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Container transport mode choice analysis with a binary logit model case study: Northeastern Thailand

Siradol Siridhara*[1)], Wilasinee Paonoi[2)], Sutthipong Meeyai[2)] and Vatanavongs Ratanavaraha[2)]

[1)]The Cluster of Logistics and Rail Engineering, Faculty of Engineering, Mahidol University, Nakhon Pathom 73170, Thailand
[2)]School of Transportation Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand

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Abstract

This research aimed to develop a model to forecast container transport mode choice for processed agricultural products including tapioca starch, rice, and sugar from northeastern Thailand. The study applied the stated preference survey technique and developed a binary logit model from the results. It was found that the factors influencing container transport mode choice include transport time, cost, punctuality, availability of scheduling staff, and distance from the factory to railway station. The stated preference questionnaires were distributed, and responses were obtained from 19 manufacturers in the study area. The binary logit model was developed and proved to fit the real dataset. It was able to provide forecast precision to a satisfactory level. The calibrated model was tested with various transport policies to demonstrate possible approaches to improve rail transport mode share and promote a more sustainable freight transportation option.

Keywords: Binary logit model, Stated preference survey, Container transport, Mode choice, Thailand

1. Introduction

The government of Thailand is focusing on reducing energy consumption in the transportation business by shifting to railway and water transportation. Railway infrastructure improvement programs have been planned or are underway throughout the country. Intermodal transportation strategies have been established with an aim to reduce logistic costs to under 15% of the gross domestic product [1-2]. It is essential to understand railway characteristics that offer transportation advantages over other modes and encourage modal shifts.

A key freight type that generates a large sum of revenue for the State Railway of Thailand (SRT) is containers. The majority of rail freight containers are used to transport agricultural and processed agricultural products including rice, tapioca, and sugar. The northeastern part of Thailand is a production base for these products, most of which are for export. The final domestic destinations are Laem Chabang, Si Chang, and Bangkok Ports. Recent interviews with the manufacturers show a decreasing trend of rail transport. Manufacturers who used or intended to use rail transport have turned to road with a few different reasons.

Research in the past addressed mode choice behavior and freight transport services [3] for various products. A great number of studies involved modeling freight transport for consumer products and electronic goods [3-14]. Only a few took into account grain container transport [15] and there have not been studies on rice, tapioca, and sugar. Researchers of similar studies often selected factors in experimental design using the conjoint analysis technique [6, 9], importance-performance analysis [16-17], and quadrant analysis [3]. Some also used exploratory factor analysis [18] and confirmatory analysis [5]. The latter applied some factors from the principle of service marketing mix, namely service, price, and location. This led to a strategy that responded to part of customers' needs [19-20].

This research focused on factors influencing manufacturers' mode choice and SRT's operation. A freight container transport mode choice model for the three specific agricultural products was developed. The influential factors were based on the full range of the principles of service marketing mix. Information on a detailed level was gathered from a literature review and interviews with some of the manufacturers in the study area. The research applied confirmatory factor analysis to explain the relationships between variables and factors while reducing measurement errors [21-22]. The expected outcomes included guiding principles for designing and developing service criteria that truly meet customers' needs. The ultimate goal was to encourage manufacturers to shift from road to rail transport to reduce transport costs and enhance the nation's trade competitiveness.

*Corresponding author. Tel.: +6689 667 5767
Email address: siradol.sir@mahidol.ac.th
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Figure 1 Northeastern Line Double Track Program, Phases 1 and 2 (Source: http://www.thailandtrains.com) [23]

2. Methodology

2.1 Study area

The SRT provides services for container freight, industrial freight including cement, liquefied petroleum gas (LPG), gasoline and fuel oil, bulk commodities such as iron ore, grains, coal, phosphate, bauxite and alumina, construction materials, and other miscellaneous commodities. This research focused on rice, tapioca, and sugar manufacturers from the northeastern region of Thailand since it is the major cultivation and manufacturing base of the country for these commodities. The products from this region also represent most of the nation's export volume. These processed agricultural products are low value-to-weight goods that are suitable for rail transport.

The government is implementing a double-track program to enhance railway transport capacity. The 2010 Railway Master Plan included all northeastern double-track railway projects in Phases 1 and 2 as is shown in Figure 1. The first phase involves improvement from Map Kabao Station in Saraburi, then the end point of the double-track section, to Thanon Chira Junction in Nakhon Ratchasima, continuing to Khon Kaen Station. The second phase would extend the double track to Nong Khai and branch out to the south to Ubon Ratchathani. This phase would also embrace the "new route" Kang Khoi – Lam Narai – Bua Yai Junction.

As the nationwide double-track railway projects were underway, it was assumed in this study that future rail freight transport activities would be taken on the completed double-track network of 14 stations, each of which is equipped with a container yard (CY).

2.2 Survey design

A government survey in 2018 showed 571 manufacturers producing rice, tapioca, and sugar in the northeastern region. Among these, 98 medium-to-large-sized manufacturers produced goods for export [16-17]. In this research, interviews were carried out with senior logistics or transport executives from some of these manufacturing firms. These executives have decision-making power to choose a mode of transport and set up relevant policies. The survey was mostly conducted by phone or mailed questionnaires along with a few personal in-depth interviews.

2.3 Survey tool

The population of this research was medium to large manufacturers, represented by their executive officers. The population size was rather small (98 manufacturers). The nature of generic variables in the utility function and labeled experimental design allowed a small stated preference choice dataset. It was suggested that as small as 50 observations were required to develop an efficient mode choice model [24-25]. Thus, data was needed from at least 9 executives, each of whom answered to 6 hypothetic scenarios for a total of 54 choice data points.

A self-administered questionnaire was designed for data collection. The questionnaire consisted of two parts. Part 1 comprised the fundamental data of the manufacturer such as products, daily capacity, final domestic destination, and current transport mode. Part 2 included the hypothetical scenario which presented two choices of transport under various conditions. The respondents were presented with different sets of 6 scenarios. They had to choose between road and rail for a given set of transport costs, times, and other factors.

2.4 Attribute selection

The researchers took into account the following factors from the in-depth interviews with the executives and from a literature review. The observed variables or attributes were identified in line with the "7P Market Mix" theory of

Table 1 The results of second-order confirmatory factor analysis

7P Market Mix	Indicators	Factor loadings
P1: Place	**Component 1: Location of the station**	**0.974**
	Convenient access to the station	0.997
	Railway station is located near factory	0.917
	Railway station is on the former transport line	0.902
P2: People	**Component 2: Service provider**	**0.945**
	Staff provide clear information and advice	0.980
	Staff's attentive and enthusiastic manners and willingness to serve customers	0.978
P3: Promotion	**Component 3: Service promotion**	**0.921**
	Advertisement and public announcement through various channels such as radio, television, print media and websites	0.964
	Sufficient insurance coverage for goods in case of loss or damage	0.952
	Discounts and promotions	0.942
P4: Product	**Component 4: Rail service**	**0.898**
	Punctuality and regularity of the rail transportation	0.819
	Availability of transportation and schedule management agency	0.920
	Container loading and unloading time	0.864
	Door-to-door service time	0.859
P5: Price	**Component 5: Fees and tariff**	**0.884**
	Proper distance-based transportation charges for each type of goods	0.991
	Proper container handling charges	0.998
P6: Process	**Component 6: Service process**	**0.758**
	Modern equipment and technology for goods deposit	0.989
	Multiple payment channels	0.954
	Online checking of the product status during transportation	0.971
P7: Physical evidence	**Component 7: Environment**	**0.701**
	Station cleanliness	0.960
	Area separation between passengers and cargo	0.908

service business [19-20]. As the preference survey was conducted, and the results were examined by the confirmatory factor analysis technique. It was found that 19 observed variables were indicators that affected all seven latent variables. These were also exogenous latent variables affecting the executives' decision to shift to rail transport. Since each of the variables carried factor loading coefficient values greater than 0.5, it was considered acceptable [21]. It should also be noted that any variables with the factor loading coefficient values more than 0.6 were considered good [22]. The study ranked indicators from the greatest to the smallest as follows:

1) Station Location (Place) had a factor loading coefficient value, β = 0.974, consisting of three observed variables: (1) convenient access to railway station, (2) railway station is near the factory, and (3) railway station on the current route.

2) Service Provider (People) had a factor loading coefficient value, β = 0.945, consisting of two observed variables: (1) staff ability to provide information/suggestions and answer questions, and (2) staff's attentiveness, enthusiasm and willingness to help.

3) Service Promotion (Promotion) had a factor loading coefficient value, β = 0.921, consisting of three observed variables: (1) public relations through various channels such as radio, television, printed media, and websites, (2) insurance, and (3) discounts and promotions.

4) Railway Service (Product) had a factor loading coefficient value, β = 0.898, consisting of four observed variables: (1) scheduling staff availability, (2) container handling time, (3) transport time from the origin to the destination, and (4) transport punctuality.

5) Fees and Tariff (Price) had a factor loading coefficient value, β = 0.884, consisting of two observed variables: (1) container handling fees, and (2) distance-based tariffs.

6) Service Process (Process) had a factor loading coefficient value, β = 0.758, consisting of three observed variables: (1) modern handling equipment and technology, (2) online status traceability, and (3) multiple channels to pay.

7) Environment (Physical evidence) had the smallest factor loading coefficient value, β = 0.701, consisting of two observed variables: (1) station cleanliness, and (2) separation between passengers and freight areas. Table 1 summarizes the statistical results from the factor analysis.

From the above analysis, it can be seen that the indicators involving Service Provider (P2), Service Promotion (P3), Service Process (P6), and Environment (P7) were variables with a nominal scale. The SRT must invest a large amount of its budget to improve these factors to an acceptable level. This would also require 5 to 10 years to completely develop them. Meanwhile, exogenous latent variables involving Station Location (P1), Service (P4), and Fees and Tariffs (P5) were numeric variables. In other words, these factors could be assigned attribute levels from available information. These factors were also specific to the rail mode. When the study draws its final conclusions, the SRT can establish guidelines in an improvement plan to achieve better and efficient freight rail service.

Observed variables were selected as inputs to the model by standardized weight of these indicators. The selected variables included convenient access to the station, availability of scheduling staff, transport punctuality, container handling time, transport time from the origin to the

Table 2 Attribute definitions

Name of attribute	Symbol	Description
Distance	DistA	Distance referred to the distance between the manufacturer's plant and the closest station in kilometers.
Scheduling	TTAB	Scheduling referred to the availability of the staff who schedule transport for each manufacturer. This was a dummy variable.
Punctuality	PunctA	Punctuality referred to the proportion of goods arriving at the destination on time in percentage.
Time	ODT	Time referred to transport and handling time from the origin factory to the final domestic destination where the shipper's responsibility ends, in hours.
Costs	ODC	Costs referred to transport and handling costs from the origin factory to the final domestic destination, in baht.

Table 3 Attributes and attribute levels of truck and rail transport

Attributes	Levels	Truck	Rail
Distance (kilometers)	1	Current level	15
	2		30
	3		45
Scheduling	1	Current level	Yes
	2		No
Punctuality (%)	1	Current level	100
	2		95
	3		90
Time (hours)	1	Current level	2 hours longer than truck
	2		3 hours longer than truck
	3		4 hours longer than truck
Costs (baht)	1	Current level	20 % lower than truck
	2		25% lower than truck
	3		30% lower than truck

destination, container handling fees, and distance-based tariffs. To reduce the complexity of the scenarios, container handling time and transport time from the origin to the destination were combined into a single variable "transport time". Container handling fees and distance-based tariffs were also combined into a variable "transport costs". Thus, the model development eventually relied on five variables, which are convenient access to the stations in the form of distance to the rail station, the availability of scheduling staff, transport punctuality, transport time, and transport costs. The first three were used as dummy variables. The other two were generic variables with units of hours and baht, where they were considered with equal sensitivity between truck and rail.

The factors that were likely to influence rail transport mode choice included distance from the plant to the station, transport scheduling, punctuality, transport time and transport cost. These factors could be adopted to established service policy or improve rail service in various aspects. The researchers defined the factors as follows in Table 2.

2.5 Orthogonal experimental design

In this study, a hypothetical questionnaire was created using the stated preference technique. Factors or "attributes" were defined from revealed preference questionnaires previously carried out with the selected group of manufacturers. The scenarios presented various levels of attributes for the respondents to choose the most satisfying choice from the available choice set [26-27]. Each attribute was assigned either two or three levels to represent possible transport conditions in the future as shown in Table 3. The respondents made decisions based on these characteristics of transport modes, which may become reality after the rail improvement program is in place. At the end, this would also reflect sensitivity to attributes in the utility function [24].

More attribute levels led to a larger number of the combinations of the scenarios that the respondents need to consider. All the main effects and the interaction of the variables could be analyzed by full factorial design [24, 27], but it would require a far greater number of combinations than a practical set upon which a respondent could make rational decisions. The researchers thus reduced the hypothetic scenarios to a reasonable number by fractional factorial design. SAS (student version) was used to analyze attribute levels and it was found that 100% D-efficiency could be achieved by 36 scenarios. These scenarios were constructed using the orthogonal design principle using N-gene software [28]. The questionnaires were divided into six sets. Each respondent completed only one of these sets, which contained only six questions or scenarios. This reduced the complexity of the questionnaires and helped respondents make rational decisions with small sets of data.

3. Relevant theories

3.1 Utility theory

Utility theory is used to explain consumer mode choice behavior based on microeconomic principles. The consumers will rationally make decision under budget constraints and upon different preferences, based on the assumption that the consumers receive the highest satisfaction or "utility" from consuming that product. The relationship between utility and factors affecting utility is represented in a utility function [24, 29-30].

The utility function is expressed in the following form:

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

where U_{in} is the utility of mode i gained by person of type n. V_{in} is the systematic component of the utility of mode i gained by person of type n, *and* ε_{in} is the disturbance (or random components) of the utility of mode i gained by person of type n.

Container freight mode share can be forecast from it utility which is based on independent variables affecting transport mode choice [31-32]. These variables represent various types of "costs", for instance, the distance from the factory to the railway station, punctuality, and shipping costs. The factors will be weighted by their importance. With utility theory, the utility function for truck and rail freight transport can be expressed as:

$$U_T = V_T + \varepsilon_T \tag{2}$$

$$U_R = V_R + \varepsilon_R \tag{3}$$

where V_T and V_R are linear parametric functions taking into account quantifiable characteristics of the respective modes. If we denote $\beta = [\beta_1, \beta_2, \dots, \beta_K]$ as a vector of K unknown parameters [30],

$$\begin{aligned} V_T &= \beta_1 x_{T1} + \beta_2 x_{T2} + \beta_3 x_{T3} + \dots + \beta_K x_{TK} \\ V_R &= \beta_1 x_{R1} + \beta_2 x_{R2} + \beta_3 x_{R3} + \dots + \beta_K x_{RK} \end{aligned} \tag{4}$$

3.1.1 Mode choice analysis by the binary logit model

The logit model was selected to estimate transport mode share between truck and rail [15, 31]. The principle of the logit model assumes that the random components of utilities or ε_{in} are independently and identically distributed (IID). The logit model is widely used as it takes a simple form and provides a unique estimation for a given set of variables and parameters. Providing all ε_{in} are IID, the model estimates the proportion of person of type-n using mode i as follows:

$$P_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}} \tag{5}$$

where $P_n(i)$ is the probability of executive of type n choosing mode i. V_{in} and V_{jn} are the deterministic parts in the utility function of mode i and j for executive of type n, and C_n is the set of available transport modes.

As the available transport modes are limited only to truck (T) and rail (R), the probability of the manufacturer choosing truck and rail can be estimated by the logit model which takes the binary form. To simplify the scenario where there is only one group of executives, the binary logit model takes the following forms:

$$P_T = \frac{1}{1 + e^{V_R - V_T}} \tag{6}$$

$$P_R = 1 - P_T \tag{7}$$

3.1.2 Parameter estimation

One of the most common methods to estimate parameters in the utility function is maximum likelihood [30]. The maximum likelihood function can be expressed as:

$$L(\beta) = \prod_{n=1}^{N} \prod_{i \in C_n} P\left(i \middle| x_{in}, \beta\right)^{d_{in}} \tag{8}$$

Thus, from the above equation, the log likelihood function is given as:

$$LL(\beta) = \sum_{n=1}^{N} \sum d_{in} \ln P\left(i \middle| x_{in}, \beta\right) \tag{9}$$

where N is the number of individuals in the random sample, $i \in C_n$ are alternatives in the choice set C for individual n. x_{in} is the vector of attributes associated with alternative i and individual n. d_{in} is an indicator variable equal to 1 if individual n selects alternative i, and 0 otherwise, and $P(i|x_{in}, \beta)$ is the probability of selecting alternative i given a sample of attributes x_{in}, and estimates β.

3.1.3 Goodness-of-fit test

The goodness-of-fit test is performed to validate the efficiency of the model in forecasting manufacturers' choices of transport. The Likelihood Ratio Index is an indicator used for comparing the goodness of fit of the theoretical model and the observed values. It takes the form of:

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{10}$$

where $LL(\beta)$ is the maximum log likelihood function, and $LL(0)$ is the log likelihood function where all parameters equal to zero. If the Likelihood Ratio Index (ρ^2) approaches 1, the model can explain the relationship between the variables and the outcomes.

The value ρ^2 cannot determine whether the parameters and forecast are biased. Every time a variable or "predictor" is added to the model, ρ^2 increases. Conversely, the adjusted likelihood ratio index, ρ^2, only increases if the new predictor improves the model more than expected by chance. Thus, it better reflects the goodness of fit of the model as illustrated by a number of previous studies [13, 16]. When a model consists of k parameters, the adjusted likelihood ratio index can be expressed as:

$$\bar{\rho}^2 = 1 - \frac{LL(\beta) - k}{LL(0)} \tag{11}$$

4. Results

4.1 Descriptive statistics

The stated preference questionnaires were distributed to 98 manufacturers. Responses were obtained from the

Table 4 Manufacturer characteristics

Information	Items	Number of Manufacturers				%
		Rice	Starch	Sugar	Total	
Manufacturer	Rice mill	7			7	36.84
	Starch factory		3		3	15.79
	Sugar factory			9	9	47.37
Domestic	Bangkok metropolitan region	4	2	2	8	25.00
Destination	Central region	3		4	7	21.88
	East/west regions			3	3	9.38
	Southern region	2		1	3	9.38
	Northern region	1	1		1	3.13
	Northeastern region	2		5	8	25.00
	Not for domestic sale	1		1	2	6.25
Current Transport Mode	Train	1			1	3.85
	Ship (inland)	1	1		2	7.69
	Ship (coastal)			4	4	15.38
	Truck	7	3	9	19	73.08

Table 5 Coefficients in transport utility functions

Attributes	Coefficients	t-ratio	p-value
Odt	-0.44364	-2.03	.0422
Odc	-0.00043	-2.76	.0057
Ttab	1.51888	2.42	.0156
PunctA	2.65689	3.69	.0002
DistA	1.13053	1.97	.0483
Number of observations			78
Log likelihood Function			-54.0398
Adjust Pseudo R^2			0.1475

executives of 19 manufacturing firms, which accounted for 19.38 percent of the total sample size. This number was sufficient for model development [3, 24-25]. Table 4 shows the distribution of the manufacturers by product, domestic destination and transport mode.

The sample contains more sugar manufacturers since there are a lot more sugar factories in the northeastern region than the other two types. Most products were for export, while some were reserved for domestic sales in the form of consumer products. The areas with the highest purchasing power were Metropolitan Bangkok and the northeastern region, followed by the central, eastern, western and southern regions, respectively. It was found that all executives favored trucks to transport and distribute goods. This was because they all had their own truck fleets. After the manufacturing and packaging process was completed, they could plan and manage transportation using their available resources. Additionally, the frequency of train service was unable to reasonably meet the executives' expectations.

4.2 Freight transport mode choice model

The results from the interviews with executives were analyzed to formulate a utility function. The function provided the preliminary concept of the factors influencing mode choice decisions and identified the development priority to create a mode shift to rail.

A total of 114 stated preference (SP) choice observations were collected. The researchers divided the SP data into two parts in a 70:30 proportion. The first 78 observations were used in model calibration and the other 36 observations were used for model validation. Coefficients in the utility function were determined and are shown in Table 5.

Thus, the utility function can be expressed as:

$$V_T = -(4.44364)Odt - (0.00043)Odc + (2.657)PunctA \quad (12)$$

$$V_R = (1.519)Ttab - (4.44364)Odt - (0.00043)Odc + (1.131)DistA + (2.657)PunctA \quad (13)$$

where V_T is the utility of truck transport, V_R is the utility of rail transport, *Ttab* is the availability of scheduling staff (dummy variable where 1 = yes and 0 = no), *Odt* is the transport time (hours), *Odc* is the transport costs (baht), *PunctA* is proportion of transport punctuality (dummy variable where 1 = 100% on time and 0 = otherwise), and *DistA* is the distance from the factory to the railway station (dummy variable where 1 = distance not greater than 15 kilometers, and 0 = otherwise).

Utility functions (12) and (13) did not show the alternative specific constant (ASC) with a .05 statistical significance. In other words, the ASC yielded t-statistics within the range of ±1.96, which resulted in its omission from the equations. This suggest that the executives did not particularly hold a negative attitude towards future rail transport. They merely focused on quantifiable factors and chose rational choices that best suited their needs. Additionally, it could also be inferred that the factors in the utility function captured most of the mode choice behavior for these commodities. Such an outcome was different from previous studies [8, 11-12, 15] in which sample groups were comprised of manufacturers as well as logistics and transport providers.

In summary, punctuality appears to be the most crucial factor the manufacturers would consider, followed by transport costs and staff assistance at the station. The factors

Table 6 Factors with significant effect to transport mode choice

Order	Attributes	Description	t-ratio
1	*PunctA*	Transport punctuality	3.69
2	*Odc*	Transport costs	-2.76
3	*Ttab*	Availability of scheduling staff	2.42
4	*Odt*	Transport time	-2.03
5	*DistA*	Distance from the factory to the railway station	1.97

Table 7 A set of hypothetical scenarios for the second executive

Scenarios	Truck mode			Rail mode				
	ODC	ODT	PunctA	TTAB	ODC	ODT	DistA	PunctA
1	12,000	6	0	1	8,400	10	0	0
2	12,000	5.5	1	1	9,000	7.5	0	1
3	12,000	6	1	1	9,600	9.5	0	1
4	12,000	5.5	0	0	8,400	8.5	1	0
5	12,000	6	0	0	9,000	10	0	0
6	12,000	6	1	1	9,600	8	0	1

with significant effect to the transport mode choice of the executives are ranked in Table 6 in their respective order.

4.3 Model validation

4.3.1 Coefficient signs

The signs of the coefficients were probably one of the most noticeable elements in model validation. If the sign suggested that the variable changes into the irrational direction with respect to the response variable, the model could not be sensibly applied to the real situation. The utility function from this study presented reasonable signs for all coefficients, i.e., positive signs for punctuality, availability of scheduling staff, and the distance not greater than 15 km, while the negative signs for transport costs and time.

4.3.2 Significance of the independent variables

The independent variables were examined to determine if they significantly affect the response variable. In other words, the coefficient of the variable of interest should not be close to zero in the linear utility function. This could be examined using t-statistics at the 95% level of confidence ($t_{0.95}$). If a t-statistic was in the critical value range of ±1.96, the coefficient of the variable would be considered not different from zero and the variable would not affect the utility. In this study, none of the t-statistics values in the model were in that range. It was then concluded that all variables have significant effects on utility.

4.3.3 Goodness-of-fit test

The goodness-of-fit test showed pseudo ρ^2 and adjusted pseudo ρ^2 of the model were 0.2021 and 0.1475 respectively. This indicated that the model could explain 14.75% of the variation in the response variable, which was considered low. However, it was found that truck to rail choice ratio is 1 to 1.3. It could be concluded that the model fitted the observed values even though, in some cases, ρ^2 may not be large [25], which was in line with previous studies [16, 31, 33-34].

The coefficients obtained from the analysis could be substituted into any sample set of data for validation. For example, transport utilities for the second executive under the second scenario, as shown in Table 7.

Systematic utilities could be calculated using eq. (12) and (13). Thus V_T = -4.943 and V_R = -3.022. The probabilities of the manufacturers choosing truck and rail transport were found to be 12.77% and 87.23% respectively. The calculation suggested that this executive would most likely choose rail over truck transport, which was consistent with the actual choice.

4.3.4 Forecast accuracy

Finally, the accuracy of the model was examined in the form of percentage of correct forecasts. The model was tested against six choice tasks for a total of 36 scenarios. It yielded 26 correct forecasts, accounting for 72.2% of accuracy. The verification matrix is shown in Table 8.

Table 8 Verification of forecast accuracy

Predicted choice	Observed choice		% Correct
	Truck	Rail	
Truck	3	3	= 3/6 (50.0%)
Rail	7	23	= 23/30 (76.7%)
Total			= 26/36 (72.2%)

5. Model application

The binary logit model was developed to forecast the transport mode choice made by the manufacturers' decision makers, providing two modes were available. The model was essentially used for short-term forecasting including freight transport policy in the near future as detailed below.

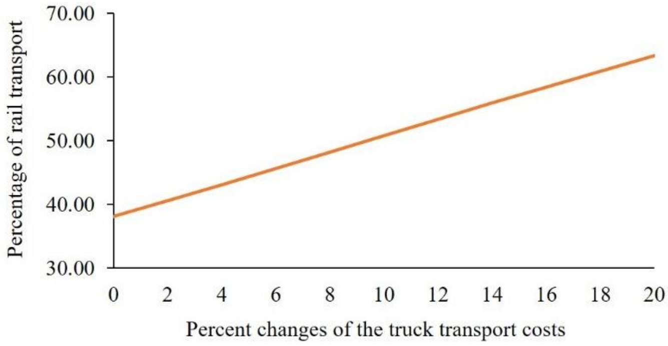

Figure 2 Effects of the truck transport costs to percentage of rail transport.

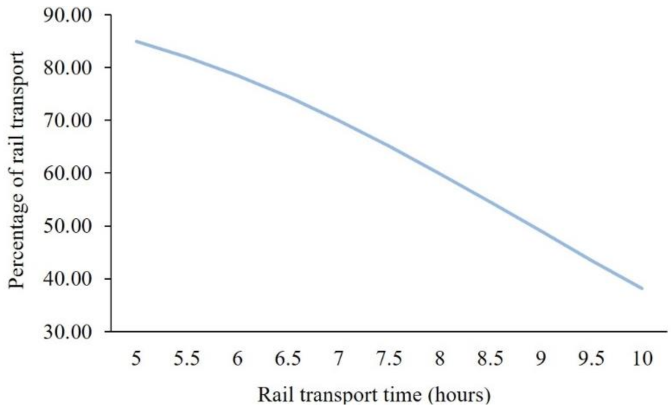

Figure 3 Effect of rail transport time to percentage of rail transport.

5.1 Impact to transport policy

The private sector's choice of transport depended on the quality of service of the available transport modes in the future. The model would be used to calculate mode share under different sets of transport characteristics. The impact of varying these characteristics would be appreciated through the mode shift forecasted from the model. The relevant government agencies could design and manage freight transport operations of each mode to actually meet the needs of the target customers.

Sensitivity analysis was performed to learn the impact of each variable to the executives' mode choice. It would also suggest the critical variables that needed to be focused on to improve the transport operation. This research set up case studies for truck and rail container transport for the following sensitivity analysis.

5.1.1 Truck transport costs

Although truck transport incurred higher costs per tonne-kilometer, it was normally preferred as it held advantages in the form of accessibility and convenience. This resulted in traffic congestion that even increased the transport costs further. This study assumed the current truck transport costs of 12,000 baht per 1 TEU. Disregarding inflation, truck transport costs were 2% to 20% higher, while all other variables were held constant i.e., *Odt* = 6, *Odc* = 12,000 and *PunctA* = 0. Using eq. (12) and (13), the percentage of truck transport at different price levels are shown in Figure 2.

Sensitivity analysis was performed using Scenario 5 of the 2nd executive as shown in Table 7. It was assumed that truck transport time was 6 hours with a transport costs of 12,000 baht/TEU, which would increase by up to 20% in the near future. An increment of 2% increase was applied to the sensitivity test. The rail transport time was assumed to be 10 hours with transport costs of 9,000 baht/TEU. The results are shown in Figure 2.

The steep slope in Figure 2 shows that the rail mode share was highly sensitive to the transport costs. A small increase in the truck transport price greatly influenced the mode choice decision. A 10% increase in the truck transport prices would reduce the truck mode share to just under 50%, which meant more volume would be shifted to rails.

5.1.2 Rail transport time

In this study, the rail and truck transport times were both assumed 6 hours. In such a case, rail would gain a 78.41% market share. If rail transport reduced its transport time by 30 minutes to 1 hour, the mode share would increase to 81.93% and 84.99%, respectively, as shown in Figure 3. This reflected that rail transport time also had a great influence on the mode choice decision, similar to the transport costs.

5.1.3 Reliability

Rail transport reliability was assumed between 90 and 100% while all other factors were constant. The analysis showed that if the railway improved reliability to 95%, it would get 35.04% market share. If the reliability was improved to 100%, the market share would rise to 38.12% as shown in Figure 4. Moreover, if a railway station was located within 30 kilometers from the factory, the probability of choosing rail transport would go up to 65.61% at a reliability of 100%, as shown in Figure 5.

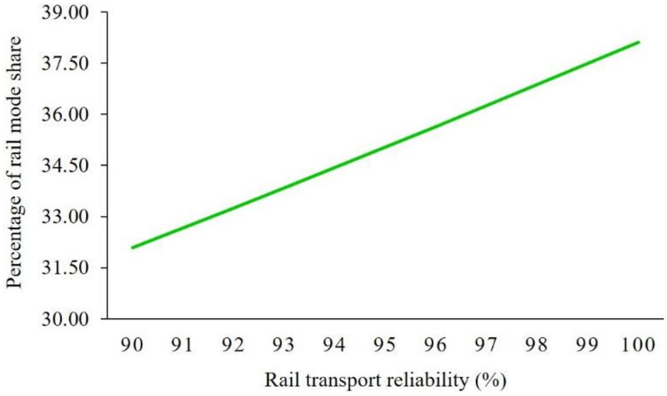

Figure 4 Effect of rail transport reliability to percentage of rail transport.

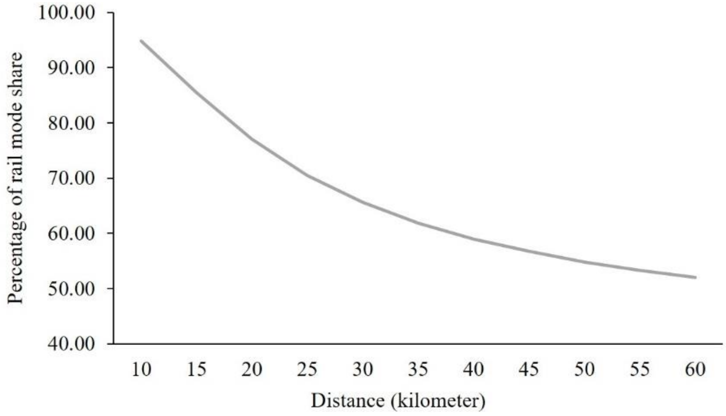

Figure 5 Probability of choosing rail transport when the railway station was located within 30 kilometers from the factory.

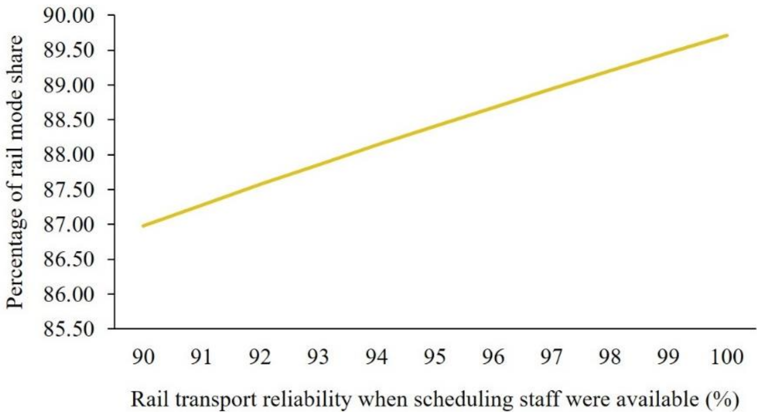

Figure 6 Probability of choosing rail transport when the railway station was located within 30 kilometers from the factory and scheduling staff were available.

5.1.4 Scheduling staff availability

From the previous scenarios, further assumptions were made that scheduling staff were available at all container stations. It was found that the availability of this staff significantly encouraged the firms to transport by rail. If the railway station was located closer than 30 kilometers from the factory, the rail transport reliability was 100% and the scheduling staff were available and efficient, the rail mode would get up to 89.70% market share as shown in Figure 6.

5.2 Effects of rail transport attributes

It can be concluded from the analysis that factors significantly affecting mode choice decision included time, costs, distance from factory to station, reliability, and availability of scheduling staff. This could be envisioned in further details as follows:

1) Transport time and costs were the most important factors to transport mode choice. These two variables were included in the utility function with great weights. With all others being equal, the manufacturers would choose an alternative with the least transport costs and time.

2) Distance to the closest railway station was another factor influencing mode choice decision. If the manufacturer was located nearer to a station, the executive had a greater

tendency to choose the rail mode. When it was located further than 30 kilometers from the station, trucks appeared to be the more preferable choice.

3) Reliability was almost as important as time and costs. Goods must be delivered to customers in a perfect condition and in timely manner as specified in the sales contract. The executives put importance on transport reliability to fulfill this objective. If the SRT could provide reliability at the same level as trucks, combined advantages of reliability and transport costs would encourage more manufacturers to choose the rail mode.

4) Availability of scheduling staff was among the factors influencing mode choice decisions. This factor gave manufacturers better control over their manufacturing plans, resource management, transport frequency, and transport mode split. In the past, some manufacturers where distracted by unclear information and inefficient coordination. This caused containers to miss their scheduled departure and were left behind. Customers did not receive the goods and the manufacturers lost money. Providing better scheduling coordination and information would increase the manufacturers' confidence in using rail transport.

6. Conclusions and recommendations

The study focused on agricultural product container freight transport from northeastern Thailand to Laem Chabang and other domestic destinations. It aimed to identify key factors of success to create a mode shift from road to rail after the SRT's double track program is implemented.

The research identified five potential factors that significantly affect mode share. From the manufacturers' point of view, the decision to shift to rail transport depended largely on punctuality followed by the transport costs. The results also revealed the significance of staff assistance at the station. Transport time played an important role, although it appeared not as crucial as punctuality and cost factors. Lastly the distance to the station was not a factor that can be directly affected by operational improvement, but could be addressed at a planning level where container yard locations would be located to meet the customers' needs.

With the right improvement plan, the rail mode share for sugar, rice, and tapioca containers could target more than 80% of the total demand volume. However, it is important to emphasize that this research presents findings from the demand side. The SRT would have to perform cost-benefit evaluation as well as supply-side considerations before making any final decisions on their rail freight strategic plan.

Further studies on this topic may be carried out using the following approaches:

1) Sample size for both a revealed preference (RP) and stated preference (SP) [9] survey should be enlarged to include third-party and fourth-party logistics. Additionally, the study should involve consumer products and other key types of goods that contribute to large tonne-km values of transport to better estimate the operational capacity that the SRT has to prepare.

2) The respondents may have been confused by the set of scenarios in the stated preference survey. Care must be taken in the questionnaire design to reduce complexity and confusion to ensure accurate responses.

3) The value of time to move freight and the manufacturer's willingness to pay should be investigated in the subsequent studies. With these values, the policy makers will better envision the structure and relationships between various types of service quality and the needs of the potential customers. As a result, decision will be systematically made and policies will be established with more confidence.

4) The model verification still shows some forecast errors. This was probably because the three industries used slightly different criteria in choosing their mode of transport where one single model failed to perfectly explain the behavior. The model could have been split into three sub-models. However, each sub-model would have to rely on a very small sample size from each industry and this might lead to larger errors. A mixed logit model is considered a feasible alternative, which will be explored at a later stage.

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