Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2019) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2019 Mumbai 26-31 May 2019

Two Levels Modelling of Container Choosing and Mode Choice between Road and Rail for Increasing the Containerized Rail Modal Share

Sayed Sina Mohria, Hossein Haghshenas[b]*, Vahid Salehi[c]

[a] M.Sc. graduate of Transportation Planning, Department of Transportation Engineering, Isfahan University of Technology, Isfahan, Iran
[b] Assistant Professor, Department of Transportation Engineering, Isfahan University of Technology, Isfahan, Iran
[c] M.Sc. Transportation Planning, Department of Transportation Engineering, Isfahan University of Technology, Isfahan, Iran

Abstract

Despite many advantages of containerized transport, a large percentage of import and export cargoes travel the inland distance in a non-containerized road transport form. The main objective of this study is to identify the important factors that can increase the share of containerized rail transport in the aggregated level and use revealed preference method. This objective is pursued by two stages of modeling, by first developing a choice model for the use of container as the mean of transport with decision tree algorithms, and then by developing a mode choice model for containerized inland transport. In the first stage, the cost of containerized transport and being a port in destination flows were found to be the most important variables that can be changed by policies to encourage the cargo owners to use the containerized mode of transport. In the second stage, Assessing the elasticity of these variables in the best model showed that three variables of road transport time, rail transport time, and rail/road transport cost ratio, increase containerized rail transport share. Thus reducing the cost of rail transport of containerized cargoes in long-distance routes leading to national ports can significantly improve the share of containerized rail transport.

Keywords: **:** Containerized transport; Mode choice; Railway; Freight transport; Iran; mode choosing.

1. Introduction

The multimodal freight transportation can contain the advantages of different transportation modes to reduce the cost and time and increased the safety and accessibility of freight transportation by using the intermodal containers. The reduction of imbalance in the development of the different transport modes and to transport freight to more sustainable modes like rail is a highly important policy for the freight sectors' sustainable developments (*1*). Also, the development of intermodal transport has played a major part in the collection a bigger share of the freight transport market (*2*, *3*). Elbert and Seikowsky (2017) have proved that the main facilitator to increase intermodal share are for instance working conditions of truck drivers, environmental constraints, and high fuel prices, respectively, whereas, low fuel prices act as a barrier (*4*). The major advantages of intermodal and containerized transport have increased the global interest to use freight containerized transportation, so that the global containerized trade has grown from 49 million TEU in 1996 to 181 million TEU in 2016 (*5*).

Early studies on freight demand analysis were conducted by Morton (1969), Boyer (1977) and Levine (1977) who used aggregated logit based on linear logarithmic regression. In these studies, the dependent variable was the proportion of freight transport modes, and independent variables were the price of method and features of transport modes. Considering fixed characteristics for transport modes and similarity of opposing elasticities caused by linear structure have been mentioned as weaknesses of these models (*6-8*). However, the study of Quandt and Baumol (1966) is one of the earliest and simplest research in this literature. In their proposed approach, freight demand in each mode only depends on features of the same mode and those of the best available mode, so changes in features of a certain mode do not affect the demand for other modes(*9*). Cullinane and Toy (2000) identified the mode choice decision factors that were previously reported by other studies by using stated preference method. This study indicated that most repeated variables in 75 assessed studies were five variables of cost, speed, time reliability, freight characteristics, and services (*10*). Arencibia and et al. (2015) have analyzed the demand for freight transport in a context of modal choice using a collected stated preference data and mixed logit models. Finally, willingness to pay for a better level of service and the elasticity of the choice probabilities for different attributes have been selected for the best model (*11*). Rangaraj (2003) analyzed the effect of pricing strategies in mode choice decision. The spatial imbalance of the supply and demand functions causes empty movement of vehicles, and the time imbalance of the supply and demand functions causes the fleet to stop in the station, and both of these events increase costs. The type of freight in this study was containerized cargo which was being transported by road, railway or a combination of both. In this study, the optimal price was calculated by using an optimization model with the objective function of maximizing the profit of the company (*12*).

Fariz et al. (2008) created different mode choice models for the railway, road and combined transport methods for the Switzerland and for four categories of domestic, import, export and transit cargos. The information was collected from 97 cargo transport companies using the stated preference method. In all models, the cost and reliability variables entered into the model and in the domestic transport model, in addition to the mentioned variables, the travel time was also found to be important. Furthermore, delivery time and cost were identified as the most important features in the choice of transport (*13*). Also, Larranaga et al. 2016 have been suggested that increasing the reliability of intermodal alternatives will have more effects than costs reductions (*14*). Shen (2012) estimated the share of road and rail transport in transit of cereals (including grain, barley, maize, etc.) in America by using the dual and regression mode choice models based on information about the year 2002. The used information included 11 origins and 22 destinations, and only those origins and destinations that used both railway and road systems to receive and send cargo were considered in the model. The considered variables included characteristics of freight, network, and fuel. In the end, the relative differences of estimation of Logit and regression model with the observed values were compared; these differences, which were 0.74 and 1.75 for the road and 1.38 and 2.14 for the railway, showed that Logit model yield better estimations (*15*). Shi et al. (2012) assessed the tariffs of rail transport based on price elasticity. In this study, the cargo was divided into bulk goods and packable goods. The study area was divided into N sections based on regional divisions, and the flow between these sections was evaluated. This study reported that correcting the railway tariff is not enough and the tariff of the rival mode (road transport) must also be considered. This study also examined the GPD variation and concluded that for some cargo types the transport always increases with the growth of GDP, but for others, as GDP increases, transport first increases but after a point it starts to decline (*16*). Reis (2014) has focused on long-distance services using an agent-based model to simulating and variables like price, transit time, reliability and flexibility. Then, it's been shown that just price could explain the freight forwarder choice for intermodality (*17*). Shinghal and Fowkes (2002) used the data collected through the stated preference method in India to study the mode choice decision for cargo transport in that country. This study proposed 4 options or modes of transport: road (the current situation), the new road service, the combined container service and the railway service (the express service). According to obtained results, valuable cargos were associated with the lowest interest in rail transport, and there was also no interest to transport export cargos through railroads. The frequency of service was also found to be one of the important factors in mode choice decision, especially for the group of industrial cargos (*18*). Ravibabu (2013) developed the mode choice model of exports for the Bombay-Delhi corridor in India. In this study, 3 types of transport (containerized transport through road, containerized transport through railway and bulk transport through road) were considered. The needed information was collected through 124 questionnaires from cargo owners as well as terminals and export companies. He concluded that the cost and time parameters are more important than other parameters and need to be corrected to increase the containerized transport. (*19*). Blauwens et al. (2006) were the first authors to assess mode choice decision for transport of containerized cargo between ports and inland terminals of Europe. These authors assessed the effect of different policies in the shift of containerized cargo from road to the inland railway and water routes in a corridor between Antwerp in Belgium and inland terminals of Germany (*20*). Feo-Valero et al. (2011) used the data collected through the stated preference method and the mixed logit method to develop a mode choice model (between road and railway) for transport of containerized cargo between the ports and inland terminals of Spain. The most important variables with the greatest effect in the increase in the share of the rail transport were found to be: rail transport cost, railway travel time, and frequency of rail freight (*21*).

Abdelwahab and Sayed (1999) have compared the efficiency of the neural network model in vehicle selection (truck or train) with that of logit and probit models. Their study has reported that neural network models are as efficient as logit and probit models (*22*). Sayed and Razavi (2000) have also compared the efficiency of neural networks with that of neuro-fuzzy algorithms and logit models, and have shown that data mining algorithms have the same classification accuracy as logit model (*23*). Tortum et al. (2009) have also evaluated the performance of logit model, neural network, and fuzzy neural network in modeling the vehicle selection for inter-city transport in four different countries. This research has reported that neuro-fuzzy algorithm is the best means of selection (*24*). Xie et al. (2003) have used logit model, decision trees, and neural networks to model the vehicle selection decisions made by travelers before business trips. The dependent variables used in their models were five different modes of travel, and their results showed that the decision tree could outperform the logit model (*25*). Rashidi and Mohammedan (2011) have also used CHAID decision trees in a hierarchical setup to predict the frequency of family travels and their vehicle of choice (*26*).

Comparing the shares of rail, road, and air transit in Iran shows that more than 90% of freights are being transported through roads and the share of rail transport is about 10%. In the case of containerized cargos, of total 6.5 million tons of cargo transported in 2014 via roads and railways, the share of the railway is just about 7% (0.5 million tons). Thus, the general weakness of system of containerized transport in Iran and ineptitude of the national railway system to handle even these low amounts of containerized transport highlight the necessity of this study for improvement of the system of containerized rail transport.

The main concern of this study is to identify and analyze the factors that can increase the share of containerized rail transport. Increasing the total rate of containerized transport while improving the desirability of railway system for the transit of containerized cargos can lead to increase in the share of containerized rail transport. In Iran, cargo owners select the mean of transport by evaluating factors such as the total cost of containerized transport (including the costs of transit and demurrage, the cost of returning empty containers, etc.), the cost of non-containerized transport, the shortage of empty containers, the probability of damage to cargo, and the facilities available at origin and destination. So in this study, some most significant differences between these two transport options (containerized and not- containerized) are analyzed as study variables. One of the most widely used methods of decision problem modeling is the decision tree. In this study, the decision tree is used to identify the most important variables affecting the choice of the container as the mean of transport in Iran, and the results are used to provide some proposals to improve the performance of containerized rail transport in this country. Application of mode choice models for the movement of containerized cargos leads to the identification of the most important variables influencing the choice of mode of transport, and determination of effective solutions for the improvement of most important mode choice decision variables obtained by the sensitivity analysis provides an approach for increasing the demand for containerized transport via railroad.

After this introduction, in Section 2, the whole methodologies used in the paper, are presented. In Section 3, firstly, the model application is done then, results are described, and finally, in Section 4 conclusions are indicated.

2. Methodology

This section of the study describes the used decision tree models and how they operate and then explains the stochastic mode choice modeling via the Logit function method.

2.1. Decision tree classification

The widely-known classification techniques include Bayesian classifiers, decision trees, SVM algorithms, conditional classifiers, regression methods, similarity-based classifiers, neural networks, genetic and fuzzy algorithms. The most advantages of decision tree classification method are listed below (*27*):

- ✓ This method is easy to understand

- ✓ This method is easily converted to a set of production rules
- ✓ This method can classify both numerical and categorical data
- ✓ This method has a desirable adjustability and accuracy
- ✓ There are no a leading assumptions about the nature of the data

2.2. Attribute selection criteria

The most common univariate splitting criteria considered for building the decision trees are briefly introduced below (*28-30*).

- Information Gain

Information Gain criteria is one of the most common measures used for building decision trees. This measure is itself based on another measure called entropy.

$$Information\ Gain(A) = Entropy(D) - Entropy_A(D) \tag{1}$$

In this formula, which calculates the information gain of attribute *A*, *D* denotes the data set, and:

$$Entropy(D) = -\sum_{i=1}^{c} P_i \times log_2(P_i) \tag{2}$$

$$Entropy_A(D) = -\sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Entropy(D_j) \tag{3}$$

In Equations (2) and (3), Pi is the probability of a sample belonging to the class *i*, *C* denotes the number of class labels in the dataset, *V* denotes the number of outcomes in the domain of attribute *A* (*n* values for a given attribute), and D_j represents that part of the primary data whose attribute has the value V_j. Also, $|D|$ denotes the size of the dataset *D*.

- GINI Index

The GINI Index of dataset *D* could be defined as Equation (4) (*29*):

$$Gini(D) = 1 - \sum_{i=1}^{c} P_i^2 \tag{4}$$

where *C* is the number of predefined classes in the dataset, and P_i is the probability of a sample belonging to the class *i*. the quality of each split on an attribute into *k* subsets D_i calculate with Equation (5) (*29*).

$$Gini_{spilit} = \sum_{i=1}^{k} \frac{|D_i|}{|D|} * Gini(D_i) \tag{5}$$

$|D_i|$ is the number of samples in subset *i* and $|D|$ is the number of samples in the given node. The $Gini_{spilit}$ is calculated for all attributes, and the attributes, with the minimum obtained value, must be selected for the current node of the decision tree. We can also select the attribute that maximizes the degree of impurity; this parameter can be calculated with Equation (6).

$$\mathrm{Gini(A) = Gini(D) - \ Gini_{spilit,A}(D)} \tag{6}$$

- Gain Ratio

Gain Ratio, which in fact normalizes the information gain, as follows (*31*):

$$GainRatio_A(D) = \frac{InformationGain\ (A)}{Entropy_A(D)} \tag{7}$$

When the denominator of above formula is zero, this criterion is not definable. The use of Gain Ratio provides the model with the more levels of accuracy and sophistication than those provided by Information Gain.

The other univariate splitting criteria include Likelihood Ratio (*32*), DKM Criterion (*33*), Distance Measure (*34*), Twoing Criterion (*35*), Orthogonal Criterion (*36*), AUC Splitting Criteria (*37*) and etc.

2.3. Decision tree algorithms

There are several algorithms for building decision trees, the most popular decision trees induction algorithms are discussed below.

- CART algorithm

This algorithm constructs a binary decision tree, where each internal node has exactly two outgoing edges (*35*). This algorithm uses information gain and Gini Index as selection criteria and also utilizes a pruning technique. The important feature of CARD is its ability to generate regression trees where leaves estimate a real number instead of a class label (*30*).

- CHAID algorithm

Since 1974, researchers of applied statistics have developed several algorithms specifically designed to build decision trees; these included THAID, MAID, AID and CHAID algorithms. CHAID algorithm was originally designed to handle nominal variables only. This algorithm can use different statistical tests based on the type of class label. This algorithm terminates when it when one of the following conditions is fulfilled:

- ✓ A predefined maximum tree depth is reached
- ✓ The number of samples in the current node is less than a defined minimum

Unlike the CART algorithm, in this algorithm, each node can be branched into more than two nodes. The CHAID algorithm does not perform any pruning technique (*30*).

- QUEST algorithm

This algorithm provides a dual classification approach for building decision trees. This technique has been developed to shorten the time of building CART trees and the skew of their solutions in the presence of continuous descriptive variables. QUEST uses a set of rules based on tests of significance to evaluate the descriptive variable determining the split. In this method, homogeneity of data at each node is calculated based on inter-group and intra-group variances and the corresponding F-statistics (*38*).

- C5 algorithm

C5 algorithm is a modified version of C4.5 and ID3 algorithms (*39*). It arranges the nodes based on their Information Gain and is a common tool for selecting the split attribute in tree development process (*40*). In this method, sample homogeneity is represented by entropy measure. So to calculate the information gain, we need first to calculate the entropy.

$$Entropy(D) = -\sum_{i=1}^{c} P_i \times \log_2(P_i)\ ^{s} \tag{8}$$

Entropy represents the quality of data with respect to a given option, and information gain determines the effect of an attribute in the classification process. Information Gain (D, A) that relate to attribute A and data D is calculated via the following formula:

$$Gain(D, A) = Entropy(D) - \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Entropy(D_j)^s \qquad (9)$$

Each attribute appears only once in each tree branch.

2.4. Structure of the Binary Logit Model

In stochastic mode choice models, it is assumed that cargo owner considers the desirability of each mode of transport, which is defined as a function of the mode's features and the cargo's characteristics. The desirability of option (i) for the individual (n) has an invisible part that is random because we cannot have full access to information about all factors affecting the decision-makers and decision-making process (*41*). In cases where there are only two options, option one is chosen only when it is more desirable for individual n than option two:

$$U_{1n} \geq U_{2n} = V_{1n} + e_{1n} \geq V_{2n} + e_{2n} \qquad (10)$$

$$P_n(1) = \frac{e^{v_{1n}}}{e^{v_{1n}} + e^{v_{2n}}} \qquad (11)$$

$P_n(1)$: the probability of option 1 being chosen by individual (n)
V_{1n}: the visible part of the desirability of option 1 for individual (n)
V_{2n}: the visible part of the desirability of option 2 for individual (n)

2.5. Evaluation of the logit models

There are different tests for evaluation of the logit model such as assessing the reasonability of the model's coefficients, assessing the ρ^2 and ρ_C^2 indices to evaluate the fitness of the model similar to linear processual models, conducting t-test for determining the importance of each explanatory variable at different levels of confidence, and performing the chi-square test to evaluate the fitness of the set of variables in the model. The mentioned reasonability test checks the reasonability of the relationship between independent and dependent variables. For example, increased rail travel time must decrease the desirability of this mode of transport, so the positive sign of the rail travel time variable in the railway utility function is by no means reasonable (*41*).

3. Model application and results

Figure 1 shows the framework of different states of containerized transport. In upper level (A), cargo owners face the issue of choosing between containerized or non-containerized method for transporting their cargo. In the case of choosing the containerized mode, in the lower level (B), cargo owners must choose the mode of containerized transport.

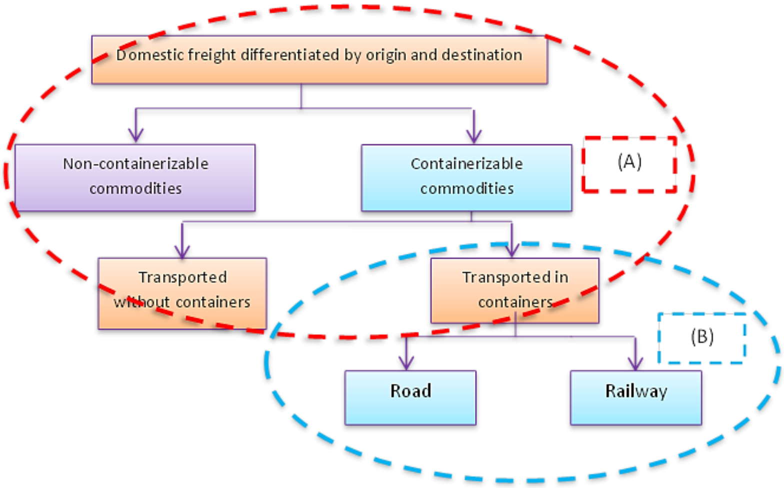

Figure 1 the structure of the container choice model and the mode choice model for containerized transport

In this study, road transport is divided into two categories: transport of containerizable cargos and transport of non-containerizable cargos. Transport of containerizable cargos is Transport of those cargos that are either currently being transported in a containerized form or have been previously transported from/to the origin/destination in containers in volumes of more than 100 tons. Also two models are proposed. Model A is called container choice model and model B is called mode choice model. The independent variables are considered for developing these models are summarized in Table 1. The variables are extracted from the comments of cargo owners, transport companies, experts, characteristics of the transport mode in the country, and the nature of the cargoes. e of their cargo and characteristics of the company. The procedures are used for constructing the variables are explained in next sections.

Table 1 Variables defined to build the decision tree and mode choice model

Model	No.	Variable name	Method of determination
A	1	Tariff of containerized road transport	Analysis of bills of lading (2013), customs data (2013), and data collected from trading companies, cargo owners, and ports notifications about the cost of demurrage, tariffs, etc.
A	2	Tariff of non-containerized road transport	Analysis of bills of lading, data of customs offices, and data collected from trading companies for the year 2013
A	3	Weight and value of exports and imports of origin/destination province	Import-export reports (2013) published by customs administration
A	4	Perishable commodities	Analysis of bills of lading with emphasis on the type of cargo and defining it as a binary variable
A	5	Breakable commodities	Analysis of bills of lading with emphasis on the type of cargo and defining it as a binary variable
A	6	Valuable commodities	Analysis of data from customs offices for cargos valued more than 4$/kg and defining these cargos as valuable with a binary variable
A	7	origin/destination being a port	Identification of eligible port cities based on reports published by Iran's shipping and ports organization
A	8	origin/destination being an international border	Identification of eligible border cities using GIS maps
A	9	transport distance	The distance between the origin and destination of the trip

Model	No.	Variable name	Method of determination
B	1	Rail transport time	Geographical information of Iran’s routes
B	2	Road transport time	departure/arrival timetables reported by railway organization
B	3	Tariff of containerized road transport	Identification and analysis of all costs associated with road transport
B	4	Tariff of containerized rail transport	Identification and analysis of all costs associated with rail transport
B	5	Cost of changing transport mode from railway to road	The ratio of the cost of rail transport to the cost of road transport for containerized cargos
B	6	the origin or destination being a port	Identification of the port cities based on the information of Iran’s shipping and ports organization
B	7	Transport distance (road)	the map of Iran’s roads
B	8	Bulk loads	Identification of border cities using the GIS map of Iran’s roads
B	9	High traffic origin-destination	Customs import and export data for the year 2014
B	10	Railway accessibility	map of Iran’s railway network and stations
B	11	The presence or absence of railway station in the city	map of Iran’s railway network and stations
B	12	Presence of active rail transport hub at the origin/destination	Assessment of the railway tonnage produced or absorbed by different cities

3.1. Container choice model (model A)

The dependent variable is considered to be a discrete variable with two values: one (containerized transport) and zero (non-containerized transport). Two important variable Tariff of containerized road transport and Tariff of non-containerized road transport are prepared as follow:

- Tariff of containerized road transport

Overall tariff of containerized transport per tonne-km of transport consists of the cost of container loading at the origin, the cost of transferring the container to the destination, the cost of container unloading at the destination and the cost of transferring the empty container, (according to transport experts, this cost was considered to be as much as 70% of the transport cost for loaded container). In cases where the round-trip time is longer than container lease time, a demurrage cost must also be added.

- Tariff of non-containerized road transport

The tariff of non-containerized transport (in ton.kilometer) depend on the loading cost at the origin, the transferring cost, unloading cost and a strip cost if container striped at the maritime border.

3.2. Results of Container choice model (model A)

To build the decision tree, a database containing 20,762 rows of data was imported into the SPSS CLEMENTINE 12 software. All decision tree models were constructed through two phases, training and testing, using C&R, QUEST, CHAID and C5 algorithms. Results obtained by each algorithm are shown in Table 2. The fourth column of this table shows the most important variables and their impact on the model.

Table 2 an instance of data prepared for decision tree-based modeling

No.	decision tree algorithm	Depth of the tree	The effective variables (the extent of effect)	Correct prediction (%)	
				training	testing
1	C&R	4	Perishable commodities (49%), distance (26%), destination (15%), type of commodity (8%) origin (2%)	78.11	70.24
2	CHAID	5	Perishable commodities (35%), breakable commodities (32%), distance (20%), the value of exports of origin (5%)	78.16	71.01
3	QUEST	5	the weight of exports of origin (37%), the value of exports of origin (36%), type of commodity (13%) perishable commodities (10%)	76.61	69.18
4	C5	8	Perishable commodities (30%), container tariffs (23%), distance (18%), breakable commodities (11%), destination (7%), destination being a port (7%), valuable commodities (2%)	79.87	71.89
5	Pruned C5	5	Container tariffs (29%), destination being a port (26%), distance (21%), perishable commodities (21%) and value of export of destination (4%)	78.18	71.45

Based on these results, the pruned C5 model has provided the best combination of accuracy and simplicity and the variables identified by this method seem to be more desirable; meanwhile, the highest accuracy has been achieved by typical C5 model. These results showed that the model developed by C5 algorithm is the best model for identifying the most important attributes in containerized or non-containerized transport of cargo. The model developed via pruned C5 algorithm is shown in Figure 2.

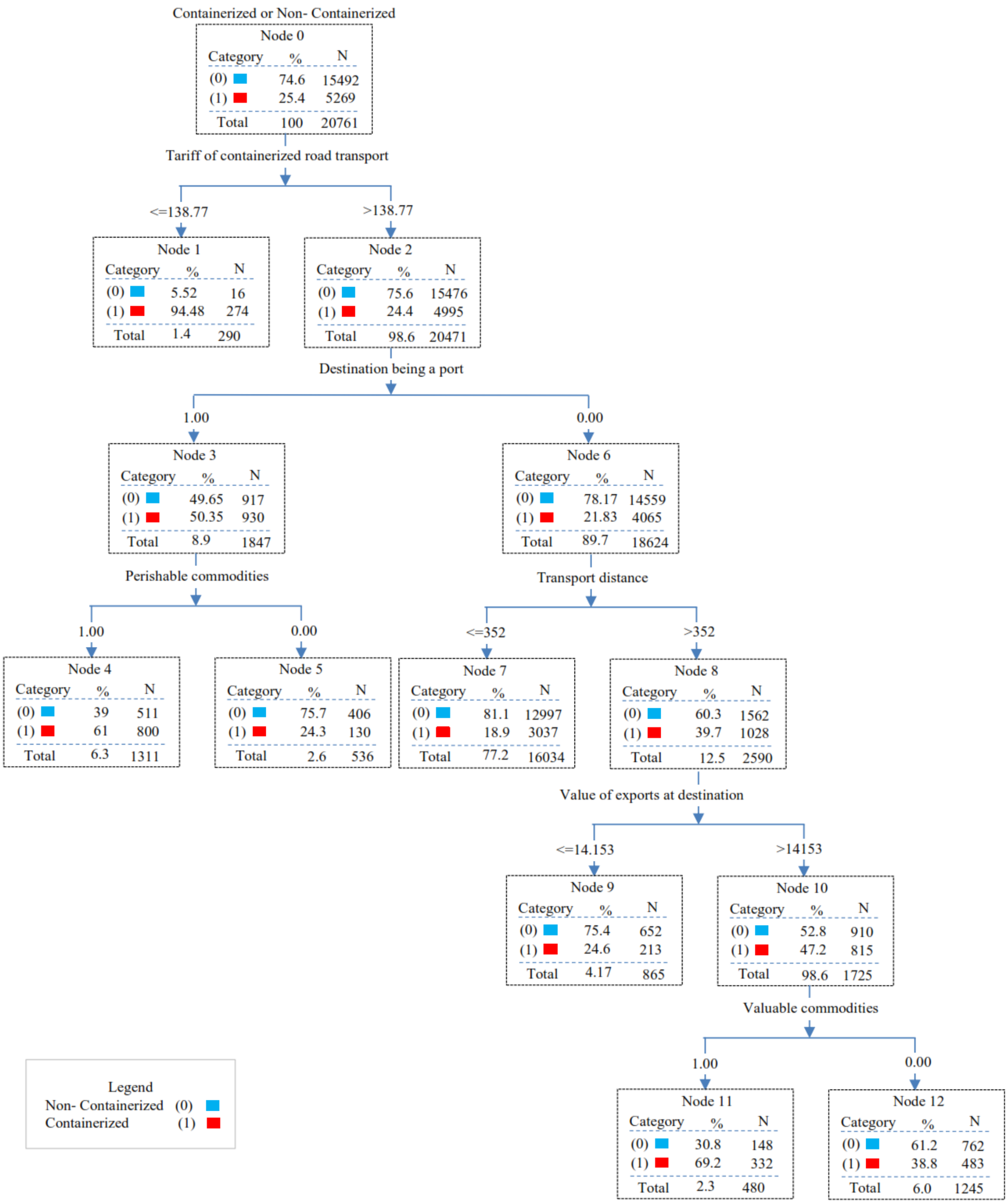

Figure 2 An overview of the decision tree model developed via pruned C5 method

3.3. Mode choice model (model B)

In this model, the dependent variable is Share of containerized rail transport. The variable is the ratio of rail transport to road transport for containerized cargos in each origin-destination. The important and unfamiliar variables are described in below with more details.

- Rail transport time

One of the most important factors in selecting the mean of transport is the resulting time of delivery, and according to inputs of experts, one of the most important reasons behind the undesirability of rail transport is its inadequate travel time. The main reason behind this inadequacy is the limited capacity railways routes, especially in single-track routes (*13*). We first calculate the average duration of travel between network blocks and the average time that railcars wait in railway stations, and then the shortest path algorithm was used to calculate the rail travel time of all origin-destinations. For towns having no rail station, rail travel times was obtained from Equation (12).

$$Ti_{rail} = (D_o + D_d) * Ti_{road} + Ti'_{rail} \tag{12}$$

In the above equation, Ti_{rail} is the final travel time, D_o is the road distance between the origin and its nearest railway station (in kilometers), D_d is the road distance between the destination and its nearest railway station (in kilometers), Ti_{road} is the average road travel time per kilometer for the distance between the origin/destination and their respective nearest railway stations, and Ti'_{rail} is the average rail travel time between the station nearest to the origin and the one nearest to the destination.

- The time of road transport

Road travel time is a function of various factors such as distance, road infrastructure, terrain, weather conditions, etc. (*42*). In this study, the road travel time was calculated based on the slopes of roadways and the average speed of freight vehicles in different slopes of different sections of the roads. Ultimately, the shortest path algorithm was used to calculate the road travel time of all origin-destinations. In the end, the average driver break times (mandated by law) were added to the road travel times.

- The tariff of containerized rail transport

The total cost of rail transport of containerized cargo consists of container loading cost (at the origin), container transit cost, and container unloading costs (at the destination), the cost of returning empty containers, in addition to a demurrage cost for cases where total travel time exceeds the maximum duration of container lease contract. The cost of containerized transport to destinations where there is no rail station was obtained based on a combination of costs associated with rail and road transport.

- The percentage of bulk cargo in an origin-destination

This variable represents the percentage of bulk cargo in the total load transported in an origin-destination. In this study, bulk cargo was assessed in the levels of 5000, 10000, 15000, and 20000 tons. For example, in the 10000-tonnes level, when the total tonnage of rail and road transport of a commodity in an origin-destination was greater than 10000, this value was divided by total tonnage of transport in that origin-destination, giving the percentage of bulk cargo in that origin-destination (for the level of 10000-tonnes). The purpose of this variable is to find the significant differences in the behavior of owners of bulk cargo and other cargo owners regarding the selection of the mode of transport.

- High traffic origin-destinations

The high-traffic or low-traffic status of each origin-destination was assessed by defining a dummy variable with a value of either zero or one based on the presence of traffic with volumes greater than 20000, 30000, 40000 and 50000 tons. For example, for the 20000-tonnes level, when the tonnage of transport of a commodity in one leg of origin-destination was greater than 20000, the value of this variable was assumed to be 0ne, and otherwise, it was assumed to be zero.

- Access to railways

The variable was considered to be the distance of provincial capitals to the nearest railway station. Considering the adequate coverage of road network and the negligible difference between road distance and aerial distance to the nearest railway station, the aerial distances (in kilometers) were used for this variable.

- The presence or absence of railway at origin and destination

This variable was defined as a dummy binary variable, which was assumed to be 1 for cities having direct access to railway and zero for the rest.

- Presence of active rail transport hub at origin and destination

A binary dummy variable was defined to represent the generation or absorption of rail transport at origin or destination at levels of 20000, 30000, 40000 and 50000 tons. For example, in the 20000-tonnes level, the value of this variable for cities that had a rail transport generation or absorption of greater than 20000 tons was considered to be one.

Results of mode choice model for containerized transport (Model B)

The binary choice models estimated using the maximum likelihood method. First, Pearson's coefficient of correlation between the dependent variable (share of containerized rail transport) and other variables was determined. Then, variables having the highest correlations were incorporated into the model one by one, and this trend continued with other variables, and each variable failing to improve the model was eliminated. Improvement of the model was evaluated based on described fitness tests, and ultimately, the model shown in Table 3 was obtained as the model with the best utility.

Table 3 Variables and properties of the final mode choice model for containerized transport based on maximum likelihood method

Variable	coefficient	t-statistic	Error%	Marginal effect	Elasticity
constant number	-1.383***	-2.21	0.0274	-	-
Origin being a port	1.9673***	5.01	0	0.0051	0.5398
destination being a port	1.5774***	3.3	0.001	0.001	0.3298
Bulk loads greater than 10,000 tonnes	0.0392***	6.02	0	0.00001	0.0594
Road transport time (breaks included)	0.41***	8.25	0	0.00013	5.296
Rail transport time	- 0.126***	-7.47	0	-0.0004	-6.9735
Rail/road transport cost ratio	-2.105***	-5.49	0	-0.00064	-5.5599
Origin/destination being a rail transport hub	3.2337***	9.52	0	0.0068	0.5617
High traffic origin/destination	1.2873***	2.32	0.0206	0.00079	0.0287
Number of observations: 5276					
LL(β)= -177.8					
LL(0)= -322.2					
X^2 =308.85 ρ_0^2 =0.464					

In Figure 3, (a) and (b) describe a comparison between the tonnages estimated by the model are the real tonnages for all OD pairs and some high-tonnage OD pairs. In these graphs, the horizontal axis represents the real values, and the vertical axis represents the values estimated by the model. Also (c) shows the estimated and real tonnage of rail transport for high-tonnage OD pairs.

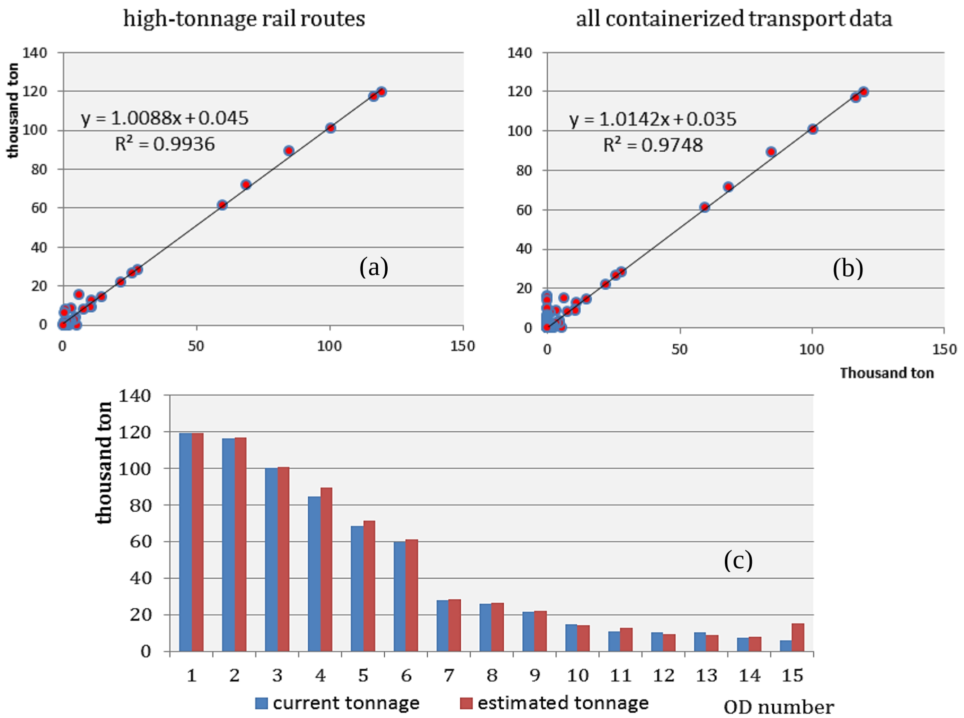

Figure 3 Comparison of the real and the estimated tonnage of rail transport based on model B

As Figure 3 shows, model's estimation of the current situation is very close to reality. Predictions of the model especially those made for high tonnage rail transport are very close to reality so that the slope of the line is very close to unity the obtained fitness index (R^2) is 0.99. According to the final mode choice model for containerized transport, the variables expressing Origin being a port, destination being a port, Bulk loads of greater than 10,000 tonnes, road transport time (breaks included), rail transport time, rail/road transport cost ratio, origin/destination being a rail transport hub, and high traffic origin/destination are the variables influencing the share of containerized rail transport. According to elasticity factor of each variable in the final model, three variables of rail/road transport cost ratio, rail transport time, and road transport time are much more sensitive than other variables. One of the problems of the railway system that pushes the cargo owners toward containerized road transport is 100% greater cost of transit of a container via railway in comparison to the road. The price of rail transport is currently being calculated based on a railcar-kilometer measure instead of a tonne-kilometer one, and this has increased the cost of this service for cargo owners. The high sensitivity of the cost variable in the final model reflects the high importance of this issue. The negative sign of variable rail transport time points out another problem of containerized rail transport, i.e. the low speed of the process, as the increased time of rail transport reduces the desirability of this transport mode. As the results of the model show, other variables such as origin or destination being a port can also increase the desirability of containerized rail transport.

4. Conclusion

This study presented a two-level model composed of container choice model for the selection of container as the mean of transport based on decision tree method and a mode choice model for containerized transport developed by the use of binary logit method. The results of the former model showed that more frequent use of a non-containerized mode of transport is mainly due to factors such as high tariffs of containerized transport, long transport distance, and domestic source of cargos. The results of mode choice model for containerized transport showed that weaknesses of containerized rail transport are its long travel time and high costs, but in routes leading to national ports or having bulk loads of greater than 10000 tons, the containerized rail transport has better desirability than containerized road transport. The role of containerized rail transport can be strengthened by alleviating the mentioned weaknesses against current advantages of the road and especially non-containerized road transport. Thus, reducing the transport time and cost of containerized transport in routes leading to national ports (especially for export cargos) and in long-distance routes will increase the share of containerized transport and particularly the containerized rail transport.

5. Acknowledgements

The authors acknowledge Transportation Research Institute of the Isfahan University of Technology and Islamic Republic of Iran Railways.

6. References

1. Mobility, E.C.D.-G.f. and Transport. *White Paper on Transport: Roadmap to a Single European Transport Area: Towards a Competitive and Resource-efficient Transport System*: Publications Office of the European Union2011.
2. Woxenius, J. and R. Bergqvist. Comparing maritime containers and semi-trailers in the context of hinterland transport by rail. *Journal of Transport Geography*. Vol. 19, NO. 4, 2011, pp. 680-688.
3. Behrends, S. The modal shift potential of intermodal line-trains from a haulier's perspective: drivers and barriers in the mode choice process. *World Review of Intermodal Transportation Research*. Vol. 5, NO. 4, 2015, pp. 369-386.
4. Elbert, R. and L. Seikowsky. The influences of behavioral biases, barriers and facilitators on the willingness of forwarders' decision makers to modal shift from unimodal road freight transport to intermodal road–rail freight transport. *Journal of Business Economics*. Vol., NO., 2017, pp. 1-41.
5. DEVELOPMENT, U. *REVIEW OF MARITIME TRANSPORT 2016*: UNITED NATIONS 2016.
6. Morton, A.L. A statistical sketch of intercity freight demand. *Highway research record*. NO. 296, 1969.
7. Boyer, K.D. Minimum rate regulation, modal split sensitivities, and the railroad problem. *Journal of Political Economy*. Vol. 85, NO. 3, 1977, pp. 493-512.
8. Levin, R.C. Allocation in surface freight transportation: does rate regulation matter? *The Bell Journal of Economics*. 1978, pp. 18-45.
9. Quandt, R.E. and W.J. Baumol. The demand for abstract transport modes: theory and measurement. *Journal of Regional Science*. Vol. 6, NO. 2, 1966, pp. 13-26.
10. Cullinane, K. and N. Toy. Identifying influential attributes in freight route/mode choice decisions: a content analysis. *Transportation Research Part E: Logistics and Transportation Review*. Vol. 36, NO. 1, 2000, pp. 41-53.
11. Arencibia, A.I., et al. Modelling mode choice for freight transport using advanced choice experiments. *Transportation Research Part A: Policy and Practice*. Vol. 75, NO., 2015, pp. 252-267.
12. Rangaraj, N. An analysis of Operations, Mode Choice, Pricing and Network Economics of Container Movement. *International Workshop on IT-Enabled Manufacturing, Logistics and Supply Chain Management*. 2003.
13. Fries, N., et al. *Modal split functions for a Swiss national freight transport model*. in *EUROPEAN TRANSPORT CONFERENCE 2008; PROCEEDINGS*. 2008.
14. Larranaga, A.M., J. Arellana, and L.A. Senna. Encouraging intermodality: A stated preference analysis of freight mode choice in Rio Grande do Sul. *Transportation Research Part A: Policy and Practice*. 2016.
15. Shen, G. and J. Wang. A freight mode choice analysis using a binary logit model and GIS: the case of cereal grains transportation in the United States. *Journal of transportation technologies*. Vol. 2, NO. 02, 2012, pp. 175.
16. Shi, Y., X. Fang, and Z. Chen. Price Analysis of Railway Freight Transport under Marketing Mechanism. *Physics Procedia*. Vol. 25, NO., 2012, pp. 2038-2044.
17. Reis, V. Analysis of mode choice variables in short-distance intermodal freight transport using an agent-based model. *Transportation research part A: Policy and practice*. Vol. 61, 2014, pp. 100-120.
18. Shinghal, N. and T. Fowkes. Freight mode choice and adaptive stated preferences. *Transportation Research Part E: Logistics and Transportation Review*. Vol. 38, NO. 5, 2002, pp. 367-378.
19. Ravibabu, M. A nested logit model of mode choice for inland movement of export shipments: A case study of containerised export cargo from India. *Research in Transportation Economics*. Vol. 38, NO. 1, 2013, pp. 91-100.
20. Blauwens, G., et al. Towards a modal shift in freight transport? A business logistics analysis of some policy

measures. *Transport reviews*. Vol. 26, NO. 2, 2006, pp. 239-251.
21. Feo-Valero, M., et al. The importance of the inland leg of containerised maritime shipments: An analysis of modal choice determinants in Spain. *Transportation Research Part E: Logistics and Transportation Review*. Vol. 47, NO. 4, 2011, pp. 446-460.
22. ABDELWAHAB, W. and T. SAYED. Freight mode choice models using artificial neural networks. *Civil Engineering Systems*. Vol. 16, NO. 4, 1999, pp. 267-286.
23. Sayed, T. and A. Razavi. Comparison of neural and conventional approaches to mode choice analysis. *Journal of Computing in Civil Engineering*. Vol. 14, NO. 1, 2000, pp. 23-30.
24. Tortum, A., N. Yayla, and M. Gökdağ. The modeling of mode choices of intercity freight transportation with the artificial neural networks and adaptive neuro-fuzzy inference system. *Expert Systems with Applications*. Vol. 36, NO. 3, 2009, pp. 6199-6217.
25. Xie, C., J. Lu, and E. Parkany. Work travel mode choice modeling with data mining: decision trees and neural networks. *Transportation Research Record: Journal of the Transportation Research Board*. NO. 1854, 2003, pp. 50-61.
26. Rashidi, T.H. and A. Mohammadian. Household travel attributes transferability analysis: application of a hierarchical rule based approach. *Transportation*. Vol. 38, NO. 4, 2011, pp. 697-714.
27. Zhao, Y. and Y. Zhang. Comparison of decision tree methods for finding active objects. *Advances in Space Research*. Vol. 41, NO. 12, 2008, pp. 1955-1959.
28. Borgelt, C., M. Steinbrecher, and R.R. Kruse. *Graphical models: representations for learning, reasoning and data mining*: John Wiley & Sons, 2009.
29. Gorunescu, F. *Data Mining: Concepts, models and techniques*, Vol. 12: Springer Science & Business Media, 2011.
30. Rokach, L. and O. Maimon. *Data mining with decision trees: theory and applications*: World scientific, 2014.
31. Quinlan, J., *C4. 5: Programs for Machine Learning. C4. 5-programs for machine learning/J. Ross Quinlan*. 1993, Morgan Kaufmann Publishers.
32. Attneave, F. Applications of information theory to psychology: A summary of basic concepts, methods, and results. 1959.
33. Kearns, M. and Y. Mansour. *On the boosting ability of top-down decision tree learning algorithms*. in *Proceedings of the twenty-eighth annual ACM symposium on Theory of computing*. 1996. ACM.
34. De Mántaras, R.L. A distance-based attribute selection measure for decision tree induction. *Machine learning*. Vol. 6, NO. 1, 1991, pp. 81-92.
35. Breiman, L., et al. Classification and regression trees. Wadsworth & Brooks. *Monterey, CA*. 1984.
36. Fayyad, U.M. and K.B. Irani. *The attribute selection problem in decision tree generation*. in *AAAI*. 1992.
37. Ferri, C., P. Flach, and J. Hernández-Orallo. *Learning decision trees using the area under the ROC curve*. in *ICML*. 2002.
38. Kass, G.V. An exploratory technique for investigating large quantities of categorical data. *Applied statistics*. 1980, pp. 119-127.
39. Quinlan, J.R. *C4. 5: programs for machine learning*: Elsevier2014.
40. Kotsiantis, S.B., I. Zaharakis, and P. Pintelas, *Supervised machine learning: A review of classification techniques*. 2007.
41. de Dios Ortuzar, J. and L.G. Willumsen. *Modelling transport*: Wiley New Jersey1994.
42. Morgul, E.F., et al. *Commercial vehicle travel time estimation in urban networks using gps data from multiple sources*. in *Transportation Research Board 92nd Annual Meeting*. 2013.