(Araştırma)

PRICING DECISIONS IN LINER SHIPPING INDUSTRY: A STUDY ON ARTIFICIAL NEURAL NETWORKS[1]

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ABSTRACT

Price is the strategic tool of the marketing mix and the only element that generates revenue. Therefore, pricing decisions are both strategically and tactically important for the companies. Particularly, in liner shipping industry which is an oligopolistic and highly volatile market. Despite the fact, price and pricing are the most neglected area of both marketing and liner shipping industry. Considering the characteristics of the liner shipping industry, where there are unpredictable shipping cycles, high volatility and various variables that have an impact on price, there is a need to make forecasts since there are various factors that affect price. In this sense, the purpose of the study is to model an artificial neural network as a forecasting method for pricing strategies of liner shipping companies. For the analysis of the study, first both structured and unstructured interviews conducted with the executives of a shipping company. Afterwards, 62 monthly rate data obtained from the company records. Other variables that have an effect on rate are downloaded from financial databases for the analysis. Then, by trial-and-error the design of the network selected, then trained, tested and validated. Finally, the next month is forecasted successfully by the network.

Keywords: Pricing, liner shipping industry, artificial neural network, forecasting methods

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DÜZENLİ HAT TAŞIMACILIĞI (LINER) SEKTÖRÜNDE FİYATLANDIRMA KARARLARI: YAPAY SİNİR AĞLARI ÜZERİNE BİR ÇALIŞMA

ÖZ

Fiyat pazarlama karmasının stratejik bir aracı ve gelir sağlayan tek elemanıdır. Bu nedenle hem stratejik olarak hem de taktiksel olarak firmalar için çok önem arz etmektedir. Bilhassa, düzenli hat taşımacılığı sektörü gibi oligopolistik ve değişken (volatil) pazarlarda. Buna rağmen, fiyat ve fiyatlandırma hem pazarlama alanında hem de düzenli hat taşımacılığı alanında en çok ihmal edilen konudur. Düzenli hat taşımacılığı (liner) sektörünün özellikleri düşülürse, öngörülemez dalgalanmaların, yüksek değişkenliğin ve çeşitli değişkenlerin fiyat üzerinde etkisinin olduğu bir ortamda fiyat öngörüsü firmalar için yararlı bir araç olabilir. Bu bağlamda, çalışmanın amacı düzenli hat taşımacılığı (liner) yapan şirketlerin fiyatlandırma kararları için bir öngörü modeli olan yapay sinir ağı modellemektir. Çalışmanın analizi için öncelikle bir deniz taşımacılığı firmasının yöneticileri ile hem yapılandırılmış hem de yapılandırılmamış mülakatlar yapılmıştır. Ardından, analiz için firma kayıtlarından 62 aylık fiyat verisi temin edilmiştir. Fiyata etki eden diğer değişkenler de finansal veri tabanlarından indirilmiştir. Daha sonra, deneme yanılma yolu ile ağ seçilmiş, eğitilip, test edilmiş ve geçerliliği sınanmıştır. Son olarak, bir sonraki ay ağ tarafından başarıyla tahmin edilmiştir.

Anahtar Kelimeler: Fiyatlandırma, düzenli hat taşımacılığı (liner) sektörü, yapay sinir ağları, öngörü modelleri

1. Introduction

Liner shipping industry (LSI), especially container liners, is a complex market with a freight rate mechanism different than the explanations of economics with its supply and demand positioning. Under demand and supply, there are different variables to be considered, which make it difficult to set the equilibrium price (going price). Likewise, most of the industries, there are uncertainties in the LSI. One thing is clear about LSI, like in the other industries companies are vulnerable to crisis and profitability is seriously important which leads the sustainability of a company. Container liner shipping industry (since 1956), has faced many crises; oil crises (two oil price shocks of 1973 and 1979), and financial crises (financial crisis of the US in the early 1990s, the Asia crisis of 1997, in 2001 the stock market crash, and the mortgage/credit crisis in 2008/9).

As a result of the crises, now most of the companies are facing with increasing maturity debt levels (Kelly et al., 2016). LSI becomes more vulnerable to any change in world economic growth and the companies recorded losses (e.g., Maersk Line lost $2.1 billion, other carriers collective loss was recorded as approximately $20 billion) after 2008 crisis period which made 2009 the worst year of container shipping history (UNCTAD, 2010). Despite the recovery after 2010, fluctuations and unpredictable cases (bankruptcy of Hanjin Shipping Line; world's 7th biggest container shipping line) raises the uncertainty in the market and make it harder to set the prices (Damas, 2016). Though it is hard to give decision when future is unknown, uncertainty raises the risk of giving the right decision.

The developments in LSI and the nature of the industry shapes in a VUCA (volatility, uncertainty, complexity, ambiguity) environment which is a trendy acronym and becomes important in strategy and planning. The shipping companies can be prepared for a VUCA world by managing (investing, interpreting, sharing) information, predictions, and experimentations (Bennett and Lemoine, 2014). Therefore, marketing strategies especially, setting appropriate pricing strategies are inevitable for the shipping companies.

In order to set pricing strategies, companies should consider many factors that affect price and they should take business forecasting tools into account for predicting the future prices. Forecasting can be a tool to overcome the difficulties in pricing decisions in VUCA environment, to sustain financial stability and cope with the competition and changing market environment. Pricing decisions of the companies should be based on sophisticated forecasting methods and these decision tools should be adapted or integrated with the companies' systems.

Besides other forecasting techniques, artificial neural networks (ANNs) have the ability to mimic human and solve complex problems with many variables.

Also, ANNs can work with less sample size and may outperform other conventional time series business forecasting methods which use a genetic algorithm to predict the future values and have the ability to model the problem according to given input variables to generate the output (target) variable (Turban et al., 2002: 541).

There are studies about sales revenue, consumer choice, analysis of marketing data and customer targeting using ANN in marketing (Penpece and Elma, 2014; West et al., 1997; Yao et al., 1998; Kim et al., 2005), however there are no studies regarding pricing using ANN methodology. Therefore, the main objective of the study is to propose a forecasting method which has not been used in pricing (both in the field of marketing and LSI) before. Additionally, the aim of the study is to explore the possibilities of using ANNs as a forecasting tool to make better pricing decisions in LSI. In this study, first of all literature of pricing, LSI and ANN are reviewed and then, the methodology of the study is explained. Lastly, the findings are reported and discussed.

2. Literature Review

2.1. Price, Pricing Objectives, Pricing Strategies

Price has a unique function in the marketing mix. Pricing is a short-term decision of a firm and price of a product or service may change in a second (Ferrell and Hartline, 2011: 229). Price is the most important element to manage in the marketing mix, since it is very flexible and dynamic (Diamantopoulos, 1991; Cavusgil, 1997; Rao and Steckel, 1995; Kotler and Armstrong, 2004: 345; Avlonitis and Indounas, 2007).

Among all other elements of the marketing mix, price is the only element that does not need any expenditure and investment. Most of the academics highlighted price as the only element in marketing mix that generates revenue, income and profits whereas the other variables are the cost components (Simon, 1992; Rao and Steckel, 1995; Lovelock, 1996; Monroe, 2003:8; Kotler and Armstrong, 2004:345; Indounas, 2006; Dolan and Gourville, 2009; Hill, 2011; Ferrell and Hartline, 2011:229).

While establishing a marketing plan, pricing decisions among all other decisions are the most complex decision in marketing strategy (Ferrell and Hartline, 2011: 235). The boundary of pricing decisions are not just the cost and the demand structure, but also include competitive action. These issues in pricing decisions are tied to each other and most of them raise uncertainty (e.g.; reactions of customers, competitors and supply chain partners to pricing). Other issues are firm's pricing objective, supply and demand, and the cost structure of the firm. All these issues are critical while setting initial prices and then the pricing strategy can be adjusted over time (Phillips, 2005:18; Keegan and Green, 2013: 334).

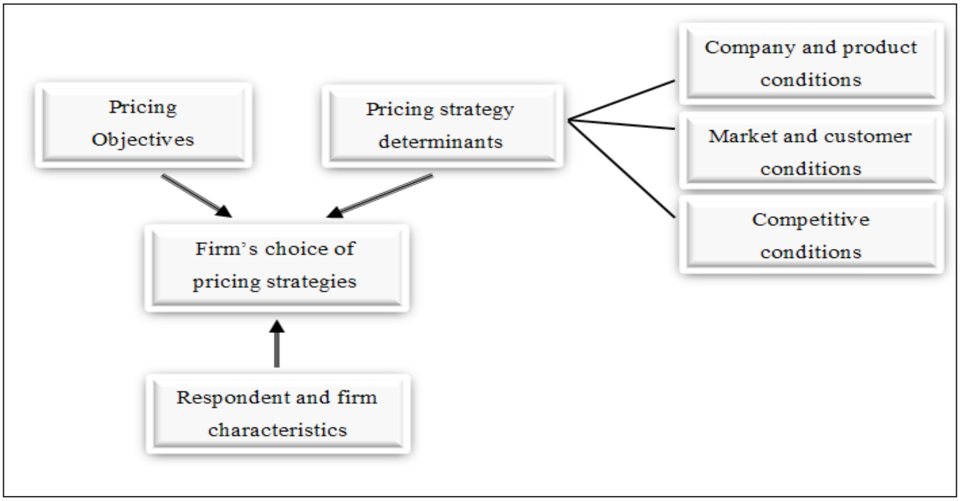

Figure 1. The Pricing Decision: A Framework for Analyzing a Firm's Choice of Pricing Strategies (Source**:** Rao and Kartono, 2009: 14.)

Choosing a pricing strategy is related to company's pricing objectives and the determinants of pricing strategy. The pricing objectives determine the way that price is supposed to help implementing the marketing strategy. Therefore, pricing objectives should be realistic, measurable, and attainable. Among all pricing objectives that have been proposed in the literature, the ones that are related to profits, survival, sales volume, sales revenue, market share, image creation, competitive parity or advantage, barriers to entry, and perceived fairness are the most important and widely specified objectives in the studies (Guiltinan and Paul, 1991: 226; Shipley and Jobber, 2001; Avlonitis and Indounas, 2007; Rao and Kartono, 2009: 14).

Addition to above, pricing strategy is the coordinator of interrelated marketing, competitive and financial decisions for maximizing the capability of setting profitable prices (Nagle and Holden, 2002: 147-150). Foundations of pricing strategy illustrated as a tripod by Lovelock and Wright (2002) which of its three legs are (1) costs (to the provider), (2) competition, and (3) value to customer. The costs represent minimum or the floor price for a particular service offering, whereas the perceived value of the service offering to customers represent maximum or ceiling price. The price quoted by the competitors is the determination of where the price should be set between the floor-to-ceiling range (Lovelock and Wright, 2002: 175).

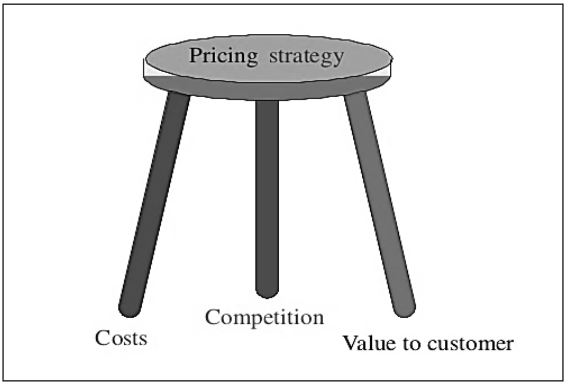

Figure 2. The Pricing Tripod
(Source: Lovelock and Wright, 2002: 175.)

Rao and Kartono (2009: 26) stated that cost-plus pricing is the most popular pricing strategy and it is implemented by different industries and countries. Maintaining profit and a rational pricing structure are the most significant pricing objectives in following cost-plus pricing which bring financial prudence. It is accepted as a conservative approach which has a balance between risks and returns, seek to accomplish a fair financial viability level instead of maximum profitability. Firms try to find a balance between cost-plus pricing and others therefore implement multiple pricing strategies. This is to balance the trade-off between cost and other issues (Rao and Kartono, 2009: 26-28).

Table 1. Alternative Approaches to Pricing

Approach	Based on	Ignores	Liked by
Cost-plus	Costs	Competition, customers	Finance
Market based	Competition	Cost, customers	Sales
Value based	Customers	Cost, competition	Marketing

(Source: Phillips, 2005: 22.)

Price is dangerously explosive and complex marketing variable which is used as a strategic weapon. It is not easy to manage the changes in price and pricing policies, since it involves large number of highly uncertain and variable factors. Many of the academics and professionals avoid using, studying price and pricing as a competitive tool (Udell, 1964; Oxenfeldt, 1973). Therefore, pricing is the most neglected element of the marketing mix which did not win enough recognition in business practice, economics and marketing (Shapiro, 1968; Simon, 1982: 459; Malhotra, 1996; Shipley and Jobber, 2001; Nagle and Holden, 2002: 1; Docters et al., 2004; Hinterhuber, 2004; Avlonitis and Indounas, 2005; Carricano et. al, 2010). The lack of interest on pricing is due to its complexity and fuzzy business thinking (Indounas, 2006).

2.2. Liner Shipping

Maritime transportation handled approximately, 85% of global trade volume that constitutes 90% of international trade volume of developing countries (UNCTAD, 2015a). This exhibits the importance and the role of maritime transportation and seaborne trade in international trade. According to maritime transportation industry division, liner shipping is one of the industry which refers to regular, fixed scheduled services between ports, and mostly carrying cargo at fixed prices for each commodity, although there can be discounts for regular customers. Liner business has high overheads and also should maintain a regular service eventhough the vessel capacity utilized or not. This makes the business vulnerable to marginal cost pricing by other shipowners that operate on the same trade routes (Stopford, 2009a: 80).

Globalization and its effects in late 1990s, put transport in the mainstream of economics and relevant sciences again. Undoubtly, the liberalization and globalisation of the maritime business have brought decreasing transport costs, that promotes the globalisation of trade and global production. There is a mutual relationship between trade volumes, transport costs, and the quality of transport costs. There are several factors (ports, trade flows, imbalance, volume, shipping operating costs, facilitation, shipped product etc.) as the determinants of maritime transport costs (UNCTAD, 2015a). On the other hand, as an important component of globalization, international standardization has a vital role in the shipping industry. Globalized intermodal would not be possible without standardized containers (Kumar and Hoffmann, 2002: 42-43). Therefore, containerasation remarked as a triggering event in maritime transportation which decreases the costs of carrying general cargo (Lun et al., 2010: 62).

All types of market situations can be observed in maritime transportation industries which causes a challenging situation for pricing. The results of Sys' (2009) recent study verified that container liner shipping industry is an oligopoly which represents mutual indeterdependece between various sellers. (Sys, 2009; Coyle et al., 2011: 100). Pricing is the central issue for liner service operators and price purports freight rate which is simply the amount paid for the carriage (Stopford, 2009a: 160, 519). Freight rates have an important role in shipping industry since they are the adjusting mechanism that link supply and demand. Price changes according to the sellers and buyers transaction in the market.

Price elasticity of shipping supply is the measure of its response to the changes in the freight rate. The supply of sea transport is very elastic during recessions when many of the vessels are laid up. The elasticity of shipping supply is totally elastic when the output of vessels is strained severely. In case all vessels are in service, then the supply is inelastic. As it is seen from Figure 3 the supply curve has a J-shape which represents the amount of carrying capacity that the carriers offer at each level of the freight rate to sea transportation (Lun et al., 2010: 24-25). The sea transport function in Figure 3 represents the capacity at the each freight level and the demand for sea transport represents the shippers ready to purchase at each level of the freight rate. The intersection of the supply and demand curves is the equilibrium price in the shipping market (Lun et al., 2010: 28).

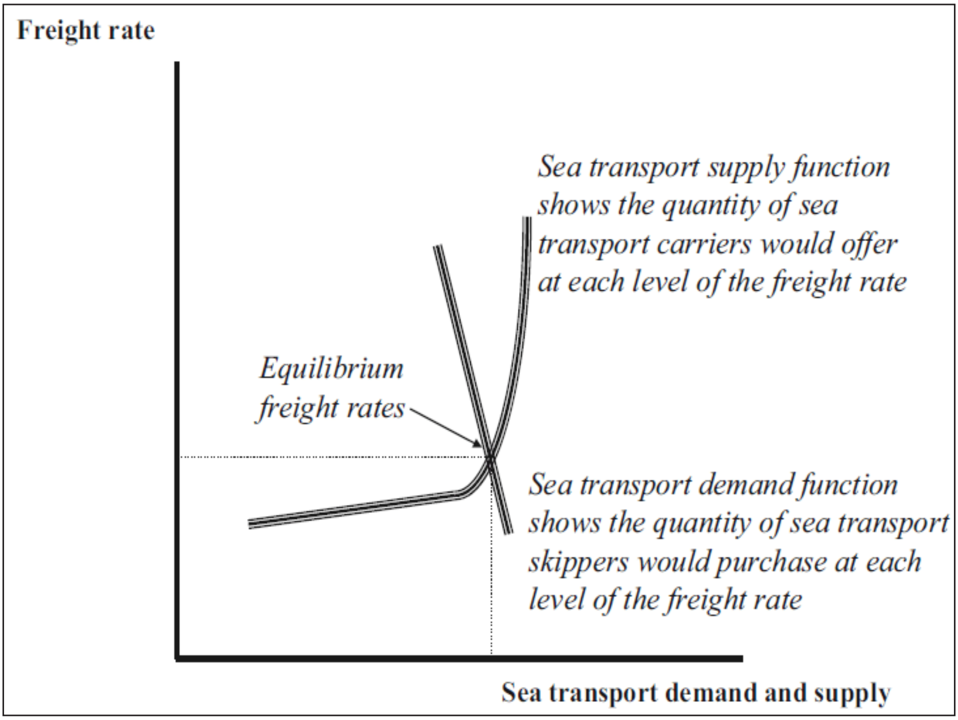

Figure 3. The Freight Rate Mechanism (Source**:** Lun et al., 2010: 28.)

Container liner shipping industry is very dynamic, complex and also vulnerable to crisis. Stopford (2009a) and Grammenos (2010) highlighted that shipping cycles are affected from the business cycles in the world economy. When the historical data of world industrial production and seaborne trade retrieved, the similarities between both cycles and their interrelation seem clearly (See Figure 4). Especially during the major economic crisis in 1957, first and second oil crises in 1973 and 1979, 1981 respectively, Asia crisis in 1997, and the latest mortgage (credit) crisis in 2009 the correlation was obvious (Stopford, 2009a: 132-133; Grammenos, 2010: 250).

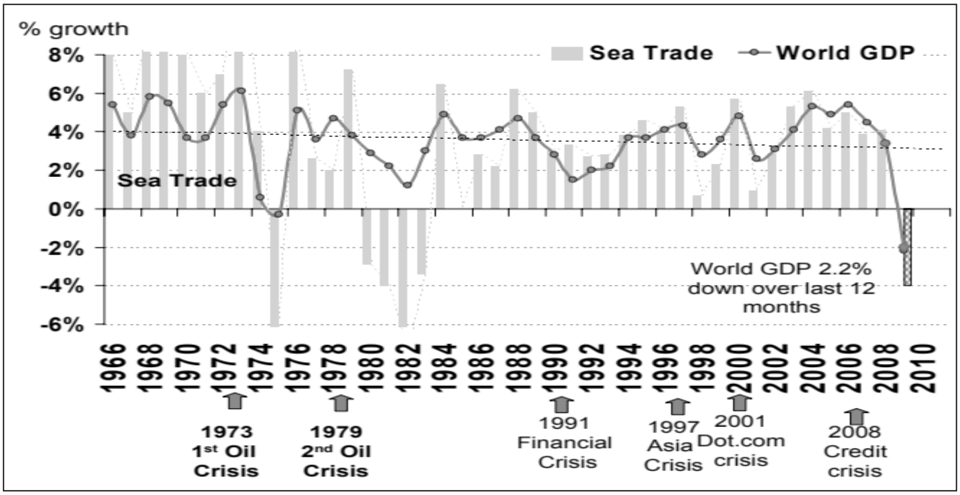

Figure 4. World GDP and Sea Trade Cycles (Source**:** Stopford, 2009b)

Also the effect of the crises can be observed in Figure 5 which exhibis the supply and demand growth for 16 years. The most difficult times were the 2008 and 2009 where there was a huge gap between supply and demand. The vessel carrying capacity was increased however, due to the crisis there was a sharp decline in the demand which in turn makes it difficult to determine the rate in the market. Both figures (Figure 4 and 5) show the market volatility and uncertainty.

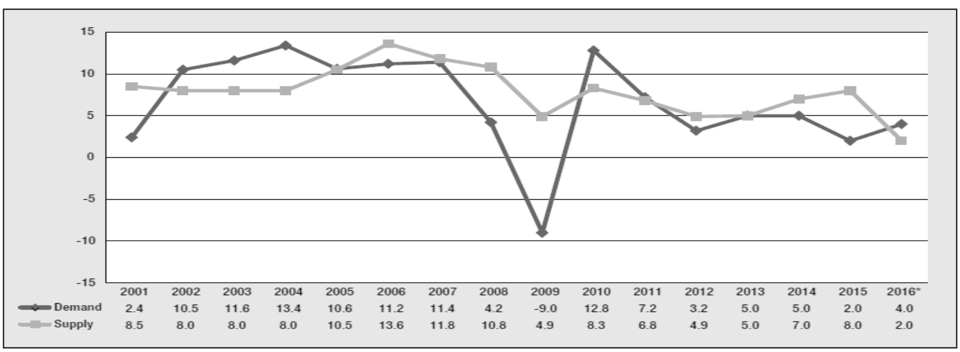

Figure 5. Growth of Supply and Demand in Container Shipping, 2001-2016 (Annual growth rates in percentage) (Source**:** UNCTAD, 2016)

As decision making under uncertainty is hard, it is important to utilize from the forecasting methods in LSI. Forecasting is not respectable human activity that Stopford (2009) addressed the difficulties in maritime forecasting whereas the future of the maritime industry seem unpredictable. He gave an example about the future freight rates which depend on new ship orders and cannot be predictable

(Stopford, 2009a:698). Although forecasting is seriously important, there are few empirical studies about freight rates that use forecasting methods in LSI (Luo et al., 2009; Fakhr-Eldin and Notteboom, 2012; Nielsen et al., 2014; Munim and Schramm, 2016).

2.3. Artificial Neural Networks

As a sub division of artificial intelligence (AI), ANN can be defined as computer systems, a set of non-linear equations, mathematical models which has the ability to mimic human brain. ANN inspired by human brain in a way of its capability in creating information, knowledge by learning, developing new information, discovering new talents therefore, ANN can be stated as a science of adaptive information processing which is useful for the cases that are difficult or seem impossible. With these features, the brain is capable of organizing structural constituents, as to perform certain computations (e.g., pattern recognition, perception, and motor control). In performing these tasks, the brain is many times faster than a highly sophisticated digital computer that is available today (Turban et al., 2002: 346, 541; Ericsson, 2004: 393; Haykin, 2009: 31; Öztemel, 2012: 29).

ANNs have the ability to "learn" from the data, they have nonparametric nature (i.e., no rigid assumptions), and they have the ability to generalize. Due to these reasons, ANNs are very promising systems in many forecasting applications and business classification applications. Human beings have learning ability and are capable of applying the things learnt. Furthermore, intuitively they find solutions to the problems. By stimulating the way of how human think, ANNs started to be used in multiple disciplines by researchers and also in many business applications in order to solve challenging problems in decision making, optimization, prediction, forecasting, pattern recognition, classification, associative memory and control (Jain et al., 1996; Elmas, 2003: 32; Möller and Reuter, 2007: 106; Turban et al., 2007: 346).

Artificial neurons are called as the processing elements that made up ANN. Likewise biological neurons, they can process information collectively and have the capabilities of learning, self-organization, and fault tolerance. There are five elements that help processing knowledge in ANN. These are the inputs, the weights, summation function, transformation (activation) function, and the output. Input vector represents the independent variables, whereas the output vector represents the depent variable. There is no information provided by ANN how the input vector transformed to output vector. Due to that reason engineers called this process as black box (Öztemel, 2012: 34; Turban et al., 2007: 346-541).

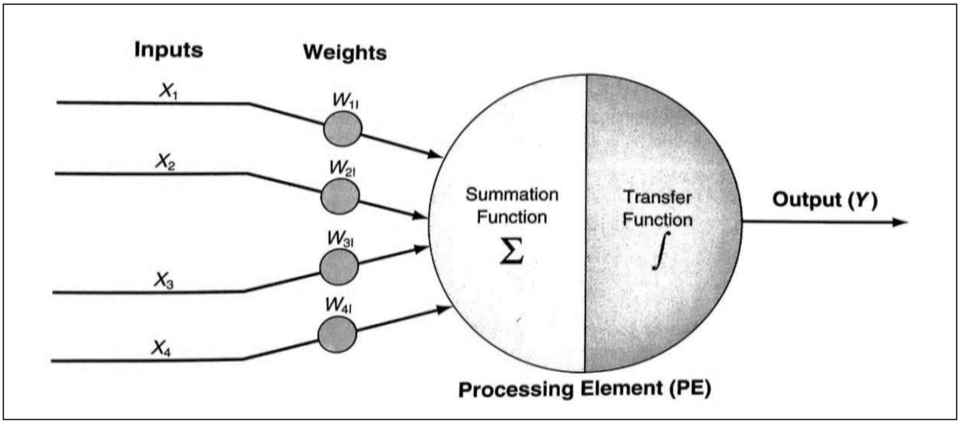

Figure 6. Processing Information in an Artificial Neuron
(Source**:** Turban et al., 2002: 541.)

The sigmoid (logistical activation) function (or sigmoid transfer function) is S-shaped and very popular as well as a useful nonlinear transfer function. It combines a linear function of the inputs with a nonlinear "squashing" function in the range of 0 to 1:

$$Y_T = {}^{1}/_{(1 + e^{-Y})} \tag{1}$$

Y_T represents the transformed (i.e., normalized) value of Y. The output levels modified to reasonable values (typically between 0 and 1) by the transformation. Before the output reaches the next level, this transformation should be performed. The reason behind such a transformation is to avoid large values in the output when there are several layers of neurons in the network. Instead of transformation function, sometimes a *threshold value* is used (Turban et al., 2007: 353). Sigmoid function has a benefit of decreasing the effect of extreme input values. Hence, it provides a degree of robustness to the network (Makridakis et al., 1998: 437).

Weight, bias and activation function generate an artificial neuron. Input signals x_1, x_2, …, x_n received by each neuron which are attached with respective synaptic weights of neuron indicating the connection strength for a specific input for each connection. Every input (x) multiplied by the matching weight (w) of the neuron connection to generate the output signal of the neuron (Y). Bias b_i is a type of connection weight that has a constant nonzero value and is added to the summation of inputs and corresponding weights (Ericsson 2004: 221-2; Haykin, 2009: 41).

The network architecture (connection pattern) can be classified as feed-forward networks (FFN) with no loops, and recurrent (feedback) networks that have loops.

Most frequently used one is under FFN called multilayer perceptron (MLP). Since learning is the fundamental trait of intelligence the learning paradigm, learning algorithm should be identified. Supervised, unsupervised and reinforcement learning are the paradigms, whereas back-propagation algorithm (BPA) is the most frequently used learning algorithm (Jain et al., 1996). In this study MLP, supervised learning and BPA are applied.

ANN provides nonlinear forecasting models in case of application to time series. ANN as a forecasting tool can perform better in large number of observations than the other business forecasting methods (exponential smoothing, decomposition, ARIMA etc.). It also supports the models that are more flexible and complicated to be fitted (Makridakis et al., 1998: 435). There are similarities between ANN and conventional forecasting methods that try to search variables that predict the dependent variable successfully. However, there is a theoreticel advantage of ANN to specify relationships by using the provided examples, the method learn the relationships. No assumptions needed about the population distributions and, differing from the conventional forecasting methods ANNs can perform with incomplete data (Hanke and Reitsch, 1998: 499). Also ANNs are very valuable in case there is a high correlation between inputs, or any missing value, or highly nonlinear systems are available (Hanke and Reitsch, 1998: 500).

The strength of ANN is to generate its own model and ability to work with complex variables. Therefore, in this study ANN is selected for modeling pricing decisions. As ANN functions on trial-and-error basis, the rationale should be to add all available variables then let the system drop or keep them for the analysis. After investigating business forecasting methods, ANN is more sophisticated when compared to others. When considering the variables for freight calculations and the correlation between them, ANN is more suitable for the study. Also, in LSI the pricing decision cannot be made according to calculations only. Expert opinion plays an important role, which means the pricing professionals intuions, judgement and experience in related market is important. ANN mimics the human brain, and in this study training of the network by an expert is important.

3. Methodology

In this study, the judgement sampling is used due to the fact that the shipping company may provide information about only their Turkey – Africa shipments and the relevant freight data (Sekaran, 2003: 277). The data set consist of destination port country from the West Mediterranean region in Africa which is one of the developing economies in its region (UNCTAD, 2015b) and the origin port is one of the important export ports of Turkey. The name of the shipping company name kept confidential, therefore, mentioned as XYZ shipping company that operates in Turkey-West Mediterranean (Med) trade which is an oligopolistic market. Turkey-West Med trade is based on spot or tariff rates which mean, they can be volatile according to changes in demand patterns. The shipping line is a small-sized carrier, and does not have its own vessel therefore, charters vessels for providing service.

3.1. Data Collection

In this study, both unstructured and structured interviews conducted with XYZ shipping company's director, branch managers, sales and marketing export/import managers, and also line account manager since they are the pricing decision-makers. The interviews started as unstructured and online (via e-mail), then continued by telephone and face-to-face. Unstructured interviews were conducted to determine the variables for the study and form a base for the questions of the structured interviews. Through these interviews, information regarding the market structure, freight rate mechanism, the positioning of the company are gathered to describe the phenomena, and also structure the pricing model to identify the problem of forecasting then evolve a theory of the factors in pricing decisions (Sekaran, 2003: 225-227).

Secondary data used for the analysis and the internal data obtained from XYZ shipping company records through January 2011 – February 2016 which consists of 62 months. Also government publications of economic indicators, financial databases are the other sources of secondary data. Besides other things, secondary data can be used for forecasting and by constructing models based on past figures, and through extrapolation (Sekaran, 2003: 223). The study takes into account 11 variables (10 input variables and 1 output variable) according to the information provided form the interviews and data availability.

Table 2. Variables in Data Set

INPUTS	
Month	TIME
Sea Freight	SF
Bunker Adjustment Factor	BAF
Port Congestion Charge	PCS
Security Surcharge Destination	SSD
Brent Oil Prices	OILBRE
Containership Charter Rates (1700 TEU)	CCR
Gross Domestic Product (World annual growth rate %)	GDP
Supply (World seaborne trade %)	SUPPLY
Demand (World seaborne trade %)	DEMAND
OUTPUT	
Total Freight	TOTAL FREIGHT

The monthly total freight rate is related with the price of the shipment between two ports; port of loading (in Turkey) and port of discharge (in Africa). Total freight data is the sum of other freight variables which are sea freight (SF), bunker adjustment factor (BAF), port congestion surcharge (PCS), security surcharge at destination (SSD) for this data set.

$$\text{TOTAL FREIGHT} = \text{SF} + \text{BAF} + \text{PCS} + \text{SSD} \quad (2)$$

Also for the analysis, brent oil (OILBRE) prices, containership charter rates (CCR), and also world seaborne trade growth in terms of container shipping supply and demand figures, quarterly world gross domestic product (GDP) are taken into account since they affect the total freight. Monthly brent oil prices downloaded from IMF database (IMF, 2016) and containership charter rates gathered from HARPEX (Harper Peterson & Co, 2016) database for relevant years. Quarterly GDP data downloaded form World Bank (The World Bank, 2016). Supply and demand figures of World seaborne trade are downloaded from UNCTAD which can be seen in Figure 5.

The data set show some discrepancies. There is a breakdown of total freight in the data set for years 2011 and 2012 (first 24 months), but in the beginning of 2013 XYZ shipping company has changed its pricing policy and started to quote all in rate (did not manifest any charge rather than SF). Since customers has been started to bargain on decrease due to fluctuating oil prices, the directors stated that they started to offer all in rates where BAF absorbed by the SF. ANN is suitable for modeling the pricing decision of XYZ shipping company since it has the ability to perform with incomplete data.

3.2. Data Analysis

For ANN modeling, open source programs Rapid Miner Studio 7.4 and Alyuda NeuroIntelligence 2.2 are used. Afterwards for forecasting the next month rate Forecaster XL is used. Before starting the analysis and introduce the variables to the network, most of the data transformed in order to eliminate wide ranges between the value. For monetary values especially, natural logarithm is frequently used, therefore, natural logarithm of SF, BAF, PCS, SSD, TOTAL FREIGHT, OILBRE, CCR are taken and then they are introduced to the system. Then the variables should be normalized which means transforming the variables in a range that is acceptable by ANN (Öztemel, 2012: 101). In this study, the systems perform the normalization and use the scaling range for input columns as [-1, 1] and selects the output range according to the activation function. The activation function is selected as sigmoid and the output range is [0, 1]. This preprocess in ANN modeling is important to find the best performing model.

3.3. Design of ANN for Pricing

The design of ANN has some steps like data normalization, selection of the network architecture, training, validation and test of the network and finally the results of the performance (Sağıroğlu et al., 2003: 20-85). During these processes, variables can either be dropped or added again and again, since the best model or the optimal model can be found by trial-and-error (Efe and Kaynak, 2000: 15). The trials are started with 10 input (independent) variables. Firstly, 10 neurons introduced as the input variables to the network to form the input layer. Addition to 10 variables, there is also "bias" term which represents the type of connection weight that has a constant nonzero value and is added to the summation of inputs and corresponding weights (Ericsson 2004: 221-2; Haykin, 2009: 41) and included in input layer. There is only 1 dependent (output) variable therefore there is only 1 neuron in the output layer. Supervised learning implemented in order to make the system predict the next step by taking into account the given output values.

For the analysis, data presentation is very important, especially in ANN. So, in the systems data set and the values introduced according to their characteristics. Due to the system requirement, TIME introduced as date and id, TOTAL introduced as numeric, target variable or as label, whereas the input variables are introduced as numeric and regular. For instance, TIME should be set as id and stabilized the values to the time setting.

3.4. Network Typology and Architecture

Systems are used to find a better network architecture and to select the most suitable architecture for the analysis. During data normalization, the system warned that BAF, PCS, SSD have the same value (zero) for all months. As mentioned above XYZ shipping company manifested BAF, PCS, and SSD values for 24 months which have the same value, then the company included these amounts in the SF and did not manifest them. Therefore, according to the data and information provided by the company all values are inserted as the same for 62 months. After normalization process, all these variables transformed to zero by the system. Since the inputs (here BAF, PCS, and SSD) are multiplied by the weights and it is not meaningful to include zero values in summation, these variables dropped by the system before preprocessing the values. After the training completed it is seen that the SF become the best predictor variable which has been determined by the system. Considering the data analysis process and high correlation between SF and TOTAL, and the similarity, SF also removed from the inputs.

The typology and the architecture of the ANN can be determined by the analyst or by the system. The model architecture for this study is FFN with one hidden layer using BPA in order to minimize the error. In pre-process phase, data normalized and ready for the selection of the network. The system also searches for possible network architectures with number of weights, fitness, train-validation-test errors, Akaike information criterion (AIC), correlation and R^2.

After several trials to determine the number of neurons and hidden layers finally, 5 input variables and Bias with one hidden layer had the best fitness for the model whereas TIME considered as id and stabilized by the system during the analysis. Hidden layers activation function is logistic (sigmoid function) and the error function is sum of squares. The activation function used between the neurons of hidden layer and output layer is the same activation function which is sigmoid function.

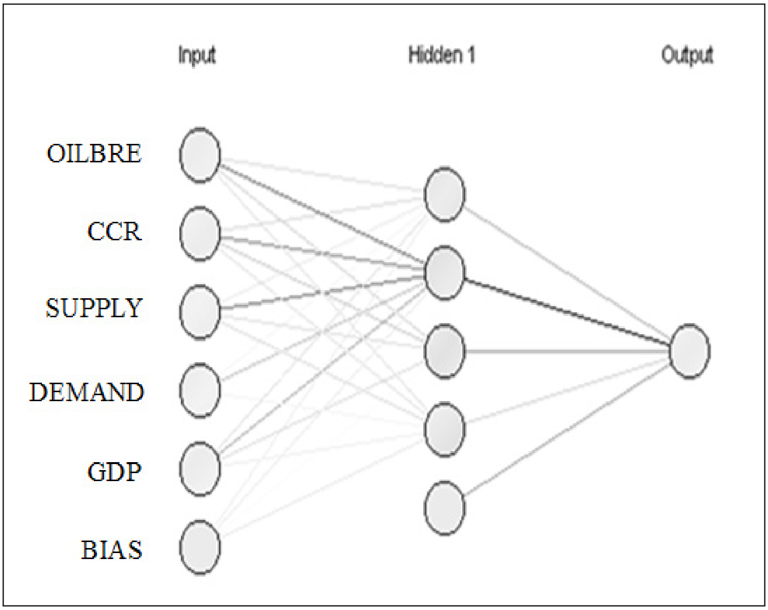

Figure 7. Network with 5 Attributes

I. Training and Test of the ANN Model

The training of a NN is the learning process which can be considered as "curve fitting" problem. The network itself is a nonlinear input-output mapping (Haykin, 2009: 194). There is no optimal model in ANN, but the important issue is to find best fitting model which has an explanatory power. Learning rule and the error term calculation should be determined. Since this is the first attempt to predict price (freight rate), most of the financial analyses and the learning algorithms that are used are considered. In the development of the model, MLP, and supervised learning strategy and BPA are used.

II. Training of the Network

There is no rule for the separation of the data set but, the ratios of 80% to 20% or 70% to 30% are the frequently used ones (Zhang et al., 1998). After completing the data preparation, the system split data set randomly for the analysis. Training set considered as 70%, validation set as 20% and the test set as 10% for this study. Training set consists of randomly selected 45 months. Remaining 17 months also split into validation and test set which are randomly selected by the system. Validation set considered as 11 months whereas 6 months selected as test set.

For the training of the data set, the learning rate and momentum rate are selected as ,10 at first. After several trials learning rate selected as ,30 and also the momentum rate selected as ,30. Certain amount of epochs (number of iterations) should be run and the trials should last until reaching the lowest root mean squared error (RMSE). The training stops automatically after 5002 iterations since, all iterations are done. The system found the best network and stored it automatically. The system achieved maximum number of iterations to find the best absolute error (AE), mean squared root error (MSE) at 943 iterations. During the iterations, the system automatically assigns the weights and changes them in order to find the optimum model. The training process completed when the error terms are reached at acceptable levels.

III. Test of the Network

In order to measure the performance of ANN, the determination coefficient R^2 and the accuracy measures MSE and RMSE have been used. Accuracy measures have been used to evaluate the performance of forecasting methods. Error terms calculated by actual value minus forecasted value, are used in accuracy measures (Gooijer and Hyndman, 2006).

$$e_t = Y_t - F_t \tag{3}$$

After calculations of the error terms both MSE and RMSE are calculated. There are several methods that can summarize the errors generated by forecasting technique most of which used averaging of residuals MSE is the widely used error indicator and formulized as:

$$\mathrm{MSE} = \frac{1}{N}\sum_{t=1}^{N} e_t^2 \tag{4}$$

N denotes the total number of training patterns, and e_t is the error measure. RMSE is the also one of the error estimation criterion. According to these criteria, high R^2 and low MSE and RMSE values are indicating a well-fitting model. It is easy to interpret RMSE. Low RMSE is expected to find the best model.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N} e_t^2} \tag{5}$$

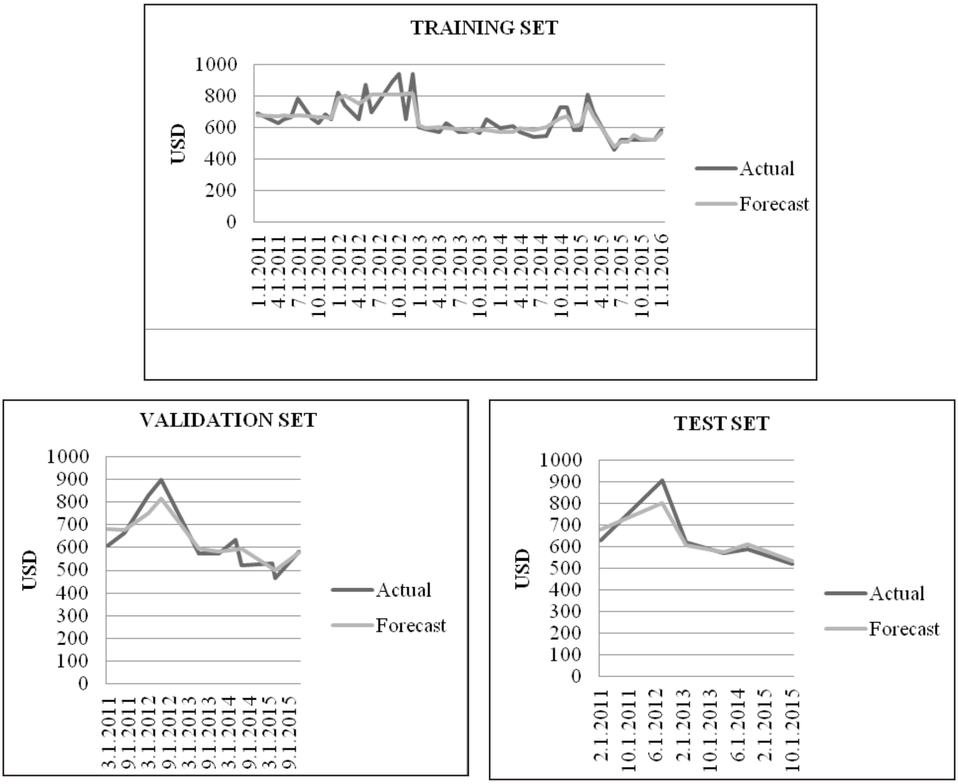

Figure 8. Training, Validation and Test Results

All sets are illustrated in Figure 8. Actual and forecasted data in training set shows discrepancies in the first lags then become closer, but in both validation and test sets show similar patterns. Forecasting values are higher than the actuals ones at first lags then intersect. Afterwards actual values become higher than the forecasted ones then again there is an intersection for a long while. Finally, for the last lag points values become closer.

The last lags of the validation and test sets are also show similar behavior like the training set. As a result of black box process, the weights are not seen from the system but changed according to the learning and momentum rates. This shows that the data trained with unknown weights but generates parallel results in training, validation and test sets.

4. Findings and Evaluation of ANN Performance on Data Set

In order to find a proper model, the variables add and removed from the data set. First 10 attributes are considered, but according to the system and data analysis results 5 attributes removed. There are several models that have been tried to find the optimal model for forecasting. Among the others those that have generated reasonable results are considered for comparison. The comparison of the models is made according to performance accuracy and accuracy measures (error terms). For more robust analysis, the study intends to produce as much model as possible by trial and error and then show the best performing model among all.

Table 3. Comparison of Training, Validation and Test Results

	Training Set	**Validation Set**	**Test Set**
Correlation	,879	,929	,958
R^2	,686	,730	,779
MSE	,480	2,784	,861
RMSE	,629	1,265	1,452

R^2 is expected to be high for performing better results and the error terms MSE and RMSE are expected to be low. According to Table 3, R^2 values are increasing from training set to test set. Training set has 87,90 % explanatory power as seen from the correlation value and also the value increased in validation set to 92,90 % and in test set to 95,80 %. This means that the model has a good fit to the data. Generally, R^2 is expected to be high since it shows the variance of the model. In training model, the independent variables can explain 87,90 % of the variance in the dependent variable.

It is not enough to get high R^2 value to consider that model fits the data. Also, accuracy measures are expected to be low. As seen in Table 2, both MSE and RMSE values are low. Mostly the error terms are selected in training set, therefore the measures of the accuracy measures are more important than the validation and test set.

After the analysis completed, via Forecaster XL program the next month (March 2016) has been forecasted. After several trials, the system generated the forecasts between the range of USD 581,75 and USD 601,85. Also the data set trained and tested by Rapid Miner Studio 7,4 in order to see the forecasting trend accuracy. After the train and test processes are finished the system generated the forecasting trend accuracy as ,818. These results that are generated by both systems can be interpreted as there will be an increase in the next month's value. Both systems make the predictions in the same direction and 82 % increase in March 2016 rate is expected.

5. Conclusion and Discussion

Recent developments in the container shipping industry push the companies to make their decisions in a most effective and efficient way than ever before. It is not just the increasing information technology adoption in the business processes or the high bargaining power of the customers, but the unpredictable crises that become a headache for the industry. Especially after the bankruptcy of Hanjin Shipping Company in 2016 and the increasing maturity debt levels, now to manage the freight rate and the freight revenue are vitally important for the companies.

Considering the changing market conditions, pricing in volatile markets is getting harder. Therefore, this study proposes an ANN model to assist the decision maker. The primary task of ANN is to find the optimal network architecture that is related to the number of both hidden layers and the neurons. Through trial-and-error, the number of hidden layers and the neurons, and also the value of the training parameters for training algorithm are determined. In the modeling of ANN, the BPA for learning and FFN used with one hidden layer for the analysis. Supervised learning applied to the study whereas 5 inputs and 1 output introduced to the system.

The results of the study revealed that ANN may generate good forecasts in case there is high correlation between independent variables. The model reach to a high explanatory power and then the training finished. Also prediction of trend accuracy (82%) is important which in this case guide the user as the price will increase for March 2016. This is important and another validation of the forecasting results since, both prediction accuracy is high and expects increase in the freight also the results generated by forecast are higher than the last month data value.

The findings of the study is important because price is not just all about numbers. It is important to predict the next month, year in business forecasting. Also understanding the trend whether there will be an increase or decrease in the prices is important. Crisis and its reasons are very important for the industry to be prepared for the future. Therefore, forecasts have great importance for the shipping market. Especially sustainability of the industry is based on better forecasts and decisions, which does not mean trying to predict the unpredictable.

There are few studies in the LSI that attempt to forecast the rates and to explain the price, rate mechanism. The study is the first to attempt modeling a shipping company's pricing decision by using ANN as a forecasting tool. Considering the world economic crises and their intensity, breadth and depth, the study may have a contribution in eliminating some of the unpredicted issues in pricing decisions.

The study also attempts to contribute pricing literature in terms of both marketing and services marketing. There are many studies in finance related with forecasting that use ANNs, however in marketing for pricing decisions there are not sufficient studies about forecasting yet no studies using ANN methodology. The ones that attempt to forecast prices (rates) are related with conventional business forecasting methods. Therefore, this study has originality and value since time series data are not linear all the time and ANN has the capability to work with nonlinear data. Especially using ANN for forecasting in VUCA environment and adapting AI technologies are very helpful and important for giving pricing decisions and setting marketing strategy.

One of the limitations of the study is the sample size which is 62 months. The sample size is important for more accurate results, but it is constrained by the data availability in reality (Zhang et al., 1998: 17). However, ANNs do not need larger sample size to perform better when compared to other linear models. Kang's study (1991) provides a strong evidence for this study which emphasized that ANN performed better even with sample size less than 50.

The study cannot take into account competitors' rate, market growth rate and therefore, do not consider them in forecasting. As XYZ Shipping Company applies value-based pricing strategy and positions its price above the market rate, this information may be important for decision-making. Whatever pricing strategy that a firm may employ, for long-term rate agreements it is important to take into consideration the business forecasting method to employ. Since costs are not easy to calculate in LSI, this study shed a light on the importance of predictions in such vulnerable industry and may avoid any losses of the company.

For further studies, the variables that cannot be put in to the analysis can be included. If the relevant data related to market growth rate, certain trade volume, supply and demand figures, freight indices (if any) can be found they should be added to the data set. These are important variables to take into account and may generate better forecasting results. In this study, the data provided by the shipping company and other open source data available are used. For instance, break-even point of the liner shipping company is unknown due to confidentiality reason. For further research, if the break-even can be provided then it can be either introduced to ANN as a threshold value by selecting an activation function or can be used to form a decision tree model. The break-even point can be accepted as a point to give decisions, if the calculated rates from ANN are higher than the break-even then it can be quoted to the customer.

The study covers monthly data of 2011-2016 (February). For further studies, if it is possible to obtain real market data the years between 2000 and 2017 can be taken into account. The reason behind this is to see the effects of 2008/9 crisis and Hanjin's bankruptcy in 2016. Crisis can be introduced as a dummy variable to the system to enable ANN to identify the effects then generate forecasts.

Another suggestion for the further studies is to apply either Decision Tree, Naïve Bayes or Rule based induction model after generating forecasts by ANN model to give more precise pricing decisions. As a managerial decision-making process for pricing it is important to utilize such decision tools and the results may be useful in long term decision making. During the modeling process, most of the studies and programs were suggesting support vector machines for the data set. For further researches support vector machines can be used. Finally, the further studies may consider a decision support system based on ANN model.

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