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A Freight Mode Choice to Transport Oil Products Using an Artificial Neural Network Model

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Abstract

Transporting oil products by truck has many issues, including increased accident risk, adverse environmental effects, and increased congestion in traffic. This study aims to compare trucks and trains for transporting fuel oil between intercity locations and to develop freight mode-choice models using an artificial neural network and statistical software. Freight trips collected in this study are (277) collected by a tracking device, questionnaires, and personal interviews. The data included the delivery time, average speed, quantity transported per trip, and transportation cost. According to the findings, the average speed of trucks and trains is (48.79) km/h and (24.13) km/h, respectively. This indicates that the average speed of a truck is nearly twice that of a train. Trucks and trains have average delivery times of (12.40) h and (25.92) h, respectively. This indicates that the average delivery time for a truck is half that of a train. The quantity transported each trip is (993.16) tons/trip for trains and (30.47) tons/trip for trucks. Train transportation is approximately 33 times as costly per trip as truck transportation. Transportation by train is a cheaper option than transportation by truck. Establishing an effective schedule can reduce delays at freight train intersections and during railway maintenance, potentially reducing delivery time by approximately 20 hours.

Keywords: Complete separation in data, Doura refinery, Freight transportation, Geographical positioning system, Iraqi trains, Iraqi trucks.

1. Introduction

Freight transportation refers to the movement of raw materials, products, and cargo from one location to another using various modes of transport, such as trucks, trains, ships, and aircraft [1]. The prosperity and development achieved in this sector extend to other sectors; therefore, it plays an essential role in the economy's development and growth at the regional and global levels. Crude oil and oil products are essential commodities in demand because they are primary energy sources across sectors such as transport, production processes, and heating. Several modes of transportation are used to transport oil products, including pipelines, ships, trucks, and trains. Many factors and considerations determine the appropriate mode for transporting petroleum products, such as the type of oil product, delivery time, transport cost, reliability, flexibility, frequency, security, shipment quantity, infrastructure availability, environmental and geographic conditions, and others [2], [3].

Transportation of oil products by trucks and trains is a common mode of distribution for crude oil and refined petroleum products, including gasoline, diesel, and fuel oil. Each transport mode has its pros and cons. Trucks are typically used for short-distance transport or for delivering smaller quantities of petroleum products. They offer flexibility in delivery times and locations, as they can reach areas that may not be accessible by train. However, truck transportation can be more expensive than train transportation, especially for longer distances, and it can also contribute to traffic congestion and air pollution. Trains, on the other hand, are used for longer distances and larger quantities of petroleum products. They are more fuel-efficient than trucks, thereby reducing environmental impacts. However, train transportation is generally less flexible than truck transportation, as it is limited to rail lines and may require additional transportation by truck from the rail yard to the final destination [4].

Few studies examine freight mode choice using the Artificial Neural Network (ANN) approach. Some of this research is as follows: Abdelwahab and Sayed [5] employed the ANN approach to produce freight mode selection models between trucks and rails in the United States. The data included shipment characteristics such as shipment value, weight, density, specific handling requirements, and period of validity; modal characteristics such as transport time and reliability; shipping costs; sensitivity to damage; and market characteristics such as geographical region, traffic volume between the origin and destination, and trip distance. The results showed that the ANN technique performed better than the conventional methods (logit and probit) in prediction and was more effective in identifying explanatory factors contributing to freight mode selection.

Using a binary logit and a regression model, Shen and Wang [6] studied cereal grain transportation by truck and train in the United States. The same variables are included in both models: mode-split probability, good weight, value, network transit time, and fuel cost. The results indicate that the binary logit model produces more accurate truck and train mode split estimates. Wang et al. [7] used binary probit and logit models to analyze the factors influencing the choice between truck and rail shipments from Maryland to other states. The study found that several variables significantly impacted transportation mode selection, including the distance ratio between truck and rail, the value of time for the commodity being transported, the type of trade, the origin of the shipment, and fuel costs. Jensen et al. [8] estimated a discrete freight transportation chain choice model for Europe. The choice of transport chain depended on transport costs, transport times, commodity density, direct access to rail and waterways, and the type of goods. A combination of linear and logarithmic transport cost specifications is most effective for dry bulk goods. In contrast, a linear spline cost function performs best for liquid bulk, whereas a logarithmic cost function performs best for container products and general freight.

In general, delivery time and transportation cost are the two main factors in selecting shipping modes for all types of goods; however, other factors also have relative importance depending on the type of goods. Reliability (delivering the goods within the specified time without delay). It is important for perishable goods, such as food. Security is also essential for high-value goods. Flexibility is a priority for the mode of transport, in terms of its capacity to ship outside scheduled times and its ability to deliver goods to areas without infrastructure for other modes. Quantities transported per trip and frequency affect freight mode choice in certain goods and shipping conditions.

There is increasing demand in Iraq for trucks to transport oil products between cities and over long distances, despite the availability of infrastructure for other modes of transportation, such as trains. This increasing demand has many adverse effects, such as the increased risk of accidents due to the flammable nature of the cargo, the limited capacity of trucks compared to other modes of transportation requiring more trucks to transport the same amount of oil products, therefore, caused traffic congestion and emit large amounts of greenhouse gases and other pollutants, as well as damage to roads and infrastructure [9], [10]. Higher transportation costs can reduce the competitiveness of long-distance transportation.

There are no local studies and few international studies on the selection of shipping modes for oil products. This study aims to identify the most critical factors influencing the choice of the modes of shipping oil products and employ the ANN approach in creating models to choose the method of shipping oil products (fuel oil) as a case study transport from the Doura refinery located in the capital, Baghdad, to the port of Umm Qasr in the governorate of Basra, Iraq, which is transported using trucks and trains. Finally, the output of this study assists decision-makers in improving transport efficiency and maximizing economic and environmental benefits.

2. Study Area

The Doura refinery has the third-largest refining capacity in Iraq, estimated at 140 thousand barrels per day. It is located on an area of 2.5 million square meters near the Tigris River in southeastern Baghdad [11], as shown in Fig. 1. This refinery supplies oil derivatives to Baghdad and the surrounding cities. In contrast, the fuel oil product above the local need is exported through the southern port of Umm Qasr, located in the Basra Governorate in the far south of Iraq, as shown in Fig.2. The process of transporting fuel oil from the refinery to the port is carried out by trucks and trains, due to the availability of the infrastructure for these two modes and the absence of other modes of transport that secure the transport process, such as pipelines. The trains transport approximately 1,000 tons per trip by pulling 22 locomotives, each with a capacity of 45.5 tons, and cover 588 km to reach the port directly (from door to door). Trucks transport approximately 30 tons per trip, covering 567 km.

Figure 1. Doura refinery (highlighted).

Figure 2. Umm Qasr port (highlighted).

Fig.3 shows the path of trucks and trains between the refinery and the port. Continuing fuel oil exports contribute to increased Iraq's financial revenues, particularly given its sixth-place global oil production [12] and fifth-place oil reserves [13]. Accordingly, a high percentage of the national economy depends on oil export revenues.

3. Research Methodology

3.1. Method of Data Collection

The freight trip data collected in this study comprise the delivery time of the oil product shipment (hours), the cost of transporting the shipment (US$/ton), the quantity of freight transported (tons per trip), and the average speed (kilometers/hour). These data were obtained using different techniques. Freight train trips were obtained by the General Company for Iraqi Railways (IRR) via GPS tracking devices installed on all trains. It records the train departure time from the refinery and arrival time at the port for each trip. The tracking devices calculate the delivery time (the difference between the time of departure from the refinery and the time of arrival at the port, including total-stop delay) and average speed (the result of dividing the track distance by the delivery time) of the freight train for each trip, and also calculate total stop delay time for the freight train (turning off the engine) at the intersections with the passenger train at some stations on the journey path., Finally, this data, along with the quantity of shipped fuel oil, is transmitted via the internet to the control room at the central train station in Baghdad, where it is automatically saved in Excel format. The cost of transporting fuel oil by train was constant throughout the study period. The number of freight train trips collected is 88, and their collection was delayed because the trips are repeated at one trip per day or every two days. Collecting freight train trips took approximately five months, from June 7 through November 4, 2022.

Figure 3. Truck and train route between two cities [14].

Regarding freight truck trips, data were collected through personal interviews with truck drivers at the refinery entrance after they completed fuel oil deliveries at the port. The questionnaire included the same four variables mentioned above: delivery time, shipment quantity (which varies by tank size for each truck), and average speed during the trip. Finally, the shipping cost is a fixed value for trucks as well. The 189 truck trips were collected from October 15 to 20, 2022, specifically during the day from 9:00 AM to 12:00 PM.

It is also worth noting that the period for collecting data on truck trips overlaps with that for collecting data on train trips. The period difference does not affect the four variables. The sample size for this study comprised 277 trips, of which 88 were train trips and 189 were truck trips. The sample size was calculated according to (1) with a tolerance of ±0.6 and a standard deviation of 5:

$$N \geq \frac{Z^{2} \cdot d^{2}}{e^{2}} \qquad (1)$$

Where N is the sample size, Z is the confidence level (1.96 for 95%), Sd is the standard deviation, and e is the tolerance.

3.2. Preliminary Data Analysis

Fig. 4 presents descriptive statistics for the freight trip data. It notes that the average speed is (48.79) km/h and (24.13) km/h for trucks and trains, respectively. This means that the average speed of a truck is twice that of a train. The average delivery time is (12.40) h and (25.92) h for trucks and trains, respectively. This means that a truck's average delivery time is half that of a train.

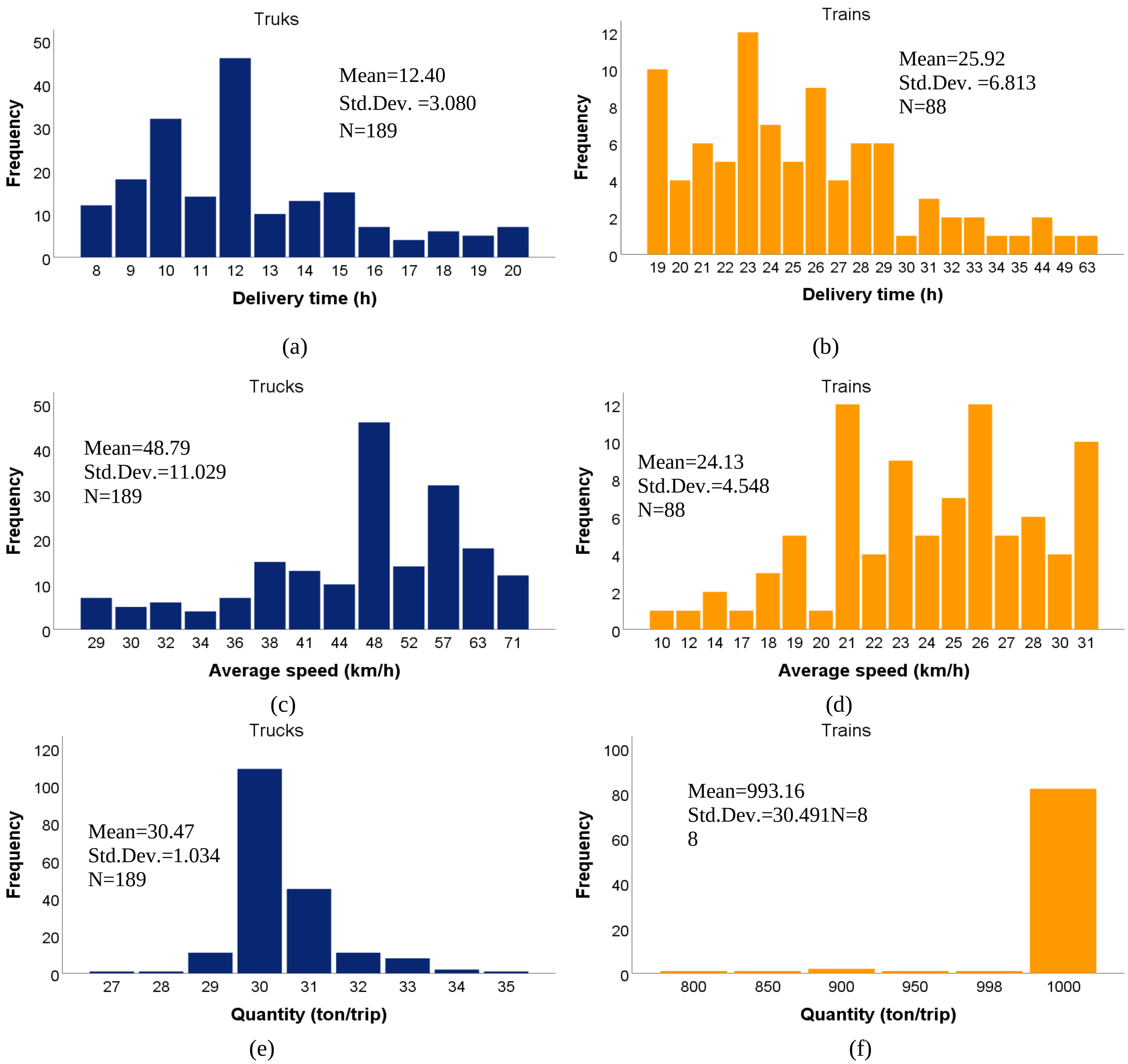

Figure 4. Descriptive statistics of freight trips data.

As for the quantity transported per trip, at a rate of (993.16) tons/trip and (30.47) tons/trip for trains and trucks, respectively. Train transport is approximately 33 times more expensive per trip than truck transport. The cost of transporting by train is lower than that of transporting by truck, as shown in Fig. 5.

The difference between the minimum and maximum delivery time (Range) for transporting shipments by trucks and trains is attributable to several factors. Regarding trucks, the reason is differences in drivers' behavior in selecting vehicle speed and in delays caused by drivers stopping to rest, as well as delays at certain security checkpoints along the route. As for the trains, the main reason is the delay caused by the intersection of the freight train with the passenger train at some stations, which necessitates stopping the freight train (turning off the engine), and the other reason is the delay resulting from reducing the train speed in some railway sectors due to structural damage in the rail. Fig.6 shows the delay statistics for train trips. The average delay is 6 hours.

3.3. Freight Mode Choice Modeling Using Artificial Neural Network

ANN is a computational model inspired by the structure and function of the biological neural networks in the human brain [15]. It consists of multiple layers of interconnected nodes or neurons that process and transmit information. The architecture of an ANN typically includes an input layer, one or more hidden layers, and an output layer. The input layer receives input data, which is then processed by the hidden layers. Each neuron in the hidden layers applies weights and biases to the input data and performs a nonlinear transformation (activation function) to produce an output, which is then passed on to the next layer. The final production, which can be a single node or multiple nodes, is produced by the output layer, depending on the task.

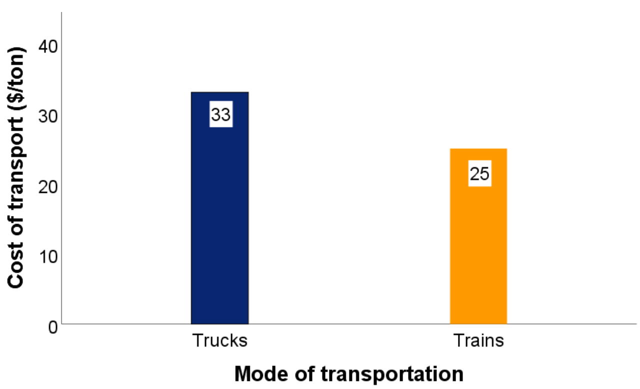

Figure 5. Transportation costs by mode of transport.

This study has four explanatory variables: delivery time, transportation cost, the quantity of freight transported, and average speed. The average speed variable was excluded from the modeling. It has a strong negative correlation (-0.895) with the delivery time variable, as it is computed by dividing the travel distance by the delivery time. Therefore, the delivery time variable is interpreted primarily as an influencing factor in freight mode selection. As for the quantity of the shipping-transported variable, it is also excluded because it exhibits complete separation in the data (Perfect prediction), with truck transport ranging from approximately 27 to 35 tons per trip and train transport from approximately 1,000 to 1,500 tons per trip.

(800-1000) tons per trip. Because there are no overlapping values between the two values (35-800), modeling with this variable creates a perfect predicted model. The model cannot be used to determine the probability of choosing between the two freight modes.

Two models were created; the first includes the delivery time only without rescaling input data, and the second model consists of the combination of the delivery time variable multiplied by the transport cost because the latter suffers from complete separation in the data, so the combination of a variable that suffers from complete separation with another variable is considered one solution to the problem of complete separation suggested by Allison [16]. In addition, data normalization was applied in the second model to improve accuracy.

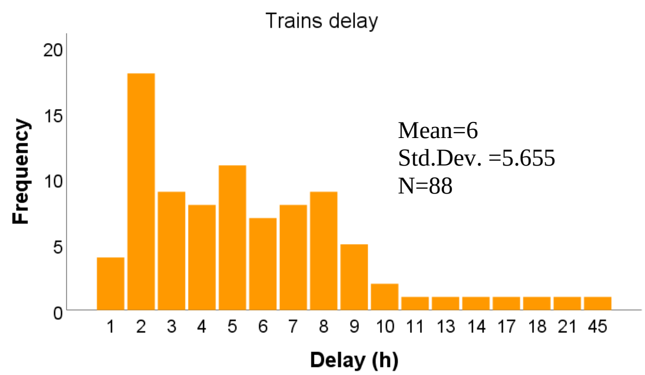

Figure 6. Descriptive statistics for train trip delays.

The collected data were analyzed using Feedforward Multilayer Perceptrons (MLPs) and trained with the backpropagation algorithm (Scaled conjugate gradient method) in the Statistical Package for the Social Sciences (SPSS) version 26. An MLP is a supervised-learning neural network. This type of neural network was selected in this study for several reasons. Firstly, it addresses complex problems, such as classification. Secondly, it can run nonlinear problems. Thirdly, it has a higher accuracy than other Neural Networks. Finally, it has a quick prediction rate.

The available data were divided randomly into two sets (70% of the sample to train the neural network and the remaining sample (30%) to test the network capabilities in prediction. The input layer contains continuous variables, and the output layer contains nominal variables, represented by transport modes, coded as 0 (Truck) and 1 (Train). Regarding the number of neurons in the input and output layers, the input layer has one neuron because it depends on the number of variables. Meanwhile, the number of neurons in the output layer depends on the problem type. This study comprises two neurons because the classification is binary (trucks versus trains). Regarding the number of hidden layers and neurons, there is no universal rule for determining them. This study used a single hidden layer, provided that sufficient connection weights are specified. Using more than one hidden layer often dramatically slows training. Therefore, a single hidden layer was used, and several attempts were made to determine the number of neurons required to achieve good performance with the simplest neural network architecture. The hyperbolic tangent activation function was used in the hidden-layer neurons because it typically performs better than the logistic sigmoid, and its output ranges from -1 to +1. For the activation function in the output layer, softmax was used because it is commonly employed in classification models. The output values of this function range from 0 to 1, and their sum is 1 [17].

4. Results and Discussion

4.1. Freight Mode Choice Models

Fig. 7 shows the neural network architecture, which is identical for both the first and second models. The network consists of three layers: an input layer with one neuron, representing the variables.

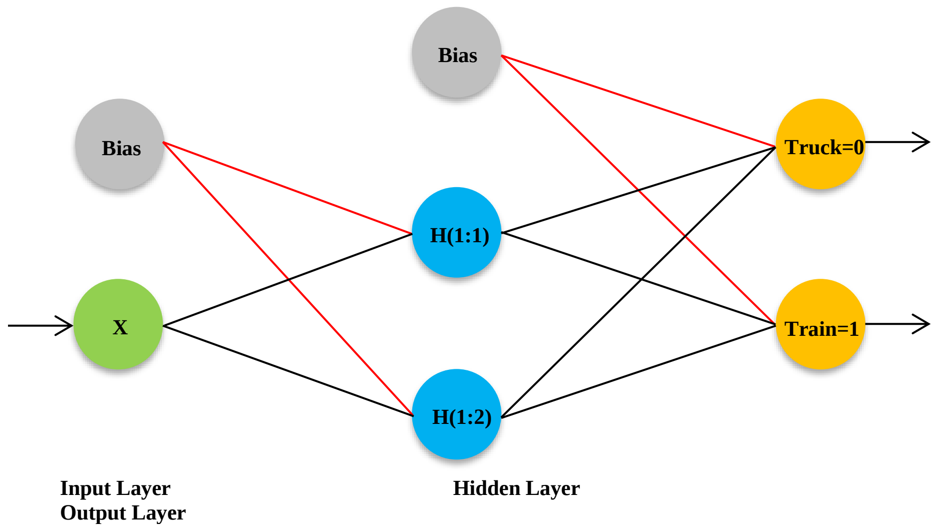

Figure 7. Architecture of the ANN.

A two-neuron hidden layer is used to improve accuracy; the two-neuron output layer represents the probabilities of choosing trains and trucks, and the two neurons represent the biases. The neurons in the three layers are connected via synapses, and synaptic weights represent the strength of these connections. Table 1 and Table 2 show variables and weights for the first and second models, respectively.

Table 1. Variables and weights of the first model.

Predictor		Predicted: Hidden Layer H (1:1)	Hidden Layer H (1:2)	Output Layer Truck=0	Output Layer Train=1
Input Layer	X*	-1.281	0.172		
	Bias	-0.421	-3.146		
Hidden Layer	H (1:1)			-0.550	0.467
	H (1:2)			-4.111	3.439
	Bias			0.031	-0.306

X*=Delivery time

Table 2. Variables and weights of the second model.

Predictor		Predicted: Hidden Layer H (1:1)	Hidden Layer H (1:2)	Output Layer Truck=0	Output Layer Train=1
Input Layer	X*	11.336	4.734		
	Bias	-1.352	-3.208		
Hidden Layer	H (1:1)			-5.293	4.874
	H (1:2)			-2.890	2.377
	Bias			2.342	-2.506

X*= Delivery time multiplied by transportation cost

The output of each neuron is represented in three steps: first, each input is multiplied by a weight. Next, all weighted inputs are summed with a bias term. Finally, the sum is passed through an activation function, as shown in (2) [18].

$$y_i = f(c) = f(b_i + \sum_{k=0}^{m} w_{ki} . x_k) \quad (2)$$

Where y is the output of the neuron, x is the

input vector, w is the weight, b is the bias, and f is the activation function; for hidden layer neurons, f is the hyperbolic tangent, as shown in (3), and for output layer neurons, f is softmax, as shown in (4).

$$f(c) = tanh(c) \quad (3)$$

$$f(c_k) = \frac{e^{(c_k)}}{\sum_j e^{(c_j)}} \quad (4)$$

4.2. Accuracy of Derived Models

The accuracy of the ANN models in SPSS is assessed using a confusion matrix, which summarizes the neural network's performance in predicting correct class labels for observations in a dataset. Table 3 shows the classification table for the first model. The percentage of accurate predictions in the training sample is 97.0% for trucks and 85.0% for trains, with an overall accuracy of 93.2%. High training accuracy indicates that the neural network is learning patterns in the training data. In the test set, the total accuracy is 95.3%; therefore, test accuracy is a more critical measure of its ability to generalize to new data. The model predicts accurately because there is a slight overlap in delivery times between trucks and trains, ranging from 19 to 20 hours, as shown in Fig. 4 (a) and 4 (b).

The second model in the training sample correctly classified 83.7% of the truck cases and 82.9% of the train cases, with an overall accuracy of 83.4%. In the testing sample, the improvement in prediction accuracy was 87.2%, as shown in Table 4. Combining delivery time with transportation cost to address the problem of complete data separation increased data overlap more than in the first model, reducing the model’s predictive performance.

Other indicators for evaluating the prediction accuracy of ANN models include the Receiver Operating Characteristic (ROC) curve and the Area under the ROC Curve (AUC). The ROC curve is a graphical plot used to evaluate the performance of a binary classifier, showing the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) at different classification thresholds. Based on [19], the classifier performs better when more curves lie within the plot's left and top borders. AUC is a commonly used metric for evaluating classifier performance, ranging from 0 to 1, with 0.5 indicating random chance and 1 indicating perfect performance. A higher AUC indicates better discrimination between positive and negative cases. Fig.8-9 shows the ROC of the first and second models; it is noted that the first model curve is close to the upper left border, which indicates the accuracy of the prediction, while the second model is less close to the upper left border.

Table 3. Classification table for the first model.

Sample	Observed	Predicted Truck	Predicted Train	Predicted Percent Correct
Training	Truck	128	4	97.0%
	Train	9	51	85.0%
	Overall Percent	71.4%	28.6%	**93.2%**
Testing	Truck	54	3	94.7%
	Train	1	27	96.4%
	Overall Percent	64.7%	35.3%	**95.3%**

Table 4. Classification table for the second model.

Sample	Observed	Predicted Truck	Predicted Train	Predicted Percent Correct
Training	Truck	108	21	83.7%
	Train	12	58	82.9%
	Overall Percent	60.3%	39.7%	**83.4%**
Testing	Truck	52	8	86.7%
	Train	2	16	88.9%
	Overall Percent	69.2%	30.8%	**87.2%**

According to [20], the AUC values for the first and second models are 0.993 and 0.924, respectively, both exceeding 0.9, indicating that the two models are considered excellent. Finally, based on the above, the first model is statistically more accurate in its predictions than the second.

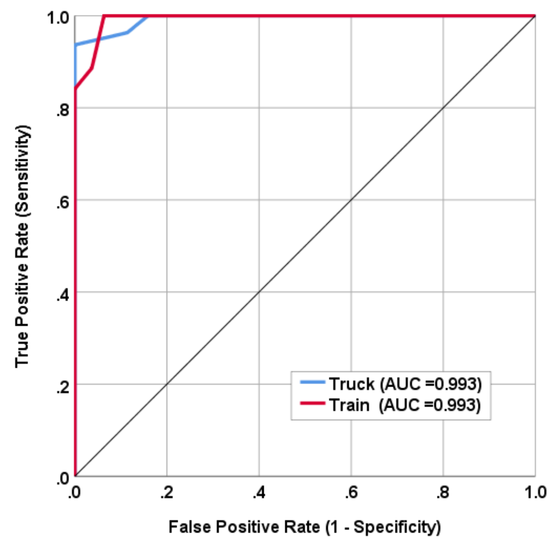

Figure 8. ROC curve for the first model.

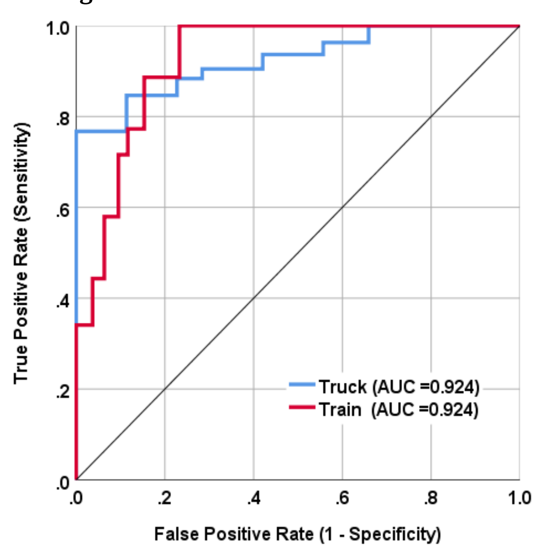

Figure 9. ROC curve for the second model.

5. Conclusions

In this study, we conclude that the average speed of a truck is twice that of a train. The average quantity transported per train trip is approximately 1000 tons, which is 33 times the quantity transported by truck. Regarding cost, train transportation is cheaper than truck transportation. From all of the above, trains are still considered a strong competitor and shifting from trucks to trains in transporting oil products between the refinery and the port led to achieving many positive gains, the first of which was reducing the number of trucks and this had a positive impact in terms of reducing congestion caused by trucks on the roads secondly, reducing transportation costs by 8,000 US dollars for an increase of one train trip. Finally, it reduces the adverse impacts of trucks. The average train delay is 6 hours; therefore, it is recommended to establish effective schedules and maintenance protocols for certain railway sectors, which may reduce delivery time from 25.92 hours to 20 hours.

For the first and second models, the overall prediction accuracies were 95.3% and 87.2%, respectively. From a statistical perspective, the first model is better at prediction than the second. Also, the first model's simplicity in application is advantageous, as the second model's combined variables obscure the distinct influence of each factor. The outputs of this study help decision-makers determine the share of trucks and trains used to transport oil products, and knowledge of freight mode characteristics helps select the appropriate mode when designing new transport lines. Finally, this study encourages the use of trucks for short-distance transport and recommends reducing reliance on them for intercity travel, particularly when rail infrastructure is available.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Author Contribution Statement

Both authors proposed the research problem, developed the research model, and computed the results. They also discussed the findings and contributed to the final manuscript.

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