*	*% gap*	*Time (mins)*	*% Time red.*	*Avg. % gap (time)*
1 (small)	1A	Optimal	6.96	183.2	1500	499.62	17,414,395.14	0.00	1	0.00	-7.69
		Heuristic	6.96	183.2	1500	499.62	17,414,395.14		1		
	1B	Optimal	36.76	224.48	1500	499.56	16,087,653.48	0.00	1.3	-23.08	
		Heuristic	36.76	224.48	1500	499.56	16,087,653.48		1		
	1C	Optimal	28.18	221.5	1000	985.24	13,979,880.94	0.00	1	0.00	
		Heuristic	28.18	221.5	1000	985.24	13,979,880.94		1		
2 (medium)	2A	Optimal	7.56	106.34	3000	494.5	32,160,993.24	0.00	8	-87.50	-81.87
		Heuristic	7.56	106.34	3000	494.5	32,160,993.24		1		
	2B	Optimal	43	154.46	2000	1471.6	25,804,116.42	0.00	18	-88.89	
		Heuristic	43	154.46	2000	1471.6	25,804,116.42		2		
	2C	Optimal	45	358.74	2500	1000	28,602,829.36	4.63	13	-69.23	
		Heuristic	120.88	25.32	3000	909.3	27,278,505.44		4		
3 (large)	3A	Optimal	29.38	44.66	4000	485.06	40,842,721.22	0.00	36	-91.67	-86.09
		Heuristic	29.38	44.66	4000	485.06	40,842,721.22		3		
	3B	Optimal	63.46	85.42	3500	971.04	36,850,580.54	0.00	124	-99.19	
		Heuristic	63.46	85.42	3500	971.04	36,850,580.54		1		
	3C	Optimal	75.58	124.28	3000	1450	36,135,770.46	3.40	442	-67.42	
		Heuristic	75.58	124.28	3000	1450	34,907,631.24		144		
4 (very large)	4A	Optimal	-	-	-	-	-	-	out.	-	93.25
		Heuristic	-	-	-	-	-		out.		
	4B	Optimal	94.62	105.8	5000	975.46	50,468,029.68	0.35	489	93.25	
		Heuristic	31.52	71.3	4500	1446.9	50,288,876.34		33		
	4C	Optimal	-	-	-	-	-	-	out.	-	
		Heuristic	75.62	97.62	4000	1937.9	46,015,757.52		118		

Abbreviation: Exp. = experiment, Int. = Instance, Out. = out of memory, res. = response, Avg. = average

4.6.4 Overall

In summary, from table 19, heuristic model affords to contribute the optimal result for about 26 out of 32 instances or 81.25% of the total number of computable instances from all cost function. More importantly, there are 4 instances from experiment 4 which the optimal model failed to Figure out the calculation as the memory ran out, but our heuristics were able to solve the problem within applicable time. From table 16, for average total profit gap comparison, the results are 0%, 0.78%, 0.46% and 0.04% for experiment 1 (small), 2 (medium), 3 (large) and 4 (very large) respectively. Thus, heuristic contributed 0.32% of average total profit gap. Table

18 also shows the maximum percentage gap of each experiment size from each cost function.

Table 19:
Total profit comparison

Experiment no. (size)	*Average total profit gap (%)*			*Average*	*Maximum total profit gap*		
	S-Shaped	*Convex*	*Concave*		*S-Shaped*	*Convex*	*Concave*
1 (small)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2 (medium)	0.25	0.53	1.54	0.78	0.75	1.60	4.63
3 (large)	0.00	0.24	1.13	0.46	0.00	0.72	3.40
4 (very large)	0.00	0.00	0.18	0.04	0.00	0.00	0.35
Average				0.32			

According to table 20, for experiment 1, the computational time reduction for experiment is not mentioned as the computational time of every instance is just about 1 minute for both heuristic and optimal model. For experiment 2, 3 and 4, the average computational time reductions are 61.31%, 73.38% and 80.27%. The average among 4 experiments is 71.65%. Moreover, the computational time reduction based on 3 cost functions; s-shaped, convex and concave are 81.94%, 44.37% and 83.98% respectively.

Table 20:
Computational time comparison

Experiment no. (size)	*Computational time reduction (%)*			*Average*
	S-Shaped	*Convex*	*Concave*	
1 (small)	-	-	-	-
2 (medium)	79.82	22.22	81.87	61.31
3 (large)	84.05	50.00	86.09	73.38
4 (very large)	86.67	60.88	93.25	80.27
Average	81.94	44.37	83.98	71.65

Chapter 5
Conclusion

This paper proposed a stochastic programming for two stages supply chain with single-commodity, multi-facilities, multi-retailers, short response facility and piecewise cost function. We have developed 4 experiments to highlight the contributions of the model.

First, for the sampling test, it literally shows that the standard deviation particularly lessens as the sample size amplified. So, we have proved that bigger sample size could produce more particular and precise results to mitigate the effect of uncertainty.

Second, for the parameter variation test, each parameter has there sensitiveness depend on their role in the model. Some parameter has significance effect on not just quantitative results but also qualitative results. One of the highlights in this part is the effect of standard deviation of the demand, we have proof that with lower S.D. results in higher demand fluctuation rate, the company can perform better and less contribution of short LT response facility is engaged. In the other hand, with higher standard deviation results in less degree of demand fluctuation, it is more difficult to control and relatively execute less profit and short LT response facility are more enforced in the system to handle the uncertainty.

Third, for the cost function testing, difference of cost function carries different nature which extremely impact on the facility segmentation and production capacity. S-shaped cost function and stable cost function seem to be familiar in term of profit and allocation. Next, the convex cost function is suitable with more number of site but smaller capacity facilities as the cost function itself incorporate the higher cost in the 3^{rd} segment. Then, for the concave cost function, this function tends to be the most difficult function to compromise. With the higher cost in the first segment, all of the segments are needed to be utilized in order to acquire the suitable average cost for production in any opening facility.

Fourth, we can conclude that by applying long and short LT response together strategy is significantly better than using whether long LT response or short LT response only. Moreover, for the short LT facility, it has to be wisely and well-planned utilized as it requires extraordinary facility which is more potentially affordable.

For *heuristic part*, we develop the linear relaxation and decomposition method of two binary variables and separate the model into two phases; (1) Location decision and (2) Segmentation decision. We applied the model relying on three types of cost function; s-shaped, convex and concave. As each cost function has different decisive nature, we set the upper bound and lower bound to manipulate the production in the first phase. For the numerical experiment, each cost function is developed by 4 sizes of problem with 3 instances each. For the result, heuristic model affords to contribute the optimal result for about 26 out of 32 instances or 82.75% of the total number of computable instances from all cost function. Moreover, our heuristics model is able to solve big size problems which the optimal model failed to do within acceptable time. The average overall total profit gap (including optimal) is 0.32%. The average computational time reduction is 71.65%. In conclusion, our heuristic is mathematically proven to be effective as it mostly contributes the optimal result with significance computational time reduction.

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Appendices

Appendix A

Cplex Source Code

- MAIN MODEL

```
*********************************************
 * OPL 6.3 Model
 * Author: Administrator
*********************************************/
{int} I = ...; //demand
{int} J = ...; //facility
{int} JL = ...; //Long response facility
{int} JS = ...; //Short response facility
int numk = ...;
range K = 1..numk; //segment
{int} K_1 = ...; //segment (k-1)
{int} S = ...; //scenario

float c[I][J] = ...;
float l[J][K] = ...;
float ac[J][K] = ...;
float fc[J] = ...;
float p = ...;  // 1 / dp
float dp = ...; //number scenario
float Sh = ...;
float Ov = ...;
float UP = ...;
float D[I][S] = ...;
float L[J][K] = ...;
float RE[S];

//First stage
dvar float+ x[I][J];
dvar float+ Sx[J][K];
dvar boolean w[J][K];
```

```
dvar boolean OPEN[J];

//Second stage
dvar float+ y[I][J][S];
dvar float+ Sy[J][K][S];
dvar float+ SQ[I][S];
dvar float+ OQ[I][S];
dvar float+ sumx;   //total long lead time production
dvar float+ sumy;   //total short lead time production
dvar float+ avgsq;  //Average shortage among scenarios
dvar float+ avgoq;  //Average overage among scenarios


maximize
UP * ( sum(i in I, j in JL) x[i][j] + sum(s in S) p * sum(i in I, j
in JS) y[i][j][s] - sum(s in S) p * sum(i in I) OQ[i][s] ) - ( sum(i
in I, j in J) c[i][j] * x[i][j] + sum(j in JL, k in K) l[j][k] *
Sx[j][k] + sum(j in J, k in K) w[j][k] * ac[j][k] + sum(j in J)
OPEN[j] * fc[j] + sum(s in S) p * ( sum(i in I, j in J) c[i][j] *
y[i][j][s] + sum(j in JS, k in K) l[j][k] * Sy[j][k][s] + sum(i in I)
SQ[i][s] * Sh + sum(i in I) OQ[i][s] * Ov ));

subject to {

ct1:  forall (i in I, s in S)
        sum(j in JL) x[i][j] + sum(j in JS) y[i][j][s] + SQ[i][s] -
OQ[i][s] == D[i][s];

ct2:  forall (j in JL)
        sum(i in I) x[i][j] == sum(k in K) Sx[j][k];

ct3:  forall (j in JS, s in S)
        sum(i in I) y[i][j][s] == sum(k in K) Sy[j][k][s];

ct4:  forall (j in JL)
            sum(i in I) x[i][j] <= OPEN[j] * 1000000;
```

```
ct5:  forall (j in JS, s in S)
            sum(i in I) y[i][j][s] <= OPEN[j] * 1000000;

//piecewise long
ct6:  forall (j in JL)
        L[j][1] * w[j][1] <= Sx[j][1];

ct7:  forall (j in JL)
        Sx[j][1] <= L[j][1];

ct8:  forall (j in JL, k in K_1)
        L[j][k] * w[j][k] <= Sx[j][k];

ct9:  forall (j in JL, k in K_1)
        Sx[j][k] <= L[j][k] * w[j][k-1] ;

ct10: forall (j in JL)
        0 <= Sx[j][numk];

ct11: forall (j in JL)
        Sx[j][numk] <= L[j][numk] * w[j][numk-1];

//piecewise short
ct12: forall (j in JS, s in S)
        L[j][1] * w[j][1] <= Sy[j][1][s];

ct13: forall (j in JS, s in S)
        Sy[j][1][s] <= L[j][1];

ct14: forall (j in JS, k in K_1, s in S)
        L[j][k] * w[j][k] <= Sy[j][k][s];

ct15: forall (j in JS, k in K_1, s in S)
        Sy[j][k][s] <= L[j][k] * w[j][k-1];
```

```
ct16: forall (j in JS, s in S)
        0 <= Sy[j][numk][s];

ct17: forall (j in JS, s in S)
        Sy[j][numk][s] <= L[j][numk] * w[j][numk-1];
```

- ct18-21: give the production, overage and shortage amount

```
//stat
ct18:  sumx == sum(i in I, j in J) x[i][j];
ct19:  sumy == sum(i in I, j in J, s in S) y[i][j][s]/dp;
ct20:  avgsq == (sum(i in I, s in S) SQ[i][s])/dp;
ct21:  avgoq == (sum(i in I, s in S) OQ[i][s])/dp;
```

- Post-script for calculating and reveal each single scenarios detail (uses for Pair-T test)

```
execute{
            var s, i, j, k;
            var File_Name = "Output.txt";
            var File = new IloOplOutputFile(File_Name);

            for(s in S){
             RE[s] = 0;
             for(i in I){
              for (j in JL){
              RE[s] = RE[s]+ UP * x[i][j];
              }
             }
             for(i in I){
              for (j in JS){
              RE[s] = RE[s] + UP * y[i][j][s];
              }
             }
```

```
for(i in I){
 RE[s] = RE[s] - UP * OQ[i][s];
}
for(i in I){
 for (j in J){
 RE[s] = RE[s] - c[i][j] * x[i][j];
 }
}
for(j in JL){
 for (k in K){
  RE[s] = RE[s] - l[j][k] * Sx[j][k];
}
}
for(j in J){
 for(k in K){
  RE[s] = RE[s] - w[j][k] * ac[j][k];
 }
}
 for(j in J){
  RE[s] = RE[s] - OPEN[j] * fc[j];
 }
for(i in I){
 for(j in J){
  RE[s] = RE[s] - c[i][j] * y[i][j][s];
 }
}
for(j in JS){
 for (k in K){
 RE[s] = RE[s] - l[j][k] * Sy[j][k][s];
 }
}
for(i in I){
 RE[s] = RE[s] - SQ[i][s] * Sh;
}
for(i in I){
 RE[s] = RE[s] - OQ[i][s] * Ov;
```

```
         }
        writeln("Scenario",s," ",RE[s]);
        File.writeln(s,"|",RE[s]);
        }
        File.close();
        }
```

- HEURISTIC(1st phase) FOR S-SHAPED FUNCTION

```
/*********************************************
 * OPL 6.3 Model
 * Author: Administrator
 * Creation Date: 6 ก.ย. 2014 at 15:46:12
 *********************************************/
{int} I = ...; //demand
{int} J = ...; //facility
{int} JL = ...; //Long response facility
{int} JS = ...; //Short response facility
{int} S = ...; //scenario

float c[I][J] = ...;
float fc[J] = ...;
float p = ...;  // 1 / dp
float dp = ...; //number scenario
float Sh = ...;
float Ov = ...;
float UP = ...;
float D[I][S] = ...;
float l = ...;
//float RE[S];

//First stage
dvar float+ x[I][J];
dvar float+ Sx[J];
dvar boolean OPEN[J];
```

```
//Second stage
dvar float+ y[I][J][S];
dvar float+ Sy[J][S];
dvar float+ SQ[I][S];
dvar float+ OQ[I][S];

dvar float+ sumx;   //total long lead time production
dvar float+ sumy;   //total short lead time production
dvar float+ avgsq;  //Average shortage among scenarios
dvar float+ avgoq;  //Average overage among scenarios


maximize
UP * ( sum(i in I, j in JL) x[i][j] + sum(s in S) p * sum(i in I, j
in JS) y[i][j][s] - sum(s in S) p * sum(i in I) OQ[i][s] ) - ( sum(i
in I, j in J) c[i][j] * x[i][j] + l * sum(j in JL) Sx[j] + sum(j in
J) OPEN[j] * fc[j] + sum(s in S) p * ( sum(i in I, j in J) c[i][j] *
y[i][j][s] + l * sum(j in JS) Sy[j][s] + sum(i in I) SQ[i][s] * Sh +
sum(i in I) OQ[i][s] * Ov ));

subject to {

ct1:  forall (i in I, s in S)
        sum(j in JL) x[i][j] + sum(j in JS) y[i][j][s] + SQ[i][s] -
OQ[i][s] == D[i][s];

ct2:  forall (j in JL)
        sum(i in I) x[i][j] == Sx[j];

ct3:  forall (j in JS, s in S)
        sum(i in I) y[i][j][s] == Sy[j][s];

ct4:  forall (j in JL)
            sum(i in I) x[i][j] <= OPEN[j] * 1000000;
```

```
ct5:  forall (j in JS, s in S)
            sum(i in I) y[i][j][s] <= OPEN[j] * 1000000;

ct6:  forall (j in JS, s in S)
        Sy[j][s] <= 500;

ct7:  forall (j in JL)
        Sx[j] <= 500;

//stat
ct8:  sumx == sum(i in I, j in J) x[i][j];
ct9:  sumy == sum(i in I, j in J, s in S) y[i][j][s]/dp;
ct10:  avgsq == (sum(i in I, s in S) SQ[i][s])/dp;
ct11:  avgoq == (sum(i in I, s in S) OQ[i][s])/dp;
```

- HEURISTIC(1st phase) FOR CONCAVE FUNCTION

```
/*********************************************
 * OPL 6.3 Model
 * Author: Administrator
*********************************************/
{int} I = ...; //demand
{int} J = ...; //facility
{int} JL = ...; //Long response facility
{int} JS = ...; //Short response facility
{int} S = ...; //scenario

float c[I][J] = ...;
float fc[J] = ...;
float p = ...;  // 1 / dp
float dp = ...; //number scenario
float Sh = ...;
float Ov = ...;
float UP = ...;
```

```
float D[I][S] = ...;
float l = ...;
//float RE[S];
int LB = ...;

//First stage
dvar float+ x[I][J];
dvar float+ Sx[J];
dvar boolean OPEN[J];

//Second stage
dvar float+ y[I][J][S];
dvar float+ Sy[J][S];
dvar float+ SQ[I][S];
dvar float+ OQ[I][S];

dvar float+ sumx;   //total long lead time production
dvar float+ sumy;   //total short lead time production
dvar float+ avgsq;  //Average shortage among scenarios
dvar float+ avgoq;  //Average overage among scenarios


maximize
            UP * ( sum(i in I, j in JL) x[i][j] + sum(s in S) p *
sum(i in I, j in JS) y[i][j][s] - sum(s in S) p * sum(i in I)
OQ[i][s] )
            - ( sum(i in I, j in J) c[i][j] * x[i][j] + l * sum(j in
JL) Sx[j] + sum(j in J) OPEN[j] * fc[j]
            + sum(s in S) p * ( sum(i in I, j in J) c[i][j] *
y[i][j][s] + l * sum(j in JS) Sy[j][s] +
            sum(i in I) SQ[i][s] * Sh + sum(i in I) OQ[i][s] * Ov ));

subject to {

ct1:  forall (i in I, s in S)
```

```
        sum(j in JL) x[i][j] + sum(j in JS) y[i][j][s] + SQ[i][s] -
OQ[i][s] == D[i][s];

ct2:  forall (j in JL)
        sum(i in I) x[i][j] == Sx[j];

ct3:  forall (j in JS, s in S)
        sum(i in I) y[i][j][s] == Sy[j][s];

ct4:  forall (j in JL)
            OPEN[j] * LB <= sum(i in I) x[i][j];

ct5:  forall (j in JL)
            sum(i in I) x[i][j] <= OPEN[j] * 100000;

ct6:  forall (j in JS, s in S)
            OPEN[j] * LB <= sum(i in I) y[i][j][s];

ct7:  forall (j in JS, s in S)
            sum(i in I) y[i][j][s] <= OPEN[j] * 100000;

ct8:  forall (j in JS, s in S)
        Sy[j][s] <= 500;

ct9:  forall (j in JL)
        Sx[j] <= 500;

//stat
ct10:  sumx == sum(i in I, j in J) x[i][j];
ct11:  sumy == sum(i in I, j in J, s in S) y[i][j][s]/dp;
ct12:  avgsq == (sum(i in I, s in S) SQ[i][s])/dp;
ct13:  avgoq == (sum(i in I, s in S) OQ[i][s])/dp;
```

- HEURISTIC(1st phase) FOR CONVEX FUNCTION

```
/*********************************************
 * OPL 6.3 Model
 * Author: Administrator
*********************************************/
{int} I = ...; //demand
{int} J = ...; //facility
{int} JL = ...; //Long response facility
{int} JS = ...; //Short response facility
{int} S = ...; //scenario

float c[I][J] = ...;
float fc[J] = ...;
float p = ...;  // 1 / dp
float dp = ...; //number scenario
float Sh = ...;
float Ov = ...;
float UP = ...;
float D[I][S] = ...;
float l = ...;
float UB = ...;
//float RE[S];

//First stage
dvar float+ x[I][J];
dvar float+ Sx[J];
dvar boolean OPEN[J];

//Second stage
dvar float+ y[I][J][S];
dvar float+ Sy[J][S];
dvar float+ SQ[I][S];
dvar float+ OQ[I][S];

dvar float+ sumx;   //total long lead time production
```

```
dvar float+ sumy;   //total short lead time production
dvar float+ avgsq;  //Average shortage among scenarios
dvar float+ avgoq;  //Average overage among scenarios



maximize
            UP * ( sum(i in I, j in JL) x[i][j] + sum(s in S) p *
sum(i in I, j in JS) y[i][j][s] - sum(s in S) p * sum(i in I)
OQ[i][s] )
            - ( sum(i in I, j in J) c[i][j] * x[i][j] + l * sum(j in
JL) Sx[j] + sum(j in J) OPEN[j] * fc[j]
            + sum(s in S) p * ( sum(i in I, j in J) c[i][j] *
y[i][j][s] + l * sum(j in JS) Sy[j][s] +
            sum(i in I) SQ[i][s] * Sh + sum(i in I) OQ[i][s] * Ov ));

subject to {

ct1:  forall (i in I, s in S)
        sum(j in JL) x[i][j] + sum(j in JS) y[i][j][s] + SQ[i][s] -
OQ[i][s] == D[i][s];

ct2:  forall (j in JL)
        sum(i in I) x[i][j] == Sx[j];

ct3:  forall (j in JS, s in S)
        sum(i in I) y[i][j][s] == Sy[j][s];

ct4:  forall (j in JL)
            sum(i in I) x[i][j] <= OPEN[j] * UB;

ct5:  forall (j in JS, s in S)
            sum(i in I) y[i][j][s] <= OPEN[j] * UB;

ct6:  forall (j in JS, s in S)
        Sy[j][s] <= 500;
```

```
ct7:  forall (j in JL)
        Sx[j] <= 500;
//stat
ct8:  sumx == sum(i in I, j in J) x[i][j];
ct9:  sumy == sum(i in I, j in J, s in S) y[i][j][s]/dp;
ct10:  avgsq == (sum(i in I, s in S) SQ[i][s])/dp;
ct11:  avgoq == (sum(i in I, s in S) OQ[i][s])/dp;
}
```

- EXAMPLE OF DATA CODE

```
/*********************************************
 * OPL 6.3 Data
 * Author: Administrator
 * Creation Date: 6 ก.ย. 2014 at 15:46:12
 *********************************************/
SheetConnection sheet("Full1.1.xlsx");
I from SheetRead(sheet,"'Sheet1'!A50:A79");
J = {1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20};
JL = {1,2,3,4,5,6,7,8,9,10};
JS = {11,12,13,14,15,16,17,18,19,20};
numk = 3;
K_1 = {2};
p = 0.02;
dp = 50;
S from SheetRead(sheet,"'Sheet1'!B49:AY49");
c from SheetRead(sheet,"'Sheet1'!B5:U34");
fc from SheetRead(sheet,"'Sheet1'!BE5:BE24");
Sh from SheetRead(sheet,"'Sheet1'!Z42");
Ov from SheetRead(sheet,"'Sheet1'!Z43");
UP from SheetRead(sheet,"'Sheet1'!Z44");
D from SheetRead(sheet,"'Sheet1'!B50:AY79");
ac from SheetRead(sheet,"'Sheet1'!AZ5:BB24");
l from SheetRead(sheet,"'Sheet1'!AN5:AP24");
```

```
L from SheetRead(sheet,"'Sheet1'!AT5:AV24");
```

- EXAMPLE OF DATA CODE FOR 2nd phase HEURISTICS

```
/*********************************************
 * OPL 6.3 Data
 * Author: Administrator
 *********************************************/
SheetConnection sheet("Full1.1.xlsx");
I from SheetRead(sheet,"'Sheet1'!A50:A79");
J = {1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20};
JL = {1,2,3,4,5,6,7,8,9,10};
JS = {11,12,13,14,15,16,17,18,19,20};
numk = 3;
K_1 = {2};
p = 0.02;
dp = 50;
//AY,CW,GS,KO
S from SheetRead(sheet,"'Sheet1'!B49:AY49");
c from SheetRead(sheet,"'Sheet1'!B5:U34");
fc from SheetRead(sheet,"'Sheet1'!BE5:BE24");
Sh from SheetRead(sheet,"'Sheet1'!Z42");
Ov from SheetRead(sheet,"'Sheet1'!Z43");
UP from SheetRead(sheet,"'Sheet1'!Z44");
D from SheetRead(sheet,"'Sheet1'!B50:AY79");
ac from SheetRead(sheet,"'Sheet1'!AZ5:BB24");
l from SheetRead(sheet,"'Sheet1'!AN5:AP24");
L from SheetRead(sheet,"'Sheet1'!AT5:AV24");
OPEN = [1 0 1 0 1 0 1 1 1 1 1 0 0 0 0 0 0 0 1 1];
```

Appendix B:

- **EXAMPLE OF INPUT DATA FILE (HEURISTIC CASE: CONVACE / Instance 3C)**

cij	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	87	137	121	143	63	161	168	87	87	137	121	143	63	161	168	87
2	108	88	102	70	123	151	117	88	108	88	102	70	123	151	117	88
3	126	90	132	155	121	84	91	155	126	90	132	155	121	84	91	155
4	157	165	118	85	114	158	81	88	157	165	118	85	114	158	81	88
5	165	104	107	158	152	86	115	168	165	104	107	158	152	86	115	168
6	150	64	77	130	150	150	91	145	150	64	77	130	150	150	91	145
7	85	144	101	136	121	94	86	155	85	144	101	136	121	94	86	155
8	111	130	151	118	160	112	72	158	111	130	151	118	160	112	72	158
9	137	118	134	117	137	91	94	161	137	118	134	117	137	91	94	161
10	96	144	126	136	102	143	87	94	96	144	126	136	102	143	87	94
11	65	93	114	140	103	120	116	142	65	93	114	140	103	120	116	142
12	88	150	102	127	112	70	94	168	88	150	102	127	112	70	94	168
13	129	149	112	168	65	158	72	70	129	149	112	168	65	158	72	70
14	141	127	125	157	149	155	88	67	141	127	125	157	149	155	88	67
15	75	147	67	84	116	76	85	60	75	147	67	84	116	76	85	60
16	90	113	127	92	114	120	142	92	90	113	127	92	114	120	142	92
17	143	76	155	72	155	121	156	82	143	76	155	72	155	121	156	82
18	148	166	158	117	88	62	166	95	148	166	158	117	88	62	166	95
19	142	131	63	129	98	164	103	79	142	131	63	129	98	164	103	79
20	72	93	166	147	169	91	70	85	72	93	166	147	169	91	70	85

ljk(slope)	k1	k2	k3	Ljk(slope)	k1	k2	k3
1	26000	8000	4000	1	200	150	150
2	26000	8000	4000	2	200	150	150
3	26000	8000	4000	3	200	150	150
4	26000	8000	4000	4	200	150	150
5	26000	8000	4000	5	200	150	150
6	26000	8000	4000	6	200	150	150
7	26000	8000	4000	7	200	150	150
8	26000	8000	4000	8	200	150	150
9	26000	8000	4000	9	200	150	150
10	26000	8000	4000	10	200	150	150
11	26000	8000	4000	11	200	150	150
12	26000	8000	4000	12	200	150	150
13	26000	8000	4000	13	200	150	150
14	26000	8000	4000	14	200	150	150
15	26000	8000	4000	15	200	150	150
16	26000	8000	4000	16	200	150	150

(Sh) Shortage cost	400
(Ov) Overage value	6000
(Up) Unit privce	38000

acjk	k1	k2	k3	fc	
1	1,000,000	1,000,000	0	1	5,000,000
2	1,000,000	1,000,000	0	2	5,000,000
3	1,000,000	1,000,000	0	3	5,000,000
4	1,000,000	1,000,000	0	4	5,000,000
5	1,000,000	1,000,000	0	5	5,000,000
6	1,000,000	1,000,000	0	6	5,000,000
7	1,000,000	1,000,000	0	7	5,000,000
8	1,000,000	1,000,000	0	8	5,000,000
9	1,000,000	1,000,000	0	9	7,000,000
10	1,000,000	1,000,000	0	10	7,000,000
11	1,000,000	1,000,000	0	11	7,000,000
12	1,000,000	1,000,000	0	12	7,000,000
13	1,000,000	1,000,000	0	13	7,000,000
14	1,000,000	1,000,000	0	14	7,000,000
15	1,000,000	1,000,000	0	15	7,000,000
16	1,000,000	1,000,000	0	16	7,000,000

Dis	1	2	3	4	5	6	7	8	9	10
1	139	141	189	171	194	173	181	167	178	150
2	176	179	172	199	166	173	204	171	171	175
3	183	162	181	149	172	164	197	217	199	197
4	205	221	153	203	189	146	151	180	166	163
5	158	180	195	223	176	175	156	187	150	189
6	181	189	196	193	175	200	188	196	191	193
7	176	155	159	152	193	148	185	195	192	149
8	171	215	194	190	172	187	193	165	180	172
9	152	166	171	177	191	187	205	190	175	172
10	178	176	153	173	201	157	183	209	163	168
11	170	191	165	131	191	169	222	180	190	183
12	178	162	173	194	200	179	147	177	211	162
13	124	172	204	163	187	194	165	212	183	155
14	171	239	193	198	192	183	208	176	183	203
15	193	207	214	203	191	217	192	179	187	174
16	182	189	173	188	163	175	187	176	200	196
17	186	174	169	167	163	181	190	190	160	173
18	151	188	190	178	155	196	185	164	179	167
19	204	189	180	171	185	159	188	150	177	182
20	168	218	192	170	183	152	195	182	172	182

11	12	13	14	15	16	17	18	19	20
201	195	194	177	144	165	152	165	181	202
155	196	178	178	165	177	182	204	171	178
177	176	203	162	175	176	181	163	174	171
180	184	147	201	206	184	175	140	173	178
156	204	168	206	188	160	143	174	177	169
164	193	162	168	184	193	207	175	180	206
182	162	157	167	175	196	178	203	195	202
212	210	170	218	204	158	185	216	170	192
141	174	161	200	203	217	190	170	162	160
200	187	181	154	156	167	182	157	151	181
190	241	162	173	171	172	204	154	186	167
182	196	132	151	183	179	191	174	191	190
216	208	179	185	184	198	199	203	172	191
183	176	174	193	183	175	193	151	193	217
199	225	170	168	203	168	187	185	169	215
179	208	202	212	185	200	178	198	181	205
182	192	159	192	174	157	202	187	174	171
211	184	183	132	198	212	179	163	195	217
184	164	185	199	187	166	181	164	176	165
204	170	173	166	175	192	160	162	172	199

21	22	23	24	25	26	27	28	29	30
227	192	156	180	177	181	199	169	167	163
195	138	187	183	200	225	115	168	180	191
199	219	149	172	176	180	137	152	192	170
214	149	176	178	218	217	193	175	174	170
204	160	203	148	196	170	175	158	170	136
148	145	165	177	183	202	160	167	201	182
166	178	156	178	158	221	219	176	169	159
203	171	172	147	189	177	155	214	177	181
197	155	180	197	167	176	188	206	169	173
181	198	168	205	223	180	148	193	168	197
191	153	176	157	159	186	196	203	169	177
165	191	205	194	177	198	163	173	182	185
177	188	183	210	152	158	151	151	180	162
190	167	207	174	199	181	182	207	186	167
201	200	173	210	159	208	164	160	160	181
168	142	174	161	176	181	188	174	146	149
196	179	177	182	161	165	200	169	196	176
166	182	174	210	168	194	196	192	177	156
188	160	192	155	170	208	170	203	167	200
173	200	166	187	182	191	173	165	198	194

31	32	33	34	35	36	37	38	39	40
179	164	186	206	156	198	170	156	223	207
203	137	195	182	168	186	169	152	184	230
148	187	196	179	168	173	180	156	210	167
183	166	164	161	159	141	164	182	225	213
183	143	149	160	185	178	168	181	145	176
192	206	153	207	197	197	193	157	179	158
187	146	180	196	170	191	198	158	194	236
130	173	157	154	142	177	206	172	166	209
154	158	177	190	201	185	200	176	193	185
143	155	161	210	220	167	194	193	198	193
133	215	177	183	216	176	189	195	146	176
177	179	178	184	188	171	180	175	174	173
159	179	175	192	196	174	211	164	208	167
198	159	159	181	172	173	176	168	153	190
197	197	192	167	182	182	220	185	163	151
180	179	194	180	179	162	174	162	180	176
166	164	200	180	193	196	175	174	187	159
195	172	205	156	173	143	169	154	158	158
126	181	168	199	208	161	175	175	167	179
196	174	155	175	200	170	176	154	200	191

41	42	43	44	45	46	47	48	49	50
179	185	178	209	167	206	195	178	172	183
176	200	180	184	163	175	195	168	209	189
192	182	205	204	162	191	164	170	181	165
193	175	180	196	186	175	174	150	170	211
193	221	161	191	186	154	188	220	165	177
188	191	133	200	178	187	187	170	154	198
179	201	152	185	206	178	184	158	203	180
218	196	158	173	179	195	124	197	181	170
206	191	168	202	195	163	192	194	169	154
158	166	177	191	171	197	152	159	197	174
149	193	160	167	168	186	185	221	155	198
179	162	159	177	194	181	165	153	175	185
145	191	171	179	195	193	179	166	167	197
175	180	172	161	186	146	172	177	164	186
165	198	180	163	180	193	183	196	170	182
172	148	221	151	185	202	179	167	176	187
173	171	183	194	166	174	156	166	176	168
168	205	182	211	187	192	172	195	153	196
169	177	165	135	165	195	182	145	181	195
183	187	182	180	184	205	197	166	173	195

- **EXAMPLE OF OUTPUT DATA FILE (HEURISTIC CASE: CONVACE/ LARGE SIZE)**

W_{ij}

J (size 20)	K (size 3)	W	J (size 20)	K (size 3)	W
1	1	1	11	1	0
1	2	1	11	2	0
1	3	0	11	3	0
2	1	0	12	1	0
2	2	0	12	2	0
2	3	0	12	3	0
3	1	1	13	1	0
3	2	1	13	2	0
3	3	0	13	3	0
4	1	0	14	1	0
4	2	0	14	2	0
4	3	0	14	3	0
5	1	1	15	1	0
5	2	1	15	2	0
5	3	0	15	3	0
6	1	1	16	1	0
6	2	1	16	2	0
6	3	0	16	3	0
7	1	1	17	1	0
7	2	1	17	2	0
7	3	0	17	3	0
8	1	1	18	1	0
8	2	1	18	2	0
8	3	0	18	3	0
9	1	1	19	1	1
9	2	1	19	2	1
9	3	0	19	3	0
10	1	1	20	1	0
10	2	1	20	2	0
10	3	0	20	3	0

$OPEN_{ij}$

J (size 20)	OPEN
1	1
2	0
3	1
4	0
5	1
6	1
7	1
8	1
9	1
10	1
11	0
12	0
13	0
14	0
15	0
16	0
17	0
18	0
19	1
20	0

For ***$OPEN_j$***

1 = Open

0 = close

- For each J of ***W_{ij}***
  - 1,1,0 = open all 3 segments
  - 1,0,0 = open first 2 segments
  - 0,0,0 = open 1 segment or close (we can know which facility is opened from ***OPENj***

Sx

J (size 20)	K (size 3)	Sx
1	1	200
1	2	150
1	3	150
2	1	0
2	2	0
2	3	0
3	1	200
3	2	150
3	3	150
4	1	0
4	2	0
4	3	0
5	1	200
5	2	150
5	3	150
6	1	200
6	2	150
6	3	150
7	1	200
7	2	150
7	3	150
8	1	200
8	2	150
8	3	150
9	1	200
9	2	150
9	3	150
10	1	200
10	2	150
10	3	150
11	1	0
11	2	0
11	3	0
12	1	0
12	2	0
12	3	0
13	1	0
13	2	0
13	3	0
14	1	0
14	2	0
14	3	0
15	1	0
15	2	0
15	3	0
16	1	0
16	2	0
16	3	0
17	1	0
17	2	0
17	3	0
18	1	0
18	2	0
18	3	0
19	1	0
19	2	0
19	3	0
20	1	0
20	2	0
20	3	0

Sy

J (size 20)	K (size 3)	S (size 50)	Sy
19	1	1	200
19	1	2	200
19	1	3	200
19	1	4	200
19	1	5	200
19	1	6	200
19	1	7	200
19	1	8	200
19	1	9	200
19	1	10	200
19	1	11	200
19	1	12	200
19	1	13	200
19	1	14	200
19	1	15	200
19	1	16	200
19	1	17	200
19	1	18	200
19	1	19	200
19	1	20	200
19	1	21	200
19	1	22	200
19	1	23	200
19	1	24	200
19	1	25	200
19	1	26	200
19	1	27	200
19	1	28	200
19	1	29	200
19	1	30	200

J (size 20)	K (size 3)	S (size 50)	Sy
19	1	31	200
19	1	32	200
19	1	33	200
19	1	34	200
19	1	35	200
19	1	36	200
19	1	37	200
19	1	38	200
19	1	39	200
19	1	40	200
19	1	41	200
19	1	42	200
19	1	43	200
19	1	44	200
19	1	45	200
19	1	46	200
19	1	47	200
19	1	48	200
19	1	49	200
19	1	50	200
19	2	1	150
19	2	2	150
19	2	3	150
19	2	4	150
19	2	5	150
19	2	6	150
19	2	7	150
19	2	8	150
19	2	9	150
19	2	10	150

J (size 20)	K (size 3)	S (size 50)	Sy
19	2	11	150
19	2	12	150
19	2	13	150
19	2	14	150
19	2	15	150
19	2	16	150
19	2	17	150
19	2	18	150
19	2	19	150
19	2	20	150
19	2	21	150
19	2	22	150
19	2	23	150
19	2	24	150
19	2	25	150
19	2	26	150
19	2	27	150
19	2	28	150
19	2	29	150
19	2	30	150
19	2	31	150
19	2	32	150
19	2	33	150
19	2	34	150
19	2	35	150
19	2	36	150
19	2	37	150
19	2	38	150
19	2	39	150
19	2	40	150

J (size 20)	K (size 3)	S (size 50)	Sy
19	2	41	150
19	2	42	150
19	2	43	150
19	2	44	150
19	2	45	150
19	2	46	150
19	2	47	150
19	2	48	150
19	2	49	150
19	2	50	150
19	3	1	150
19	3	2	150
19	3	3	150
19	3	4	118
19	3	5	136
19	3	6	121
19	3	7	150
19	3	8	150
19	3	9	92
19	3	10	96
19	3	11	150
19	3	12	150
19	3	13	150
19	3	14	150
19	3	15	132
19	3	16	150
19	3	17	150
19	3	18	150
19	3	19	150
19	3	20	150

J (size 20)	K (size 3)	S (size 50)	Sy
19	3	21	122
19	3	22	150
19	3	23	150
19	3	24	150
19	3	25	149
19	3	26	61
19	3	27	150
19	3	28	119
19	3	29	150
19	3	30	150
19	3	31	128
19	3	32	150
19	3	33	150
19	3	34	102
19	3	35	150
19	3	36	150
19	3	37	150
19	3	38	150
19	3	39	150
19	3	40	150
19	3	41	150
19	3	42	114
19	3	43	114
19	3	44	150
19	3	45	55
19	3	46	122
19	3	47	89
19	3	48	150
19	3	49	150
19	3	50	83

avgog: 29.38 (average overage amount)

avgsq: 44.66 (average shortage amount)

sumx: 4000 (total long lead time production)

sumy: 485.06 (total short lead time production)