แบบจำลองการกำหนดราคาสำหรับการปฏิบัติการขนส่งด้วยรถบรรทุกแบบเต็มคัน
ภายใต้ความไม่แน่นอน

นางสาวฐิติมา วงศ์อินตา



วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรดุษฎีบัณฑิต
สาขาวิชาวิศวกรรมโยธา ภาควิชาวิศวกรรมโยธา
คณะวิศวกรรมศาสตร์ จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2553

PRICE DETERMINATION MODEL FOR FULL TRUCKLOAD OPERATION
UNDER UNCERTAINTY

Miss Thitima Wonginta



A Dissertation Submitted in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy Program in Civil Engineering
Department of Civil Engineering
Faculty of Engineering
Chulalongkorn University
Academic Year 2010

| | |
|---|---|
| Thesis Title | PRICE DETERMINATION MODEL FOR FULL TRUCKLOAD OPERATION UNDER UNCERTAINTY |
| By | Miss Thitima Wonginta |
| Field of Study | Civil Engineering |
| Thesis Advisor | Associate Professor Sompong Sirisoponsilp, Ph.D. |

---

Accepted by the Faculty of Engineering, Chulalongkorn University in Partial Fulfillment of the Requirements for the Doctoral Degree

..........................................Dean of the Faculty of Engineering

(Associate Professor Boonsom Lerdhirunwong, Dr.Ing)

THESIS COMMITTEE

..........................................Chairman

(Assistant Professor Manoj Lohatepanont, Sc.D. )

..........................................Thesis Advisor

(Associate Professor Sompong Sirisoponsilp, Ph.D.)

..........................................Examiner

(Associate Professor Kasem Choocharukul, Ph.D.)

..........................................Examiner

(Anupap Somboonsavatdee, Ph.D.)

..........................................External Examiner

(Associate Professor Nakorn Indra-Prayoong, Ph.D.)

ฐิติมา วงศ์อินตา : แบบจำลองการกำหนดราคาสำหรับการปฏิบัติการขนส่งด้วยรถบรรทุกแบบเต็มคันภายใต้ความไม่แน่นอน. (PRICE DETERMINATION MODEL FOR FULL TRUCKLOAD OPERATION UNDER UNCERTAINTY) อ. ที่ปรึกษาวิทยานิพนธ์หลัก : รศ.ดร.สมพงษ์ ศิริโสภณศิลป์, 123 หน้า.

การกำหนดราคาค่าขนส่งสินค้าเป็นปัจจัยสำคัญอย่างหนึ่งที่ผู้ประกอบการขนส่งสินค้าต้องทำการตัดสินใจ รูปแบบการกำหนดราคาค่าขนส่งโดยทั่วไปจะคิดมาจากต้นทุนเฉลี่ย ซึ่งประกอบด้วยต้นทุนคงที่และต้นทุนผันแปร ซึ่งการคิดราคาโดยวิธีดังกล่าวอาจไม่สามารถป้องกันโอกาสที่จะสูญเสียหรือขาดทุนจากราคาที่ไม่สามารถครอบคลุมต้นทุนที่มีความแปรปรวนสูง อันเนื่องมาจากความต้องการจัดส่งที่และระยะเวลาในการบริการที่ไม่แน่นอน

ดังนั้นงานวิจัยนี้จึงมีวัตถุประสงค์เพื่อพัฒนาแบบจำลองในการกำหนดราคาค่าขนส่งสินค้าสำหรับการปฏิบัติการขนส่งด้วยรถบรรทุกแบบเต็มคันภายใต้ปัจจัยความไม่แน่นอน โดยได้กำหนดกรอบการศึกษาออกเป็น 2 ส่วนคือการพัฒนาแบบจำลองสถานการณ์และแบบจำลองการกำหนดราคาค่าขนส่งสินค้าแบบเต็มคัน โดยการพัฒนาแบบจำลองสถานการณ์เพื่อใช้ในการจำลองลักษณะความไม่แน่นอนที่เกิดขึ้นกับกิจกรรมการขนส่งสินค้าแบบเต็มคัน ในขณะที่การพัฒนาแบบจำลองการกำหนดราคา ได้ประยุกต์ใช้เครื่องมือในการวัดความเสี่ยง ได้แก่ แวลู่แอทริส (วาร์) และ คอนดิชั่นนอลแวลู่แอทริส (ซีวาร์) เป็นเงื่อนไขในการกำหนดราคาค่าขนส่งโดยคำนึงถึงโอกาสที่จะขาดทุนจากราคาค่าขนส่งที่เสนอลูกค้า

ผลการวิเคราะห์แบบจำลองสถานการณ์และการกำหนดราคาค่าขนส่งสินค้า พบว่าการกำหนดให้รถบรรทุกของบริษัทจัดส่งสินค้าในเส้นทางไกลและว่าจ้างภายนอกในกรณีที่เป็นเส้นทางใกล้ส่งผลให้ต้นทุนการขนส่งและราคาค่าขนส่งต่ำ นอกจากนี้การวิเคราะห์ราคาค่าขนส่งสินค้าที่ระดับความเชื่อมั่น 95 พบว่าราคาที่เงื่อนไขวาร์และซีวาร์ สูงกว่าราคาที่ได้จากการการคิดโดยวิธีดั้งเดิม การเพิ่มความแปรปรวนของความต้องการจัดส่งส่งผลให้ราคาค่าขนส่งสูงขึ้นในขณะที่การลดระยะเวลาการให้บริการส่งผลให้ราคาค่าขนส่งลดลง

การคิดราคาแบบนี้เหมาะสำหรับผู้ประกอบการขนส่งที่ชอบความเสี่ยง โดยการควบคุมความเสี่ยงให้อยู่ในระดับที่ยอมรับได้


ภาควิชา วิศวกรรมโยธา ลายมือชื่อนิสิต..............................

สาขาวิชา วิศวกรรมโยธา ลายมือชื่อ อ.ที่ปรึกษาวิทยานิพนธ์หลัก..............................

ปีการศึกษา 2553

# # 4871859321 : MAJOR CIVIL ENGINEERING

KEYWORDS : FULL TRUCKLOAD / UNCERTAINTY / VALUE AT RISK (VaR) / CONDITIONAL VALUE AT RISK (CVaR)

THITIMA WONGINTA : PRICE DETERMINATION MODEL FOR FULL TRUCKLOAD OPERATION UNDER UNCERTAINTY. ADVISOR : ASSOC. PROF. SOMPONG SIRISOPONSILP, Ph.D., 123 pp.

Pricing is one of the fundamental management decisions faced by a truckload carrier. Traditional pricing based on an average of all relevant costs including fixed and variable costs is not capable of providing adequate margins and guarding the carrier against losses caused by uncertainties inherent in truckload operation including mainly demand variability and variation in service times.

Hence, the objective of this study is to develop a model for determining prices for full truckload operation under uncertainty. The research work consists of two parts, development of a simulation model and development of a pricing model. A simulation model is developed to capture the stochastic patterns inherent in the operation of truckload network. In the pricing model, the Value at Risk (VaR) and Conditional Value at Risk (CVaR) are adopted as measures of risk when demand and service conditions are unpredictable.

The analysis results indicate that lower cost can be achieved if the company's own trucks are given first priority for long-distance deliveries while outsourced trucks are used mostly for the remaining short-distance deliveries that cannot be fulfilled by the available own trucks. Prices based on the 95% of VaR and 95% of CVaR appear to be higher than those proposed by traditional average-cost pricing. As expected, increasing demand variation leads to higher trucking prices while the reduction in service time including waiting time, uploading and unloading time results in lower prices.

The proposed pricing methodology is particularly suitable for transportation carriers who are relatively risk averse and would like to stay away from unacceptable high risk.

Department : Civil Engineering ............ Student's Signature Thitima Wonginta

Field of Study : Civil Engineering ......... Advisor's Signature ..................

Academic Year : 2010

## Acknowledgements

My deepest gratitude is to my advisor, Assoc. Prof. Sompong Sirisoponsilp, who accepted me as his Ph.D. student without any hesitation, when I first applied to the Ph.D. program. His patience and support helped me overcome many crisis situations and finish this dissertation. Without his help I could not have finished my dissertation successfully.

Special thanks are also given to Prof. Dr. Antony Chen. He is the one who invited me, as a visiting scholar, to Utah State University for my visiting research in 2008. He introduced me to risk measurement techniques and his teaching inspired me to apply Value at Risk (VaR) and Conditional Value at Risk (CVaR) to my dissertation. He instructed and helped me sort out the technical details of my work.

I gladly express my gratitude and appreciation to Assist. Prof. Dr. Manoj Lohatepanont, Assoc. Prof. Dr. Nakorn Indra-Payong, Assoc. Prof. Kasem Choojarukul, and Dr. Anupap Somboonsavatdee for taking part in my dissertation committee and for their valuable suggestions and comments, which enabled me to notice the weaknesses of my dissertation and make the necessary improvements based on their comments.

I would like to express special thanks to all staff who are working at Transportation Institute, Chulalongkorn University, especially Mr. Wirach Hirun, Ms. Wanna Wadboonleang, and Ms Visarat Sunyaluckleuchai for their help in providing facilities and materials for my dissertation experiment. I wish to thank my friend Mr. Sarawut Jansuwan for supporting me when I was doing research at Utah State University. Also, I would like to express special thanks to Ms. Thitinun Pholsuk, for her help and support in simulation model developing.

I express profound appreciation to Assoc. Prof. Dr. Nakorn Indra-Payong for giving me the opportunity to receive a doctoral scholarship from the Ministry of Higher Education under the Logistics Faculty at Burapha University. Also, this work was supported by the Higher Education Research Promotion and National Research University Project of Thailand, Office of the Higher Education Commission.

Most importantly, I would like to thank my parents and two younger sisters for the greatest love and believing in me. They have supported me at every step I have taken so far. My graduation would not be achieved without their best wishes. Finally, I would like to express my heart-felt gratitude to my husband for bringing happiness into my life. His love and support without any complaint or regret has enabled me to complete this dissertation.

## Contents

## List of Tables

Table Page

Table Page

Table Page

## List of Figures

Figure Page

# CHAPTER I

# INTRODUCTION

## 1.1 Background

Today truck transportation is the dominant mode of freight transportation in Thailand. Several studies have revealed that over 85% of domestic freight movement by weight is currently served by trucks, and that truck transportation demand continues to rise dramatically in conjunction with the nation's high economic growth. Full truckload service plays a major role in Thailand because a large proportion of freight moved in Thailand lends itself to truckload movement, such as bulk agriculture products and construction materials. In Thailand, the truckload carrier market is highly competitive due to the ease of market entry resulting from the intrinsic simplicity of Full Truckload operation that provides point-to-point trucking services compared to Less-Than-Truckload (LTL) operation that requires a network of local terminals for consolidation and break-bulking activities.

Given the extremely competitive nature of the market, price is a key driver of business success. Specifying the "right" price offering to potential customers is a challenging task that can affect the long-term survival of the carriers, as over-pricing will turn potential customers away while under-pricing will result in eventual financial losses. Moreover, pricing trucking services is certainly a difficult task if one considers the various uncertainties that may possibly affect the complexities and the cost of trucking operations. These uncertainties include not only those internal to the carrier operation such as the availability of trucks, but also those that lie outside the direct control of carriers such as fuel price, customer demand, and road accidents.

Among all external uncertainties encountered in daily truckload operation, variability in demand is possibly the most important factor because it can simultaneously affect both the revenue and the cost of a trucking operation. Higher-than-expected demand may be favorable in the first instance because it means greater revenue but the unexpected demand will have severely adverse effects on the operation, and the additional cost of mobilizing resources to serve this unforeseen demand may exceed the revenue earned.

The second most significant source of uncertainties in truckload operation is the time required to complete a delivery, because this will affect the use of available trucks. As truckload movements usually involve intercity long-haul movement, the transit time is relatively constant, but the time associated with waiting at the customers' premises and loading/unloading vehicles may vary greatly among different shipments due to changing customer requirements. Customer demand and service times are the two factors of uncertainty which will be considered in this study.

Since these uncertainty factors can give rise to the risk of potential loss from unusual equipment requirements or extreme levels of use, pricing that is based purely on the cost-plus approach does not fully capture the financial and investment or extra expenses from outsourcing trucks implications of these unusual requirements. The literature describes risk measures which can be used to evaluate a system's riskiness. Over the past few years, the financial engineering field's managers have increasingly used Value at Risk (VaR) and Conditional Value at Risk (CVaR) to measure and manage risk exposure.

VaR is defined as the expected loss arising from an adverse market movement with specified probability over a period of time (Tapiero, 2005). It answers the question of how much one can lose with $p\%$ probability over a period of time. Hence, to control the risk of loss, we apply a VaR constraint to estimate full truckload pricing in this paper. Full truckload pricing is considered with the probability of an acceptable loss which is less than the expected target under a specified confidence level. The VaR concept is particularly relevant for the truckload industry because as the market is extremely competitive the carriers are price-takers rather than price-setters.

CVaR measures the conditional expected loss exceeding VaR and accounts for risks beyond the VaR value (Aker, 2005). CVaR is a convex function with respect to positions (Rockafellar and Uryasev, 2000), allowing the construction of efficient optimization algorithms. In particular, CVaR can be minimized using linear programming (LP) techniques. The minimum CVaR approach (Rockafellar and

Uryasev, 2000) is based on a new representation of the performance function that allows the simultaneous calculation of VaR and the minimization of CVaR. Since our goal is to control risks to profitability by considering maximum loss or minimum gain, using VaR and CVaR seems to be a reasonable approach.

An advantage of this study is that it enables transportation carriers to have enough information to offer accurate transportation pricing estimates, which will contribute to a healthy profit margin and also provide a negotiation range for their customers. Shippers can also use this information to improve their ability to accurately determine the effects of variable factors, which will allow them to offer the incentive of cheaper prices.

**1.2 Statement of Problems**

As illustrated in the previous section, pricing estimation is a crucial element of TL services, so its accuracy should be a high priority for management. A minor adjustment in pricing can dramatically affect the profitability of the business and its ultimate success. However, it is not as easy to set standard prices in freight transportation service as it is in other industries such as retail or even in passenger transportation. Normally, how transportation service providers set up their service pricing depends on the company's policy.

In the transportation pricing process, depending on the assumption of deterministic demand and resources capacity, transportation pricing is generated from fixed costs and a variable cost markup with a profit margin aimed at profit maximization. Given the appropriate criteria, if uncertain demand and resources capacity are not taken into account, pricing accuracy will be inadequate. Additionally during the determination of pricing, maximum loss or minimum gain that can be reached is not taken into consideration. Inaccurate pricing will increase the risk of financial loss.

To prevent this problem, this research is established to answer the two research questions below:

- How to determine reasonable pricing for Full Truckload (TL) service considering uncertain factors
- How to control the maximum loss or the minimum gain within a specified tolerance level to enable more flexible full truckload pricing.

This research aims to answer these questions. Therefore the risk management techniques of Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) that are broadly applied in the finance field will be applied in this study. To make these techniques easy to apply, this research will develop a decision support tool that uses a user friendly interface and is easy to implement.

## 1.3 Objective of Study

The main objective of this research is to develop a price determination model for full truckload operation that considers indeterminate conditions by using Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) concepts. The specific objectives of the study can be briefly described as:

1. To examine Full Truckload (TL) pricing structure
2. To identify Full Truckload (TL) uncertainty factors
3. To examine risk levels of uncertain factors in TL service
4. To develop a suitable and efficient methodology for optimizing transportation pricing despite uncertain conditions by applying the advantages of the Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) techniques
5. To develop a visualization tool for transportation carriers as a decision support tool

## 1.4 Scope of Study

This research methodology will be applied for full truckload transportation. Daily delivery shipments in real cases will be used to validate this model. A simulation model is developed to capture the uncertainty patterns inherent in the full truckload network. Risk measurement technique is applied to control the maximum loss or minimum gain.

### 1.5 Expected Outcomes

An expected outcome from this research is price determination model for full truckload operation that accounts for uncertainty for transportation carriers.

# CHAPTER II

# LITERATURE REVIEW

In economics and business, the price is the assigned numerical monetary value of a product, service, or asset. The concept of price is central to microeconomics where it is one of the most important variables in resource allocation theory. Setting suitable prices for products and services is one of the most fundamental management disciplines in every company. Although we would like to earn more profit when we set a price, the best price or correct price is not necessarily the lowest or the highest price.

Price is one variable that a buyer will consider when deciding whether to purchase products or services. In the transportation service industry, although service quality is influential, price is one of the primary considerations when selecting a transportation carrier (Boyer, 1980; Beilock *et al.*, 1986; Dooley *et al.*, 1989; Vidal and Goetschalckx, 2001; Rothschold, 2002). Sometimes reasonable pricing is as important as service quality. It is obvious that a higher price allows a higher margin per unit sold as well (Dolan and Simon, 1996). Therefore, the primary objective of price setting is not only to remain in business but also to make a profit that will enable expansion and increase profit.

The profit system hierarchy normally generated from costing and pricing is illustrated in Figure 2.1 (Dolan and Simon, 1996).



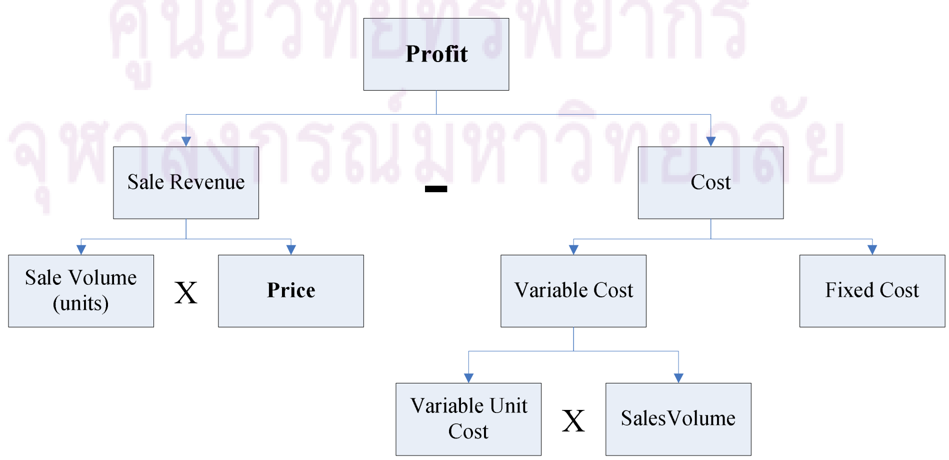



Figure 2.1 The profit system hierarchy (Dolan and Simon, 1996)

Therefore, pricing decisions made hastily without research information, analysis, and strategic evaluation can lead to the organization making less profit. Likewise in the transportation industry, accurately reflecting operating costs to customers is the primary factor driving profit. Therefore, it's absolutely crucial to have a strong understanding of actual operating costs in the initial phase of determining price to ensure acceptable profit margins.

However, there are several variable factors in transport operation, and it's very important to accurately represent these when doing pricing estimations. Uncertainty gives rise to risk and increases the potential for loss (Suri and Soni, 2006). Hence, controlling the maximum loss or minimum gain within a specified tolerance level should be considered during price setting.

The objective of this chapter is to provide the research methodology for this study. The vital topics that will be presented in this chapter are as follows:

- Basic Costing Concept
- Basic Pricing Concept
- Risk Measurement Techniques
- Value at Risk (VaR) and Conditional Value at Risk (CVaR) Technique Application
- Summary

**2.1 Basic Costing Concept**

Cost estimating is the basic component of pricing procedure in business. Accurate costing enables accurate pricing. Cost structure and cost estimation are vital concepts in price setting. This section will illustrate several studies that refer to concepts of cost estimation.

Waters (1976) explained three costing methods that are used to estimate the specific relationship between certain outputs and costs when that relationship is not obvious from available information. These are cost accounting, engineering, and statistics. The first method, cost accounting, is the process of tracking, recording, and analyzing costs associated with the products or activities of an organization. This method is generally the cheapest and most convenient method. It also uses existing data. The second method, engineering, begins by ascertaining the technical co-efficiency between inputs and outputs. Combining such co-efficiencies with the cost of each input yields the cost function for the particular output. The major shortcoming of the engineering approach is that it is fairly data and time-intensive. The third method, statistics, generally makes use of statistical techniques (usually multiple regression analysis) to infer cost-output relations from a sample of actual operating experiences. Although it costs less than the engineering method, it is also less precise.

Many studies have provided methodologies for conducting transportation costing estimates. McMullen (1987) estimated a log-linear truck costing model for full truckload firms (TL) using ton-miles, average length of haul, average load, average shipment size, insurance payments (per ton-mile) and the use of brokerage firms (rented ton-miles divided by total ton-miles) as dependent variables. The results presented evidence of constant returns to scale. TL firms may produce the same output in terms of ton-miles but may carry different commodities with varying weight loads and lengths of haul. McMullen and Stanley (1988) attempted to account for this by framing the cost function as a function of outputs, input prices, and firm attributes. The measure of output they used was ton-miles. The input prices included prices of capital, rented capital, fuel, and labor. Cost estimates were obtained by employing a translog model. They found evidence of increasing returns to scale prior to deregulation and nearly constant returns to scale afterward.

Later work by McMullen and Tanaka (1995) used a translog cost function to examine the differences between large (less-than-truckload or LTL) and small (truckload or TL) motor carriers. Their results revealed significant differences in cost structures between large and small carriers. For large firms there were significant cost implications associated with increasing average load, average length of haul, and average shipment size. Smaller firms illustrated no increases in costs due to increases in average shipment sizes or lengths of hauls and loads, indicating they had already taken advantage of these efficiencies.

Casavant (1993) described classical cost theory and presented much discussion about fixed versus variable inputs associated with a production function. To be more specific about fixed costs (depreciation on capital investment), interest charges or return on investment, license fees and taxes, insurance, housing costs, management or overhead expenses, variable costs (tire cost, fuel cost, maintenance and repair, driving labor), and the decisions that managers make within given situations, it is necessary to consider the time period under discussion. Two general time periods are useful: (1) Short run, a period of time short enough that some resources cannot be varied, and (2) Long run, a period of time long enough that all resources can be changed as desired by the manager.

However, according to Berwick and Dooley (1997), differences in truck configurations, trip and product characteristics, and input prices influence costs for individual owner/operators. They provided transportation costs from many different configurations and trip characteristics. They applied simulation techniques, sensitivity of costs and equipment use, wait time and trip distance, labor, and fuel price. The relationships of these variables and the cost of operations are important for the owners/operators and users if owners/operators.

Holguin-Veras and Brom (2007) discussed the results of a comparative analysis of two alternative approaches to estimate truck cost models, econometric modeling and cost accounting. The analyses revealed that both approaches exhibit similar ability to estimate the stated cost. However, the econometric model did not consider the lack of data about the handling cost (loading the truck plus delivery costs), but compensated for this omission with larger coefficients of distance and tour time, whereas the cost accounting approach considered handling costs to produce estimates of the coefficients of distance and time.

According to the basic cost concept mentioned above, cost estimation will be the initial value for estimating prices. There are several methods for applying cost to price, as will be illustrated in the next section.

## 2.2 Basic Pricing Concept

In general terms, pricing is a component of an exchange or transaction that takes place between two parties, buyers and sellers. Price is commonly confused with the notion of cost. Technically, these are different concepts. Price is what a buyer pays to acquire products from a seller while cost refers to the seller's investment in the product being exchanged with a buyer. Stated another way, the price for a seller is the cost for a buyer. Generally, organizations aim to make a profit and hope that price will exceed cost. To set the specific price level that achieves their pricing objectives, decision makers might apply several pricing methods. Pricing procedures are discussed below.

### 2.2.1 Factors Influencing for Pricing

The final price for a product may be influenced by many factors; however these can be broadly categorized into two groups[1]:

- Internal Factors
- External Factors

These factors are described in more detail below.

**Internal Factors**

Internal factors that affect pricing decisions include the following:

- Company and Marketing Objectives

When setting a price, decision makers have different objectives for different products. The main marketing objectives that normally affect price are:

- *Return on Investment (ROI)* – The objective requirement is that all products return a certain percentage of what the organization spends to market them.
- *Cash Flow* – Pricing is set at a level that ensures sales revenue will at least cover product production and marketing costs.

[1] http://www.knowthis.com

- *Market Share* – Pricing is set with the objective of gaining a hold in a new market or retaining a certain percent of an existing market.
- *Maximize Profits* – The objective is to set the price at a level that optimizes profits.

- Marketing Strategy

Since price is only one of the key marketing decisions, the product's final price will be influenced by other marketing decisions as well.

**External Factors**

The pricing decision can be affected by several factors that are not directly controlled by an organization. They include:

- Elasticity of Demand

Elasticity of demand relates to how purchase quantity changes as prices change. Elasticity is evaluated under the assumption that only price is adjusted while other factors are not changed.

- Customer and Channel Partner Expectations

Decision makers have to consider customer research to determine what "price points" are acceptable. Pricing beyond these price points could discourage customers from purchasing.

- Competitive and Related Products

Pricing may be affected by competitors or by the prices of related products. Therefore, decision makers will undoubtedly look to market competitors for indications of how prices should be set.

- Government Regulation

Normally government regulation is a powerful dynamic in any business. So, decision makers must be aware of regulations that impact how price is set in the markets.

### 2.2.2 Price Setting Methodology

After determining price objectives and listing all influencing factors, the next step is to determine an initial price for products or service. There are several approaches to setting the initial price, which include (Simon, 1989; Montgomery, 1988; Dolan and Simon, 1996; Rowley, 1997):

- **Cost plus pricing**

Cost plus pricing is a pricing method commonly used by several businesses. This type of pricing includes the variable costs associated with the products, as well as a portion of the fixed costs of operating the business. It is calculated as illustrated below:

Cost = (Average Variable Cost + % Allocation of Fixed Costs) x (1 + Markup %)

- **Demand-oriented pricing**

Demand-oriented pricing, also called *demand-based pricing*, establishes the price for a product or service based on the level of demand. Normally, it is applied in travel and theater ticket prices, and in any time-dependent differential charges for access to telephone networks.

- **Price differentiation**

Price differentiation is the charging of different prices for the same product to different social or geographic sectors of the market.

- **Geographic pricing**

Geographic pricing can be regarded as a special case of price differentiation. Prices might be set differently for different geographical markets. For instance, in an international marketplace, they need to take into account currency exchange rates of different countries.

- **Competition-oriented pricing**

Competition-oriented pricing means prices are set with regard to the prices of competitors. This approach helps to support an objective to increase sales or market share. Normally, it is often combined with other approaches to reach a price that will yield a satisfactory profit.

- **Historical pricing**

Historical pricing means that today's prices are based on yesterday's prices.

Besides these methods above, there are many ways to present the price for products or services to the customers. Some of the more well known methods are summarized below[2].

- Break even, meaning whatever it costs to produce the product or provide the service
- Target profit
- Perceived value
- Competitive related
- Sealed bid
- Bundled pricing that combines multiple products and/or services under one price
- Discounts for cash payment
- Quantity discounts
- Trade-in price
- Update price for an improvement to an existing product
- Discounted price to a reseller
- Seasonal discount
- Sales price
- Psychological pricing
- Price plus shipping (catalog/mail order type of sales)



Based on the general basic pricing concepts previously described, each pricing method is proper depending upon the business or product. 'Pricing in the transportation industry, besides its usual usage for revenue management as in many other industries, is also a useful tool for cost management' (Lee and Zhou, 2009).

[2] http://www.businessplans.org/Pricing.html

According to Maner *et al.* (2008), 'pricing and rating transportation services is a more unique and diverse activity than pricing most products and many services. Specifically, truckload transportation is a customized service nearly every time. Moving two different shipments the same distance may have radically different associated costs, and therefore quoted rates, depending on the shipment characteristics.' Some major characteristics include:

1. Distance transported, commonly referred to as the length of the haul (LOH)
2. Specific points of origin and destination
3. Expected loading and unloading activities
4. Consistency and seasonality of shipment volumes
5. Commodity characteristics
6. Equipment type requirements
7. Cargo claims exposure
8. Fuel cost basis

Corresponding with Bowersox (2002), he noted that transportation prices were driven by seven factors: (1) distance, (2) volume, (3) density, (4) stowability, (5) handling, (6) liability, and (7) market. For distance factors, we need to consider both the full running distance and also empty running simultaneously (Beilock and Kilmer, 1986).

Gorman (2001, 2002) studied a freight carrier's pricing strategy in a network by considering equipment repositioning. Because the demand flow in the network was unbalanced, equipment repositioning was considered. He applied a mathematical programming model and provided an efficient computational algorithm to solve the problem. Later, Lee and Zhou (2009) figured out how to set the price optimally in a transportation market with empty equipment repositioning. Transportation equipment in their study is trucks and containers. They aimed to construct and analyze a mathematical model which explicitly considered empty equipment repositioning cost by focusing on a two-location transportation system with two firms. Moreover, fleet management decisions of freight carriers in a network also incorporate pricing problems (Topaloglu and Powell, 2007).

Another previous pricing study was proposed by Lin *et al.* (2009). They provided a pricing and operational plan for LTL in Taiwan to maximize a carrier's profit. The constraints in pricing planning for time-definite LTL freight delivery common carriers are based on the following assumptions: (1) the demand is a continuous and invertible function, (2) the revenue function is a concave continuous function, and (3) the capacity in the hub-and-spoke network is fixed.

Transportation activities are stochastic due to several underlying conditions that change over time, such as daily demand fluctuation, variation of commodity type, weight and size, variation of origin and destination, proportion of empty truck miles, variation of fuel price, or extra customer requirement. A few studies have considered these uncertain factors during price setting.

Tsai *et al.* (2008) applied concepts from the theory of Real Options to craft a derivative contract for full truckload service, using truckload options to hedge the uncertainties. They developed truckload model pricing with given minimum, average, and maximum prices for all transactions included during a set period (typically one month) considering uncertainty. There were three causes that changed: demand for shipping over a given lane, the number of empty containers bound for a destination ('deadhead' moves), and the price of oil. The benefits of the truckload option could be guaranteed truckload services and decreased storage costs for shippers, as well as compensation for 'deadhead' carrier movements.

Although this model investigated full truckload pricing to maximize profits, some kind of risks in pricing preprocessing were not taken into consideration. Examples include losing a more than acceptable level or gaining less the desired minimum. For running a business, it is very important to know that probability of risk either to lose a more than acceptable level or to gain a less than expected level when setting a price. Therefore, the next section will provide the methodology to measure the probabilities of losses with a specified confidence level.

## 2.3 Risk Measurement Techniques

In the real world, many problems arise from uncertain conditions such as stochastic conditions or fuzzy conditions. In the freight logistics business, industry and service providers are strongly pressured by increasingly individualized and dynamic consumer demands (Duin, *et al.*, 2007). Pompeo and Sapountzis (2002) note that risks in freight transportation arise largely from three sources: changes in demand caused by the economic cycle, anomalies in the way contracts are drawn up, and uncertainty over prices. De Vany and Saving (1977) presented a model of a trucking firm encountering uncertain conditions in which both quality of service (as measured by waiting times) and price were decision variables.

However, under competition freight rates could vary not only with the inventory costs for the particular commodity but also with the supply conditions of carriers at the origin and the supply of backhauls at the destination. The effect of the likelihood of a backhaul on carrier behavior is discussed by Beilock and Kilmer (1982) and by Kilmer, Ramirez, and Stegelin (1983). In-house risks exist, particularly human error in daily transport service operation. Human errors can result in incomplete or inaccurate freight deliveries or inaccurate documentation. This can result in delays with goods delivery or paperwork handling. Other uncertain conditions in transportation services include product mix-ups, fuel price fluctuation, unpredictable transit time, fleet size, vehicle schedule, and route (Min *et al.*, 1998).

Handling uncertain conditions is a very significant and inspiring research topic in the financial engineering field. The right decision typically needs to be made to optimize portfolios where the price is considered as a random variable. Decision making under uncertain conditions will sometimes introduce some kinds of risk. Therefore, there many efforts have concentrated on how to reduce the risk of high losses using different measures and optimization techniques. Furthermore, the theory and model of the decision making under risk should be able to include as much information on risky prospects as possible (He, Y. and Huang, RH., 2007). Two risk measurement techniques are:

- Value-at-Risk (VaR)
- Conditional Value-at-Risk (CVaR)

### 2.3.1 Value at Risk (VaR)

In the financial world nowadays, Value-at-Risk (VaR) has become one of the most important if not the most important measure of risk (Rogachev, 2002). It can describe the loss that takes place over a given period and at a given confidence level, due to exposure to market risk. For a given time horizon $t$ and confidence level $p$, the value at risk is the loss in market value over the time horizon $t$ that is exceeded with probability 1- $p$ (Duffie and Pan, 1997).

VaR was first used by major financial firms in the late 1980s to measure the risks of their trading portfolios. VaR is now widely accepted not only by financial institutions and regulators for assigning risk capital and monitoring risk, but also by retail banks, insurance companies, institutional investors, and non-financial enterprises. According to Rogachev (2002), theoretical research that relied on the Value at Risk as a risk measurement was initiated by Jorion (1997), Down (1998), and Saunders (1999), who applied the VaR approach based on risk management resulting in it becoming the industry standard either by choice or by regulation. In principle, VaR furnishes quantitative and synthetic measures of risk.

The functions that define VaR metrics can be fairly intricate. An expected tail loss (ETL) VaR metric indicates a portfolio's expected loss conditional on that loss exceeding some specified quantile of loss (Dowd, 2002). To approach VaR, for example, the Derivatives Policy Group has proposed a standard for over-the-counter derivatives broker-dealer reports to the Securities and Exchange Commission that would set a time horizon $t$ of two weeks and a confidence level $p$ of 99%, as illustrated in Figure 2.2 (Duffie and Pan, 1997).

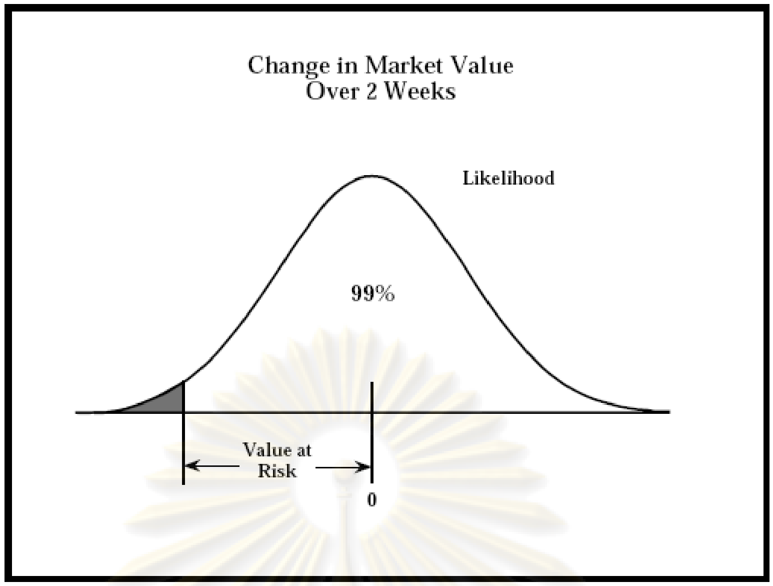



Figure 2.2 Value at Risk (DPG Standard, 1995)

A basis for the formula to calculate VaR is depicted by the following equation:

$$VaR = p \cdot \sigma\sqrt{T} \tag{2-1}$$

where $p$ is the confidence level ($p$ is the distance of the means measured in number of standard deviations: for example, 1.65 corresponds to 95% confidence level); $\sigma$ is the portfolio volatility, which is measured as a standard deviation of the yields; and $T$ is the time period (Rogachev, 2002).

The existing Value at Risk (VaR) related academic literature focuses mainly on measuring Value at Risk from different estimation methods to various calculation models. There are three basic methods of calculating VAR: the variance-covariance method and two simulations are the two historical simulation methods, and the Monte Carlo simulation is the third method. Each has particular strengths and weaknesses and should be viewed not as competing methodologies, but as alternatives which might be appropriate in certain circumstances (Stambaugh, 1996).

- **The Variance-Covariance Method**

In 1994, JP Morgan launched the risk measurement technique, the so-called RiskMetrics$^{TM}$. It is a methodology and database to measure and describe risk. Since its introduction, RiskMetrics$^{TM}$ has served as a catalyst and a focal point for the debate on VaR methodology, and it has served the market extremely well in that regard. It is now the most visible advocate for the variance-covariance methodology for measuring risk and has become virtually synonymous with it.

The Variance-Covariance Method makes two critical assumptions about the nature of portfolio market risk, and as a result is able to calculate risk with a single closed-end formula. The first assumption is that movements in market variables, such as interest rates and exchange rates, are normally distributed and zero-mean. It is said that their probability distributions form the familiar 'bell curve' shape with no underlying upward or downward bias. The second assumption is that every risk position can be expressed in terms of a position of a certain size, known as the "delta equivalent," in one or perhaps more than one market variable. If these assumptions are valid, it can be concluded that not just market movements, but also the set of possible portfolio gains and losses, conforms to a normal distribution.

This method assumes that stock returns are normally distributed. In other words, it requires that we estimate only two factors – an expected (or average) return and a standard deviation – which allow us to plot a normal distribution curve. More details of these two assumptions are described below.

1. The portfolio is composed of assets whose deltas are linear; more exactly the change in the value of the portfolio is linearly dependent on (i.e., is a linear combination of) all the changes in the values of the assets, so that the portfolio return is also linearly dependent on all the asset returns.
2. The asset returns are jointly normally distributed.

The implication of (1) and (2) is that the portfolio return is normally distributed because a linear combination of jointly normally distributed variables is itself normally distributed.

The normality assumption allows us to z-scale the calculated portfolio standard deviation to the appropriate confidence level. So for the 95% confidence level VaR we get:

$$VaR = -V_p(\mu_p - 1.645\sigma_p) \tag{2-2}$$

where:

$$\mu_p = \sum_{i=1}^{N} \omega_i \mu_i \ , \ \sigma_p = \sqrt{\omega^T \sum \omega} \tag{2-3}$$

and

$$\omega_i = V_i / V_p \tag{2-4}$$

Notations:

| | |
|---|---|
| $\omega$ | vector of all $\omega_i$ (T means transposed) |
| $i$ | of the return on asset $i$ for $\sigma$ and $\mu$ of asset $i$ (otherwise) over the holding period |
| $p$ | of the return on the portfolio" (for $\sigma$ and $\mu$) of the portfolio (otherwise) over the holding period |
| $\mu$ | expected value |
| $\sigma$ | standard deviation |
| $V$ | initial value (in currency units) |

The benefits of the variance-covariance model are the use of a more compact and maintainable data set which can often be bought from third parties, and also the speed of calculation using optimized linear algebra libraries. Drawbacks include the assumption that the portfolio is composed of assets whose delta is linear and the assumption of a normal distribution of asset returns such as market price returns.

- **Historical Simulation Method**

The historical method simply re-organizes actual historical returns, putting them in order from worst to best. It then assumes that history will repeat itself, from a risk perspective. This involves running the current portfolio across a set of historical price changes to yield a distribution of changes in portfolio value, and computing a percentile (the VaR). The benefits of this method are its simplicity to implement, and the fact that it does not assume a normal distribution of asset returns. Drawbacks are the requirement for a large market database and the computationally intensive calculation.

For a simple example, using the historical simulation method to evaluate the VaR of the portfolio, we can use simple data and equation 2-5.

$$VaR = M * \sigma_p * \sqrt{10} * 2.33 \tag{2-5}$$

where

| | |
|---|---|
| $M$ | Market value of the Portfolio |
| $\sigma_p$ | Historical volatility of the portfolio |
| 10 | Number of days: here we used 10 days |
| 2.33 | Number of sigma needed for a level of certainty of 99% |

According to Stambaugh (1996), this approach has several advantages. For one thing, no assumptions are made about the distributions of the underlying price changes. The changes themselves, not an abstraction of them, are used to calculate the prospective gains and losses, so any fat tails or other distribution is fully captured. For another thing, this methodology calls for full valuation of the positions, be they cash, derivative, or option holdings. The column of possible gains and losses is thus a set of realistic outcomes. Finally, it is a simple matter to aggregate the risks of different positions.



However, there are some problems with the historical simulation approach. One is that there is disagreement on the appropriate number of days to use. The longer the series the less risk of sampling error, but older data has less validity. A related problem is that a few large movement trading days will dominate the VaR number until they drop out of the sample at which point the number could fall suddenly.

- **Monte Carlo Simulation**

The other principal form of simulation approach is Monte Carlo simulation. This operates according to a similar principle as historical simulation with the important difference that the price changes against which the portfolio is revalued are simulated rather than historical. A Monte Carlo simulation refers to any method that randomly generates trials, but by itself does not tell us anything about the underlying methodology.

The first step in this approach is to design a series of models to forecast market behavior, incorporating volatilities and correlations as well as other stochastic factors considered appropriate. These models are then used to generate several thousand scenarios of correlated price movements in the relevant markets.

Perhaps the greatest drawback to Monte Carlo simulation is that it is a ravenous consumer of computer resources. Designing the models, running the daily scenarios, and then performing the multiple revaluations require significant computing power. Nor it is simple to distribute the processing, as with historical simulation, since the scenarios would must first be generated centrally, and then distributed for calculation before returning results to the center. This sets up conflicts with units in different time zones.

As illustrated above, these methods differ in their ability to capture the risks of options and option-like instruments, ease of implementation, ease of explanation to senior management, flexibility in analyzing the effect of changes in the assumptions, and reliability of the results. The best choice will be determined by which dimensions the risk manager finds most important (Linsmeier and Pearson, 1996). They also provided the differences in the three methods illustrated in Table 2.1.

Table 2.1 Comparison of Value at Risk Methodologies

| | Historical Simulation | Variance/Covariance | Monte Carlo Simulation |
|---|---|---|---|
| Able to capture the risks of portfolios which include options? | Yes, regardless of the options content of the portfolio | No, except when computed using a short holding period for portfolios with limited or moderate options content | Yes, regardless of the options content of the portfolio |
| Easy to implement? | Yes, for portfolios for which data on the past values of the market factors are available. | Yes, for portfolios restricted to instruments and currencies covered by available "off-the-shelf" software. Otherwise reasonably easy to moderately difficult to implement, depending upon the complexity of the instruments and availability of data. | Yes, for portfolios restricted to instruments and currencies covered by available "off-the-shelf" software. Otherwise moderately to extremely difficult to implement. |
| Computations performed quickly? | Yes. | Yes. | No, except for relatively small portfolios. |
| Easy to explain to senior management? | Yes. | No. | No. |
| Produces misleading value at risk estimates when recent past is atypical? | Yes. | Yes, except that alternative correlations/standard deviations may be used. | Yes, except that alternative estimates of parameters may be used. |
| Easy to perform "what-if" analyses to examine effect of alternative assumptions? | No. | Easily able to examine alternative assumptions about correlations/standard deviations. Unable to examine alternative assumptions about the distribution of the market factors, i.e. distributions other than the Normal. | Yes. |

*Source : Linsmeier and Pearson, 1996*

With numerical Value at Risk (VaR) as mentioned above, 'we can make further progress if we focus on the random process that describes the behavior of the portfolio's daily return (i.e. if we make some assumptions about the probability density function of the portfolio return)' (Dowd, 1998). In this case, VaR will be called parametric VaR. Since VaR has been adopted as a performance measure that evaluates the maximum loss with a specified confidence level, then parametric VaR is as described below.

Assume the specified probability level is $p$. The $\beta - VaR$ of a portfolio is the lowest amount $\varepsilon$ such that with probability $p$, the loss will not exceed $\varepsilon$.

Let $f(x, y)$ be the loss related to the decision vector $x$, which represent a portfolio, and the random vector $y$, which acts for uncertainties, e.g., market variables, etc. that affect the loss. Therefore, for each $x$ the loss $f(x, y)$ is a random variable having a distribution induced by the random vector $y$. Assume the underlying probability density function of $y$ is denoted by $p(y)$. Then, the $p-VaR$ values for the loss random variable related with $x$ and any specified probability level $p$ will be denoted by $\varepsilon_p(x)$, which are given by:

$$\varepsilon_p(x) = \min \{\varepsilon \in R | \psi(x,\varepsilon) \geq p\} \tag{2-6}$$

where

$$\psi(x,\varepsilon) = \int_{f(x,y)\leq\varepsilon} p(y)dy$$

is the probability of $f(x, y)$ not exceeding a threshold $\varepsilon$, which is the cumulative distribution function for the loss associated with $x$.

### 2.3.3 The Conditional Value-at-Risk (CVaR)

Conditional Value-at-Risk (CVaR) is also known as Mean Excess Loss, Mean Shortfall, or Tail VaR. By definition with respect to a specified probability level $p$, the $p\ -VaR$ of a portfolio is the lowest amount $\varepsilon$ such that, with probability $\beta$, the loss will not exceed $\varepsilon$, whereas the $p\ -VaR$ is the conditional expectation of losses above that amount $\varepsilon$. CVaR measures the conditional expected loss exceeding VaR and accounts for risks beyond the VaR value. The CVaR measure is able to quantify dangers beyond the VaR value. To avoid the undesirable characteristics of VaR, Conditional Value-at-Risk (CVaR) will be applied as an alternative measure of risk, with more attractive properties.

The $p-CVaR$ values for the loss random variable associated with $x$ and any specified probability level $p$ will be denoted by $\phi_p(x)$, which are given by:

$$\phi_\beta(x) = (1-p)^{-1} \int_{f(x,y)\geq\varepsilon_\beta(x)} f(x,y)p(y)dy \tag{2-7}$$

In equation 2-7, the probability that $f(x,y) \geq \varepsilon_p(x)$ is therefore equal to $1-p$. Therefore, $\phi_p(x)$ is the conditional expectation of the loss associated with $x$ relative to that loss being $\varepsilon_p(x)$ or greater. It can be ensured that the $p-VaR$ is never more than $-CVaR$, which means CVaR will naturally give low VaR as well.

In addition, Rockafellar and Uryasev (2002) derive the fundamental properties of CVaR as a measure of risk with significant advantages over VaR for loss distributions in finance that can involve discreetness. CVaR is able to quantify dangers beyond VaR. It provides optimization shortcuts through the linear programming techniques.

**2.4 Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) Technique Application**

The VaR and CVaR are important risk measures that originated in financial models. Since the end of 1997, banks have been allowed to measure their risks by internal VaR models, and the concept of VaR has become an essential tool of risk management (Jorion, 2001). Subsequently, VaR and CVaR have been applied in many fields for several years. Cabedo and Moya (2003) propose VaR using the historical simulation approach for oil price risk quantification. VaR provides estimation of the maximum oil price change associated with a likelihood level, and can be used for designing risk management strategies. In inventory management, Aker (2005) uses Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) as the risk measures in a newsvendor framework. He investigates the multi-product newsvendor problem using VaR and CVaR constraints. VaR's characteristics are described below.

$$\text{VaR} = \inf\{\, \pi_0 \,|\, P(\xi \geq \pi_0) \geq p \,\} \tag{2-8}$$

where

$\pi_0$ = target profit value

$p$ = threshold probability value of the downside risk constraint

$\xi$ = random variable

The VaR-constrained optimization problem is defined as the maximization of the expected profit with a downside risk constraint. The model for one product was solved by Gan *et al.* (2003). The decision problem is as follows:

Objective

$$\max_{q\geq 0} \quad E\left[\pi(q,D)\right] \tag{2-9}$$

Subject to

$$\Pr(\pi(q,D) \leq \pi_0) \leq p \tag{2-10}$$

where

$r$ = unit selling price of a product

$c$ = unit variable cost of a product

$s$ = unit salvage price of a product

$q$ = order quantity for a product

$D$ = demand for a product

$\pi(q,D)$ = profit function

= $r\min\{q,D\} - cq$ (salvage value is assumed to be zero)

CVaR's characteristics are:

$$\text{CVaR} = E[\xi \mid \xi \geq \pi_{0_p}(\xi)] \tag{2-11}$$

where

$\pi_{0_p}$ = target profit value for $p$ threshold probability

The CVaR function is defined in terms of profit distribution of a newsvendor problem. The model for one product is described below.

$$\max_{q\geq 0,\pi_0} \quad CVaR_p(\pi(q,D)) \tag{2-12}$$

where

$$CVaR_p(\pi(q,D)) = \pi_0 + \frac{1}{p}\int_D [(r-c)q - (r-s)(q-D)^+ - \pi_0]^- \, dF(D)$$

and $[a]^- = \min(a,0)$

In a multi-product newsvendors setting, Gotoh and Takano (2008) and Zhou *et al.* (2008) independently consider the Conditional Value at Risk (CVaR) minimization problem.

Even though Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) have become the major tool in risk management worldwide, the literature reveals that there is no risk application in full truckload (TL) pricing estimation. Therefore, the advantages of these risk measurement techniques will be applied in this study.

## 2.5 Summary

This chapter reviews literature which is relevant to theoretical methodologies and previous studies of full truckload costing and pricing. Also, it investigates risk measurement techniques which control the risk of earning less than the desired profit or losing more than an acceptable level due to uncertain factors. The risk measurement techniques are Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). This study should provide a transportation pricing interval within a specified tolerance level to enable more flexible full truckload pricing. The different tolerance levels should provide a negotiable price range for customers. An example of this is illustrated in Figure 2.3. The maximum price customers are willing to pay should be at or above the absolute minimum the carriers will take. The difference between these two points is the only area of negotiation in which an agreement can take place considering different confidence levels (Burt *et al.*, 1990).



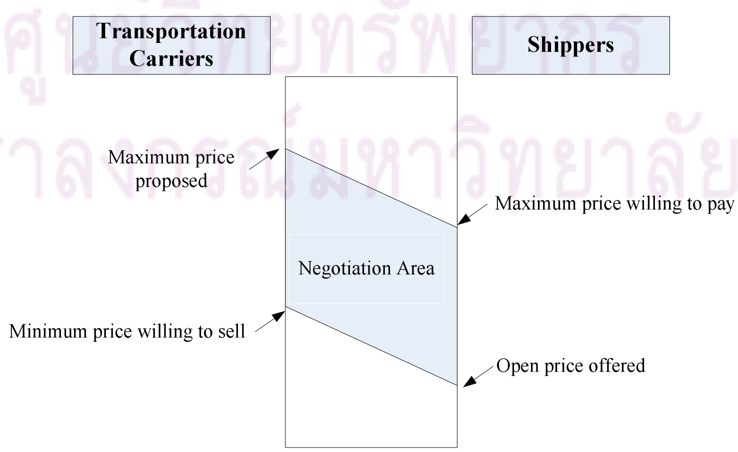



Figure 2.3 Establishing a Price (Burt *et al.*, 1990)

# CHAPTER III

# RESEARCH METHODOLOGY

The proposed research framework has two basic components, the full truckload simulation model and the full truckload pricing model, as illustrated in Figure 3-1. A simulation model is developed to capture the stochastic patterns inherent in the operation of a full truckload network. The stochastic patterns considered in this study are demand uncertainty and service time uncertainty, from both existing customers and new customers. The full truckload pricing model applies the risk measurement techniques of Value at Risk (VaR) and Conditional Value at Risk (CVaR) to control the maximum loss or the minimum gain within a specified tolerance level to enable more flexible full truckload pricing.

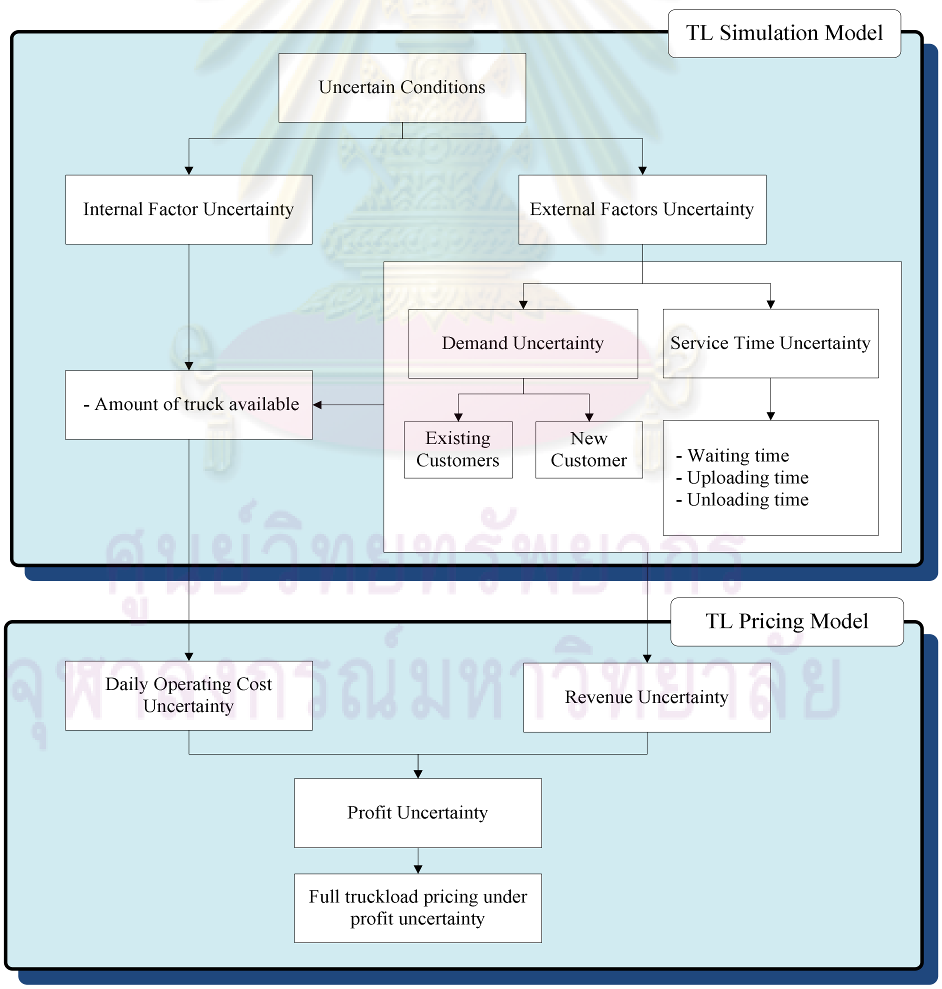



Figure 3.1 Research Framework

To achieve the proposed research framework, the overall research procedure and methodology will be meticulously performed as illustrated in Figure 3.2.

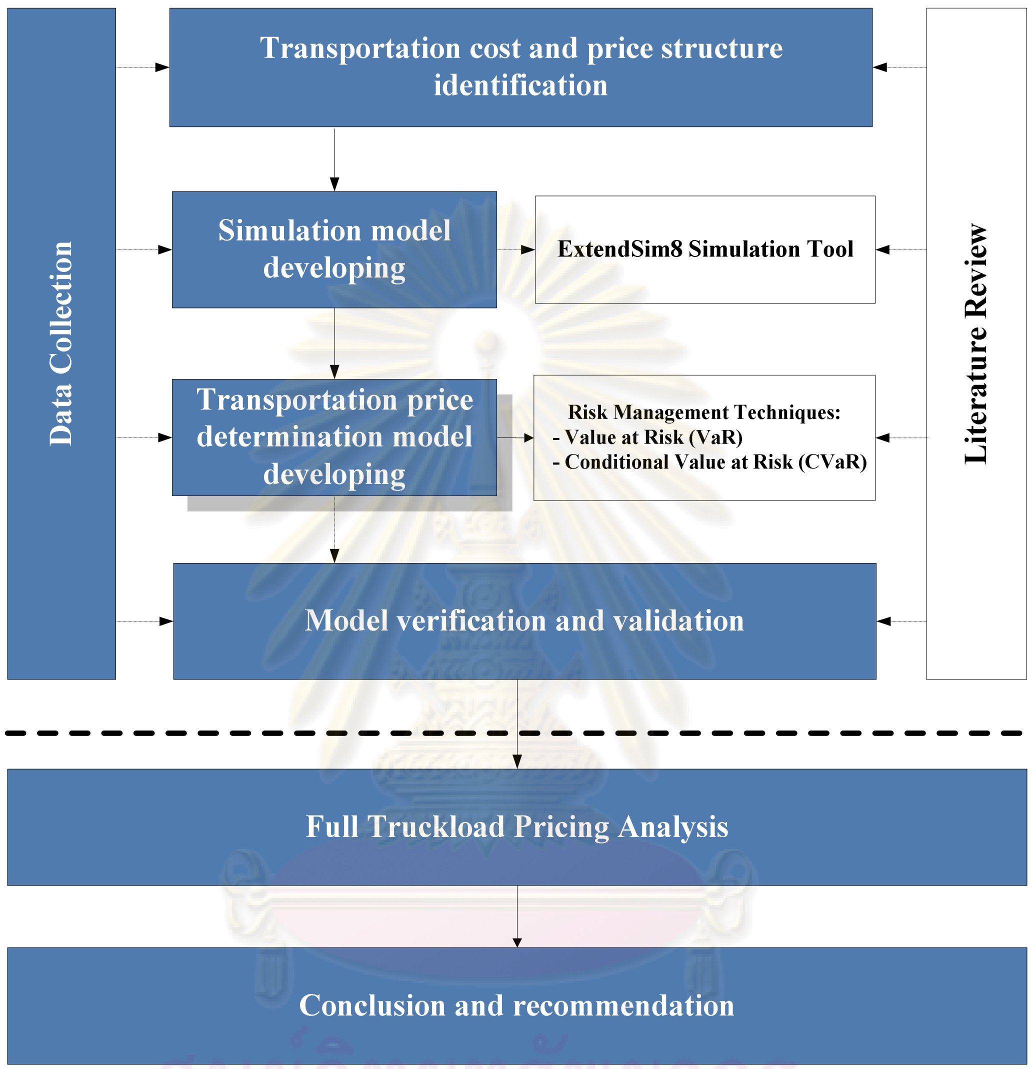



Figure 3.2 Research procedure and methodology

### 3.1 Transportation cost and price structure identification

The freight transportation structure in Thailand is quite complicated. Unlike other products, it has no standard pricing. Transport rates are determined individually and depend on a company's strategies, customer requirements, market price, etc. Therefore, this study will deeply investigate current transportation costs and price structures of full truckload (TL) service in Thailand. Traditionally, transportation pricing is derived from the transportation cost, which consists of fixed costs and variable costs, plus a profit margin. The amount of profit margin added depends on specific company policy or service level. Normally, driven cost components such as weight, volume, origin, destination, etc. are considered as deterministic variables. A different quantity consequently generates various levels of services and pricing. Also, generated pricing can be by baht per trip, per kilometer, per box, per ton, per volume, etc. To deeply understand transportation cost and price structure, this task will be clarified using these details:

- **Identifying transportation cost and price components**

During this research, transportation cost will be separated into two parts:

  - **Fixed Costs** are often considered "sunk" costs and are those that do not change as mileage changes. They generally include depreciation on capital investment, interest charges or return on investment, license fees, taxes, insurance, rental costs, management or overhead expenses, etc.
  - **Variable Costs** are directly related to mileage. These costs include tires, fuel maintenance, repairs, driving labor, etc.

The total cost mentioned above will be converted to transportation cost and price per unit. Normally, pricing units can be baht per trip, baht per box, baht per ton-km, baht per km, etc.

- **Selecting a transportation carrier to be the case study**

This task aims to select an appropriate full truckload (TL) carrier to be the case study for obtaining information about transportation cost and price structure. The selected TL carrier should provide reliable service and enough information to represent the population. Most trucks on the highway serve consumer product shipments. Hence this study mainly focuses on transportation carriers who offer nationwide services for consumer products.

Normally, a vehicle in full truckload operations is loaded with freight that meets either the cubic capacity or weight capacity of the vehicle, and carries it to a single destination where it is completely unloaded. TL carriers usually charge a service price per kilometer. The service pricing varies depending on the distance, geographic location of the delivery, items being shipped, equipment type required, and service times required. The characteristics of a Full Truckload (TL) carrier are illustrated in Figure 3.3.

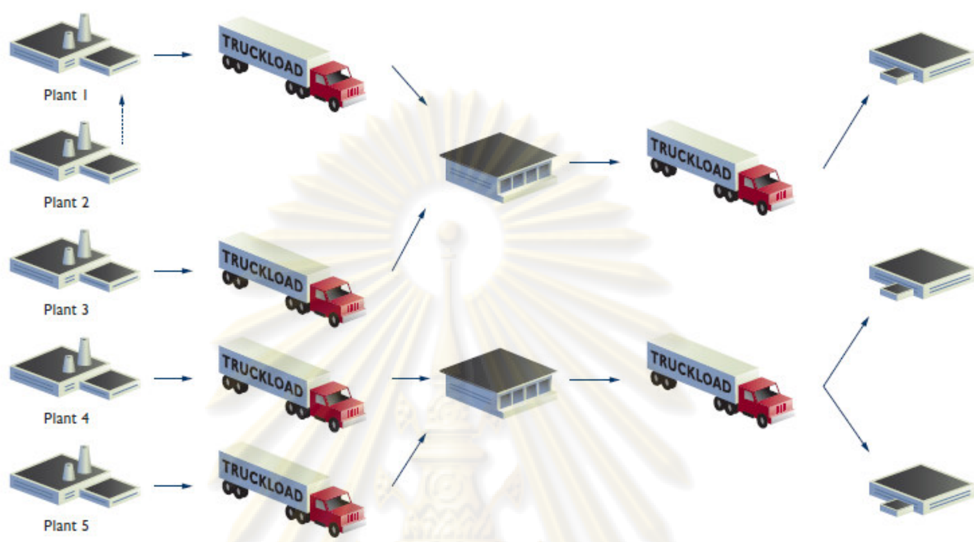



Figure 3.3 Full Truckload (TL) Operation

### 3.2 Developing the full truckload simulation model

A simulation model is developed to capture the stochastic patterns inherent in the operation of full truckload networks. The stochastic patterns originate from both existing and newly-approached customers' operations. The model is used to illustrate how a new customer's operation affects existing customer operation. For instance, transportation carriers might not have enough resources to serve the new customer demand. Hence, they need to invest in new trucks and other equipment to fulfill new customer requirements. Simulation results can imitate this situation and provide this information to carriers before making any decision.

The model was developed using ExtendSim8, which is discrete event modeling, to mimic demand and service time uncertainty in daily operation. Outputs from the simulation will be uncertain demand and also daily operation costs. This output will be used as input data for the full truckload pricing model.

### 3.3 Developing the full truckload price determination model

This task aims to develop a full truckload price determination model for newly-approached customers by considering the operational uncertainty that originates from both existing and potential customers. The outputs from the simulation model in the previous section will be the initial information for the full truckload (TL) pricing model in this task. Since pricing for current customers cannot be changed, the problem is how to determine truckload pricing for new customers by considering uncertain current operational costs and also additional costs from new or potential customers.

Therefore, a full truckload pricing model for new customers is developed using Value at Risk (VaR) and Conditional Value at Risk (CVaR) to determine the minimum service price offering by controlling the risk of earning less than the desired profit or losing more than an acceptable level due to uncertain factors. In this case, uncertain operating costs from current customers will be included.

### 3.4 Data Collection

This task aims to collect data from the case study to develop a full truckload simulation and pricing model. The chosen TL carrier has been providing full truckload service for several years. Customer types can be grouped into two types, current customers and new customers. This research will mainly concentrate on customers who sign a delivery contract with the selected carrier.

Daily operation information such as volume and size of shipments, number of trucks used, labor requirements, shipment origin and destination, truck assignment rules, etc. will be collected. The major uncertainty factors needing study are waiting time to upload, uploading time, travel time, waiting time to unload, and unloading time. This data will be used as input data for the full truckload simulation and pricing model.

### 3.5 Model Verification and Validation

The developed model's reliability must be verified. This is done using a real case. To validate the full truckload simulation model, full truckload real data will be used to compare. For pricing model validation, we will go back to work with transportation carriers and fine tune this model until it is usable and reliable.

### 3.6 Full Truckload Pricing Analysis

After checking the model's reliability, next process is to implement the developed model in a practical working environment. It will be applied to investigate pricing for new customers based on case study data from field survey.

### 3.7 Conclusion and recommendations

The objective of this task is to prepare a report summarizing the objectives of the study, the methodology, the results, and recommendations for further study.

# CHAPTER IV

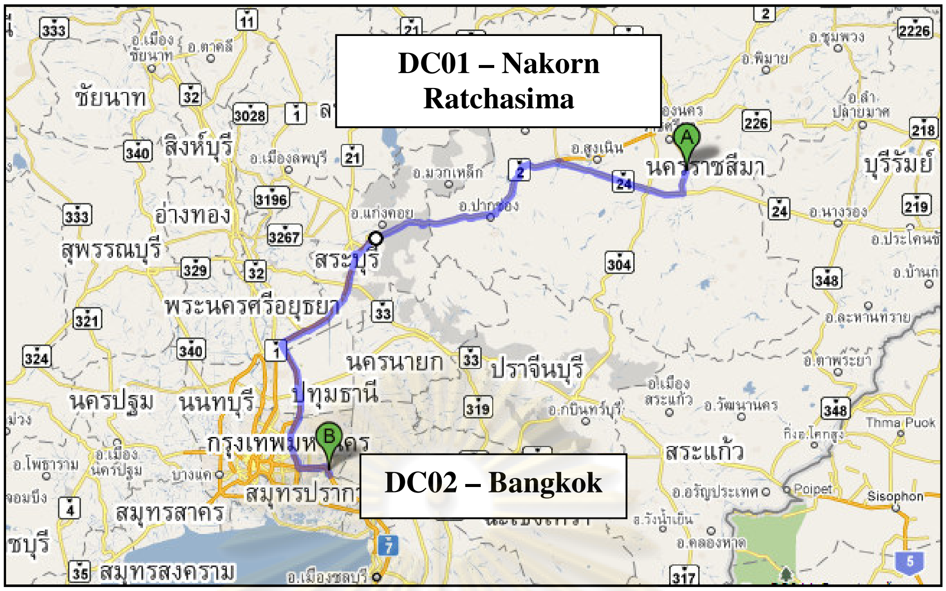
# DATA COLLECTION

This chapter presents the survey data related to the full truckload simulation and pricing model. Collecting related data will be performed while developing the simulation and also during pricing. Collected data are used to adjust and refine the simulation model so it is more realistic and reasonable. For this reason, a full truckload transportation carrier is selected to be a case study for the simulation and pricing model. All related information that is applied in this study is explained below.

## 4.1 Case study background

### 4.1.1 Overview

The selected transportation carrier, MCK Ltd., is located in Nakorn Ratchasima province, northeastern Thailand. It has provided full truckload transportation service for more than over 25 years. Initially, their transport service provided for agriculture products and only covered the northeast of Thailand. Nowadays, their service has expanded to include agricultural products, construction goods, consumer products, fertilizer, etc. Their transport service network is nationwide. Besides the distribution center in Nakorn Ratchasima province which is a head office, they have another distribution center that in Truck Terminal Station, Lad Krabang, Bangkok, that acts as a parking area. The second distribution center is about 280 kilometers from the first one as shown in Figure 4.1.




Source: Google Maps

Figure 4.1 Distribution centers location

### 4.1.2 Truck Type Services

The company MCK has 142 trucks as described in Table 4.1. However, this research framework focuses on six-wheeled semi trailers, as these are the largest proportion and are often use in MCK's daily operation.

Table 4.1 MCK truck types and fuel types

| Truck Type | Fuel Type | | Total |
|---|---|---|---|
| | Diesel | NGV | |
| **Full Trailer 10 Wheels** | 13 | 32 | 45 |
| **Semi Trailer** | 55 | 41 | 96 |
| • Semi Trailer 10 Wheels | 5 | 31 | 36 |
| • Semi Trailer 6 Wheels | 50 | 10 | 60 |
| **Truck 6 Wheels** | 1 | - | 1 |
| Summary | 69 | 73 | 142 |

Besides full truckload transport service for customers, MCK also provides warehouse service for customers. Full truckload service is provided for agricultural products and also agricultural products' processing.

## 4.2 Customer Demand Information

Even if this research aims to investigate full truckload pricing for new customers; however, existing customer demand uncertainty is still a concern.

Therefore, customer demand information required for this study can be divided into two groups:

- Existing customers' demand information
- New customers' demand information

The details for each customer type are explained in detail below.

### 4.2.1 Existing Customer Demand

Existing customer means current customers to whom MCK provides full truckload service using semi trailer 6-wheel trucks. Currently, MCK provides semi trailer 6-wheel truck service for 22 routes for its existing customers. The historical data were collected for 7 months (June 1, 2010 – December 30, 2010) to develop the simulation and pricing model. The total historical demand is described in Table 4.2.

Table 4.2 Exiting average demand per day

| Route | DC Start | Route | Origin | Destination | Total demand (7 months) | Average shipments per day | STD |
|---|---|---|---|---|---|---|---|
| 1 | BKK | AYA-NMA | Ayudhaya | Korat | 791 | 3.7 | 7.04 |
| 2 | BKK | AYA-SPK | Ayudhaya | Samutprakan | 366 | 1.7 | 5.07 |
| 3 | BKK | BKK-BKK | Bkk | Bkk | 57 | 0.3 | 0.60 |
| 4 | BKK | BKK-MDH | Bkk | Mukdahan | 43 | 0.2 | 0.58 |
| 5 | BKK | BKK-NMA | Bkk | Korat | 420 | 2.0 | 2.41 |
| 6 | BKK | CBI-NMA | Chonburi | Korat | 164 | 0.8 | 2.34 |
| 7 | BKK | LRI-NMA | Lopburi | Korat | 243 | 1.1 | 1.63 |
| 8 | BKK | PTE-NMA | Pathumtani | Korat | 82 | 0.4 | 0.76 |
| 9 | BKK | SKN-NMA | Samutsakorn | Korat | 131 | 0.6 | 1.03 |
| 10 | BKK | SPK-NMA | Samutprakarn | Korat | 580 | 2.7 | 3.66 |
| 11 | BKK | SRI-MDH | Saraburi | Mukdahan | 171 | 0.8 | 2.02 |
| 12 | BKK | SRI-NMA | Saraburi | Korat | 268 | 1.3 | 2.02 |
| 13 | NMA | KKN-NMA | Khonkaen | Korat | 714 | 3.4 | 5.73 |
| 14 | NMA | KPT-NMA | Kumpangpet | Korat | 660 | 3.1 | 3.98 |
| 15 | NMA | NMA-AYA | Korat | Ayudhaya | 749 | 3.5 | 7.40 |
| 16 | NMA | NMA-BKK | Korat | Bkk | 1,034 | 4.9 | 7.20 |
| 17 | NMA | NMA-CBI | Korat | Chonburi | 235 | 1.1 | 2.19 |
| 18 | NMA | NMA-NMA | Korat | Korat | 2,382 | 11.2 | 8.12 |
| 19 | NMA | NMA-RBR | Korat | Ratchaburi | 74 | 0.3 | 0.86 |
| 20 | NMA | NMA-RYG | Korat | Rayong | 449 | 2.1 | 3.16 |
| 21 | NMA | NMA-SPK | Korat | Samutprakan | 1,006 | 4.7 | 8.03 |
| 22 | NMA | SSK-NMA | Srisakate | Korat | 267 | 1.3 | 3.20 |
| | | | | Total | 10,886 | | |

This historical data reveals uncertain existing customer demand. Since most of the products that MCK delivers are related to agricultural products, demand varies seasonally, leading historical demand to vary on a daily basis. This study uses the Stat::Fit function in ExtendSim8 simulation program to fit a demand distribution curve. The function feature of Stat::Fit in ExtendSim8 is demonstrated in Figure 4.2.

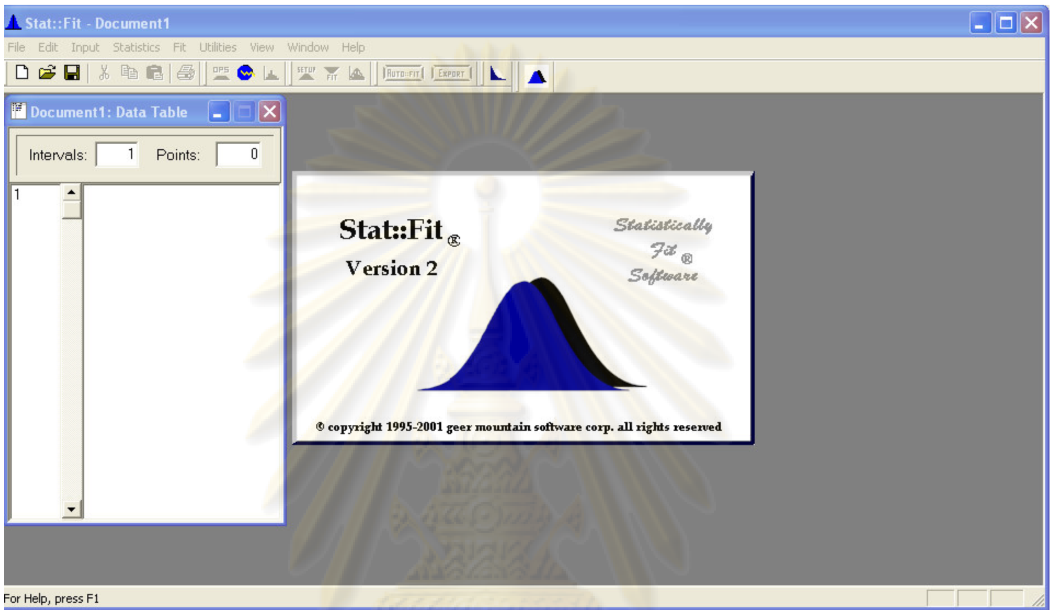



Figure 4.2 Stat::Fit function in ExtendSim8 simulation model

After inputting historical demand data for each route, the Stat:: Fit function has a menu to select the pattern by user or by the Auto:: Fit menu to fit distribution as illustrated in Figure 4.3. After the distribution pattern is chosen, the Stat::Fit function will provide the best distribution fit report and graph for the input data as shown in Figure 4.4 and Figure 4.5 respectively. It also provides statistics test report as described in Figure 4.6.

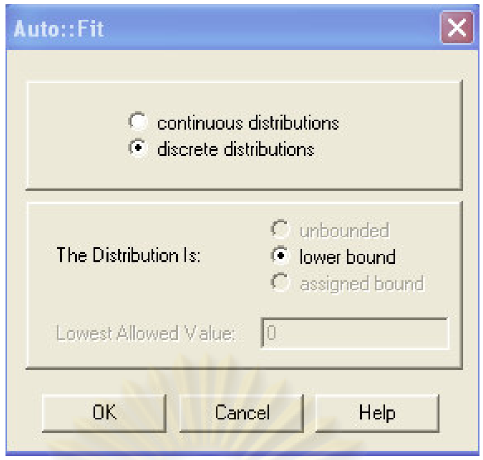



Figure 4.3 Auto::Fit menu for selecting distribution pattern

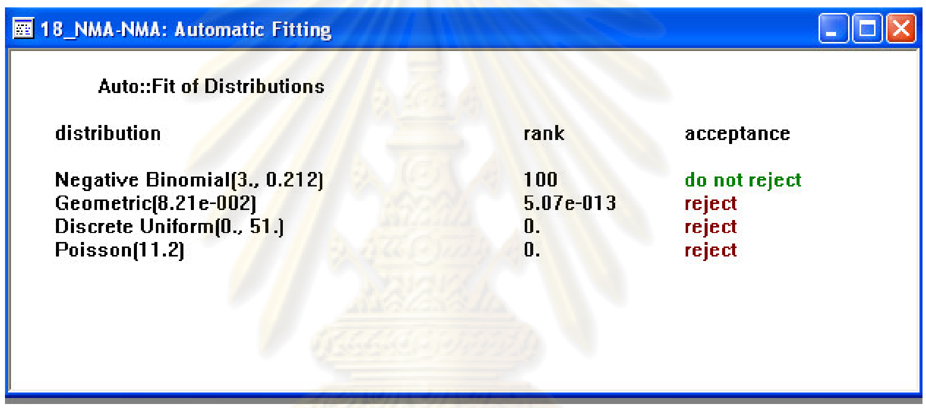



Figure 4.4 Distribution fit report from Stat::Fit function

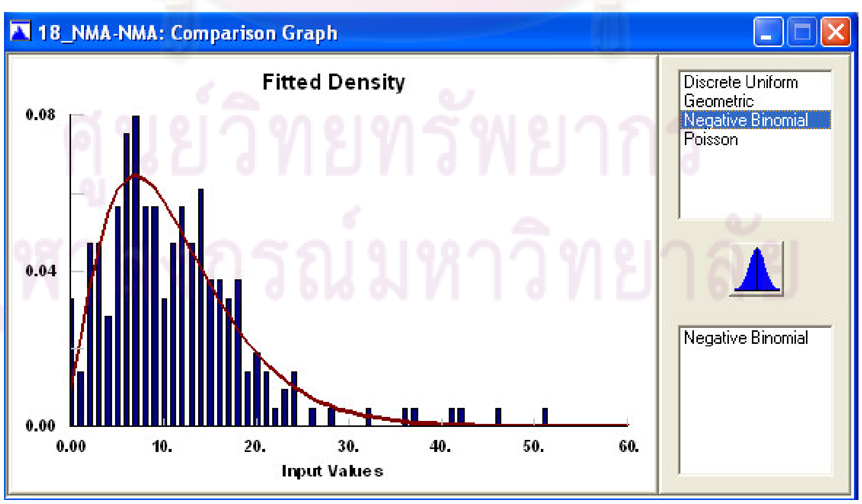



Figure 4.5 Distribution fit curve from Stat::Fit function

| | | |
|---|---|---|
| **Negative Binomial** | | |
| k | = | 3. |
| p | = | 0.211519 |
| Chi Squared | | |
| total classes | | 10 |
| interval type | | equal probable |
| net bins | | 21 |
| chi**2 | | 15.9 |
| degrees of freedom | | 20 |
| alpha | | 5.e-002 |
| chi**2(20,5.e-002) | | 31.4 |
| p-value | | 0.723 |
| result | | DO NOT REJECT |
| Kolmogorov-Smirnov | | |
| data points | | 213 |
| ks stat | | 3.05e-002 |
| alpha | | 5.e-002 |
| ks stat(213,5.e-002) | | 9.22e-002 |
| p-value | | 0.986 |
| result | | DO NOT REJECT |

Figure 4.6 Statistics test report from Stat:: Fit function

After applying Stat::Fit for all demand routes, the demand distribution of each route is illustrated in Table 4.3. The table shows that all historical demand distribution is Negative Binomial distributed. The negative binomial distribution is a discrete probability distribution of the number of successes in a Bernoulli sequence. Suppose there is a sequence of independent Bernoulli trials, each trial having two possible outcomes called "success" and "failure." In each trial the probability of success is *p* and of failure is *(1-p)*. The predefined number r is the total number of success required. The number of trial is X. The probability function of Negative Binomial distribution can be constructed as below:



$$f(x;r,p) = \begin{cases} \binom{x-1}{r-1} p^r (1-p)^{x-r}, & x = r, r+1, \ldots \\ 0, & if\ other \end{cases} \quad (4.1)$$

where the characteristics of this functions are:

$$E(X) = \frac{r}{p}$$

$$Var(x) = \frac{r(1-p)}{p^2}$$

Table 4.3 Demand distribution for existing customers

| No | Route | Origin | Destination | Distance (km) | Distribution | Parameters | | Kolmogorov-Smirnov | E(X) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | K | P | P-Value | |
| 1 | AYA-NMA | Ayudhaya | Korat | 215.38 | Negative Binomial | 1 | 0.212 | 0.05 | 4.7 |
| 2 | AYA-SPK | Ayudhaya | Samutprakan | 101.18 | Negative Binomial | 1 | 0.368 | 0.05 | 2.7 |
| 3 | BKK-BKK | Bkk | Bkk | 20 | Negative Binomial | 1 | 0.789 | 0.998 | 1.3 |
| 4 | BKK-MDH | Bkk | Mukdahan | 634.29 | Negative Binomial | 1 | 0.832 | 0.979 | 1.2 |
| 5 | BKK-NMA | Bkk | Korat | 254.74 | Negative Binomial | 1 | 0.603 | 0.256 | 1.7 |
| 6 | CBI-NMA | Chonburi | Korat | 272.19 | Negative Binomial | 1 | 0.565 | 0.05 | 1.8 |
| 7 | LRI-NMA | Lopburi | Korat | 196.6 | Negative Binomial | 1 | 0.467 | 0.257 | 2.1 |
| 8 | PTE-NMA | Pathumtani | Korat | 226.56 | Negative Binomial | 1 | 0.722 | 0.819 | 1.4 |
| 9 | SKN-NMA | Samutsakorn | Korat | 290.22 | Negative Binomial | 1 | 0.619 | 1 | 1.6 |
| 10 | SPK-NMA | Samutprakarn | Korat | 276.69 | Negative Binomial | 1 | 0.269 | 0.185 | 3.7 |
| 11 | SRI-MDH | Saraburi | Mukdahan | 537.28 | Negative Binomial | 1 | 0.555 | 0.05 | 1.8 |
| 12 | SRI-NMA | Saraburi | Korat | 148.73 | Negative Binomial | 1 | 0.443 | 0.101 | 2.3 |
| 13 | KKN-NMA | Khonkaen | Korat | 188.41 | Negative Binomial | 1 | 0.23 | 0.05 | 4.3 |
| 14 | KPT-NMA | Kumpangpet | Korat | 409.93 | Negative Binomial | 1 | 0.244 | 0.05 | 4.1 |
| 15 | NMA-AYA | Korat | Ayudhaya | 215.38 | Negative Binomial | 1 | 0.221 | 0.05 | 4.5 |
| 16 | NMA-BKK | Korat | Bkk | 254.74 | Negative Binomial | 1 | 0.171 | 0.125 | 5.8 |
| 17 | NMA-CBI | Korat | Chonburi | 272.19 | Negative Binomial | 1 | 0.475 | 0.05 | 2.1 |
| 18 | NMA-NMA | Korat | Korat | 30 | Negative Binomial | 3 | 0.212 | 0.986 | 14.2 |
| 19 | NMA-RBR | Korat | Ratchaburi | 339.28 | Negative Binomial | 1 | 0.742 | 0.302 | 1.3 |
| 20 | NMA-RYG | Korat | Rayong | 330.51 | Negative Binomial | 1 | 0.322 | 0.05 | 3.1 |
| 21 | NMA-SPK | Korat | Samutprakan | 276.69 | Negative Binomial | 1 | 0.175 | 0.05 | 5.7 |
| 22 | SSK-NMA | Srisakate | Korat | 294.5 | Negative Binomial | 1 | 0.444 | 0.05 | 2.3 |

### 4.2.2 New customer demand information

Since this research aims to develop full truckload pricing for new customers, new customer demand information is required. This new customer demand information to be used in this study is assumed as shown in Table 4.4. Five routes of new customer demand are assumed to arrive DC BKK and DC NMA every morning. Moreover, customer demand distribution is determined as Negative Binomial.

Table 4.4 Demand distribution for new customers

| No | DC Start | Origin | Destination | Distance (OD) | Distribution | Parameter | | E(X) |
|---|---|---|---|---|---|---|---|---|
| | | | | | | k | p | |
| 1 | BKK | BKK | NSN | 254.67 | Negative Binomial | 1 | 0.447 | 2.2 |
| 2 | BKK | BKK | UBN | 600.19 | Negative Binomial | 2 | 0.728 | 2.7 |
| 3 | BKK | BKK | UDN | 564.11 | Negative Binomial | 1 | 0.275 | 3.6 |
| 4 | NMA | NMA | CMI | 741.36 | Negative Binomial | 3 | 0.341 | 8.8 |
| 5 | NMA | NMA | SKA | 1210.88 | Negative Binomial | 1 | 0.621 | 1.6 |

## 4.3 Service Time Information

Service time is most significant source of uncertainties in truckload operation, because this will affect the use of available trucks. As truckload movements usually involve intercity long-haul movement, the transit time is relatively constant, but the time associated with waiting at the customers' premises and loading/unloading vehicles may vary greatly among different shipments due to changing customer requirements. Also, amount of equipment and equipment types at customers' factory affect to loading/unloading time. Since customers of MCK do not allow the author collecting service time data for each shipment at their factory, then MCK's transportation manager approximates this service time data of each customer in order to apply in this study.  The uploading and unloading times are assumed uniformly distributed while waiting times for uploading and unloading are exponentially distributed. Service time information for both existing and new customers is described in the next section.

### 4.3.1 Existing customer service times

Existing customer service times at the origin where goods are picked up and at the destination where they are unloaded are described in Table 4.5.

Table 4.5 Existing customer service times (min) information

| No | Origin | Destination | Waiting time to load (Expo) | Loading time (Uniform) | | Waiting time to unload (Expo) | Unloading time (Uniform) | |
|---|---|---|---|---|---|---|---|---|
| 1 | AYA | NMA | 30 | 30 | 50 | 40 | 30 | 50 |
| 2 | AYA | SPK | 30 | 30 | 60 | 40 | 30 | 60 |
| 3 | BKK | BKK | 30 | 30 | 60 | 40 | 30 | 60 |
| 4 | BKK | MDH | 30 | 30 | 60 | 40 | 30 | 60 |
| 5 | BKK | NMA | 30 | 30 | 60 | 40 | 30 | 60 |
| 6 | CBI | NMA | 40 | 30 | 40 | 40 | 30 | 40 |
| 7 | LRI | NMA | 40 | 50 | 80 | 40 | 50 | 80 |
| 8 | PTE | NMA | 30 | 30 | 60 | 40 | 30 | 60 |
| 9 | SKN | NMA | 30 | 50 | 70 | 40 | 50 | 70 |
| 10 | SPK | NMA | 30 | 50 | 70 | 40 | 50 | 70 |
| 11 | SRI | MDH | 40 | 40 | 60 | 40 | 40 | 60 |
| 12 | SRI | NMA | 40 | 50 | 70 | 40 | 50 | 70 |
| 13 | KKN | NMA | 40 | 30 | 80 | 40 | 30 | 80 |
| 14 | KPT | NMA | 40 | 50 | 80 | 40 | 50 | 80 |
| 15 | NMA | AYA | 40 | 20 | 60 | 40 | 20 | 60 |
| 16 | NMA | BKK | 40 | 20 | 60 | 40 | 20 | 60 |
| 17 | NMA | CBI | 40 | 20 | 60 | 40 | 20 | 60 |
| 18 | NMA | NMA | 40 | 20 | 60 | 40 | 20 | 60 |
| 19 | NMA | RBR | 40 | 20 | 60 | 40 | 20 | 60 |
| 20 | NMA | RYG | 40 | 20 | 60 | 40 | 20 | 60 |
| 21 | NMA | SPK | 40 | 20 | 60 | 40 | 20 | 60 |
| 22 | SSK | NMA | 40 | 50 | 70 | 40 | 50 | 70 |

### 4.3.2 New customer service time

New customer service times at the origin where goods are picked up and at the destination where they are unloaded are described in Table 4.6.

Table 4.6 New arrival customer service times (min) information

| No | Origin | Destination | Waiting time to load (Expo) | Loading time (Uniform) | | Waiting time to unload (Expo) | Unloading time (Uniform) | |
|---|---|---|---|---|---|---|---|---|
| 1 | BKK | NSN | 30 | 35 | 70 | 30 | 35 | 70 |
| 2 | BKK | UBN | 30 | 30 | 60 | 30 | 30 | 60 |
| 3 | BKK | UDN | 30 | 40 | 70 | 30 | 40 | 70 |
| 4 | NMA | CMI | 40 | 35 | 60 | 40 | 35 | 60 |
| 5 | NMA | SKA | 40 | 30 | 50 | 40 | 30 | 50 |

## 4.4 Transportation Cost Structure

Costing is an important part of pricing; therefore, to estimate transportation price, cost structure must be clarified. The cost structure of the transportation case in this study can be classified into two groups that are 1) Own cost, and 2) External costs

### 4.4.1 Own cost

Own cost is initiated from own operation cost. In this research, own cost will be separated into two parts:

- **Fixed Costs** are often considered "sunk" costs and are those that do not change as mileage changes. They generally include depreciation on capital investment, interest charges or return on investment, license fees, taxes, and insurance as seen below.

| Details | Fixed Cost | Units |
|---|---|---|
| Purchase Price | 850,000 | Baht |
| Salvage Price | 170,000 | Baht |
| Estimate Useful Life | 8 | years |
| Interest (%) | 5 | % |
| License/tax | 337.5 | Baht/month |
| Insurance | 3574 | Baht/month |
| Depreciation | 10625 | Baht/month |
| Driver Income | 250 | Baht/day |
| Total fixed cost | 735 | Baht/day/truck |

- **Variable Costs** are directly related to mileage. These costs include tires, fuel maintenance, repairs, driving labor, etc. and are shown below.

| Details | Variables Cost | Units |
|---|---|---|
| Driver (baht/day) | 400 | Baht/day |
| Checker (baht/day) | 250 | Baht/day |
| Maintenance | 0.89 | (baht/km) |
| Fuel Consume | 3.56 | (km/lit) |
| Fuel Consume Empty | 3.91 | (km/lit) |
| Fuel Price | 30 | (baht/lit) |

### 4.4.2 External costs

External costs can be divided into two groups that are 1) Outsourcing cost, and 2) Opportunity cost.

- Outsourcing cost

Using the fixed and variable costs per unit above, average cost can be estimated in baht/trip using traditional costing estimation for each route as shown in Table 4.7.

Table 4.7 Average cost in baht/trip for each route

| No | Origin | Destination | Average Cost (baht/trip) |
|---|---|---|---|
| 1 | Ayudhaya | Korat | 4,585 |
| 2 | Ayudhaya | Samutprakan | 2,544 |
| 3 | Bkk | Bkk | 2,165 |
| 4 | Bkk | Mukdahan | 12,810 |
| 5 | Bkk | Korat | 5,289 |
| 6 | Chonburi | Korat | 6,336 |
| 7 | Lopburi | Korat | 4,250 |
| 8 | Pathumtani | Korat | 4,785 |
| 9 | Samutsakorn | Korat | 6,658 |
| 10 | Samutprakarn | Korat | 6,416 |
| 11 | Saraburi | Mukdahan | 11,075 |
| 12 | Saraburi | Korat | 3,394 |
| 13 | Khonkaen | Korat | 4,103 |
| 14 | Kumpangpet | Korat | 8,798 |
| 15 | Korat | Ayudhaya | 4,585 |
| 16 | Korat | Bkk | 5,289 |
| 17 | Korat | Chonburi | 6,336 |
| 18 | Korat | Korat | 2,165 |
| 19 | Korat | Ratchaburi | 7,535 |
| 20 | Korat | Rayong | 7,378 |
| 21 | Korat | Samutprakan | 6,416 |
| 22 | Srisakate | Korat | 6,000 |
| 23 | BKK | Nakornsawan | 5,288 |
| 24 | BKK | Ubonratchathani | 12,200 |
| 25 | BKK | Udonthani | 11,555 |
| 26 | Korat | Chiangmai | 14,724 |
| 27 | Korat | Songkla | 23,854 |

In cases where the carrier has no trucks of its own available, but must instead outsource trucks from sub-contractors to meet customer demand, the cost of outsourcing for each route is as shown in Table 4.8.

Table 4.8 Outsourcing expense for each route

| No | Origin | Destination | Outsource (baht/trip) | Remarks |
|---|---|---|---|---|
| 1 | Ayudhaya | Korat | 5,963 | |
| 2 | Ayudhaya | Samutprakan | 3,615 | |
| 3 | Bkk | Bkk | 3,180 | |
| 4 | Bkk | Mukdahan | 16,111 | |
| 5 | Bkk | Korat | 6,773 | |
| 6 | Chonburi | Korat | 8,666 | |
| 7 | Lopburi | Korat | 5,577 | |
| 8 | Pathumtani | Korat | 6,193 | |
| 9 | Samutsakorn | Korat | 9,037 | |
| 10 | Samutprakarn | Korat | 8,759 | |
| 11 | Saraburi | Mukdahan | 14,117 | |
| 12 | Saraburi | Korat | 4,593 | |
| 13 | Khonkaen | Korat | 5,409 | |
| 14 | Kumpangpet | Korat | 11,498 | |
| 15 | Korat | Ayudhaya | 5,963 | |
| 16 | Korat | Bkk | 6,773 | |
| 17 | Korat | Chonburi | 8,666 | |
| 18 | Korat | Korat | 3,180 | |
| 19 | Korat | Ratchaburi | 10,046 | |
| 20 | Korat | Rayong | 9,865 | |
| 21 | Korat | Samutprakan | 8,759 | |
| 22 | Srisakate | Korat | 7,590 | |
| 23 | BKK | Nakornsawan | 6,771 | New customer |
| 24 | BKK | Ubonratchathani | 15,410 | New customer |
| 25 | BKK | Udonthani | 14,668 | New customer |
| 26 | Korat | Chiangmai | 18,313 | New customer |
| 27 | Korat | Songkla | 29,502 | New customer |

- Opportunity cost

If MCK has no trucks available and waits for a day or two rather than using a sub-contractor, they will lose money, and this loss will be a hidden cost. The hidden cost in this case is called opportunity cost, and it refers to profit lost by failing to satisfy customer demand. This study assumes that the opportunity cost of each route is equal to 15% of its average cost per route per day, or its profit margin per route per day, as illustrated in Table 4.9.

Table 4.9 Opportunity cost for existing and first-time customer routes

| No | Origin | Destination | Opportunity cost (baht/route/day) | Remark |
|---|---|---|---|---|
| 1 | Ayudhaya | Korat | 894 | |
| 2 | Ayudhaya | Samutprakan | 542 | |
| 3 | Bkk | Bkk | 477 | |
| 4 | Bkk | Mukdahan | 2,417 | |
| 5 | Bkk | Korat | 1,016 | |
| 6 | Chonburi | Korat | 1,300 | |
| 7 | Lopburi | Korat | 837 | |
| 8 | Pathumtani | Korat | 929 | |
| 9 | Samutsakorn | Korat | 1,356 | |
| 10 | Samutprakarn | Korat | 1,314 | |
| 11 | Saraburi | Mukdahan | 2,118 | |
| 12 | Saraburi | Korat | 689 | |
| 13 | Khonkaen | Korat | 811 | |
| 14 | Kumpangpet | Korat | 1,725 | |
| 15 | Korat | Ayudhaya | 894 | |
| 16 | Korat | Bkk | 1,016 | |
| 17 | Korat | Chonburi | 1,300 | |
| 18 | Korat | Korat | 477 | |
| 19 | Korat | Ratchaburi | 1,507 | |
| 20 | Korat | Rayong | 1,480 | |
| 21 | Korat | Samutprakan | 1,314 | |
| 22 | Srisakate | Korat | 1,139 | |
| 23 | BKK | Nakornsawan | 1,016 | New customer |
| 24 | BKK | Ubonratchathani | 2,312 | New customer |
| 25 | BKK | Udonthani | 2,200 | New customer |
| 26 | Korat | Chiangmai | 2,747 | New customer |
| 27 | Korat | Songkla | 4,425 | New customer |

**4.5 Summary**

This chapter explains the input data for the simulation and pricing model. This input data include the basic background of the selected transportation carrier, demand information, service information, and cost structure. This information will be input into the developed simulation model. The output of the simulation will be the input data for the pricing model later on. However, before using the simulation with a real system, the simulation must be verified and validated. The verification and validation process will be demonstrated in the next chapter.

# CHAPTER V

# SIMULATION MODEL DEVELOPMENT

This chapter describes the principal elements of the full truckload simulation framework and the full truckload pricing models. It explains the components and assumptions included in each sub-model. The simulation model will be developed in conjunction with the collection of relevant data at the transportation carrier's company. These collected data will be used to refine and increase the complexity of the model to enhance the model's reliability and its coherence with the actual behavior of a full truckload operation. The data summary and data analysis used to develop the model will be described in the next chapter. This chapter will focus on the full truckload simulation model and the full truckload pricing models.

## 5.1 Simulation Model Developing

### 5.1.1 Model Assumptions

By definition, 'simulation is the imitation of the operation of a real-world process or system over time. Simulation involves the generation of an artificial history of the system and the observation of that artificial history to draw inferences concerning the operating characteristics of the real system that is represented' (Banks, 1998). Simulation models can be used to evaluate the efficiency and effectiveness of a supply chain system (Ingalls *et al.*, 2008). It can make the entire supply chain visible, allowing users to test numerous "what-if" scenarios such as outsourcing, consolidating vendors, collaborative planning, or implementing e-business. Another key feature of a simulation which naturally supports supply chain modeling is stochastic inputs into the model where users can easily use random variables.

This study uses a simulation model advantage to imitate full truckload daily operation considering uncertain demand and service times generated by both existing customers and first-time customers. When a new customer contacts a truckload carrier for service, the customer will have a relatively firm idea of the total volume of freight to be served but will not know exactly how the demand will vary from day to day.

Moreover, the times required for a truck to wait at the customer site and to complete loading/unloading may fluctuate daily. The truckload simulation model is developed to capture these uncertainties in demand and service times. With the assumption that the carrier presently provides service to certain prior customers, the simulation model can be used to analyze the impacts of new customers' service requests on the daily operation rendered to both new and existing customers. The simulation outputs show daily operating costs and provide a number of performance measures.

The main assumptions of the full truckload simulation model can be summarized as follows:

1. A single type of truck (semi trailer six-wheeled truck) is used
2. Truck and driver are assigned as the same resource
3. Resources work no more than 8 hours per day
4. Transportation carrier has two distribution centers located at Bangkok and Nakorn Ratchasrima
5. Customer demand is assigned every morning
6. Two factors that cause uncertainty are
   - Daily demand uncertainty
   - Service time uncertainty including waiting time to upload, loading time, waiting time to unload, and unloading time
7. Full truck running speed is 50 km/hr while empty truck running speed is 70 km/hr

### 5.1.2 Simulation Model Framework

This simulation model has been developed with the other researcher who is pursuing a master's degree and working on the research topic "simulation program for full truckload operation" (Thitinun, 2011). That research is considering only current customer full truckload operation. However, this research further develops the simulation to include new (first-time) customers.

In the developed simulation model, the carrier has a prior specified truck fleet and current customers will have priority over new customers. In other words, available trucks will be first assigned to serve existing customers' demand and the remaining trucks in the fleet will then be assigned to serve new customers in everyday operation. If there are not enough trucks, the carrier will have to request additional trucks from sub-contract companies at a relatively high cost.

In serving a shipment the designated truck will process through the following stages: moving to the shipment's origin, waiting for loading, loading, moving to the destination, waiting for unloading, unloading, and moving on to the next assignment (if any). This process is illustrated in Figure 5.1.

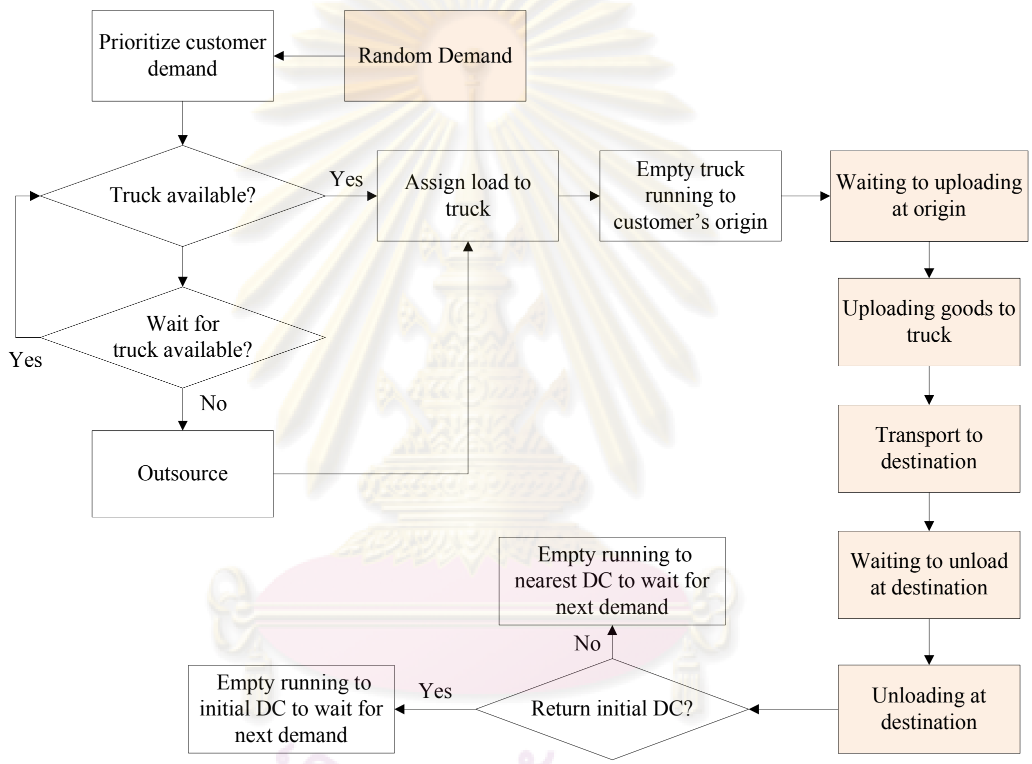



Figure 5.1 Process flow for full truckload simulation

This study uses ExtendSim8, a discrete event simulation modeling package, to develop a full truckload simulation model. It is an integral part of Six Sigma, business reengineering, risk analysis, capacity planning, throughput analysis, and reliability engineering projects. Discrete event models are also useful for examining the effects of variations such as labor shortages, equipment additions, and transmission breakdowns.

ExtendSim8 models are made up of blocks and connections as described below.

- <u>Blocks</u>

  Each block in ExtendSim8 represents a portion of the process or system that is being modeled. Blocks have names, such as Math or Queue, that signify the function they perform. A Queue block, for example, will have the same functional behavior in every model you build. Most blocks are composed of an icon, connectors, and a dialog.

  - Icons – A block's icon is usually a pictorial representation of its function.
  - Connectors – Most blocks in ExtendSim8 have input and output of the block at output connectors.
  - Dialogs – Most blocks have a dialog associated with them. Dialogs are used to enter values and settings before running simulations and to see results as the simulation runs.

- <u>Connections</u>

  Connections are the lines that are used to join blocks together. They represent the flow of information from block to block through the model.

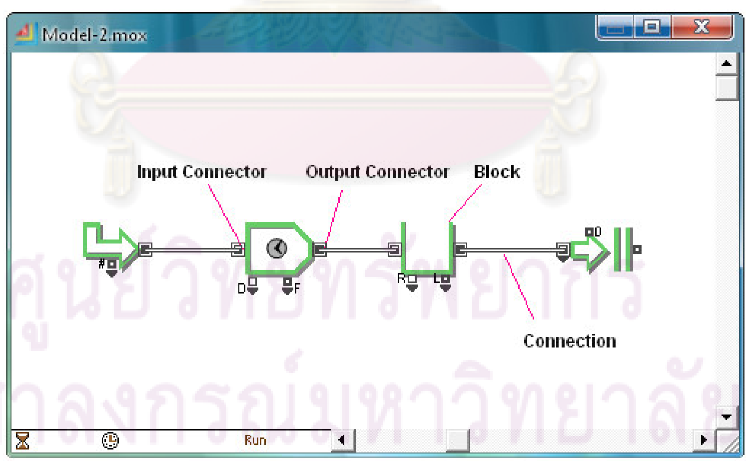



Figure 5.2 Block components of ExtendSim8

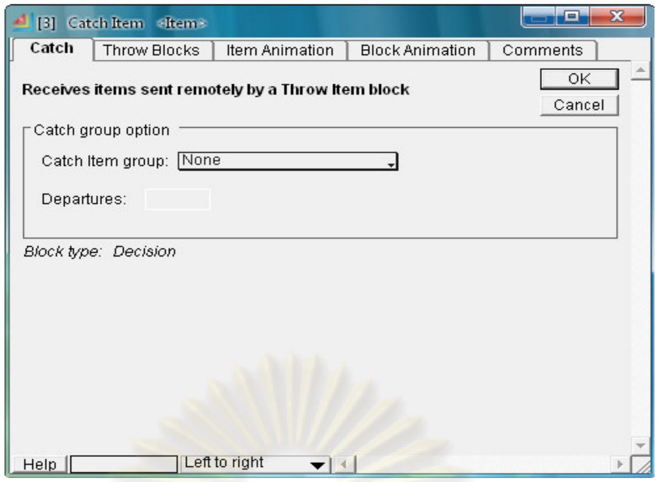



Figure 5.3 Example of ExtendSim8 dialog

The ExtendSim8 simulation program is used to imitate uncertain daily operations in the full truckload carrier company. The simulation framework begins with dispatching trucks process at carrier's distribution center (DC), then driving empty trucks to the customers' factories (places of origin), then picking up goods at these points of origin, then delivering goods to their destinations and moving on to next assignments. In this case, the next assignment can be returning to either the initial DC or the nearest DC for waiting for the next customer demand. To cover all daily operation activities, the simulation framework consists of 6 sub-models:

- Customer demand generation model
- Truck fleet management
- Origin operation model
- Destination operation model
- Vacant truck assignment model
- Truck outsourcing model



Each components of the simulation model are described below.

**A. Customer demand generation model**

This model aims to generate daily customer demand based on historical distribution data for each route. Customer demand arrival time for each route is specified as coming in every day or every 24 hours as illustrated in Figure 5.4. The amount of arrival demand per day for each route is specified in terms of probability distribution as shown in Figure 5.5. In the model, customer demand that initiated from the same origin will be batched together as a single object as illustrated in Figure 5.6.

Then, all customer demand from each origin will be merged and sent to the proper distribution center to wait for the needed truck or trucks to become available. These combined demands will be presented as arrival demand for each distribution center as seen in Figure 5.7. Moreover, the demands of new customers can be added to the simulation in this sub-model as illustrated in Figure 5.8.

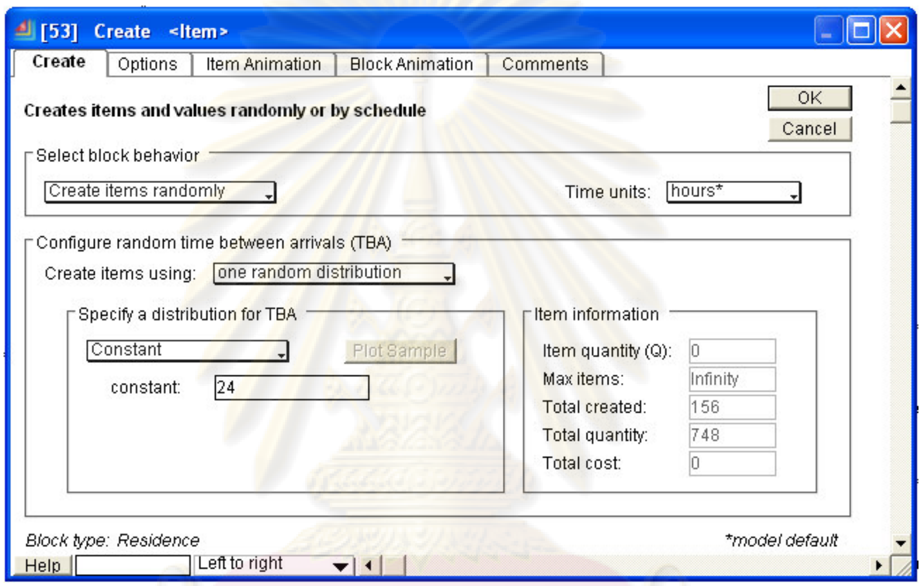



Figure 5.4 Sample block for creating demand arrival time

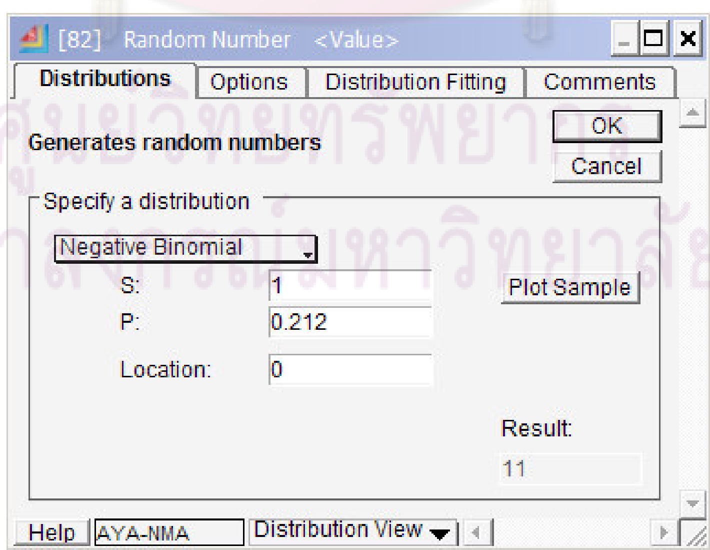



Figure 5.5 Specified random demand distribution at the origin

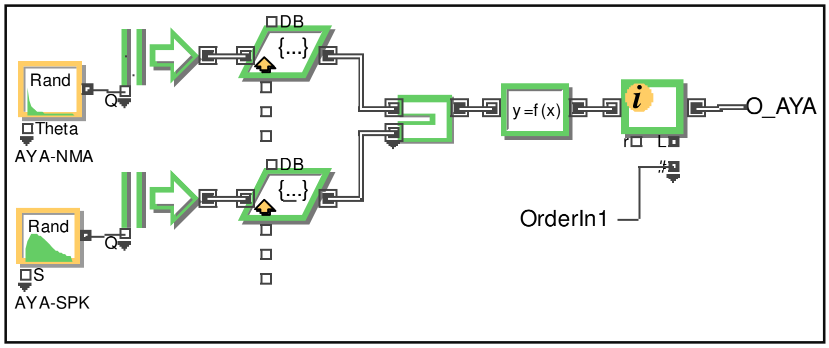



Figure 5.6 Batching customer demand originating from the same origin

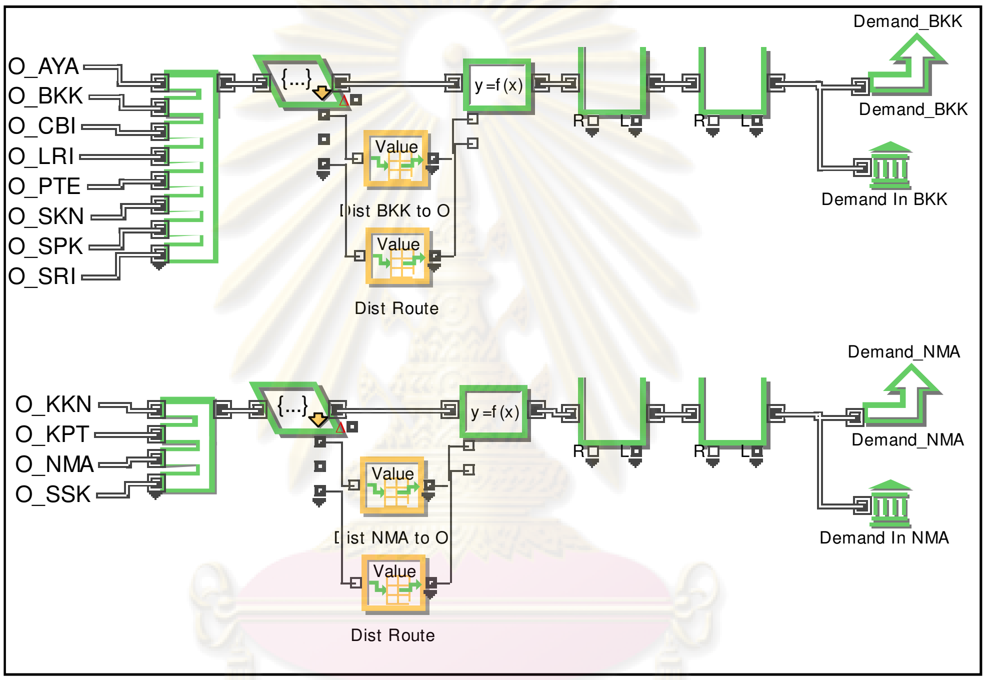



Figure 5.7 Combining customer demand from each origin to the proper distribution center

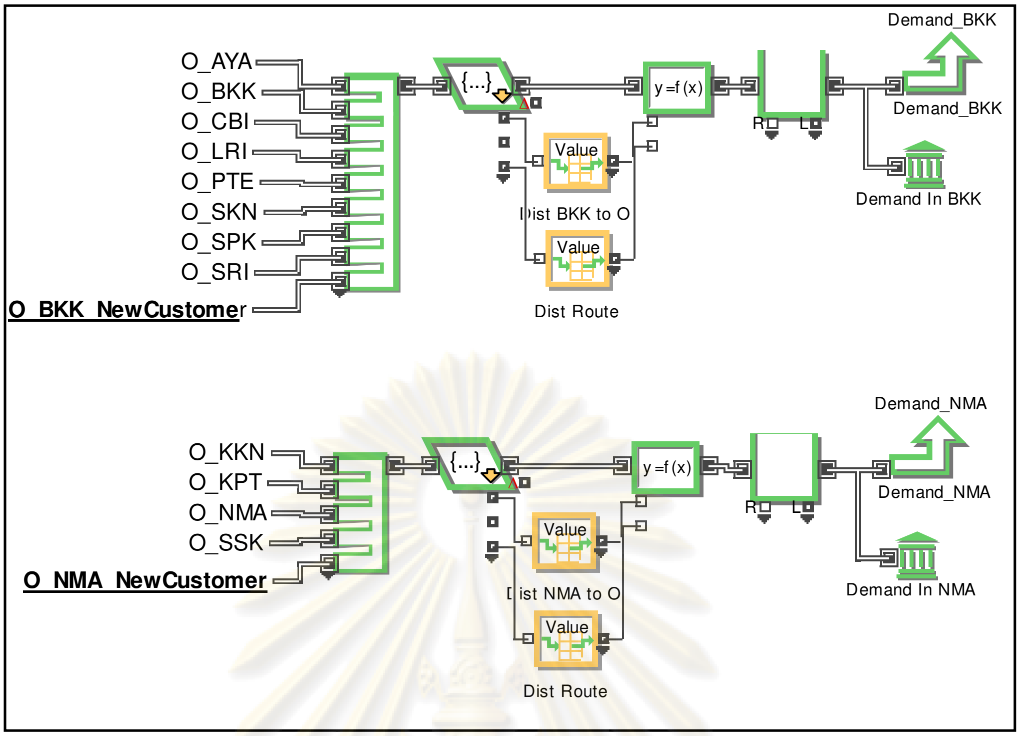



Figure 5.8 Combining new customer demand to the proper distribution center

## B. Truck fleet management model

The truck fleet management components are illustrated in Figure 5.9. Importantly, all trucks begin at the distribution center (DC) before assigned to meet customer demand. The truck fleet management module is developed to mimic truck dispatching process at distribution centers (DC) of the carrier. In this study, the selected carrier has two distribution centers. Each day trucks will be sent from distribution centers to pick up goods at the origin points. The number of trucks assigned to each origin per day will vary based on demand. Dispatching rules assign available trucks to existing customers first and then assign the remainder to serving new customers in everyday operation. If there are not enough trucks available, the carrier will request additional trucks from other sub-contract companies at a relatively high cost as illustrated in the sub-model in Figure 5.10.

In the truck assignment sub-model, trucks are assigned using a First In-First Out (FIFO) procedure. This means that the first trucks to return from deliveries to DC will be the first ones sent out to serve waiting demand. The next trucks to arrive will be sent out to serve leftover loads. After matching the trucks with the demand, batching trucks and requested demand will be sent to Origin in the operation model. Travel distance and time from DC to each origin will be recorded in this simulation sub-model.

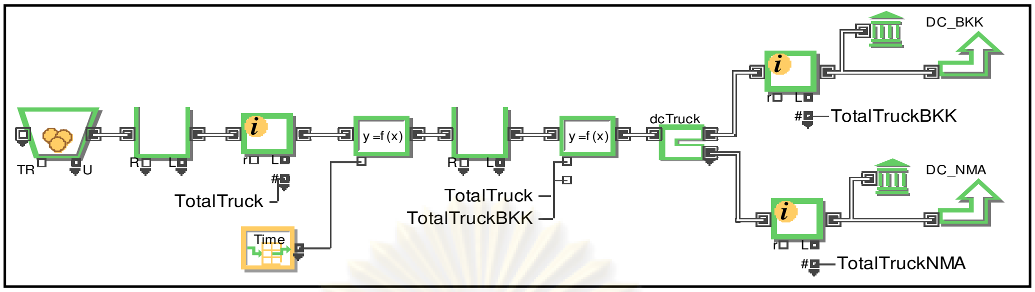



Figure 5.9 Trucks management model

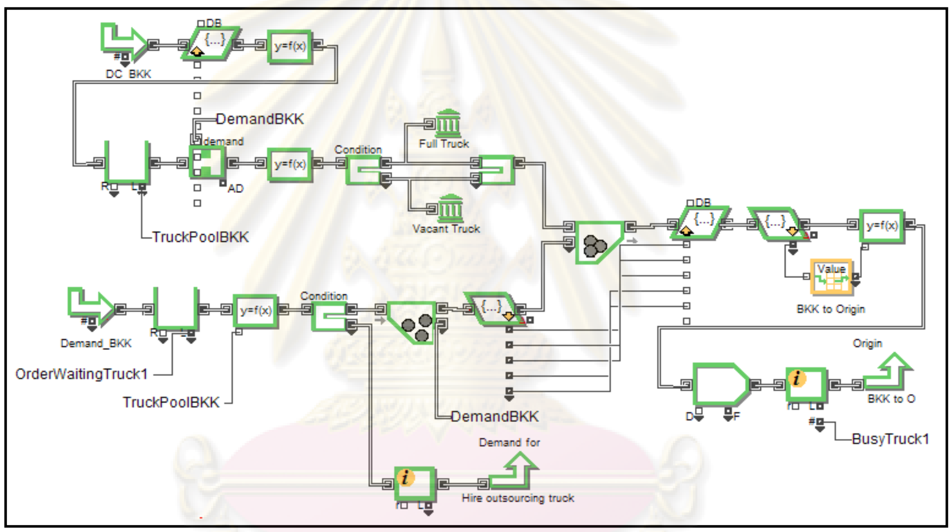



Figure 5.10 Truck dispatching model

In case more than one truck arrives at the same time, the simulation needs truck allocation rules to assign trucks for demand. Truck allocation rules will be studied using these 4 conditions:

- Truck will be allocated to the minimum distance between initial distribution and customer's origin demand firstly
- Truck will be allocated to the maximum distance between initial distribution and customer's origin demand firstly
- Truck will be allocated to the minimum distance between initial distribution and customer's destination demand firstly

- Truck will be allocated to the maximum <u>distance between initial distribution and customer's destination</u> demand firstly

### C. Origin operation model

Activities occurring at the customer's origin include waiting to upload and uploading goods to trucks, as shown in Figure 5.11. Uncertain operating times such as waiting time to upload and uploading time are also acquired from historical data and specified in terms of probability distribution in the model as seen in Figure 5.12. After loading, trucks will travel to their destinations. Travel time from the origin to the specified destination depends on distance and speed. We assume that the average full load running speed of all trucks is 50 km/h. The dialog block to specify this information as shown in Figure 5.13.

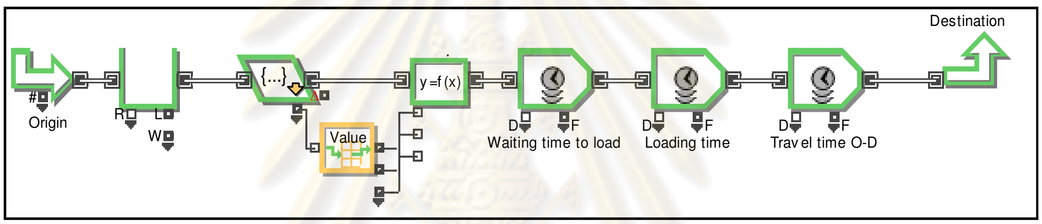



Figure 5.11 Origin operation model

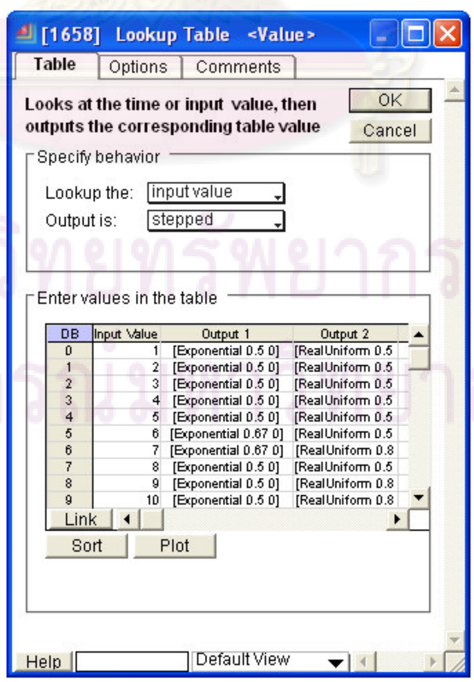



Figure 5.12 Specified service time distributions at the origins

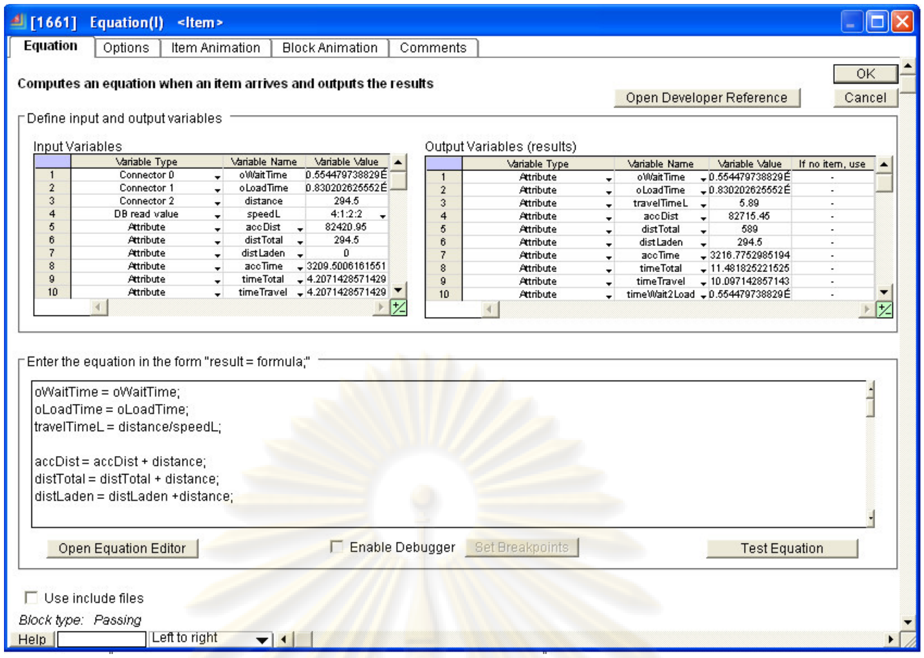



Figure 5.13 Specified travel time equations from origin to destination

## D. Destination operation model

Destination operation model elements are illustrated in Figure 5.14. This module tries to simulate the activities occurring at the destination point. These activities include waiting to unload and unloading goods at the destination. Uncertain service times such as waiting time to upload and uploading time are also acquired from historical data and specified in terms of probability distribution in the model as seen in Figure 5.15. After finishing the unloading process, vacant trucks will be sent to the truck assignment model to wait for the next assignment as described in the next section.



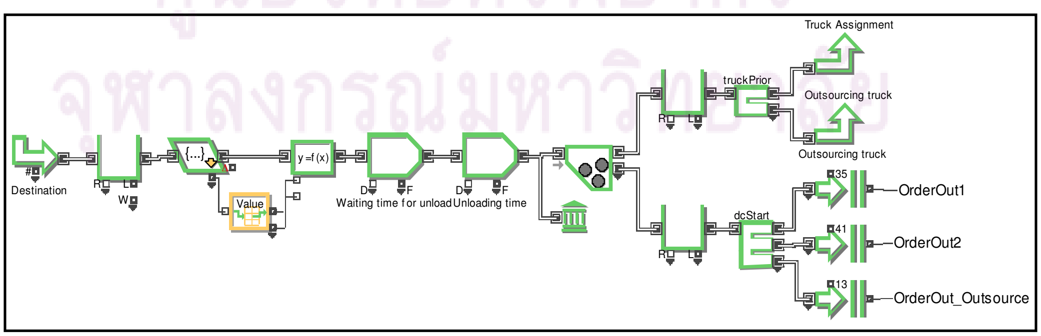



Figure 5.14 Destination Operation Model

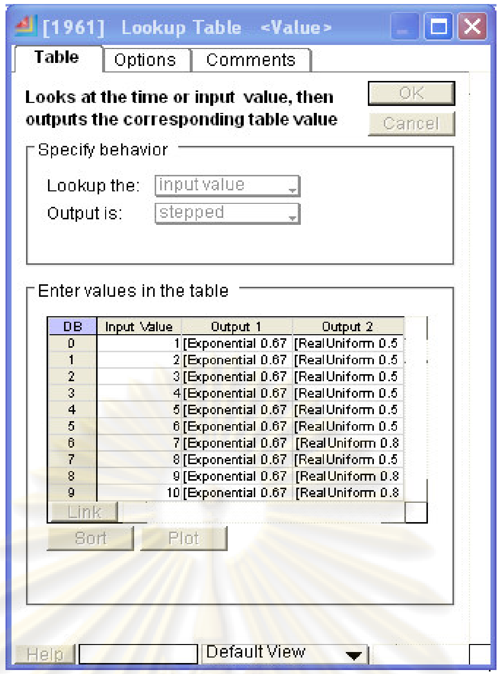



Figure 5.15 Specify service time at the destinations

**E. Vacant truck assignment model**

After unloading at the destination, a truck's status will be set as vacant and it will be available for the next assignment. Hence, the objective of this model is to assign unloaded trucks to the distribution center to wait for the next load. A vacant truck can be assigned using these two scenarios:

- <u>Scenario 1</u>: Truck will be sent to the <u>Initial Distribution Center Assignment</u> (IDC)

  After unloading at the destination, the truck will be assigned to the previous distribution center to wait for the next load as illustrated in Figure 5.16.

- <u>Scenario 2</u>: Truck will be sent to the <u>Nearest Distribution Center Assignment</u> (NDC)

  After unloading at the destination, the truck will be assigned to the nearest distribution center to wait for the next load as illustrated in Figure 5.17.

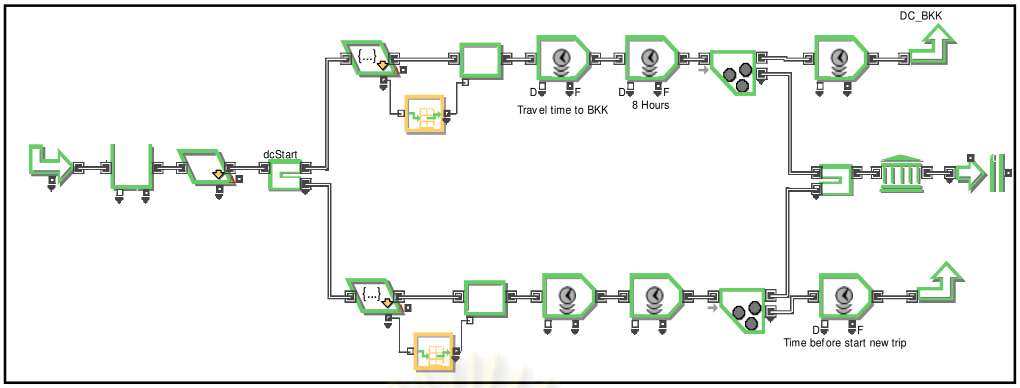



Figure 5.16 Assigned truck will be sent to Initial Distribution Center (IDC)

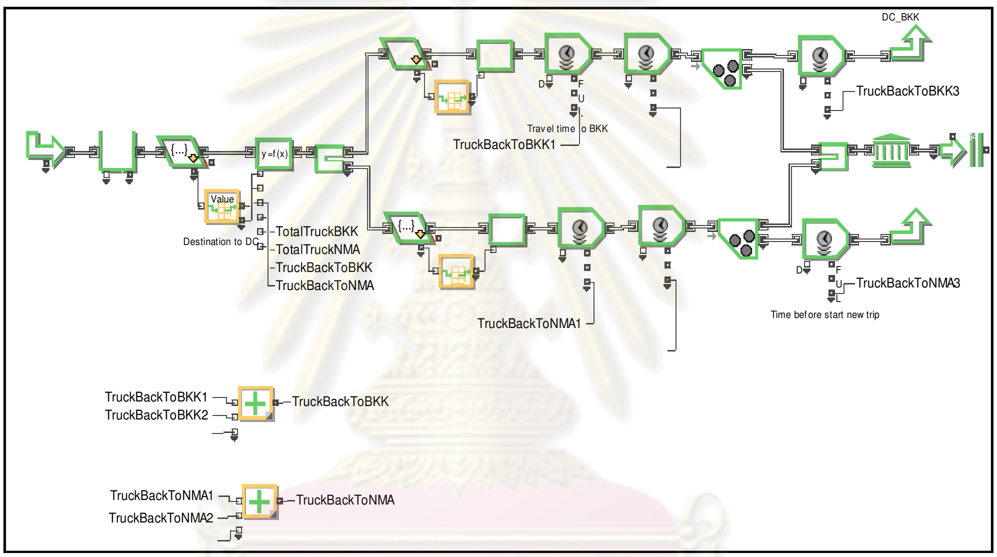



Figure 5.17 Assigned truck will be sent to Initial Distribution Center (NDC)

### F. Outsourcing model

Significantly, if there are not enough trucks, the carrier will have to request additional trucks from other sub-contract companies. Hence, the outsourcing model is developed to investigate whether or not they have the trucks available to meet the demand. If there is no truck available for customer demand, the outsourcing model is prepared to serve the customer's requirements at a relatively high cost. This model is illustrated in Figure 5.18.

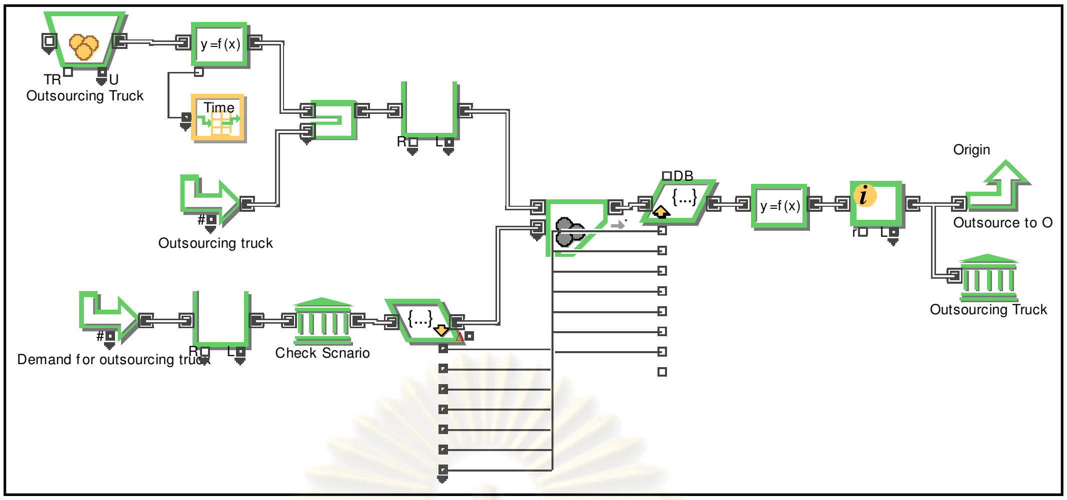



Figure 5.18 Outsourcing model

**5.2 Simulation model verification and validation**

Simulation model verification and validation is an important task that must be done to make sure that the developed model is reliable. Hence, the objectives of this step are described as follow:

- To enhance a simulation model's ability to describe actual full truckload operation behavior
- To enhance the reliability of the full truckload simulation model

Traditionally, checking model reliability consists of two important steps, model verification and validation. This will be discussed in the next section.

**5.2.1 Model Verification**

Model verification aims to check the accuracy of the simulation, whether its conceptual and logical structure matches realistic full truckload operation under specified assumptions.

To verify the simulation model, it can be conducted both during and after finishing the model developing process. For checking during the developing process, we can use the Information block to count all objects that pass through each command as illustrated in Figure 5.19. Also, the History block can show all statistics, such as arrival time of the object and object attributes, as demonstrated in Figure 5.20. Moreover, ExtendSim8 has a (2D) animation command to check how the simulation is working. For checking after finishing the simulation process, ExtendSim8 has a command called Trace to verify the accuracy of the simulation. Model tracing is useful for finding anomalies that occur as the simulation runs. The model tracing commands act like the reporting commands, but the output is much more extensive. A trace text file shows the details of block values at every step or event in the simulation. Tracing is a highly effective method for following a single block or a few blocks to watch for values that do not match expectations, as illustrated in Figure 5.21.

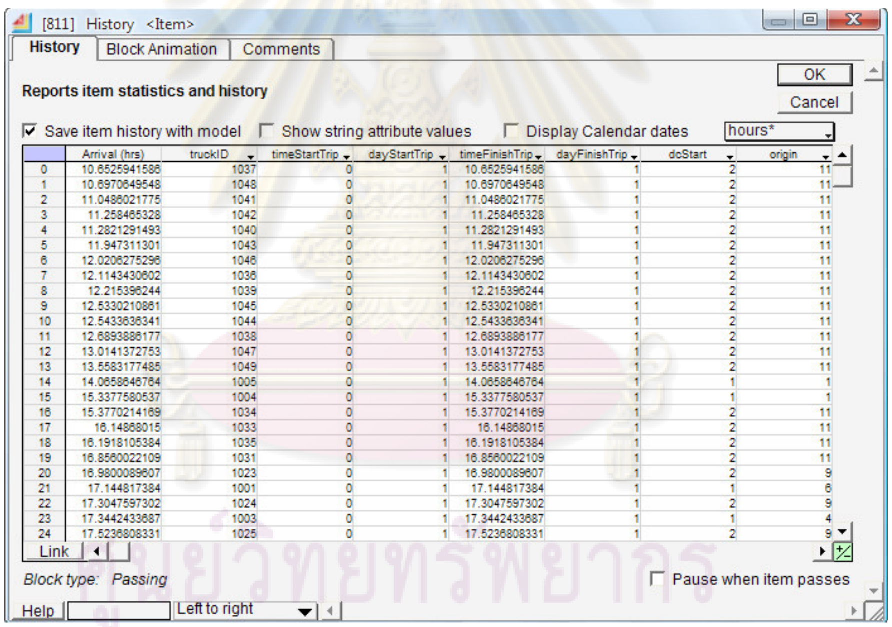





Figure 5.19 Simulation model verifications using History block

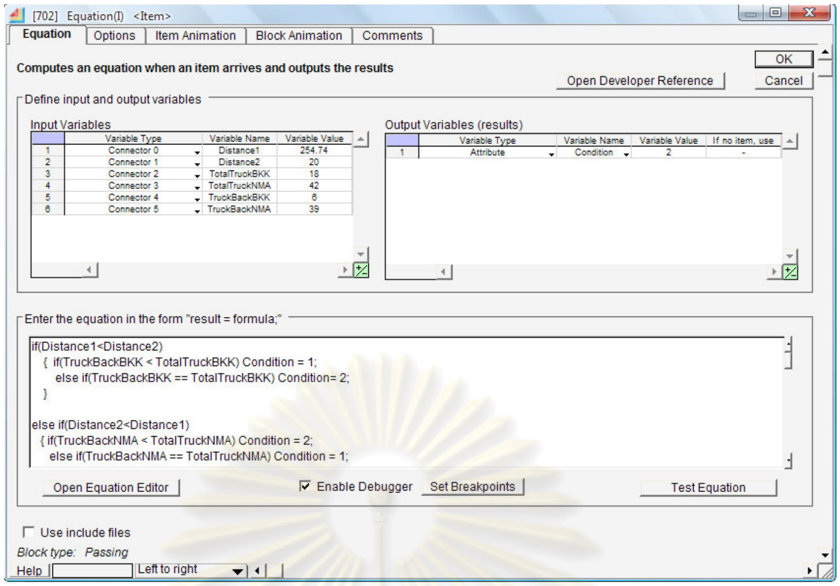



Figure 5.20 Simulation model verifications using Equation Block

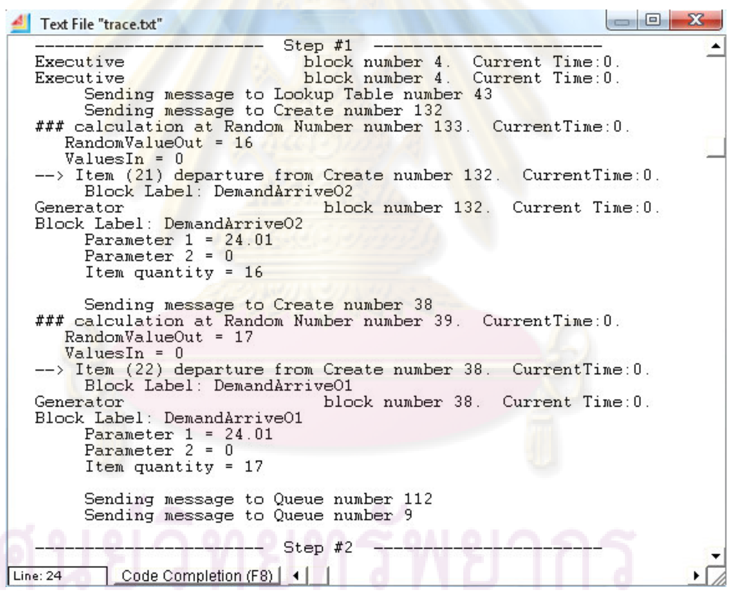





Figure 5.21 Simulation model verifications using Tracing command



Checking the simulation as described above reveals that it accurately reflects the characteristics and behavior of elements within the real system. Therefore, it can model this situation to represent the real system.

### 5.2.2 Model Validation

Model validation aims to compare simulation outputs with real data under the same constraints and conditions. This process enhances user confidence that this model can be a substitute for the real full truckload operation system. The real full truckload data from case study's company that are applied to validate the simulation model are existing customer demand and service time information. The results are described below.

#### 5.2.2.1 Customer Demand

The comparison demand results reveal that the actual demand from the field survey is not significantly different from the demand generated by the simulation model, as illustrated in Table 5.1.

Table 5.1 Comparing actual demand and generated demand from EntendSim8

| No | Route | Average Actual Shipments per day | Average Shipments from simulation per day | Actual Data Shipments (per 7 months) | Shipments for simulation | % Diff |
|---|---|---|---|---|---|---|
| 1 | AYA-NMA | 3.71 | 3.73 | 791 | 794 | **0.35** |
| 2 | AYA-SPK | 1.72 | 1.73 | 366 | 367 | 0.39 |
| 3 | BKK-BKK | 0.27 | 0.27 | 57 | 57 | -0.47 |
| 4 | BKK-MDH | 0.2 | 0.2 | 43 | 43 | 0.2 |
| 5 | BKK-NMA | 1.97 | 1.98 | 420 | 421 | 0.19 |
| 6 | CBI-NMA | 0.77 | 0.77 | 164 | 164 | -0.07 |
| 7 | LRI-NMA | 1.14 | 1.14 | 243 | 244 | 0.3 |
| 8 | PTE-NMA | 0.38 | 0.39 | 82 | 82 | 0.53 |
| 9 | SKN-NMA | 0.62 | 0.62 | 131 | 132 | 0.73 |
| 10 | SPK-NMA | 2.72 | 2.72 | 580 | 579 | -0.19 |
| 11 | SRI-MDH | 0.8 | 0.81 | 171 | 172 | 0.85 |
| 12 | SRI-NMA | 1.26 | 1.25 | 268 | 266 | -0.75 |
| 13 | KKN-NMA | 3.35 | 3.34 | 714 | 712 | -0.25 |
| 14 | KPT-NMA | 3.1 | 3.09 | 660 | 658 | -0.31 |
| 15 | NMA-AYA | 3.52 | 3.52 | 749 | 751 | 0.2 |
| 16 | NMA-BKK | 4.85 | 4.83 | 1,034 | 1,029 | -0.44 |
| 17 | NMA-CBI | 1.1 | 1.1 | 235 | 234 | -0.29 |
| 18 | NMA-NMA | 11.18 | 11.14 | 2,382 | 2,374 | -0.35 |
| 19 | NMA-RBR | 0.35 | 0.35 | 74 | 74 | 0.35 |
| 20 | NMA-RYG | 2.11 | 2.1 | 449 | 446 | -0.62 |
| 21 | NMA-SPK | 4.72 | 4.7 | 1,006 | 1,001 | -0.48 |
| 22 | SSK-NMA | 1.25 | 1.25 | 267 | 265 | -0.64 |
| | Total | 51 | 51 | 10,886 | 10,832 | -0.18 |

To be specific, the demand distribution considering each route also has the same distribution as historical demand data. For instance, demand distribution of Route NMA-NMA is Negative Binomial with parameter k=3 and p=0.210 while k=3 and p=0.212 for historical data as illustrated in Figure 5.22.

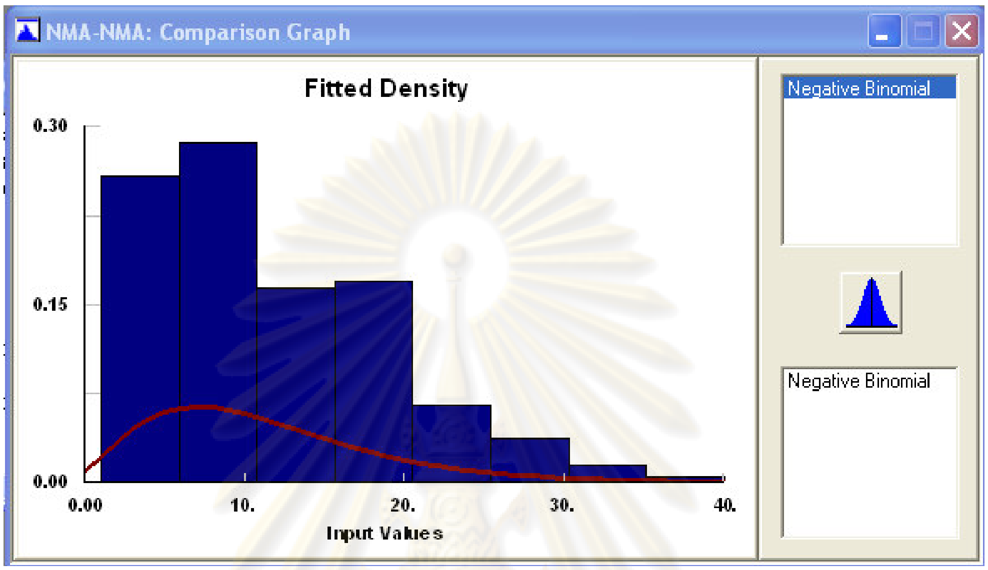



Figure 5.22 Generated demand distribution from ExtenSim8 for Route NMA-NMA

### 5.2.2.2 Service Time

- Waiting time to upload

The waiting time to upload goods on each route also has the same distribution as historical demand data. For instance, the waiting time to upload distribution of Route NMA-NMA is Exponential with parameter beta (mean) = 40.13 min while beta = 40 min for historical data as illustrated in Figure 5.23.

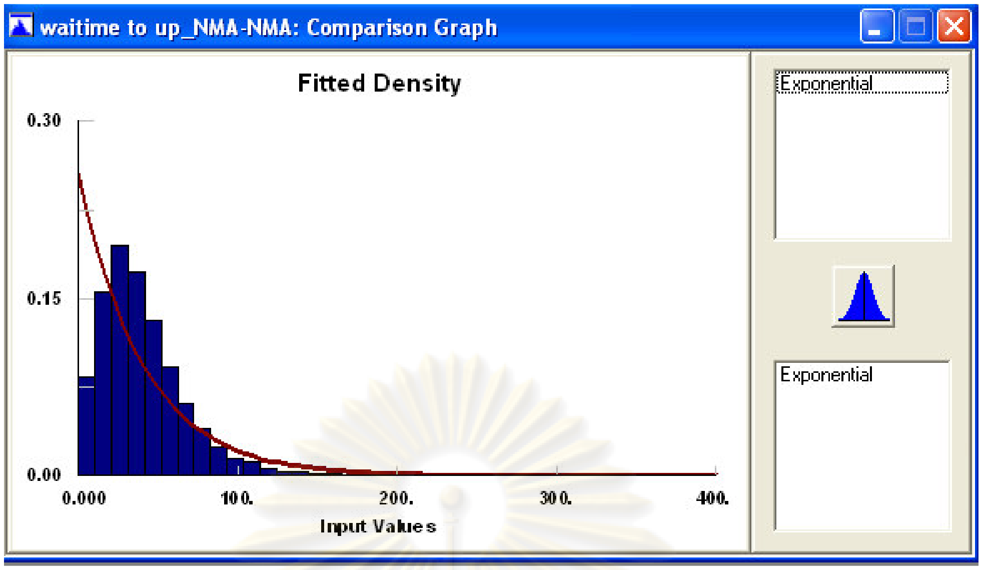



Figure 5.23 Waiting time to upload distribution from ExtenSim8 for Route NMA-NMA

- Uploading time

The uploading time distribution on each route also has the same distribution as historical demand data. For instance, the waiting time to upload distribution of Route NMA-NMA is Uniform with parameter minimum = 19.82 min and maximum = 59.98 min while minimum = 20 min and maximum = 60 for historical data as illustrated in Figure 5.24.

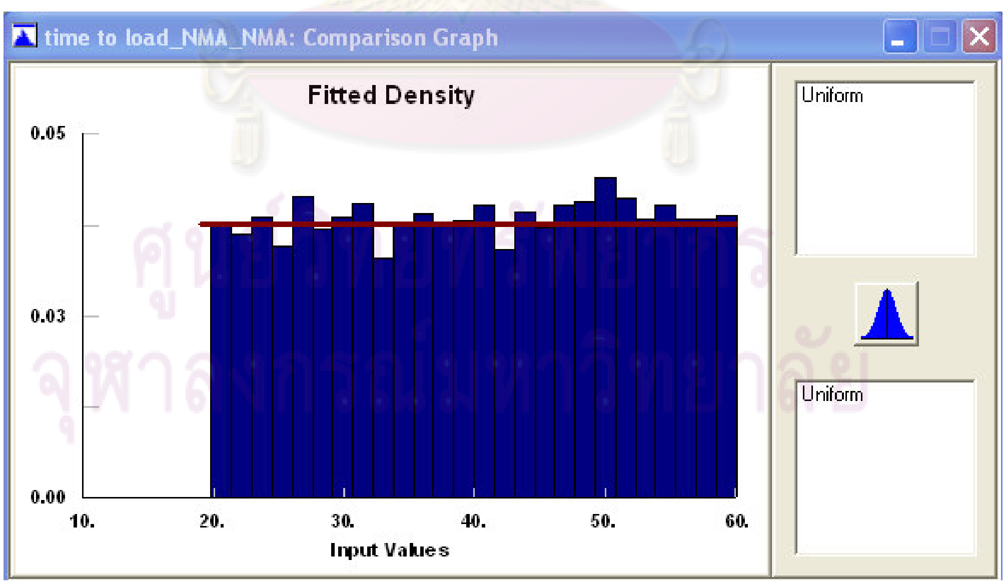



Figure 5.24 Uploading time distribution from ExtenSim8 for Route NMA-NMA

- Waiting time to unload

The waiting time to upload goods to on each route also has the same distribution as historical demand data. For instance, the waiting time to upload distribution of Route NMA-NMA is Exponential with parameter beta (mean) = 39.87 min while beta = 40 min for historical data as illustrated in Figure 5.25.

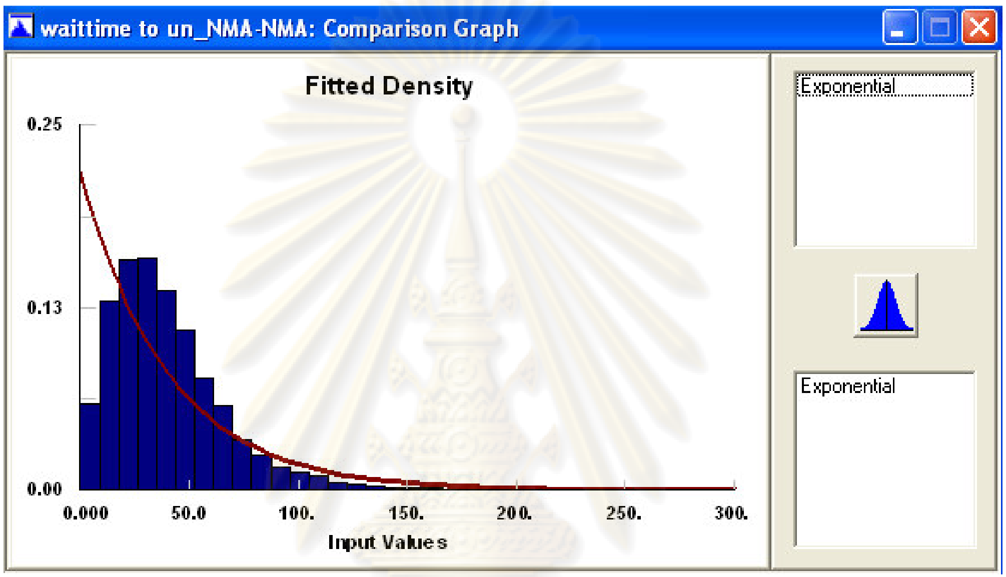



Figure 5.25 Waiting time to unload distribution from ExtenSim8 for Route NMA-NMA

- Unloading time

The uploading time distribution on each route also has the same distribution as historical demand data. For instance, the waiting time to upload distribution of Route NMA-NMA is Uniform with parameter minimum = 19 min and maximum = 60 min while minimum = 20 min and maximum = 60 for historical data as illustrated in Figure 5.26.

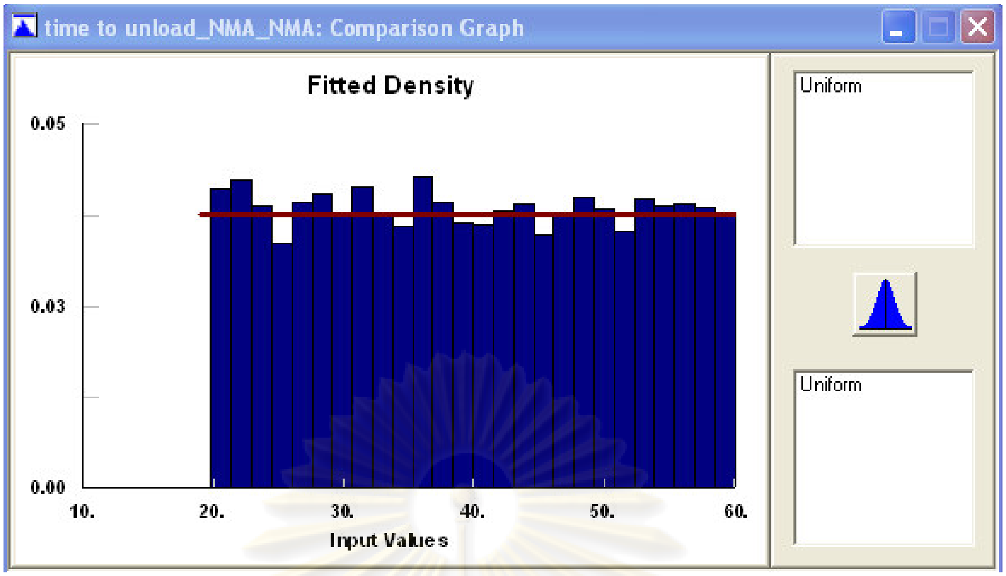



Figure 5.26 Uploading time distribution from ExtenSim8 for Route NMA-NMA

## 5.3 Summary

This chapter describes full truckload simulation model development including simulation model framework and model validation process. To cover all daily operation activities, the simulation framework consists of 6 sub-models. According to simulation model verification and validation as described above, it is obvious the developed simulation model is valid for representing full truckload operation in the real network. The simulation outputs will be used as input data for the full truckload pricing analysis that will be discussed in the next chapter.

# CHAPTER VI

# FULL TRUCKLOAD PRICING MODEL DEVELOPMENT

## 6.1 Model Assumption

This model aims to develop full truckload pricing for new customers. Although pricing is provided only for the new customers, existing customer operations are still incorporated in the process of full truckload pricing model developing. It should be realized that pricing for existing customers cannot be changed when setting a price for a new customer. Hence, the statement problem of this model is how to estimate a price for a new customer by considering existing customer pricing.

## 6.2 Pricing Model Framework

According to the simulation model as discussed in previous chapter, the outputs from the simulation model will be subsequently used as input data in the pricing model. The important outputs from the simulation model are full truckload operation performances, which will be converted to transportation operating cost per day. Demand and service time uncertainty affect full truckload operating cost uncertainty as well. This daily uncertainty can contribute to the probability of loss from either resources underutilization or extra cost from outsourcing. Hence, to estimate transportation pricing, proposed pricing must cope with this uncertainty problem.

To develop a full truckload pricing model, this research uses Value at Risk (VaR) and Conditional Value at Risk (CVaR) risk optimization techniques to determine the minimum service price offering by controlling the risk of earning less than the desired profit or losing more than an acceptable level due to uncertainty factors within a given confidence level $p$ as shown in Figures 6.1 and 6.2.

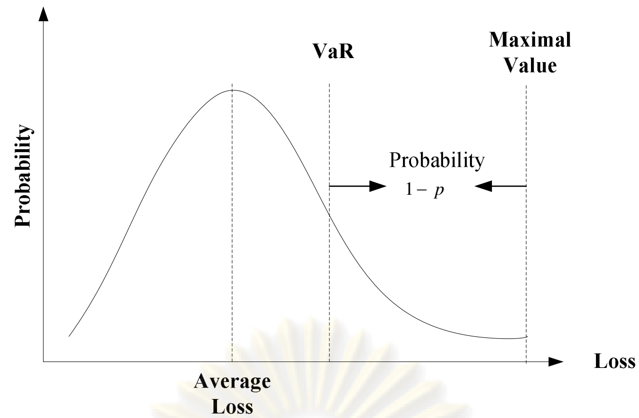



Figure 6.1 VaR of a loss distribution for a given time horizon $t$ and confidence level $p$

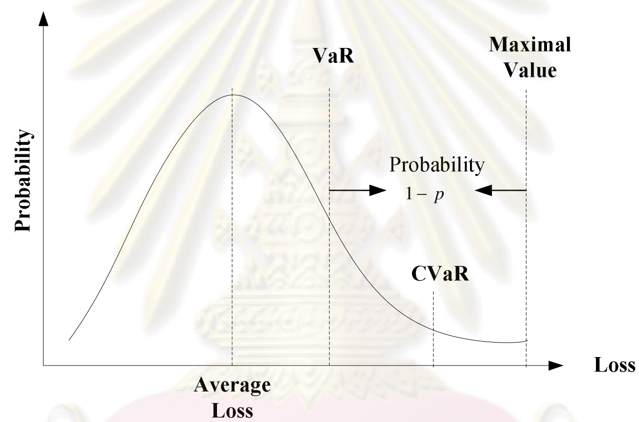



Figure 6.2 CVaR of a loss distribution for a given time horizon $t$ and confidence level $p$

We can create a profit function considering VaR and CVaR, constrained as illustrated below.

- **Value-at-Risk (VaR) application**

Let $\pi(P,Z)$ be the profit associated with the decision variable $P$, which represents full truckload (TL) pricing, and the uncertain variables $Z$. In this case, variable $Z$ includes two factors, demand and operating time uncertainty. Thus for each $P$, the profit $\pi(P,Z)$ is a random variable having a distribution induced by $Z$. Assume the underlying probability density function of uncertain variables is denoted by $\Pr(\pi(P,Z))$. In this case, existing customers and new customers are served based on the same resources such as trucks and drivers. Hence, the total operating cost of daily operation will be allocated to both existing and new customers. Moreover, total profit also originates from both types of customer. Consequently, the total profit function can be demonstrated as

$$\pi(P,Z) = \sum_{i=1}^{m} RE_i + \sum_{j=1}^{n} RN_j - (\sum_{i=1}^{m} VC_i + \sum_{j=1}^{n} VC_j + \sum_{k=1}^{q} DP_k + \sum_{l=1}^{r} DIC_l) \tag{6.1}$$

where

| | | |
|---|---|---|
| $\pi(P,Z)$ | = | Profit function |
| Z | = | Random variables including two factors, demand and operating time uncertainty |
| P | = | Full truckload pricing in terms of baht/km |
| $RE_i$ | = | Existing customer revenue for route i = 1 to m |
| $RN_j$ | = | New customer revenue for route j = 1 to n |
| $VC_i$ | = | Variable cost for route i = 1 to m |
| $VC_j$ | = | Variable cost for route j = 1 to n |
| $DP_k$ | = | Depreciation cost for truck k = 1 to q |
| $DIC_l$ | = | Fixed income for driver l = 1 to r |

For each p, the profit $\pi(P,Z)$ is a random variable having a distribution induced by Z. Assume the underlying probability density function of the random variable is denoted by Pr $(\pi(P,Z))$. For VaR, profit is the value of the $(1-p)$-percentile of the total profit, e.g., at 95% confidence level $(p)$ or a 5% chance (1-$p$) that earning will yield less than VaR as illustrated in Figure 6.3.

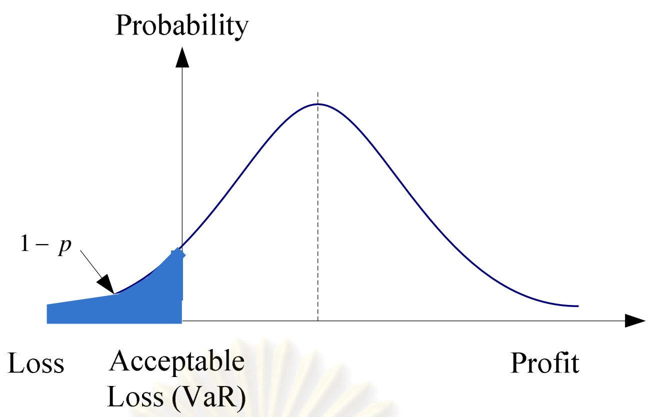



Figure 6.3 Probability of loss area with VaR constrained

Then, the VaR-constrained optimization problem is defined as the minimization of full truckload pricing per full running distance with a downside risk constraint that can be described as follows:

Objective Min $P$

Subject to

$$\Pr(\pi(P,Z) \leq \pi_0) \leq (1-p)$$
$$p \geq 0$$

**List of notations**

$\Pr(\pi(P,Z))$ Probability of profit function with demand and operating time uncertainty

$\Pr\left(\sum_{i=1}^{m} RE_i + \sum_{j=1}^{n} RN_j - \left(\sum_{i=1}^{m} VC_i + \sum_{j=1}^{n} VC_j + \sum_{k=1}^{q} DP_k + \sum_{l=1}^{r} DIC_l\right)\right)$

$\pi_0$ Acceptable loss ($\pi_0$=0)

$p$ Threshold probability value of the downside risk constraint

$P$ Full truckload pricing per revenue distance

- **Conditional Value-at-Risk (CVaR) application**

The CVaR is the conditional expectation of losses above VaR value. CVaR measures the conditional expected loss exceeding VaR and accounts for the risks beyond the VaR value. To avoid the undesirable characteristics of VaR, CVaR will be applied as an alternative measure of risk, with more attractive properties. Then the formulation of the profit function problem for the Conditional Value-at-Risk (CVaR) function can be written as a deterministic equivalent.

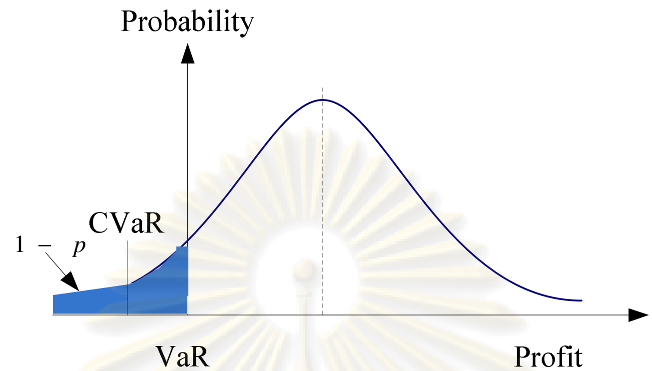



Figure 6.4 Probability of loss area with CVaR constrained

Objective Min $P$

Subject to

$$\mathrm{CVaR}_{\alpha}[\Pr\,(\pi(P,Z)] \geq CVaR_0$$

$$p \geq 0$$

**List of notations:**

$\Pr\,(\pi(P,Z))$ Probability of profit function with demand and operating time uncertainty

$\Pr\,(\sum_{i=1}^{m} RE_i + \sum_{j=1}^{n} RN_j - (\sum_{i=1}^{m} VC_i + \sum_{j=1}^{n} VC_j + \sum_{k=1}^{q} DP_k + \sum_{l=1}^{r} DIC_l))$

$CVaR_0$ Minimum acceptable profit ($CVaR_0$=0)

$p$ Threshold probability value of the downside risk constraint

$P$ Full truckload pricing per full running distance

$CVaR_p$ Conditional Value-at-Risk given $p$ confidence level

### 6.3 Pricing model analysis tool

This study develops a price determination visualization tool for transportation carriers in order to ease to apply. Price determination tool called TPM is developed in a spreadsheet program using Visual basic application on Microsoft Excel. It composes of two parts that simulation model outputs and pricing model analysis. The outputs for each run from simulation model will be converted into Microsoft excel form. Then, these outputs will be imported to TPM through user interface as demonstrated in Figure 6.5 and Figure 6.6. After finishing import data, preparation data for pricing with VaR and CVaR analysis for each simulation run outputs will be further process. Preparation data for pricing with VaR and CVaR will be collected until completely 50 simulation runs. Then pricing with VaR and CVaR at different confidence levels will be analyzed. Pricing summary report is used for full truckload pricing conclusion.


Figure 6.5 Price determination model user interface

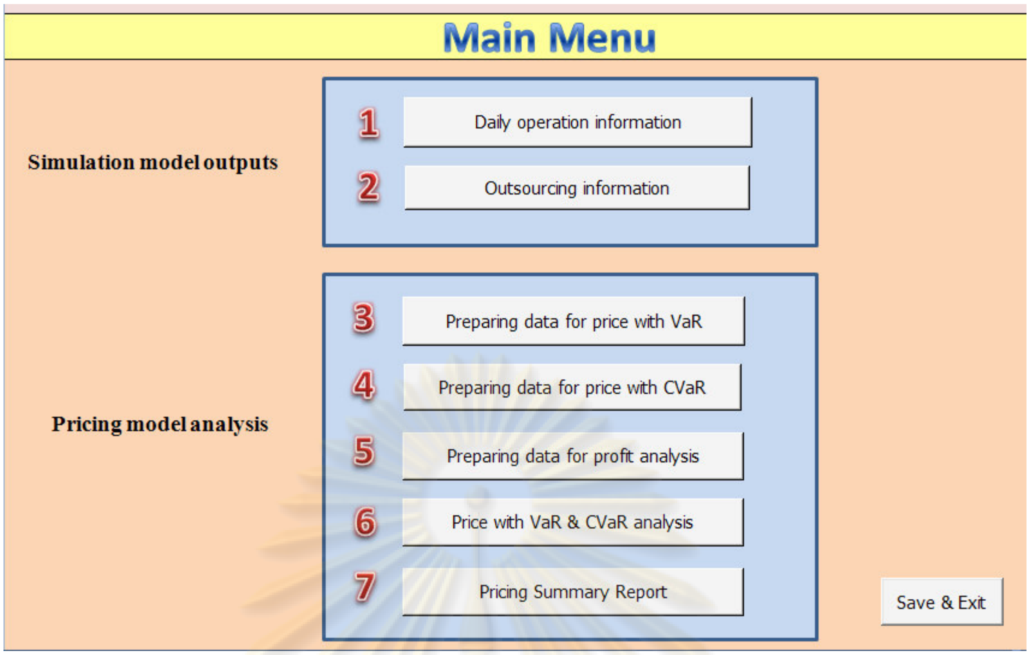



Figure 6.6 Price determination model main menu

## 6.4 Summary

This chapter describes the pricing model framework. Two risk measurement techniques, Value at Risk (VaR) and Conditional Value at Risk (CVaR), are also described in the section on full truckload pricing model developing. According to the equations, it can be ensured that the $p$-VaR is never more than the $p$-CVaR. That means pricing with CVaR constrained will naturally give a higher price than pricing with VaR constrained.

# CHAPTER VII

# FULL TRUCKLOAD PRICING ANALYSIS

This chapter applies the full truckload simulation and pricing model described in the previous chapters to quantify full truckload pricing under demand and service time uncertainty. It starts with simulation model output analysis. Then, it applies pricing with VaR and CVaR constrained to quantify pricing considering truck assignment policies. The last section is the summary.

## 7.1 Simulation Model Outputs

Generally, transportation carriers assign trucks for customer demand depending on transportation manager experiences. Different decision-making policies lead to different outputs in terms of costs and performance, and eventually pricing. To take advantage of the simulation model, this research uses it to mimic full truckload operation under different specified policies based on historical data. The vital policies considered in this study can be illustrated by the different scenarios described below.

1. Outsourcing policy
   This policy features two alternatives:
   - No-outsource
   - With-outsource
2. Assign trucks to serve customer demand policy
   To arrange trucks for customer demand, trucks will be reserved to serve each route by considering the travel distance of each route from the initial distribution center to either origin or destination. This policy consists of two sub-policies:
   - Distance from <u>distribution center to the origin</u> of the customer
     - Short-distance deliveries are given first priority
     - Long-distance deliveries are given first priority
   - Distance from <u>distribution center to the destination</u> of the customer
     - Short-distance deliveries are given first priority

- Long-distance deliveries are given first priority

3. Next truck assignment after unloading goods policy

   After unloading goods at their destinations, vacant trucks will be assigned to the distribution center to wait for the next demand on the next day under one of these two conditions:

   - Trucks return to the initial distribution center
   - Trucks move forward to the nearest distribution center

According to description above, full truckload assignment policy can be summarized as demonstrated in Figure 7.1.

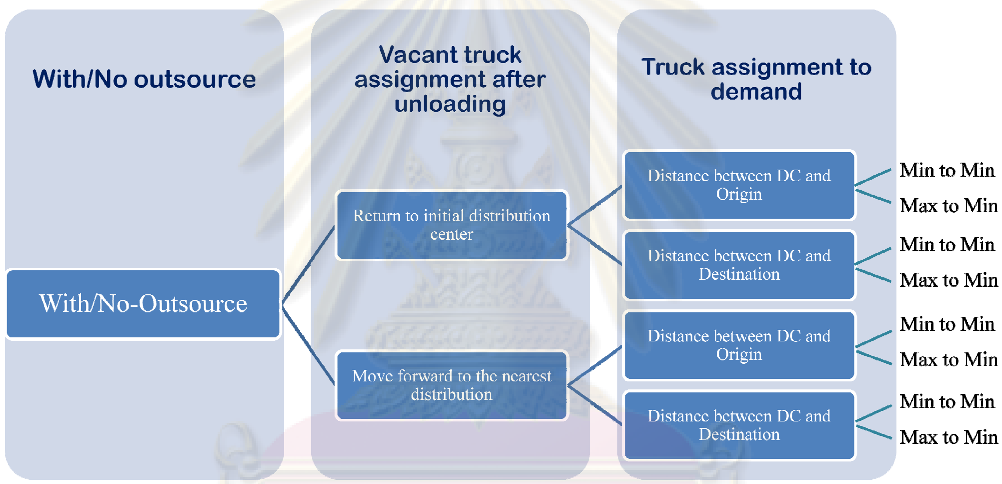



Figure 7.1 Full truckload assignment policies

According to the decision policies above, truck assignment policies can be divided into 16 scenarios as shown in Table 7.1. From this table, it is obvious that the current full truckload operation of MCK, which is our case study, is closely aligned with scenario 13.

Table 7.1 Truck assignment scenarios

| Scenario | Details | | | |
|---|---|---|---|---|
| | With/No outsource | Vacant truck assignment after unloading | Truck assignment to demand | |
| 1 | No-outsource | Return to initial distribution center | Distance between DC and Origin | Min-Max |
| 2 | | | | Max-Min |
| 3 | | | Distance between DC and Destination | Min-Max |
| 4 | | | | Max-Min |
| 5 | | Move forward to the nearest distribution | Distance between DC and Origin | Min-Max |
| 6 | | | | Max-Min |
| 7 | | | Distance between DC and Destination | Min-Max |
| 8 | | | | Max-Min |
| 9 | With-outsource | Return to initial distribution center | Distance between DC and Origin | Min-Max |
| 10 | | | | Max-Min |
| 11 | | | Distance between DC and Destination | Min-Max |
| 12 | | | | Max-Min |
| 13 | | Move forward to the nearest distribution | Distance between DC and Origin | Min-Max |
| 14 | | | | Max-Min |
| 15 | | | Distance between DC and Destination | Min-Max |
| 16 | | | | Max-Min |

With all necessary scenarios in Table 7.1 and relevant parameters as discussed in Chapter 4, this research uses a simulation model to imitate all truck assignment scenarios to investigate the resulting costs and performance. This research runs 50 simulations using the ExtendSim8 simulation program to imitate the real-life full truckload operation of 213 working days, using the existing number of trucks (semi trailer six-wheeled trucks). The simulation results in terms of costs and performances will be discussed in the next section.

### 7.1.1 Transportation Operating Cost

According to the truck assignment scenarios, it is appropriate to analyze transport operating cost by considering the different outputs from these different scenarios. The results are described below.

1) **Outsourcing policy**

With 50 simulation runs, the comparison of transportation total cost and cost per revenue distance (laden distance) between No-outsource and With-outsource for existing customers is shown in Table 7.2.

Table 7.2 Comparing transportation cost between no-outsource and with-outsource of existing customers

| **No-outsource** | | | **With-outsource** | | |
|---|---|---|---|---|---|
| Scenario | Total cost (baht/7 months) | Cost per revenue dist. (baht/km) | Scenario | Total cost (baht/7 months) | Cost per revenue dist. (baht/km) |
| 1 | 67,401,131 | 29.63 | 9 | 62,828,743 | 27.60 |
| 2 | 66,477,403 | 29.28 | 10 | 63,302,495 | 27.87 |
| 3 | 66,885,359 | 29.66 | 11 | 63,325,402 | 27.86 |
| 4 | 65,926,021 | 29.16 | 12 | 63,007,938 | 27.63 |
| 5 | 64,777,108 | 28.63 | **13** | **54,291,623** | **23.96** |
| 6 | 63,286,622 | 28.00 | 14 | 55,050,844 | 24.12 |
| 7 | 64,381,818 | 28.64 | 15 | 54,994,546 | 24.20 |
| 8 | 62,753,612 | 27.99 | **16** | **54,155,371** | **23.84** |

Table 7.2 reveals that both the total cost (baht/month) and the average cost per revenue distance of No-outsource scenarios are higher than With-outsource scenarios. Even when transportation carriers let their customers wait for delivery to avoid outsourcing cost, they still have extra cost or hidden cost from the lost opportunity to gain a profit which is approximately 15% of operating cost per route per day.

Moreover, scenario 16 has the lowest total cost and cost per revenue distance compared to other scenarios, including scenario 13 (MCK's full truckload operation's policy). The truck assignment policy of scenario 16 is that the carrier's own trucks are given first priority for long-distance deliveries while outsourced trucks are reserved for short distances. The percentage of outsourcing distance per total revenue distance of scenario 13 is about 19.90%, while it is 9.53% for scenario 16. Hence, scenario 13 consumes more highly expensive outsourcing trucks than scenario 16.

Table 7.3 also explores that same conclusion, that the outsourcing cost of scenario 13 is greater than that of scenario 16. Comparing the opportunity cost and the outsourcing cost, it shows that the opportunity cost from the No-outsource policy is not too different from the With-outsourcing policy. For example, scenario 4 of the No-outsource policy has a percentage of opportunity per total cost (8.08%) close to that of scenario 12 (8.99%) of the With-outsource policy. Scenarios 6 and 8 of the No-outsource policy have higher operating costs than scenarios 14 and 16 of the With-outsource policy respectively. It can be inferred that even when transportation carriers try to lower their cost by avoiding outsourcing, they still have losses in terms of opportunity cost. Moreover, they will turn potential customers away eventually.

Table 7.3 Comparing opportunity cost and outsourcing cost of existing customers

| **No-outsource** | | | **With-outsource** | | |
|---|---|---|---|---|---|
| Scenario | Opportunity Cost | % of Total Cost | Scenario | Outsourcing Cost | % of Total Cost |
| 1 | 6,526,882 | 9.68 | 9 | 9,400,875 | 14.96 |
| 2 | 5,652,564 | 8.50 | 10 | 6,473,441 | 10.23 |
| 3 | 6,130,749 | 9.17 | 11 | 10,102,151 | 15.95 |
| **4** | 5,326,548 | **8.08** | **12** | 5,664,652 | **8.99** |
| 5 | 14,137,890 | 21.83 | 13 | 12,991,666 | 23.93 |
| **6** | 12,666,983 | 20.02 | **14** | 9,605,573 | 17.45 |
| 7 | 14,004,247 | 21.75 | 15 | 13,842,360 | 25.17 |
| 8 | 12,526,167 | 19.96 | 16 | 8,678,998 | 16.03 |

Comparing opportunity cost and outsourcing cost results as described previously, the opportunity cost or the lost opportunity to gain profit is assumed to be approximately 15% of operating cost per route per day. In real life full truckload operation, however, carriers' profit might be less than 15% of operating cost. Hence, this study also investigates the case that opportunity cost is approximately 5% of operating cost per route per day. The comparison of cost per revenue distance (laden distance) between No-outsource and With-outsource for existing customers with opportunity costs of approximately 5% and 15% of operating cost per route per day are demonstrated in Table 7.4.

Table 7.4 Comparing cost per revenue distance (laden distance) between No-outsource and With-outsource for existing customers different opportunity cost

| No-outsource | | | With-outsource | |
|---|---|---|---|---|
| Scenario | Cost per revenue dist.* (baht/km) | Cost per revenue dist.** (baht/km) | Scenario | Cost per revenue dist. (baht/km) |
| 1 | 29.63 | 27.73 | 9 | 27.60 |
| 2 | 29.28 | 27.63 | 10 | 27.87 |
| 3 | 29.66 | 27.86 | 11 | 27.86 |
| 4 | 29.16 | 27.59 | 12 | 27.63 |
| 5 | 28.63 | 24.47 | 13 | 23.96 |
| 6 | 28.00 | 24.26 | 14 | 24.12 |
| 7 | 28.64 | 24.49 | 15 | 24.20 |
| 8 | 27.99 | 24.27 | 16 | 23.84 |

Remarks * with the opportunity to gain a profit of approximately 15% of operating cost per route per day

** with the opportunity to gain a profit of approximately 5% of operating cost per route per day

Table 7.4 obviously illustrates that applying lower opportunity cost for No-outsource scenario leads to lower cost per revenue distance. It also reveals that the cost per revenue distance for return to initial distribution center policy of vacant trucks between No-outsource and With-outsource is not very different. However, cost per revenue distance for moving forward to the nearest distribution center policy of vacant truck with No-outsource is still higher than With-outsource policy.

**2. Vacant truck assignment after unloading goods policy**

The simulation model reveals that moving vacant trucks forward to the nearest distribution center to wait for the next assignment leads to a lower transportation cost than returning to the initial distribution center, as demonstrated in Table 7.5. This policy generates lower cost because it enhances trucks use by reducing empty running distances.

Table 7.5 Comparing transportation cost for next assignment truck after unloading goods policy of existing customers

| Vacant trucks return to the initial distribution center | | | Vacant trucks move forward to the nearest distribution center | | |
|---|---|---|---|---|---|
| Scenario | Total cost (baht/7 months) | Cost per revenue dist. (baht/km) | Scenario | Total cost (baht/7 months) | Cost per revenue dist. (baht/km) |
| 1 | 67,401,131 | 29.63 | 5 | 64,777,108 | 28.63 |
| 2 | 66,477,403 | 29.28 | 6 | 63,286,622 | 28.00 |
| 3 | 66,885,359 | 29.66 | 7 | 64,381,818 | 28.64 |
| 4 | 65,926,021 | 29.16 | 8 | 62,753,612 | 27.99 |
| 9 | 62,828,743 | 27.60 | 13 | 54,291,623 | 23.96 |
| 10 | 63,302,495 | 27.87 | 14 | 55,050,844 | 24.12 |
| 11 | 63,325,402 | 27.86 | 15 | 54,994,546 | 24.20 |
| 12 | 63,007,938 | 27.63 | 16 | 54,155,371 | 23.84 |

**3. Assign trucks to load policy**

The simulation model demonstrates that to assign trucks for loading demand by considering distance from the distribution center to the destination is not distinguished in terms of cost per revenue distance (laden distance) from arranging by using distance from DC to origin. This is because total laden distances acquired from the two methods are not too different. Comparing between max to min and min to max policy, however, giving first priority to long-distance deliveries from the distribution center to the destination (max to min) provides lower pricing than min to max policy, as shown in Table 7.6.

Table 7.6 Comparing transportation cost for assigning truck to demand policy

| Distance from DC to Origin | | | Distance from DC to Destination | | |
|---|---|---|---|---|---|
| Scenario | Order | Cost per revenue dist. (baht/km) | Scenario | Order | Cost per revenue dist. (baht/km) |
| 1 | Min to Max | 29.63 | 3 | Min to Max | 29.66 |
| 2 | Max to Min | 29.28 | 4 | Max to Min | 29.16 |
| 5 | Min to Max | 28.63 | 7 | Min to Max | 28.64 |
| 6 | Max to Min | 28.00 | 8 | Max to Min | 27.99 |
| 9 | Min to Max | 27.60 | 11 | Min to Max | 27.86 |
| 10 | Max to Min | 27.87 | 12 | Max to Min | 27.63 |
| 13 | Min to Max | 23.96 | 15 | Min to Max | 24.20 |
| 14 | Max to Min | 24.12 | 16 | Max to Min | 23.84 |

### 7.1.2 Performance Analysis

Besides analyzing transportation operating cost, another advantage of the simulation model is performing truck performance analysis. This can be demonstrated in several ways as shown below.

- **Truck Utilization**

Truck utilization is an important measurement in truck performance analysis. The simulation model outputs illustrates that assigning trucks using With-outsourcing policy and moving trucks to the nearest distribution center after unloading is the most effective truck use, as shown in Table 7.7.

Table 7.7 Comparing truck use in terms of laden distance and operating day of each scenario for existing customers

| Scenario | % Laden Dist./Total Dist. | Truck Utilization | |
|---|---|---|---|
| | | Operating Day | % of Total working days (213 Days) |
| 1 | 46.23 | 196 | 92.21 |
| 2 | 46.18 | 196 | 91.98 |
| 3 | 46.20 | 195 | 91.53 |
| 4 | 46.21 | 195 | 91.78 |
| 5 | **60.79** | 195 | **91.45** |
| 6 | **60.65** | 195 | **91.64** |
| 7 | **60.68** | 195 | **91.36** |
| 8 | **60.76** | 194 | **90.89** |
| 9 | 46.49 | 172 | 80.78 |
| 10 | 46.13 | 175 | 82.04 |
| 11 | 46.12 | 172 | 80.71 |
| 12 | 46.40 | 175 | 82.33 |
| 13 | **64.20** | 162 | **76.29** |
| 14 | **62.00** | 164 | **76.78** |
| 15 | **63.80** | 163 | **76.30** |
| 16 | **62.53** | 164 | **76.90** |

- **Demand waiting for trucks**

Analyzing the demand that is waiting for trucks is useful in analyzing service performance for carriers with a No-outsource policy. This is illustrated in Table 7.8. Applying scenarios 1-8 conducts over 15% of total demand per 7 months for demand arrival in DC BKK and about 30-45% for demand arrival in DC NMA.

Table 7.8 Comparing amounts of demand waits for truck of each scenario for existing customers

| Scenario | DC BKK | | | DC NMA | | |
|---|---|---|---|---|---|---|
| | Demand wait | % of total | Period of waiting (days) | Demand wait | % of total | Period of waiting (days) |
| 1 | 1,699 | 15.64 | 0.83 | 3251 | 29.92 | 0.57 |
| 2 | 1,712 | 15.89 | 0.84 | 3164 | 29.38 | 0.57 |
| 3 | 1,663 | 15.42 | 0.81 | 2883 | 26.73 | 0.50 |
| 4 | 1,715 | 15.86 | 0.82 | 3235 | 29.92 | 0.56 |
| 5 | 1,796 | 17.16 | 1.43 | 4717 | 45.07 | 1.63 |
| 6 | 2,310 | 21.53 | 1.93 | 4230 | 39.42 | 1.30 |
| 7 | 2,007 | 18.66 | 1.49 | 4671 | 43.42 | 1.80 |
| 8 | 1,944 | 18.18 | 1.44 | 4763 | 44.54 | 1.83 |

- **Vacant truck analysis**

Vacant truck analysis is also used to analyze truck utilization performance in terms of effectiveness. The comparison of vacant trucks for each scenario is illustrated in Table 7.9. This table shows that a With-outsource policy leads to a high proportion of vacant trucks per day (Scenarios 9 – 16).

Table 7.9 Comparing average vacant trucks and number of days per vacant truck in each scenario for existing customers

| | Average Vacant Trucks per Day | | Total vacant trucks per day |
|---|---|---|---|
| Scenario | DC BKK | DC NMA | |
| 1 | 1.40 | 3.13 | 4.53 |
| 2 | 1.33 | 3.36 | 4.69 |
| 3 | 1.36 | 3.51 | 4.87 |
| 4 | 1.41 | 3.38 | 4.79 |
| 5 | 2.31 | 2.25 | 4.56 |
| 6 | 1.65 | 2.95 | 4.6 |
| 7 | 2.27 | 2.33 | 4.6 |
| 8 | 2.46 | 2.33 | 4.79 |
| 9 | 3.54 | 7.67 | 11.21 |
| 10 | 3.47 | 7.01 | 10.48 |
| 11 | 3.56 | 7.69 | 11.25 |
| 12 | 3.35 | 6.96 | 10.31 |
| 13 | 6.59 | 5.73 | 12.32 |
| 14 | 7.01 | 6.43 | 13.44 |
| 15 | 6.65 | 5.70 | 12.35 |
| 16 | 6.77 | 4.99 | 11.76 |

Based on the transportation costs and performances analysis described previously, it can be concluded that the most cost-effective policies are assigning trucks to demand by considering the distance from the distribution center to the destination from max to min, moving vacant trucks after unloading to the nearest distribution center, and having a With-outsource policy. Consequently, it is obvious that the factors influencing transportation cost are as summarized below.

- With-outsource policy
- Assign trucks to demand by considering the remote distance from the distribution center to customers' destinations
- Move vacant trucks to the nearest distribution center

For this reason, the truck assignment scenarios that will be selected to further investigate full truckload pricing in the next section are those shown in Table 7.10.

Table 7.10 Truck assignment scenarios selected to further investigate full truckload pricing

<table>
<tr><th>Scenario</th><th>Outsourcing policy</th><th>Vacant truck assignment after unloading</th><th colspan="2">Truck assignment to demand</th></tr>
<tr><td>11</td><td rowspan="6">With-outsource</td><td rowspan="2">Return to initial DC</td><td rowspan="2">Distance from DC to Destination</td><td>Min to Max</td></tr>
<tr><td>12</td><td>Max to Min</td></tr>
<tr><td>13</td><td rowspan="4">Nearest DC</td><td rowspan="2">Distance from DC to Origin</td><td>Min to Max</td></tr>
<tr><td>14</td><td>Max to Min</td></tr>
<tr><td>15</td><td rowspan="2">Distance from DC to Destination</td><td>Min to Max</td></tr>
<tr><td>16</td><td>Max to Min</td></tr>
</table>

The next section will use the scenarios selected above to analyze full truckload pricing for new customers.

### 7.2 Full Truckload Pricing Analysis

Pricing is one of the fundamental management decisions faced by truckload carriers. However, traditional pricing based on an average of all relevant costs including fixed and variable costs is not capable of providing adequate margins and guarding the carrier against losses caused by uncertainties inherent in truckload operation including mainly demand variability and variation in service and times.

To investigate traditional pricing shortcoming, this research applies a traditional price method to the truckload operation and network imitated in the simulation model for scenarios 13 (MCK's full truckload operation's policy) and 16 (Lowest cost policy). In this case, traditional pricing is determined by using average cost plus profit required. The profit required for pricing analysis is stated from No profit (average cost), 5% profit, 6% profit, 7% profit and 10% profit. Pricing analysis reveals that even when traditional prices are set to include a certain percentage of profit over the average cost, there is still a large chance that the carrier will be subjected to a loss as displayed in Table 7.11.

Table 7.11 Comparing probability of experiencing a loss with traditional pricing

| Traditional Pricing Profit | Probability of experiencing a loss with traditional pricing | |
|---|---|---|
| | Scenario 13 | Scenario 16 |
| No profit (Average cost) | 100% | 100% |
| 5% Profit | 100% | 99.5% |
| 6% Profit | 92.9% | 56.6% |
| 7% Profit | 1.2% | - |
| 10% Profit | - | - |

Because of traditional pricing shortcomings, the objective of this section is to investigate full truckload pricing for new (first-time) customers under demand and service time uncertainty based on selected truck assignment scenarios. As mentioned in Table 4.8 (Chapter 4), the five routes of new customer demand will be estimated to determine reasonable pricing by applying the risk measurement techniques of Value at Risk (VaR) and Conditional Value at Risk (CVaR). These techniques will be used to control the maximum loss or the minimum gain within a specified tolerance level to enable more flexible full truckload pricing. Investigating full truckload pricing with different company policies and conditions can be separated into three parts as described in Figure 7.2.

The first part aims to analyze how new customer demand variation affects transportation cost and pricing by maintaining the number of own trucks available without investing in additional trucks. The second part aims to analyze how service time including waiting time, uploading time and unloading time variation affect transportation cost and pricing if service times are reduced. The third part aims to analyze how resources affect transportation cost and pricing if the number of trucks is increased.

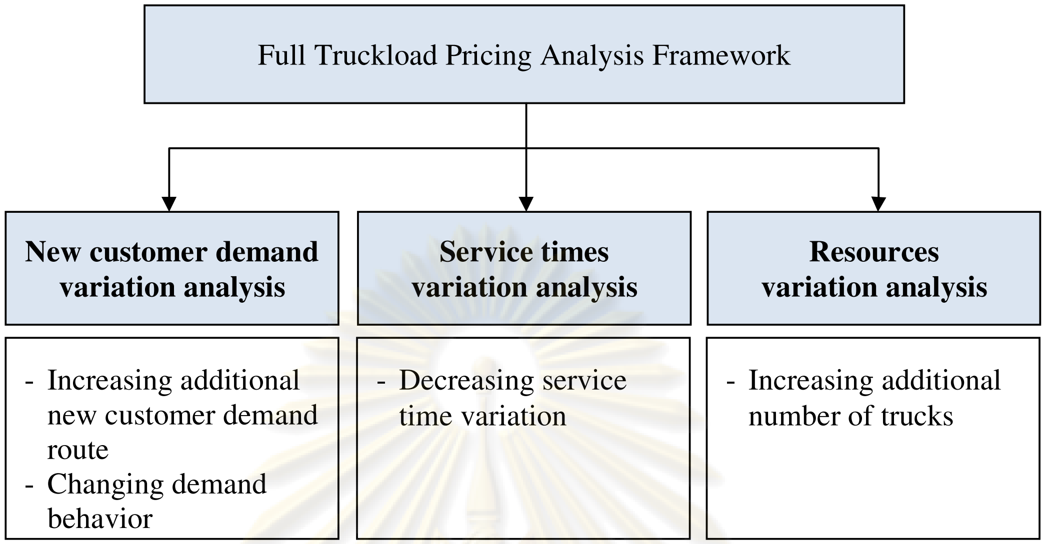



Figure 7.2 Full truckload pricing analysis framework

### 7.2.1 Customer demand variation analysis

Currently, the carrier in this study provides 60 semi trailer six-wheeled trucks for its existing customers. To analyze the effects of new customer demand, the number of trucks will remain at 60, without requesting additional trucks to serve five new customer routes. Eighteen of these 60 vehicles (30%) will be allocated to DC BKK and 42 (70%) will be allocated to DC NMA. Running 50 simulations reveals that the existing number of trucks is not enough to serve both current and new customer demand. The carrier needs to outsource trucks from sub-contractors to meet about 30-40% of total cost after including new customer demand as illustrated in Table 7.12.

Table 7.12 Comparing total costs and outsourcing cost after including new customer demand while maintaining the current number of trucks

| Scenario | Total cost (baht/7 months) | % of outsourcing cost/total cost | Total cost /revenue dist. (baht/km) |
|---|---|---|---|
| 11 | 99,839,692 | 35.93 | 26.10 |
| 12 | 99,061,454 | 31.28 | 25.98 |
| 13 | 89,051,325 | 39.73 | 23.51 |
| 14 | 89,635,974 | 35.98 | 23.57 |
| 15 | 90,818,146 | 40.54 | 23.73 |
| 16 | 89,677,609 | 35.84 | 23.41 |

According to Table 7.12, total cost per revenue distance of scenario 16 is lowest while scenario 13 (MCK's policy) is next to lowest. Comparing total cost per revenue distance of scenario 16 after including new customer demand (Table 7.12) with existing customer demand total cost per revenue distance of scenario 16 as illustrated in Table 7.2, the total cost per revenue distance including new customer demand is lower. This could mean that including new customer demand increases the use of one's own trucks and consequently lowers total cost per unit.

To analyze new customer pricing, full truckload pricing for existing customers is assumed to be previously specified and unable to be changed during new customer pricing estimation. To analyze the sensitivity of new customers' pricing with different existing customer pricing, existing customer pricing is divided into these four scenarios:

<u>Scenario A: Average cost</u>

Existing customer pricing is equal to average cost as demonstrated (No profit).

<u>Scenario B: 5% profit</u>

Existing customer pricing is equal to average cost plus 5% profit (Price = 1.05 times of average cost)

<u>Scenario C: 10% profit</u>

Existing customer pricing is equal to average cost plus 10% profit (Price = 1.10 times of average cost)

<u>Scenario D: 15% profit</u>

Existing customer pricing is equal to average cost plus 15% profit (Price = 1.15 times of average cost)

According to the specified existing customer pricing above, new customer pricing analysis results for all scenarios which maintain the same number of trucks are summarized below based on risk measurement techniques

- **Pricing with VaR**

After applying VaR constrained with a 95% confidence level or only a 5% chance that earnings will yield a less than acceptable loss, full truckload pricing of new customers under different existing customers' prices are shown in Table 7.13. It shows that new customer prices decrease when existing customer prices increase. On the other hand, transportation carriers can offer lower service prices to new customers if they acquire higher profit from existing customers.

Table 7.13 Comparing full truckload pricing applying with 95% VaR for each scenario of truck assignment while maintaining the same number of trucks

| Scenario | New customer price with 95% VaR under different existing customers' prices (baht/revenue dist.) | | | |
|---|---|---|---|---|
| | Scenario A | Scenario B | Scenario C | Scenario D |
| 11 | 30.09 | 28.35 | 26.63 | 24.94 |
| 12 | 29.92 | 28.13 | 26.38 | 24.62 |
| 13 | 23.85 | 22.09 | 20.33 | 18.60 |
| 14 | 23.99 | 22.30 | 20.62 | 18.94 |
| 15 | 24.38 | 22.65 | 20.93 | 19.21 |
| 16 | 23.64 | 21.90 | 20.22 | 18.51 |

- **Pricing with CVaR**

After applying CVaR constrained with a 95% confidence level or only a 5% chance that earnings will yield a less than acceptable loss, it is revealed that CVaR-constrained pricing is higher than VaR-constrained pricing, as illustrated in Table 7.14.

Table 7.14 Comparing full truckload pricing applying with 95% CVaR for each scenario of truck assignment while maintaining the same number of trucks

| Scenario | New customer price with 95% CVaR under different existing customers' prices (baht/revenue dist.) | | | |
|---|---|---|---|---|
| | Scenario A | Scenario B | Scenario C | Scenario D |
| 11 | 30.12 | 28.35 | 26.65 | 24.96 |
| 12 | 29.93 | 28.14 | 26.39 | 24.64 |
| 13 | 23.91 | 22.12 | 20.40 | 18.69 |
| 14 | 24.02 | 22.31 | 20.63 | 18.97 |
| 15 | 24.48 | 22.73 | 20.99 | 19.25 |
| 16 | 23.67 | 21.97 | 20.29 | 18.63 |

Tables 7.13 and 7.14 show that scenario 16 has the lowest price and scenario 13 has the next to lowest price. Hence, scenario 16 will be selected as the case

scenario to further investigate pricing considering customer demand variation. Pricing per unit in Tables 7.13 and 7.14 will be converted into full truckload pricing per trip with 95% VaR and 95% CVaR per trip for new customer routes as displayed in Tables 7.15 and 7.16 respectively.

Table 7.15 Comparing full truckload pricing per trip applying 95% VaR for scenario 16 while maintaining the same number of trucks

| Route | New customer price with 95% VaR under different existing customers' prices (baht/revenue dist.) | | | |
|---|---|---|---|---|
| | Scenario A | Scenario B | Scenario C | Scenario D |
| BKK-NSN | 6,020 | 5,578 | 5,149 | 4,714 |
| BKK-UBN | 14,186 | 13,145 | 12,135 | 11,109 |
| BKK-UDN | 13,334 | 12,355 | 11,406 | 10,442 |
| NMA-CMI | 17,523 | 16,237 | 14,990 | 13,723 |
| NMA-SKA | 28,621 | 26,521 | 24,483 | 22,413 |

Table 7.16 Comparing full truckload pricing per trip applying 95% CVaR for scenario 16 while maintaining the same number of trucks

| Route | New customer price with 95% CVaR under different existing customers' prices (baht/trip) | | | |
|---|---|---|---|---|
| | Scenario A | Scenario B | Scenario C | Scenario D |
| BKK-NSN | 6,027 | 5,596 | 5,168 | 4,745 |
| BKK-UBN | 14,204 | 13,188 | 12,180 | 11,183 |
| BKK-UDN | 13,350 | 12,395 | 11,448 | 10,511 |
| NMA-CMI | 17,545 | 16,289 | 15,045 | 13,814 |
| NMA-SKA | 28,657 | 26,606 | 24,573 | 22,562 |

95% CVaR focuses on the tail of the loss distribution and provides a measure of expected loss exceeding 95% VaR. According to Tables 7.15 and 7.16, pricing with 95% VaR and 95% CVaR is not too different. The explanation for this is that the loss distribution beyond 95% VaR does not tend to exhibit "fat tail" or "long tail." Therefore, it is not a very serious shortcoming if transportation carriers provide no handle on the extent of losses beyond the 95% VaR.

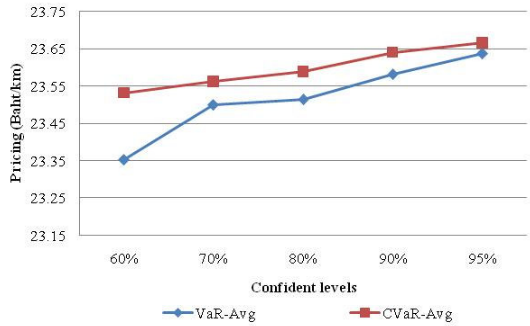
Furthermore, to compare these prices with a traditional pricing method, traditional pricing is estimated by using the cost-plus pricing method or estimated pricing from average cost plus percent of profit required. Traditional pricing is displayed in Table 7.17. The comparison results reveal that pricing with 95% VaR and 95% CVaR using existing customer pricing and a 5% profit margin are already greater than traditional pricing by average cost plus a 5% profit. It can be implied that even if a carrier adds 5% profit on top of the average cost of the traditional pricing method, the carrier will still probably lose money.

On the other hand, pricing with 95% VaR and 95% CVaR using existing customer pricing and including a 10% profit margin is already less than traditional pricing from average cost plus a 10% profit. It can be explained that if transportation carriers acquire a 10% profit margin from existing customers, they can offer lower prices to new customers.

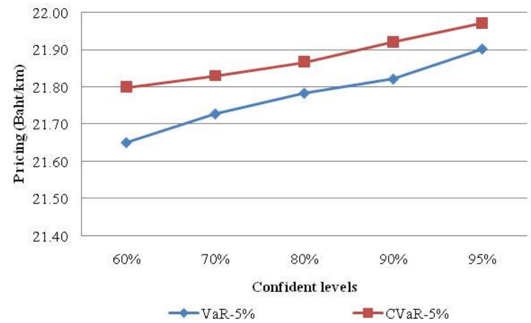
Table 7.17 Traditional pricing per trip for scenario 16 while maintaining the same number of trucks

| Route | Average cost (baht/trip) | Traditional Pricing (baht/trip) | | |
|---|---|---|---|---|
| | | 5% Profit | 10% Profit | 15% Profit |
| BKK-NSN | 5,288 | 5,552 | 5,817 | 6,081 |
| BKK-UBN | 12,200 | 12,810 | 13,420 | 14,030 |
| BKK-UDN | 11,555 | 12,133 | 12,711 | 13,288 |
| NMA-CMI | 14,724 | 15,460 | 16,196 | 16,933 |
| NMA-SKA | 23,854 | 25,047 | 26,239 | 27,432 |

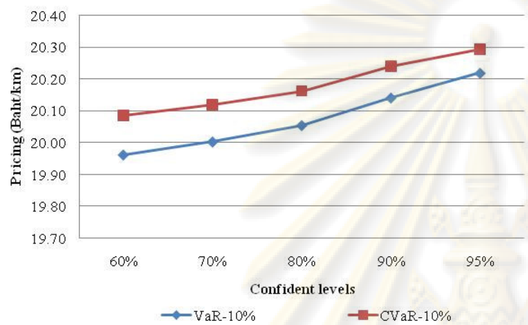
Moreover, this research uses the advantages of VaR and CVaR. When considering the full truckload pricing interval, this research applies different specified confidence levels from 60-95%. These different tolerance levels can provide a negotiable price range for customers. Differences in confidence levels will be investigated using scenario 16. This is illustrated in Figure 7.3.



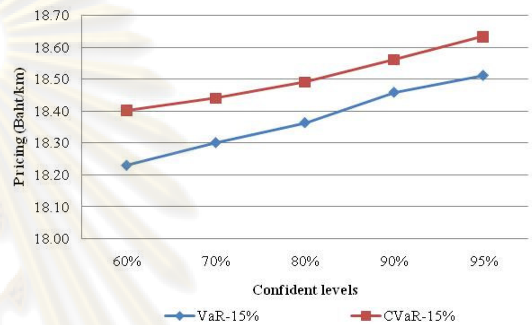

**Scenario A:** Existing customer's price = Avg. cost (No profit)




**Scenario B:** Existing customer's price = 1.05 times of average cost




**Scenario C:** Existing customer's price = 1.10 times of average cost




**Scenario D:** Existing customer's price = 1.15 times of average cost

Figure 7.3 Comparing full truckload pricing with different confidence levels of VaR and CVaR of new customer demand under different existing customers' prices for scenario 16

The figures show that the lowest confidence levels (60%) or a 40% chance that earnings less than acceptable loss lead to the lowest prices and the highest probability of losses. At the lowest confidence levels, however, applying CVaR to pricing can reduce the extent of losses compared to pricing with VaR.

Since scenario 16 provides the lowest cost and price, it will be used to further investigate pricing considering variations in customer demand. The effects of demand variation on full truckload pricing can be examined by applying these procedures:

- Increasing additional new customer demand
- Changing new customer demand behavior

The following explanations will clarify each method.

### 7.2.1.1 Increasing additional new customer demand

To investigate how new customer demand affects existing customer operation, this research adds new customer routes one by one and also by group to existing customer operation of scenario 16.

**A. Increasing additional new customer demand by route**

- **Price with VaR**

After applying VaR constrained with a 95% confidence level or only a 5% chance that earnings will yield a less than acceptable loss, it is revealed that adding route BKK-NSN to existing operation greatly increases the pricing per unit of this route as shown in Table 7.18. This high pricing results from the effect of scenario 16 on truck assignment. In this scenario, the company's own trucks are reserved for long-distance trips. Meanwhile, serving some short distance routes with outsourced trucks is highly expensive. Hence the variable costs for short distance routes, such as route BKK-NSN with an origin-destination distance of about 254.67 km, are higher and prices will consequently be higher.

Moreover, pricing results demonstrate that new customers can be offered very low price or even without charging if carriers acquire at least 10% profit (Scenario C) from existing customers, especially routes BKK-NSN, BKK-UBN, and NMA-SKA. However, pricing for route BKK-UDN and NMA-CMI can not be highly compressed to lower pricing because of high demand variation.

Table 7.18 Comparing full truckload pricing per trip by adding routes one by one with 95% VaR for scenario 16 while maintaining the same number of trucks

| Scenario | New customer price with 95% VaR under different existing customers' prices (baht/revenue dist.) | | | |
|---|---|---|---|---|
| | Scenario A | Scenario B | Scenario C | Scenario D |
| Adding Route **BKK-NSN** | 45.75 | 4.63 | 0 | 0 |
| Adding Route **BKK-UBN** | 35.45 | 6.70 | 0 | 0 |
| Adding Route **BKK-UDN** | 24.93 | 17.34 | 9.78 | 2.51 |
| Adding Route **NMA-CMI** | 25.37 | 22.58 | 19.78 | 17.12 |
| Adding Route **NMA-SKA** | 33.15 | 16.74 | 0.63 | 0 |

- **Pricing with CVaR**

After applying CVaR constrained with a 95% confidence level or only a 5% chance that earnings will yield a less than acceptable loss, a comparison of the results is displayed in Table 7.19.

Table 7.19 Comparing full truckload pricing per trip by adding routes one by one with 95% CVaR for scenario 16 while maintaining the same number of trucks

| Scenario | New customer price with 95%CVaR under different existing customers' prices (baht/revenue dist.) | | | |
|---|---|---|---|---|
| | Scenario A | Scenario B | Scenario C | Scenario D |
| Adding Route **BKK-NSN** | 48.72 | 8.02 | 0 | 0 |
| Adding Route **BKK-UBN** | 36.30 | 7.99 | 0 | 0 |
| Adding Route **BKK-UDN** | 25.02 | 17.70 | 10.59 | 3.57 |
| Adding Route **NMA-CMI** | 25.57 | 22.68 | 19.88 | 17.21 |
| Adding Route **NMA-SKA** | 33.82 | 17.25 | 2.05 | 0 |

Tables 7.18 and 7.19 show that if transportation carriers are earning at least 5% profit (Scenario B) from existing customers, they can offer lower pricing for new customers. According to this conclusion, truckload carriers can apply the advantages of this pricing method to offer lower competitive price than their competitors.

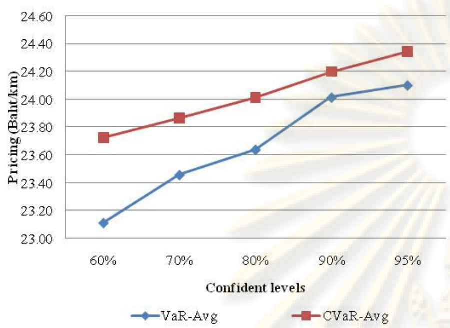
**B. Increasing additional new customer demand by group**

Instead of offering pricing to customer by route, this research examines full truckload pricing by group routes. In this case, customer routes are divided into two groups, DC BKK group and DC NMA group, depending on the distribution center, as displayed in Table 7.20.

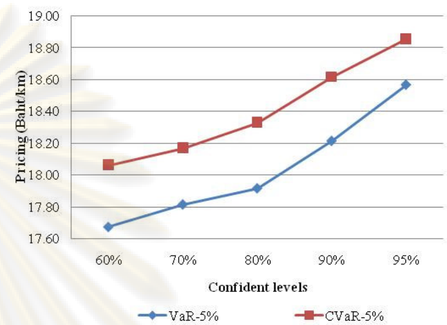
Table 7.20 New customer group routes divided by distribution center

| Group | Distribution Center | Route | Origin | Destination |
|---|---|---|---|---|
| 1 | BKK | BKK-NSN | Bangkok | Nakornsawan |
| | | BKK-UBN | Bangkok | Ubonratchathani |
| | | BKK-UDN | Bangkok | Udonthani |
| 2 | NMA | NMA-CMI | Nakorn Ratchasrima | Chiangmai |
| | | NMA-SKA | Nakorn Ratchasrima | Songkla |

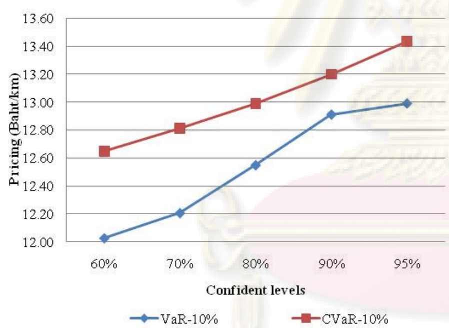
To offer pricing by group, full truckload pricing for groups 1 and 2 are displayed in Figures 7.4 and 7.5. These figures show that pricing by sub-group is higher than combining all five routes together. However, carriers can offer lower pricing for customer group route 1 (DC BKK) if they acquire more profit from existing customers. Hence, carriers can use this advantage to motivate their customers by offering service for the whole routes.



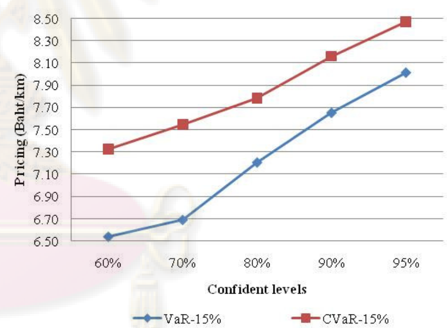

**Scenario A:** Existing customer's price = Avg. cost (No profit)




**Scenario B:** Existing customer's price = 1.05 times of average cost

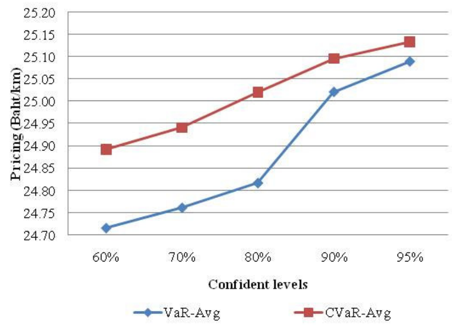



**Scenario C:** Existing customer's price = 1.10 times of average cost

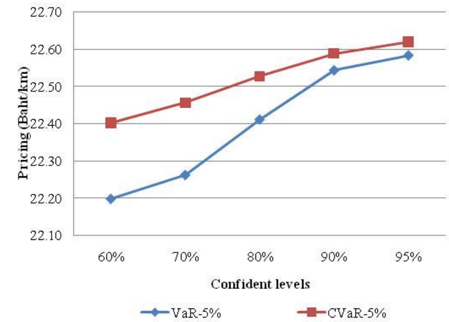



**Scenario D:** Existing customer's price = 1.15 times of average cost

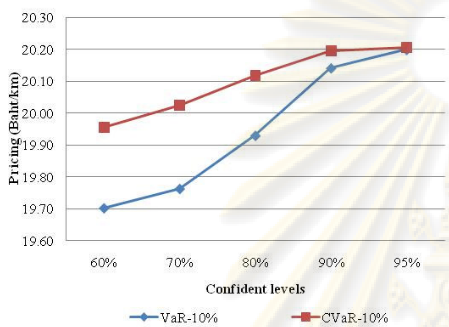
Figure 7.4 Comparing full truckload pricing with different confidence levels of VaR and CVaR of new customer demand group "DC BKK" under different existing customers' prices



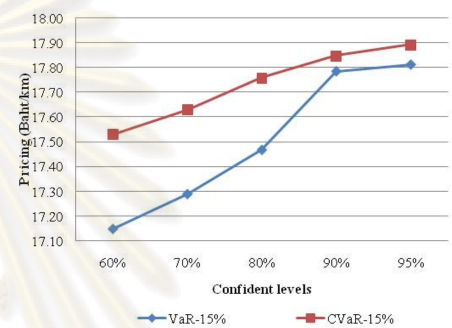

**Scenario A:** Existing customer's price = Avg. cost (No profit)




**Scenario B:** Existing customer's price = 1.05 times of average cost




**Scenario C:** Existing customer's price = 1.10 times of average cost




**Scenario D:** Existing customer's price = 1.15 times of average cost

Figure 7.5 Comparing full truckload pricing with different confidence levels of VaR and CVaR of new customer demand group "DC NMA" under different existing customers' prices

Comparing truckload pricing for the two groups reveals that pricing for group "DC NMA" is higher than that for group "DC BKK," as shown in Figures 7.6 and 7.7. This result originates from demand variation of group "DC NMA." Moreover, pricing from group "DC NMA" is not too different from average pricing (dashed line) which includes all routes. Hence, it can be implied that demand variation from group "DC NMA" is the key factor enhancing high cost and price.

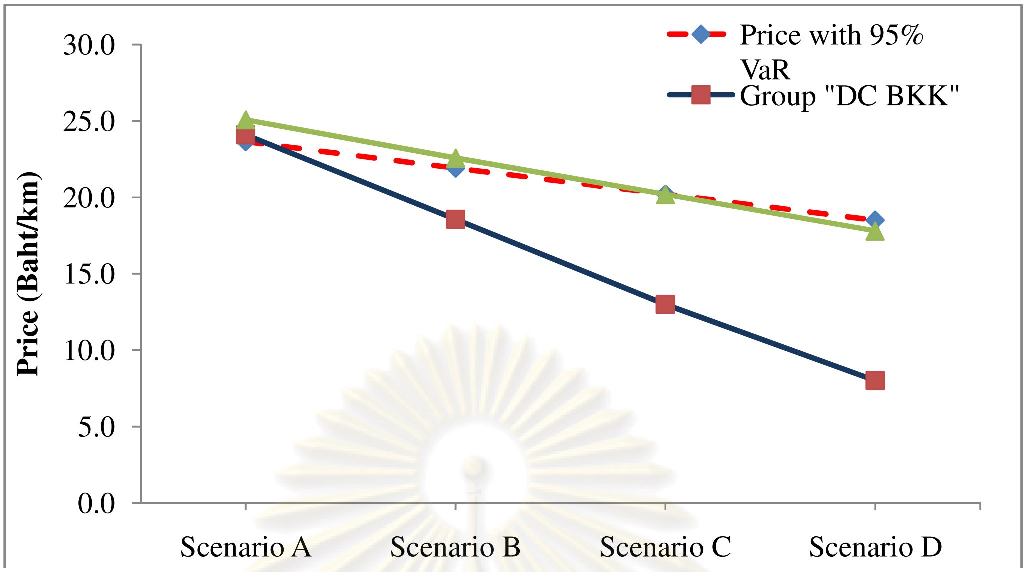



Figure 7.6 Comparing full truckload pricing applying 95% VaR of new customer demand group “DC BKK” and “DC NMA” under different existing customers’ prices

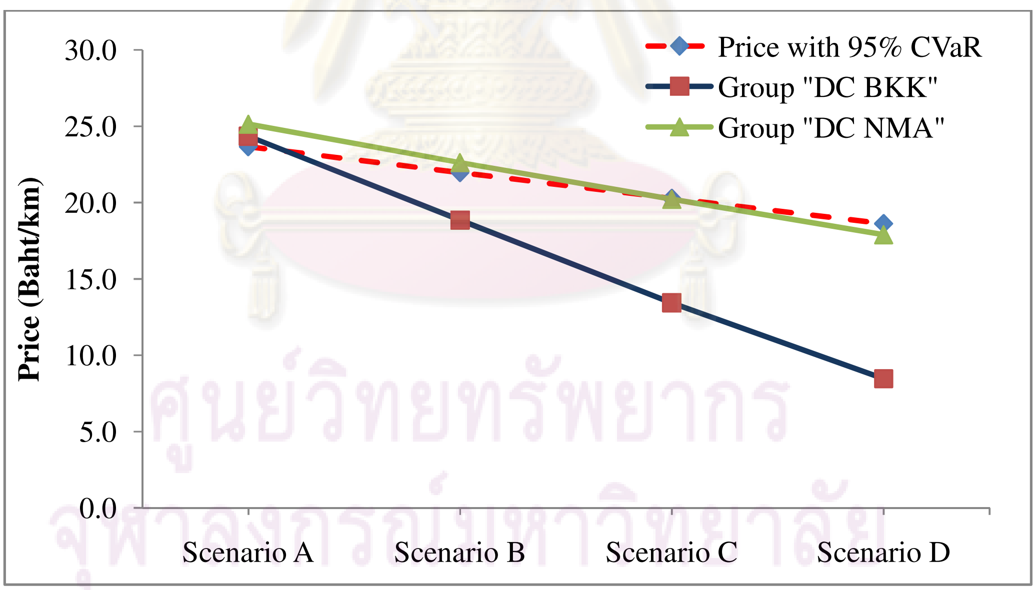



Figure 7.7 Comparing full truckload pricing applying with 95% CVaR of new customer demand group “DC BKK” and “DC NMA” under different existing customers’ prices

### 7.2.1.2 Changing new customer demand behavior

To investigate the effects of demand variation on transportation cost and price, this research applies Lognormal distribution instead of Negative Binomial distribution to explain new customer behavior. A simulation model is applied to imitate new customer demand behavior using lognormal distribution. A lognormal distribution is a probability distribution of a random variable whose logarithm is normally distributed. If *X* is a random variable with a normal distribution, then *Y = exp (X)* has a lognormal distribution. The parameters denoted $\mu$ and $\sigma$ are the mean and standard deviation respectively. The probability density function of a lognormal distribution is:

$$f_x(x;\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(lnx-\mu)^2}{2\sigma^2}}, x > 0 \quad (7.1)$$

where the characteristics of lognormal distribution are described as:

$$E(X) = e^{\mu+\frac{\sigma^2}{2}}$$

$$Var(X) = (e^{\sigma^2}-1)e^{2\mu+\sigma^2}$$

The developed simulation model is applied to imitate new customer demand behavior that is assumed to be lognormally distributed. This research investigates the effects of demand variation by considering two scenarios:

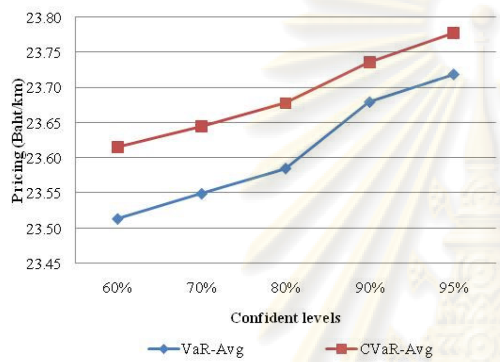
- Controlling average demand
  - 1E(x) – 1STD
  - 1E(x) – 3 STD
- Increasing demand
  - 2E(x) – 1STD
  - 2E(x) – 3STD

Further details of each scenario are explained below:

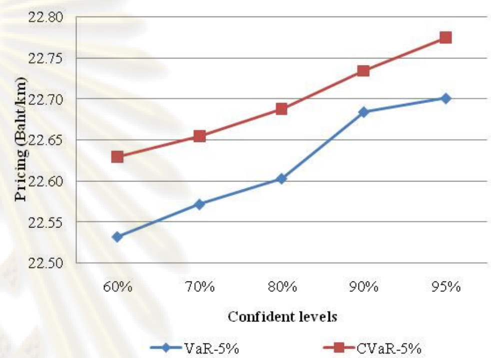
**A. Controlling average demand**

- 1E(x) – 1STD

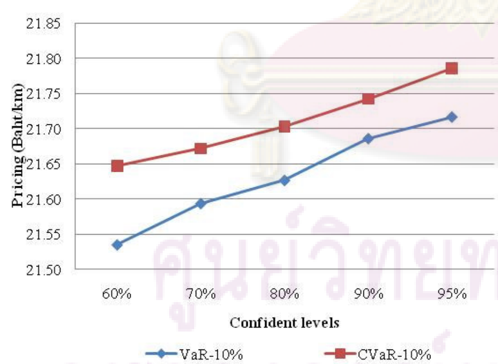
This scenario controls average demand per route and standard deviation of each route for Lognormal distribution equal to average demand and standard deviation as applied in Negative Binomial distribution. Full truckload pricing from this scenario is displayed in Figure 7.8. Pricing from Lognormal distribution is shown to be higher than pricing from Negative Binomial distribution.



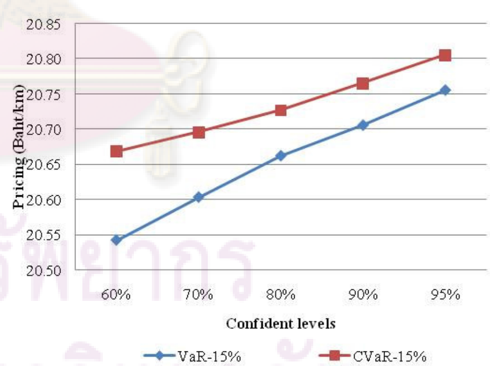

**Scenario A:** Existing customer's price = Avg. cost (No profit)




**Scenario B:** Existing customer's price = 1.05 times of average cost




**Scenario C:** Existing customer's price = 1.10 times of average cost

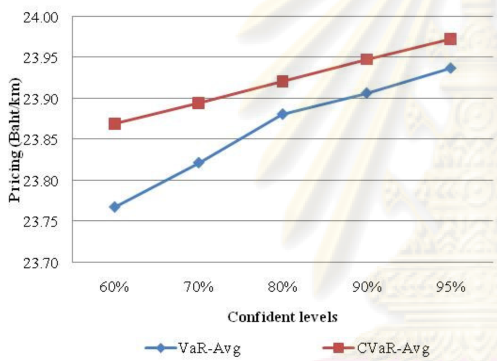



**Scenario D:** Existing customer's price = 1.15 times of average cost

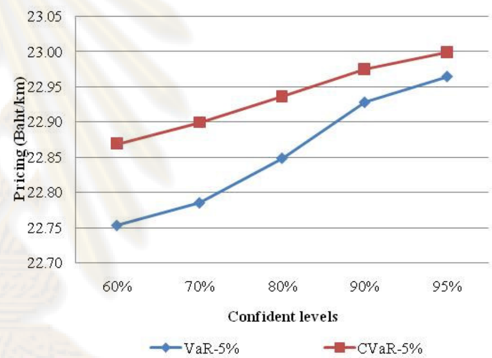
Figure 7.8 Comparing full truckload pricing with different confidence levels for VaR and CVaR of new customer demand for scenario 1E(x) – 1STD

- 1E(x) - 3STD

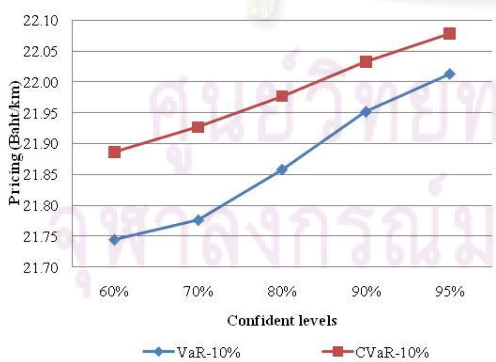
This scenario aims to investigate the effects of demand variation on full truckload pricing. Therefore, average demand for each route with lognormal distribution is controlled to equal average demand as applied in Negative Binomial distribution, while the standard deviation is increased to three times the standard deviation for Negative Binomial distribution. Full truckload pricing from this scenario is displayed in Figure 7.9. With 95% VaR, increasing the standard deviation three times can enhance full truckload pricing by about 0.22 baht/revenue distance compared to scenario 1E(X) – 1STD and 0.30 baht/revenue distance compared to based case scenario.



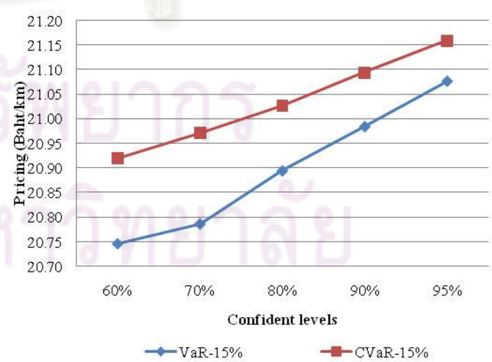

**Scenario A:** Existing customer's price = Avg. cost (No profit)




**Scenario B:** Existing customer's price = 1.05 times of average cost




**Scenario C:** Existing customer's price = 1.10 times of average cost



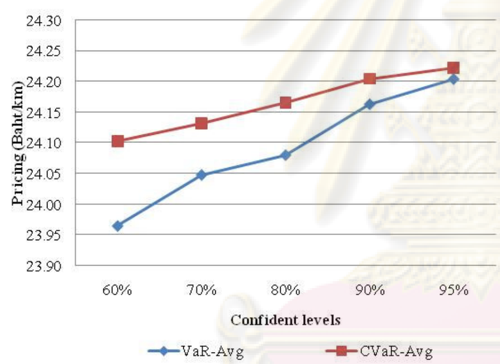

**Scenario D:** Existing customer's price = 1.15 times of average cost

Figure 7.9 Comparing full truckload pricing with different confidence levels of VaR and CVaR of new customer demand for scenario 1E(x) – 3STD

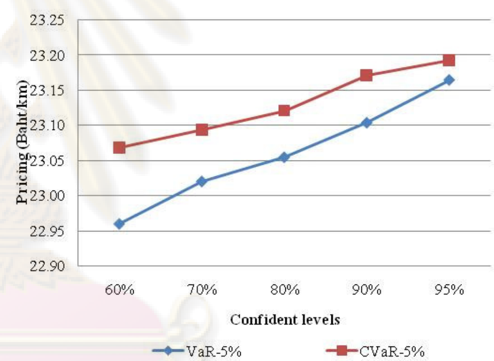
**B. Increasing demand**

- 2E(x) – 1STD

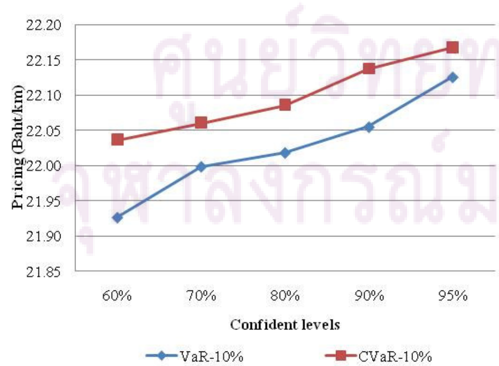
This scenario aims to investigate how the amount of customer demand affects pricing. Hence, customer demand is increased by two times while standard deviation is controlled equal to standard deviation as applied in Negative Binomial distribution. Full truckload pricing from this scenario is displayed in Figure 7.10. With 95% VaR, increasing customer demand two times can enhance full truckload pricing from the scenario 1E(X)-1STD by almost 0.50 baht/revenue distance. Compared to scenario 1E(X) – 3STD, it reveals that full truckload pricing from scenario 2E(X) – 1STD is higher. It can be implied that increasing demand affects pricing more than increasing demand variation.



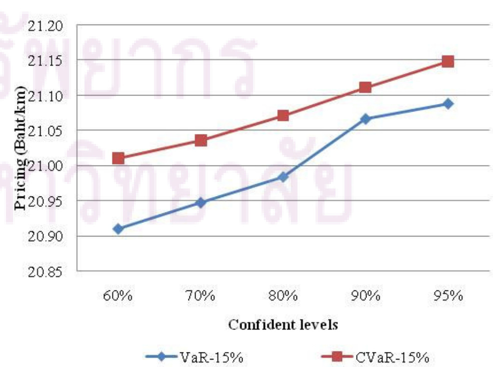

**Scenario A:** Existing customer's price = Avg. cost (No profit)




**Scenario B:** Existing customer's price = 1.05 times of average cost




**Scenario C:** Existing customer's price = 1.10 times of average cost

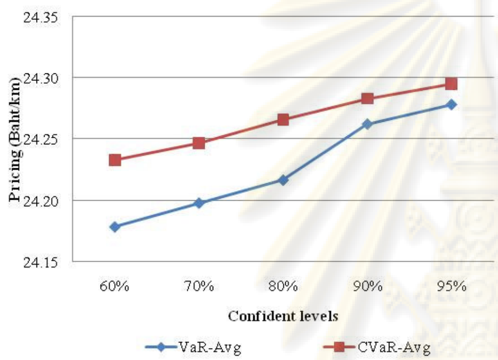



**Scenario D:** Existing customer's price = 1.15 times of average cost

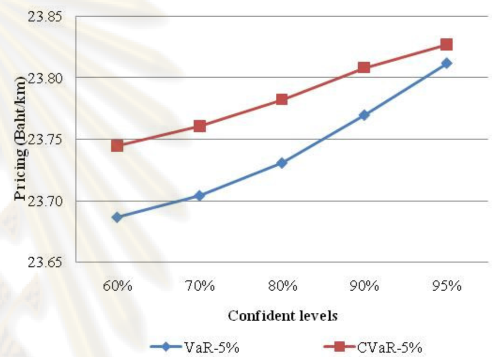
Figure 7.10 Comparing full truckload pricing with different confidence levels of VaR and CVaR of new customer demand for scenario 2E(x) – 1STD

- 2E(x) – 3STD

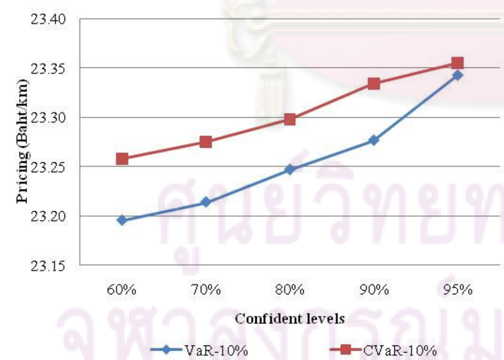
This scenario aims to investigate how customer demand affects pricing. Hence, customer demand is doubled while standard deviation is increased to three times the standard deviation as applied in Negative Binomial distribution. Full truckload pricing from this scenario is displayed in Figure 7.11. With 95% VaR, doubling customer demand and tripling standard deviation can enhance full truckload pricing from the scenario of 1E(X)-1STD by about 0.56 baht/revenue distance.



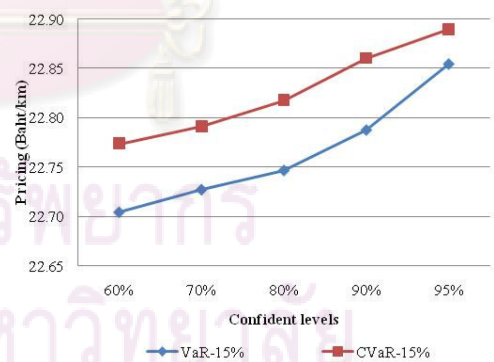

**Scenario A:** Existing customer's price = Avg. cost (No profit)




**Scenario B:** Existing customer's price = 1.05 times of average cost




**Scenario C:** Existing customer's price = 1.10 times of average cost




**Scenario D:** Existing customer's price = 1.15 times of average cost

Figure 7.11 Comparing full truckload pricing with different confidence levels of VaR and CVaR of new customer demand for scenario 2E(x) – 3STD

According to customer demand analysis as described previously, it can be concluded that increasing demand variation enhances higher pricing. However, increasing customer demand has a stronger effect than increasing demand variation as illustrated in Figures 7.12 and 7.13.

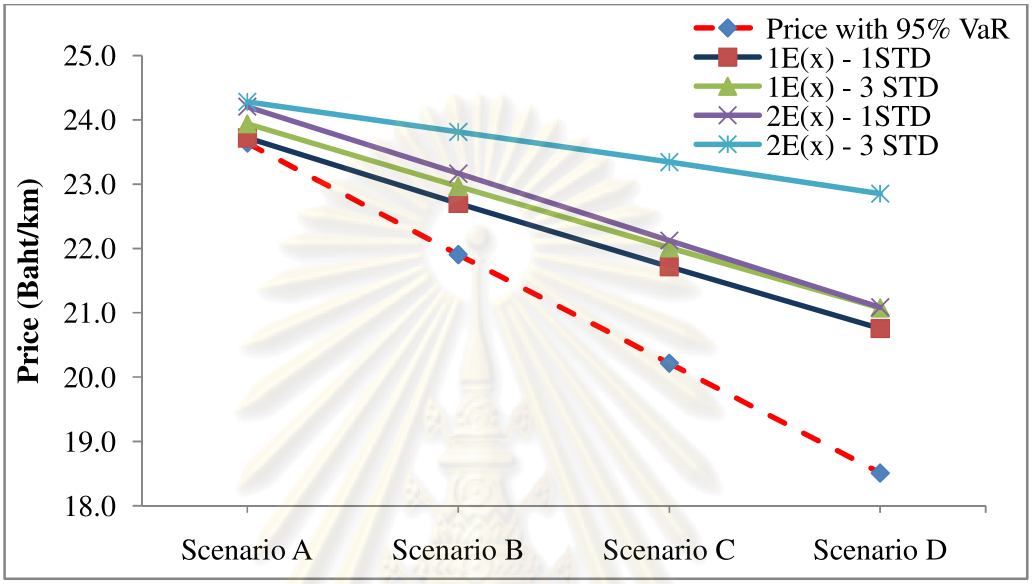



Figure 7.12 Comparing full truckload pricing applying with 95% VaR for each new customer demand behavior under different existing customers' prices

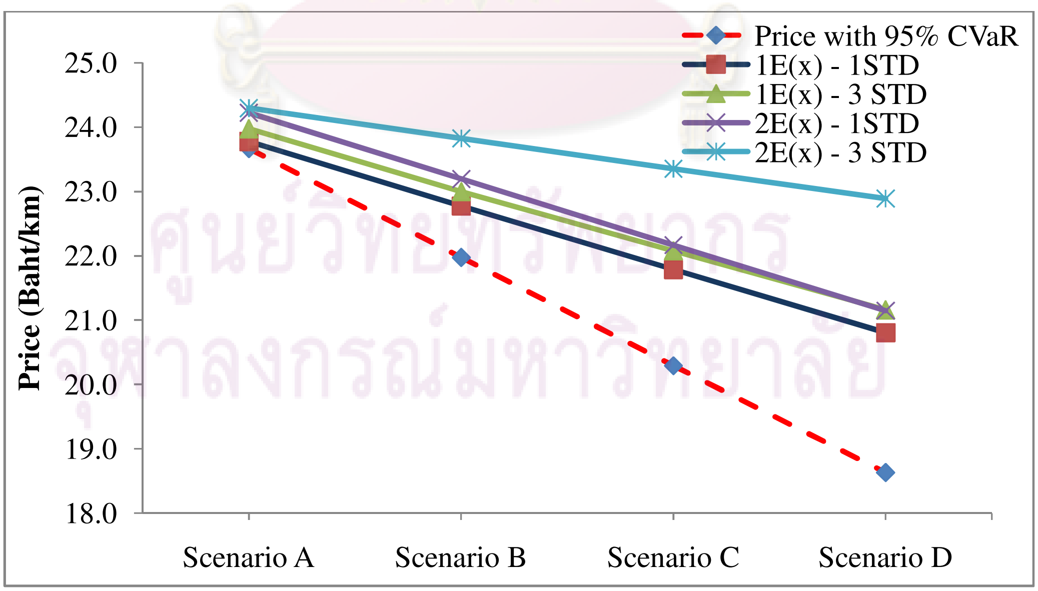
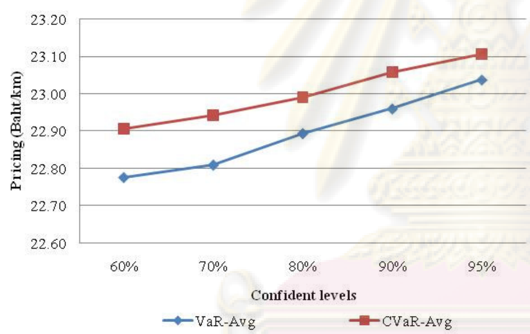


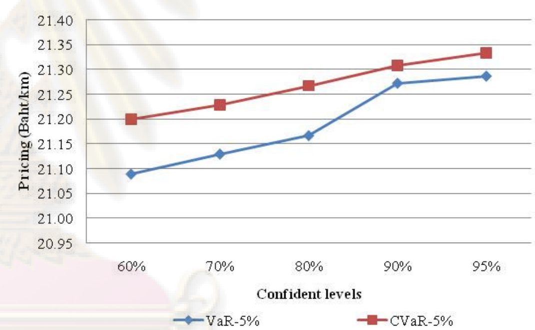

Figure 7.13 Comparing full truckload pricing applying with 95% CVaR for each new customer demand behavior under different existing customers' prices

### 7.2.2 Service times variation analysis

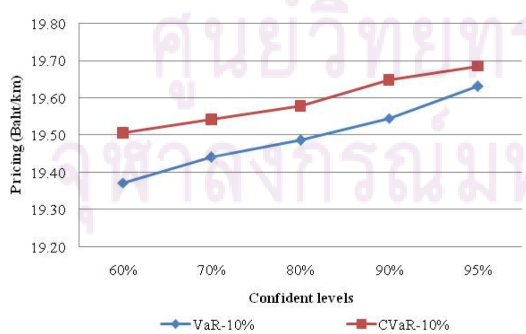
Service times including waiting time, uploading time, and unloading time greatly affect truck use. In this research, waiting time is the idle time including waiting time to upload and unloading at customer sites. Waiting time variation depends on the readiness of goods preparation at the customers' origins or destinations. Uploading time and unloading time are dedicated for handling goods at the customers' origins or destinations. They depend on the equipment used. The simulation model is applied to consider the influence of this service time variation. Applying the 16$^{th}$ truck assignment rule, this research tests the scenario by decreasing average waiting time by half. Also, the minimum and maximum of unloading and uploading time is deceased by half. Pricing results with VaR and CVaR constrained are presented in Figure 7.14.



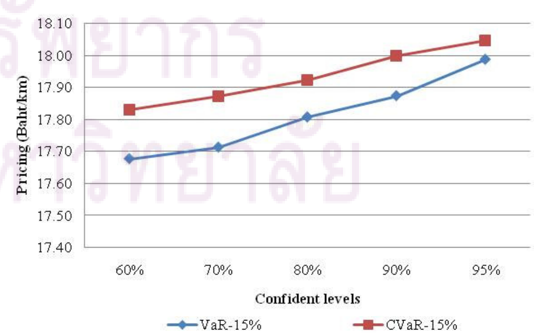

**Scenario A:** Existing customer's price = Avg. cost (No profit)




**Scenario B:** Existing customer's price = 1.05 times of average cost




**Scenario C:** Existing customer's price = 1.10 times of average cost




**Scenario D:** Existing customer's price = 1.15 times of average cost

Figure 7.14 Comparing full truckload pricing with different confidence levels of VaR and CVaR of scenario decreasing service time by half

To reduce waiting time, uploading and unloading time can increase trucks' use consequently. Figures 7.15 and 7.16 show that decreasing average service time by half can decrease full truckload pricing from the based case scenario about 0.50-0.60 baht/revenue distance. Then transportation carriers can offer lower prices for their customers. This result can be used to motivate customer to reduce variations in service times.

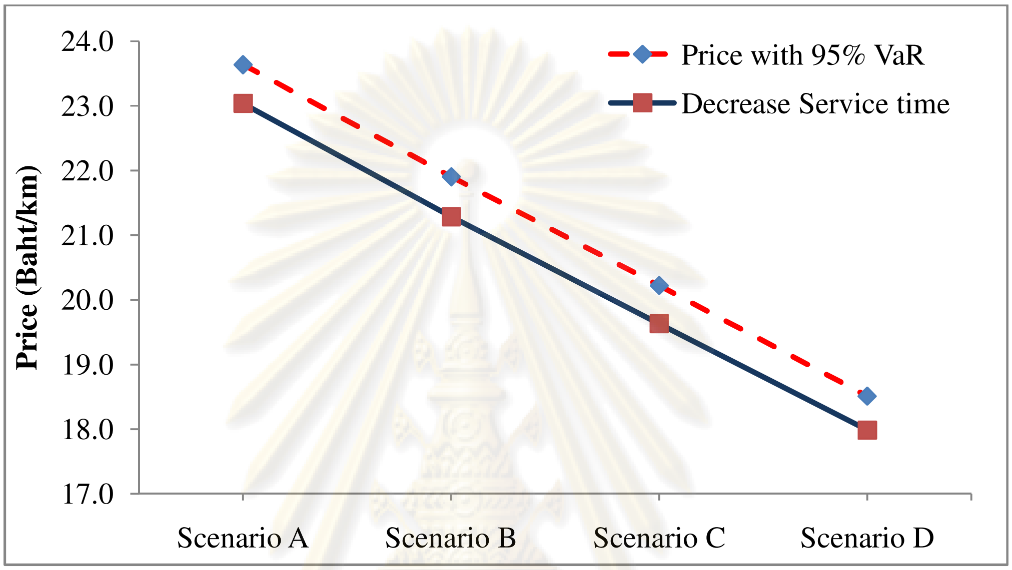



Figure 7.15 Comparing full truckload pricing applying with 95% VaR for service time variation under different existing customers' prices

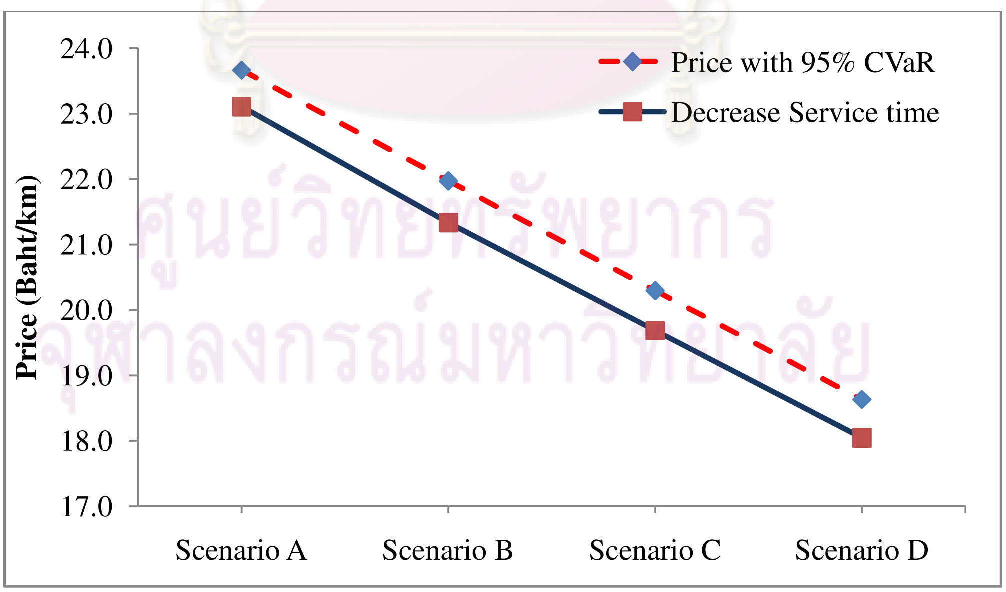



Figure 7.16 Comparing full truckload pricing applying with 95% CVaR for service time variation under different existing customers' prices

### 7.2.3 Resources variation analysis

Besides the truck assignment rules, there are other factors that may strongly affect transportation cost and price. Thus, the simulation model will be further applied to consider the influence of the number of additional trucks to be purchased to serve a new customer. Applying the 16th truck assignment rule, this study tests the scenario by changing the number of additional trucks in the simulation model. However, the proportion of number of trucks reserved for DC BKK and DC NMA is still equal to 30%:70%.

This study tests the scenario by changing the number of additional trucks in the simulation model. Additional trucks are put into the simulation model starting from 5-30 trucks. Having more trucks of its own means a company needs to outsource fewer trucks. However, we cannot increase the quantity of trucks infinitely because each additional truck requires additional investment and a higher fixed cost as illustrated in Figure 7.17.

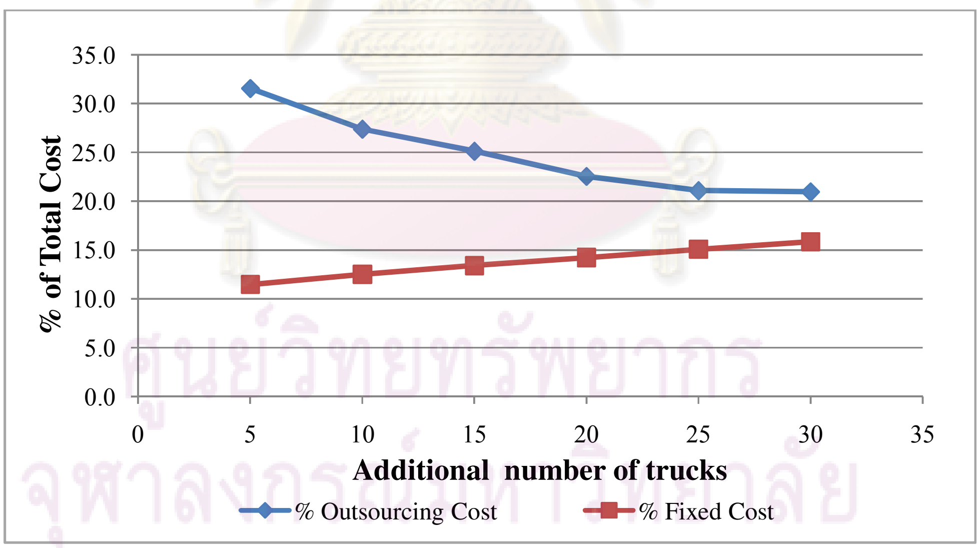



Figure 7.17 The relationship between % outsourcing cost, % fixed cost, and number of additional trucks

Hence, when deciding to invest in additional trucks to serve new customer demand, two vital factors to consider are amount of vacant trucks per day and amount of outsourcing trucks per day. That means carriers have to trade off between additional cost from investing in additional trucks and outsourcing cost when there are available trucks, and that customer service level is also taken into consideration. However, increasing additional trucks to serve customer demand uncertainty also increases the probability of vacant trucks especially on days without customer demand. The relationship between % outsourcing truck per total demand per day, % vacant truck per total own trucks, and number of additional trucks is illustrated in Figure 7.18.

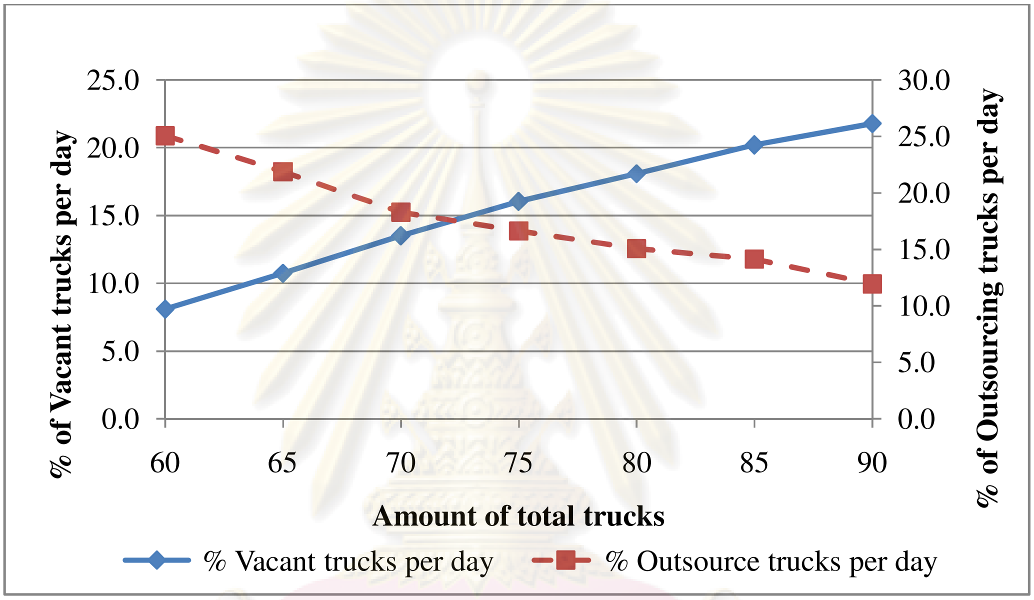



Figure 7.18 The relationship between % outsourcing truck, % vacant truck, and number of additional trucks

As shown earlier, pricing results with VaR and CVaR constrained considering the amount of trucks can be presented as the following:

- **Price with VaR**

Pricing with 95% VaR output indicate that at the beginning, increasing the number of truck leads to a lower price as displayed in Table 7.21. This logically follows from the fact that having more trucks of its own means that a company reduces outsourcing cost. However, each additional truck requires additional investment and a higher fixed cost. In this case with VaR constrained, we can increase the size of the fleet by an additional 15-20 semi trailer six-wheeled trucks; after that it will generate higher cost and price as displayed in Figure 7.19.

Table 7.21 Comparison of full truckload pricing applying 95% VaR with additional trucks

| Additional number of trucks | New customer price with 95% VaR under different existing customers' prices (baht/revenue dist.) | | | |
|---|---|---|---|---|
| | Scenario A | Scenario B | Scenario C | Scenario D |
| 5 | 23.07 | 21.39 | 19.72 | 18.02 |
| 10 | 22.92 | 21.16 | 19.42 | 17.72 |
| 15 | 22.64 | 20.93 | 19.24 | 17.56 |
| 20 | 22.58 | 20.85 | 19.20 | 17.46 |
| 25 | 22.99 | 21.23 | 19.53 | 17.85 |
| 35 | 23.49 | 21.79 | 20.10 | 18.41 |

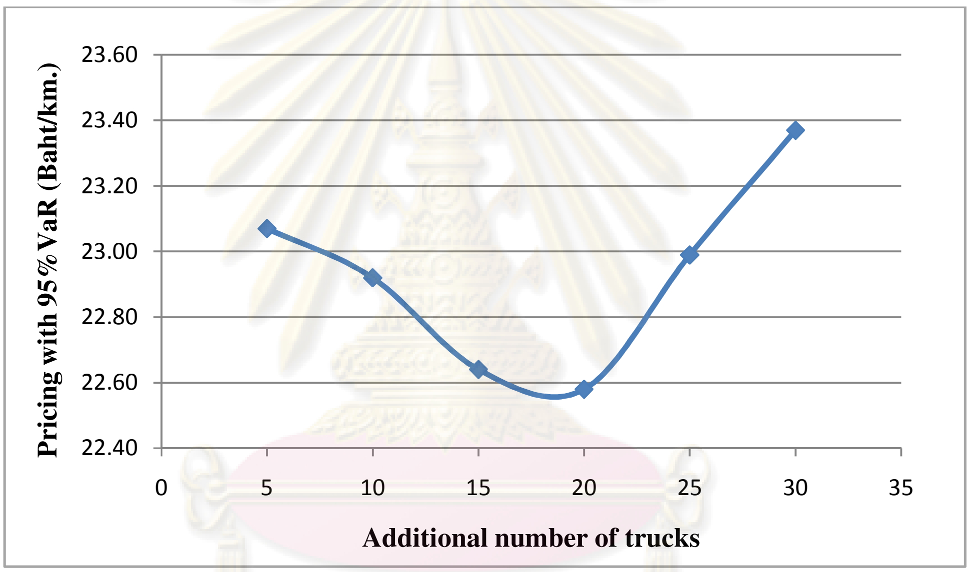



Figure 7.19 The relationship between full truckload pricing with 95% VaR and additional trucks

- **Pricing with CVaR**

Pricing with CVaR provides pricing results in the same direction as pricing with VaR, as illustrated in Table 7.22.

Table 7.22 Comparison full truckload pricing applying 95% CVaR with additional trucks

| Additional number of trucks | New customer price with 95% CVaR under different existing customers' prices (baht/revenue dist.) | | | |
|---|---|---|---|---|
| | Scenario A | Scenario B | Scenario C | Scenario D |
| 5 | 23.19 | 21.47 | 19.78 | 18.09 |
| 10 | 23.02 | 21.27 | 19.54 | 17.86 |
| 15 | 22.84 | 21.08 | 19.33 | 17.64 |
| 20 | 22.69 | 20.93 | 19.23 | 17.55 |
| 25 | 23.14 | 21.40 | 19.65 | 17.97 |
| 30 | 23.66 | 21.96 | 20.26 | 18.55 |

Moreover, taking advantage of Value at Risk (VaR) and Conditional Value at Risk (CVaR), we can estimate full truckload pricing for different levels of risk by changing different confidence levels as demonstrated in Tables 7.23 through 7.26. Therefore, transportation carriers will have room to negotiate with their customers while considering what is an acceptable probability of loss and the level of existing customer price.

Table 7.23 Comparison of full truckload pricing for different levels of risk by changing confidence levels while existing customers' prices equal average cost

| Additional number of trucks | Price with different confidence level | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 60% | | 70% | | 80% | | 90% | |
| | VaR | CVaR | VaR | CVaR | VaR | CVaR | VaR | CVaR |
| 5 | 22.85 | 22.97 | 22.90 | 23.01 | 22.92 | 23.05 | 23.04 | 23.12 |
| 10 | 22.50 | 22.70 | 22.56 | 22.75 | 22.65 | 22.82 | 22.77 | 22.95 |
| 15 | 22.28 | 22.48 | 22.36 | 22.53 | 22.41 | 22.60 | 22.62 | 22.74 |
| 20 | 22.33 | 22.48 | 22.39 | 22.51 | 22.45 | 22.56 | 22.53 | 22.62 |
| 25 | 22.41 | 22.80 | 22.65 | 22.89 | 22.81 | 22.97 | 22.93 | 23.05 |
| 30 | 22.87 | 23.21 | 22.97 | 23.31 | 23.14 | 23.56 | 23.44 | 23.56 |

Table 7.24 Comparison of full truckload pricing for different levels of risk by changing confidence levels while existing customers' prices equal 5% profit

| Additional number of trucks | Price with different confidence level | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 60% | | 70% | | 80% | | 90% | |
| | VaR | CVaR | VaR | CVaR | VaR | CVaR | VaR | CVaR |
| 5 | 21.11 | 21.24 | 21.15 | 21.28 | 21.17 | 21.33 | 21.35 | 21.43 |
| 10 | 20.81 | 20.97 | 20.86 | 21.01 | 20.89 | 21.08 | 21.04 | 21.19 |
| 15 | 20.51 | 20.76 | 20.62 | 20.82 | 20.73 | 20.90 | 20.90 | 21.00 |
| 20 | 20.61 | 20.73 | 20.65 | 20.77 | 20.69 | 20.82 | 20.82 | 20.88 |
| 25 | 22.41 | 22.80 | 22.65 | 22.89 | 22.81 | 22.97 | 22.93 | 23.05 |
| 30 | 21.11 | 21.44 | 21.23 | 21.54 | 21.38 | 21.65 | 21.52 | 21.82 |

Table 7.25 Comparison of full truckload pricing for different levels of risk by changing confidence levels white existing customers' prices equal 10% profit

| Additional number of trucks | Price with different confidence level | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 60% | | 70% | | 80% | | 90% | |
| | VaR | CVaR | VaR | CVaR | VaR | CVaR | VaR | CVaR |
| 5 | 19.39 | 19.53 | 19.42 | 19.58 | 19.48 | 19.65 | 19.66 | 19.73 |
| 10 | 19.10 | 19.26 | 19.13 | 19.30 | 19.18 | 19.37 | 19.38 | 19.47 |
| 15 | 18.75 | 19.04 | 18.89 | 19.12 | 19.07 | 19.21 | 19.22 | 19.28 |
| 20 | 18.85 | 19.01 | 18.91 | 19.05 | 18.98 | 19.10 | 19.06 | 19.17 |
| 25 | 19.04 | 19.31 | 19.10 | 19.40 | 19.29 | 19.49 | 19.49 | 19.49 |
| 30 | 19.39 | 19.69 | 19.50 | 19.77 | 19.57 | 19.88 | 19.72 | 20.10 |

Table 7.26 Comparison of full truckload pricing for different levels of risk by changing confidence levels while existing customers' prices equal 15% profit

| Additional number of trucks | Price with different confident level | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 60 % | | 70 % | | 80 % | | 90 % | |
| | VaR | CVaR | VaR | CVaR | VaR | CVaR | VaR | CVaR |
| 5 | 17.68 | 17.84 | 17.71 | 17.88 | 17.79 | 17.96 | 17.95 | 18.03 |
| 10 | 17.37 | 17.57 | 17.45 | 17.62 | 17.52 | 17.69 | 17.64 | 17.77 |
| 15 | 17.04 | 17.34 | 17.13 | 17.42 | 17.40 | 17.51 | 17.51 | 17.59 |
| 20 | 17.13 | 17.31 | 17.23 | 17.34 | 17.26 | 17.39 | 17.35 | 17.49 |
| 25 | 17.32 | 17.61 | 17.45 | 17.67 | 17.52 | 17.90 | 17.72 | 17.90 |
| 30 | 17.61 | 17.94 | 17.71 | 18.03 | 17.83 | 18.16 | 18.04 | 18.4 |

This research applies the traditional price method to the truckload operation and network imitated in the simulation model for each additional truck. Pricing analysis reveals that even when traditional prices are set to include at least 5% of profit over the average cost for additional 5, 10, 25, and 30 trucks, there is still a large chance that the carrier will be subjected to a loss as shown in Table 7.27. This is because they still need outsourcing trucks for an additional 5 and 10 trucks and carry fixed cost surplus for additional an 25 and 30 trucks.

However, if carriers still prefer to use the traditional pricing method, the amount of pricing profit required should be at least 7% over the average cost to avoid losses for an additional 5, 10, 25, and 30 trucks. On the other hand, it should be at least 5% of profit over the average cost for an additional 15 and 20 trucks.

Table 7.27 Comparing probability of experiencing a loss with traditional pricing for each additional truck

| Traditional Pricing Profit | Probability of experiencing a loss with traditional pricing for each additional trucks | | | | | |
|---|---|---|---|---|---|---|
| | Add 5 | Add 10 | Add 15 | Add 20 | Add 25 | Add 30 |
| No profit (Average cost) | 100% | 100% | 100% | 100% | 100% | 100% |
| 5% Profit | 50.50% | 9.40% | - | - | 23.80% | 53.90% |
| 6% Profit | - | - | - | - | - | 8.2% |
| 7% Profit | - | - | - | - | - | - |
| 10% Profit | - | - | - | - | - | - |

Resources variation analysis results provide full truckload pricing with different amounts of trucks for the transportation carrier. These results will be important information for the carrier to analyze the amount of additional truck investment for serving new customer. The suitable amount of total trucks reserved for customers depends on company policy.

**7.3 Summary**

This chapter provides full truckload simulation and price determination models for transportation carriers. It shows that pricing with VaR is higher than average cost and that CVaR constraint generates the highest price. This numerical analysis demonstrates a pricing method for transportation carriers who are risk averse. Transportation carriers in this group dislike risk and will stay away from high risk. Hence, pricing with 95% of CVaR is agreeable to this kind of person.

# CHAPTER VIII

# CONCLUSION AND RECOMMENDATIONS

## 8.1 Conclusion

Pricing is one of the fundamental management decisions required by a truckload carrier. Traditional pricing based on an average of all relevant costs including fixed and variable costs is not capable of providing adequate margins to prevent losses during operation uncertainties inherent in truckload operation including demand variability and variation in service times.

Since these uncertainty factors can give rise to the risk of potential loss from unusual equipment requirements or extreme levels of use, pricing that is based purely on the cost-plus approach does not fully capture the financial and investment implications of these unusual requirements. The literature describes risk measures which can be used to evaluate a system's riskiness. Over the past few years, the financial engineering field's managers have increasingly used Value at Risk (VaR) and Conditional Value at Risk (CVaR) to measure and manage risk exposure. VaR is defined as the expected loss arising from an adverse market movement with specified probability over a period of time (Tapiero, 2005). It answers the question of how much one can lose with $p\%$ probability over a period of time. Hence, to control the risk of loss, we apply a VaR constraint to estimate full truckload pricing in this paper. CVaR measures the conditional expected loss exceeding VaR and accounts for risks beyond the VaR value (Aker, 2005).

The research framework consists of two parts, simulation model and price determination model development. The full truckload simulation model is developed to imitate full truckload daily operation using the ExtenSim8 simulation program. The simulation framework begins with dispatching trucks at the carrier's distribution centers (DC), then driving empty trucks to the customers' factories (places of origin), then picking up goods at these points of origin, then delivering goods to their destinations and moving on to next assignments. In this case, the next assignment can be returning to either the initial DC or the nearest DC to wait for the next customer demand.

To develop a full truckload price determination model, this research utilizes Value at Risk (VaR) and Conditional Value at Risk (CVaR) risk optimization to determine the minimum offered service price by controlling the risk of earning less than the desired profit or losing more than an acceptable level due to uncertain factors within given confidence levels. The price determination model is developed in a spreadsheet program using Visual Basic. For user friendliness, a user interface function is also developed in this study.

The developed simulation and price determination model is applied using the historical data obtained from a truckload carrier operation whose head office is in Nakorn Ratchasrima province. This carrier has two distribution centers, one in Nakorn Ratchasrima province and one in Bangkok. A simulation model can be used to determine the pricing at varying degrees of risk and can also be applied to investigate the effects of additional trucks on cost and price. To invest in new trucks, carriers need to trade off between the fixed cost of owning the trucks and the price of outsourcing. In addition, truck assignment rules will simultaneously affect cost and price.

The simulation and pricing model analysis results show that the company's own trucks are given first priority for long-distance deliveries while outsourced trucks are reserved for long distance to provide lower transportation cost and price. Moreover, pricing with 95% of VaR and 95% of CVaR is higher than traditional pricing. Investigating full truckload pricing with different company policies and conditions can be separated into three parts. The first part aims to analyze how new customer demand variation effects transportation cost and pricing while maintaining the amount of trucks available without investing in additional trucks. The second part aims to analyze how service time including waiting time, uploading time and unloading time variation affect transportation cost and pricing if service times are reduced. The third part aims to analyze how resources affect transportation cost and pricing with additional numbers of trucks. Pricing analysis results are summarized in the following.

**1. Customer demand variation analysis**

Pricing analysis results reveal that new customer price per revenue distance with 95% VaR and 95% CVaR under the same truck assignment rules are not very different. The explanation for this is that loss distribution beyond the 95% VaR does not tend to exhibit “fat tail” or “long tail.” Therefore, it is not a very serious shortcoming if transportation carriers provide no handle on the extent of losses beyond 95% VaR.

However, this research also provides a transportation pricing interval within a specified tolerance level to enable more flexible full truckload pricing considering different confidence levels. The different confidence levels applied are 60%, 70%, 80%, 90%, and 95%. Pricing analysis results demonstrate that lower confidence levels result from lower price in terms of price with VaR and CVaR. It is revealed that pricing with CVaR is able to quantify dangers beyond the VaR value.

This research compares pricing by controlling risk to achieve a loss with a traditional pricing method that is estimated by using the cost-plus pricing method or from average cost plus percent of profit required. Moreover, we apply these traditional prices back to the truckload operation and network imitated in the simulation model and find that even when traditional prices are set to include a certain percentage of profit over the average cost there is still a large chance that the carrier will be subjected to a loss.

This research also investigates offering full truckload pricing by group routes. New customer demand is divided into two sub-groups, DC BKK group and DC NMA group, depending on distribution center. This reveals that pricing for offering each sub-group is higher than combining all five routes together. Hence, carriers can use this advantage to motivate their customers to accept service for the whole route in order to get lower pricing. For changing new customer demand behavior analysis, it can be concluded that increasing demand variation also increases pricing. However, increasing customer demand has a more pronounced effect than increasing demand variation.

**2. Service time variation analysis**

This aims to analyze how service time including waiting time, uploading time, and unloading time variation affect transportation cost and pricing if service times are decreased. To reduce waiting time (idle time), uploading and unloading time can increase trucks' use consequently. Pricing analysis results show that decreasing average service times by half can reduce full truckload pricing from the based case scenario by about 0.50-0.60 baht/revenue distance. Then transportation carriers can offer lower prices for their customer. These results can be used to motivate customers to reduce service time variations.

**3. Resources variation analysis**

This study tests scenarios by changing the number of additional trucks in the simulation and price determination model. The outputs indicate that at the beginning, increasing the number of trucks leads to a lower price. This logically follows from the fact that owning more trucks means that a company needs to outsource fewer trucks. However, we cannot increase the quantity of trucks infinitely because each additional truck requires additional investment and a higher fixed cost. With 95% VaR and 95% CVaR constrained, carrier can increase the size of the fleet by additional 15-20 semi trailer six-wheeled trucks; after that it will generate higher cost and price.

## 8.2 Recommendations



The numerical analysis full truckload pricing method in this study is suitable for transportation carriers who are risk averse. Transportation carriers in this group dislike risk and will stay away from high risk. However, if they stay extremely risk averse, pricing will be very high as a result. This will eventually lead to loss of customers.

Based on pricing analysis results, the first thing that can be done immediately is that carriers should ask their customers to reduce idle time, especially waiting time to upload and unload goods. Moreover, increasing the amount of handling equipment or using highly efficient equipment at customers' sites can reduce uploading and unloading time as well. It increases the use of the company's trucks and consequently reduces the service price.

In the case that carriers decide to invest additional trucks for serving both existing and new customer demand, two vital factors to consider are amount of vacant trucks per day and amount of outsourcing trucks per day. That means carriers have to trade off between the additional cost of investing in additional trucks and the outsourcing cost for available trucks. Customer service level must also be considered. However, increasing additional trucks for serving customer demand uncertainty also enhances the probability of vacant trucks, especially on days without customer demand.

Finally, taking advantage of Value at Risk (VaR) and Conditional Value at Risk (CVaR) risk measurement techniques, we can estimate full truckload pricing depending on different confidence levels. Therefore, transportation carriers will have room to negotiate with their customers while considering what is an acceptable probability of loss. However, a specified confidence level depends on the risk tolerance level of each carrier based on the ability and willingness to take risk. Moreover, market price is another factor that influences risk tolerance level.

**8.3 Further Research**

There are several interesting topics that should be further investigated.

- Further research is needed on applying VaR and CVaR to truckload pricing as well as to take into account other factors of uncertainty such as transit time uncertainty.
- Drivers' behavior affects consumption rate, but consumption rate for both running and empty running trips is assumed as a constant rate for all drivers in this study. To accord with real life full truckload operation, consumption rate should be treated as an uncertain factor in further research
- More research is needed on price determination model considering only potential lanes that enhance use of the company's own trucks.

- This research concentrates on the minimum offered service price by controlling the risk of earning less than the desired profit or losing more than an acceptable level due to uncertain factors within given confidence levels. Hence, further research is required on a price determination model to maximize profit rather than to minimum loss while risk of loss still be concerned.

## REFERENCES


Aker, A (2005) Single Period Stochastic Inventory Problem with Downside Risk Considerations, M.S. Thesis: Koç University, Industrial Engineering, Istanbul, Turkey.

Banks, J. (1998) Principles of Simulation. In Bank, J., Handbook of simulation: Principles, Methodology, Advances, Applications, and Practice, pg. 3, John Wiley & Son, Inc.

Becker, F. and Sims, W. (2000) Managing uncertainty: Integrated portfolio strategies for dynamic organizations, The International Workplace Studies Program, College of Human Ecology, Cornell University.

Beilock, R. and Kilmer, R.L. (1983) Regulations and empty mileage, ICC Practitioners' J, 50, 433-39.

Beilock, R. and Kilmer, R.L. (1986) The determinants of full-empty truck movements, American Journal of Agricultural Economics, 68(1), 67-76.

Beilock, R., Garrod, P. and Mikilius, W. (1986) Freight charge variations in truck transport markets: price discrimination or competitive pricing? American Journal of Agricultural Economics, 68(2), 226-236.

Berwick, M. and Dooley, F. (1997) Truck Costs for owner/operators. Upper Great Plaints Transportation Institute No. 118. North Dakota State University. Fargo.

Berwick, M. and Farooq, M. (2003) Truck costing model for transportation managers, Upper Great Plaints Transportation, North Dakota State University. Fargo.

Boles, Patrick (1980) Owner-Operator costs of hauling fresh fruits and vegetables in refrigerated trucks. Washington DC: U.S. Department of Agriculture ESCS Rep. No. 82.

Boyer, D.D (1980) Queuing analysis and value of service pricing in the trucking industry: comment. The American Economic Review, 70(1), 174-180.

Burt, D.K, Norquist, W.E and Anklesaria, J. (1990) Zero base pricing, Probus Publishing Company, Chicago, Illinois.

Cabedo, J.D. and Moya, I. (2003) Estimating oil price 'value at risk' using the historical simulation approach. Energy Economics, 25, 239-253.

Casavant, K. (1993) Basic Theory of Calculation Costs: Applications to Trucking. Upper Great Plaints Transportation Institute No. 118. North Dakota State University. Fargo.

Charnes, A., and Cooper, W.W. (1961) Deterministic equivalents for optimizing and satisfying under chance constraints, Operations Research, 11(1), 18-39.

De Vany, A.S. and Saving, T.R. (1977) Product quality, uncertainty, and regulation: The trucking industry, American Economy Review, 67, 583-94.

Dolan, R.J and Simon H. (1996) Power Pricing: How managing price transforms the bottom line. A Division of Simon & Schuster Inc.

Dooley F.J, Bertram, L.M and Wilson, W.W (1989) Backhaul opportunities for North Dakota grain truckers, Upper Great Plains Transportation Institute North Dakota State University, Fargo, North Dakota.

Dowd, K (1998) Beyond value at risk: the new science of risk management, John Wiley & Sons, London.

Down, K (2002) Measuring market risk, Chichester: John Wiley & Sons.

Duffie, D. and Pan, J. (1997) An overview of value at risk, Journal of Derivatives, 4(3), 7-49.

Duin, J.H.R., Tavasszy, L.A. and Taniguchi, E. (2007) Real time simulation of auctioning and re-scheduling processes in hybrid freight market, Transportation Research Part B: Methodological, 41(9), 1050-1066.

Feng, Y. and Xiao, B. (2006) Integration of pricing and capacity allocation for perishable products. European Journal of Operational Research, 168, 17-34.

Golub, B.W. and Tilman, L.M (2000) Risk management: approaches for fixed income markets. John Wiley & Sons, Inc.

Gorman, M., (2001) Intermodal pricing model creates a network pricing perspective at BNSF. Interface 31 (4), 37-49.

Gotoh, J. and Takano, J. (2008) Newsvendor solutions via Conditional Value at risk minimization. European Journal of Operational Research.

He, Y. and Huang, RH. (2007) Risk attributes theory: Decision making under risk, Europe Journal of Operational Research, 186, 243-260.

Holguin-Veras, J. and Brom, A.M (2008) Trucking costs in a metropolitan area: a comparison of alternative estimation approaches, Transportation Research Broad, Annual Meeting CD-ROM.

Ingalls, R.G., Cornejo, M., Methapatara, C. and Sittivijan, P. (2008) Integrating simulation and optimization research into a graduate supply chain modeling course, Proceeding of the 2008 Winter Simulation Conference, 2527-2533.

Jorion, P (1997) Value-at-Risk: the new benchmark for controlling market risk. Irwin, Chicago, I11.

Jorion, P., (2001) Value at Risk: The New Benchmark for Managing Financial Risk, second ed. McGraw-Hill, New York.

Kilmer, R.L, Ramirez, H.E. and Stegelin, F.E. (1983) Economic impact of empty backhauls in Florida fresh fruit and vegetable truck transportation. University of Florida Age. Exp. Sta. Bull., 833.

Lee, C.Y. and Zhou, W.H (2009) Pricing and competition in a transportation market with empty equipment repositioning, Transportation Research Part B.

Lin, C.C., Lin, D.Y. and Young, M.M. (2009) Price planning for time-definite less-than-truckload freight services, Transportation Research Part E.

Lui, B. (1999) Uncertainty Programming, John Wiley & Sons, New York.

Lui, B. (2002) Theory and practice of uncertain programming, Physica-Verlag Heidelberg, New York.

McKinnon, A.C and Ge, Y. (2006) The potential for reducing empty running by trucks: retrospective analysis. International Journal of Physical Distribution & Logistics Management. 36(5). 391-410

McMullen, B., (1987) The Impact of Regulatory Reform on U.S. Motor Carrier Costs. Journal of Transportation Economics and Policy. 26 (3):307-319.

McMullen, B. and Stanl. Y.L. (1988) The Impact of Deregulation on the Production Structure of the Motor Carrier Industry. Economic Inquiry. 26:299-316.

McMullen, B. and Tanaka, H. (1995) An Econometric Analysis of Differences Between Motor Carriers: Implications for Market Structure. Quarterly Journal of Business and Economics 34(4):16-28.

Min, H., Jayaraman, V. and Srivastava, R. (1998) Combined location-routing problems: a synthesis and future research directions, European Journal of Operational Research, 108, 1-15.

Montgomery, S.L (1988) Profitable pricing strategies, McGraw-Hill, Inc.

Pompeo, L. and Sapountzis, T. (2002) Freight expectations, The McKinsey Quarterly, 2, 90-99.

Rockafellar, R.T. and Uryasec, S. (2000) Optimization of conditional value-at-risk, Journal of Risk, 2, 21-41.

Rogachev, A. (2002) Dynamic value-at-risk, University of St. Gallen.

Rothschild, W. (2002) Dynamic carrier selection: delivering on the promises of procurement technology [Online]. White paper.
Available from: http://www.logisticsociety.com/[2008, June 20]

Rowley, J. (1997) Principles of price and pricing policy for the information marketplace. Library Review, Edge Hill University College, Ormskirk, UK, 46(3), 179-189.

Saunders, A. (1999) Financial Institutions Management: a modern perspective (3nd ed.). Irwin Series in Finance, McGraw-Hill, New York.

Simon, H. (1989) Price Management, Elsevier Science Publishers B.V.

Stambaugh, F. (1996) Risk and value at risk. European Management Journal, 14(6), 612-621.

Suri, P.K. and R. Soni (2006) Stochastically simulating low morale a risk factor effect on risk management. Journal of Computer Science, 2: 370-372.

Tapiero, C.S. (2005) Value at risk and inventory control. European Journal of Operational Research, 163, 769-775.

Topaloglu, H., Powell, W., (2007) Incorporating pricing decisions into the stochastic dynamic fleet management problem. Transportation Science, 41 (3), 281-301.

Waters, W.G., (Spring, 1976) Statistical Costing in Transportation, Transportation Journal, 49-62.

Zhou, Y., J., Chen, X., H. and Wand, Z.R. (2008) Optimal ordering quantities for multi-products with stochastic demand: Return-CVaR model, International Journal of Production Economics, 112, 782-795.

## Biography

The author was born in Mahasarakham province, which is located in northeastern Thailand. She graduated from Khon Kaen Wittayayon High School and then pursued a Bachelor's Degree in Civil Engineering from Khon Kaen University. After seven years of studying at Khon Kaen, she went to Bangkok to continue studying for her Master's Degree in Civil Engineering at Chulalongkorn University. She spent three years working in transport and logistics at a truck transportation carrier company. Fortunately, she earned a scholarship from Faculty of Logistics, Burapha University, Chonburi, to pursue a doctoral degree in Civil Engineering (major transportation engineering) at Chulalongkorn University. She currently works as a lecturer at Faculty of Logistics, Burapha University.