Analysing the nexus between artificial neural networks and ARIMA models in predicting customer lifetime value (CLV) for complex development of society and industrial activities

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ABSTRACT – REZUMAT

Analysing the nexus between artificial neural networks and ARIMA models in predicting customer lifetime value (CLV) for complex development of society and industrial activities

Today, the importance of customer relationship is not hidden from anyone, and predicting the value of customer life can help organizations to create an optimal relationship with their customers. The concept of industrial society represents a symbiosis between social and industrial activities using mass-production technologies. A sustainable CRM approach can generate significant benefits for the development of the textile industry. This paper compares ARIMA and neural network models in predicting customer lifetime value. The time-domain of the research is related to the year 2021 in the Lojoor company. To identify the variables needed to predict the value of customer longevity, experts in this field and university professors were used through descriptive survey method and using databases to collect other data. After collecting the data, the required variables were first identified by the Delphi method and then the databases were analysed using the artificial neural network method and the ARIMA model, for which MATLAB software was used. The results showed that both ARIMA and artificial neural network models can be used to predict customer lifetime value. In the case of the artificial neural network, it was observed that in addition to better prediction of the relationship between variables, which assumes them to be nonlinear, the artificial neural network model also performed better in terms of prediction results. In total, the values of MAPE error are 10.3% and MSE error is 11.6% for the neural network model. The neural network model is acceptable.

Keywords: *customer lifetime value (CLV), customer services, customer relationship management, artificial neural networks, ARIMA models, Markov chain, textile industry*

Analiza relației dintre rețelele neuronale artificiale și modelele ARIMA în estimarea valorii duratei de viață a clientului (CLV) pentru dezvoltarea complexă a societății și a activităților industriale

În prezent, importanța relației cu clienții nu mai reprezintă un secret pentru nimeni, iar previzionarea valorii duratei de viață a clientului (CLV) poate ajuta organizațiile să creeze o relație optimă cu clienții lor. Conceptul de societate industrială reprezintă o simbioză între activitățile sociale și cele industrial, folosind tehnologii de producție în masă. O abordare CRM sustenabilă poate genera beneficii semnificative pentru dezvoltarea industriei textile. Acest articol de cercetare compară modelele ARIMA și rețelele artificiale neuronale în estimarea valorii duratei de viață a clienților. Intervalul de timp selectat pentru efectuarea cercetării este anul 2021, în compania Lojoor. Pentru a identifica variabilele necesare pentru a previziona valoarea longevității clienților, experți în acest domeniu și profesori universitari au fost implicați prin metoda sondajului descriptiv și s-au folosit bazele de date pentru a colecta celelalte date. După colectarea datelor, variabilele necesare au fost identificate mai întâi prin metoda Delphi și apoi bazele de date au fost analizate folosind metoda rețelei neuronale artificiale și modelul ARIMA, pentru care a fost utilizat software-ul MATLAB. Rezultatele au arătat că atât modelele ARIMA, cât și modelele bazate pe rețele neuronale artificiale pot fi utilizate pentru a previziona durata valorii de viață a clientului. În cazul rețelei neuronale artificiale, s-a observat că, pe lângă o mai bună estimare a relației dintre variabile, care presupune că acestea sunt neliniare, modelul rețelei neuronale artificiale a funcționat și mai bine în ceea ce privește rezultatele predicției. În total, valorile erorii MAPE sunt de 10,3%, iar eroarea MSE este de 11,6% pentru modelul rețelei neuronale. Modelul rețelei neuronale este acceptabil.

Cuvinte cheie: *valoarea duratei de viață a clienților (CLV), servicii clienți, managementul relațiilor cu clienții, rețele neuronale artificiale, modele ARIMA, proces Markov, industria textilă*

INTRODUCTION

Today, customers have become the heart of business in any industry, and in order for companies to continue to operate in the current highly competitive environment, it is necessary to effectively manage their interactions with their customers, which is part of the strategy. Customer relationship management is discussed. One of the categories that are very important in attracting and retaining customers today and is one of the important factors in the success of companies is the value of the customer life cycle [1]. Customer relationship management is the process of establishing and maintaining relationships with consumers in the business cycle [2]. It is a set of interactive processes that aim to achieve the desired interaction between industry investments and meet customer needs in order to achieve maximum profit [3]. In this regard, paying attention to the concept of customer longevity value as a strategic weapon in attracting and retaining customers is important. Customer lifetime value is the amount of profit that a customer brings to a company during the lifetime of being a customer. Basically, one of the benefits of CRM in marketing is identifying more profitable customers through the CLV tool, customer lifetime value (CLV or often CLTV), lifetime customer value (LCV), or lifetime value (LTV) is a prognostication of the net profit contributed to the whole future relationship with a customer. Net profit is the measurement of a company's profit once operating costs, taxes, interest and depreciation have all been subtracted from its total revenues. The term is often referred to as a company's “bottom line” and may also be described as “net earnings” or “net income”. The prediction model can have varying levels of sophistication and accuracy, ranging from a crude initiative to the use of complex predictive analysis techniques.

There are some research questions that lead to a fundamental perspective, such as the following: How a certain country can be considered an industrial society? What is Customer Relationship Management? Is there a linkage between customer relationship management and certain industries such as the textile sector (textile and clothing manufacturing industry)?

CRM stands for Customer Relationship Management and aims to best manage our customer relationship and how to respond to their needs and wants. This will make our business more and more successful. In general, a neural network is a series of algorithms that endeavours to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial in nature. Neural networks can adapt to changing input; so, the network generates the best possible result without needing to redesign the output criteria. The concept of neural networks, which is rooted in artificial intelligence, is rapidly gaining traction in the development of commercial systems.

Customer Relationship Management represents a very important instrument for retailers, wholesalers, and distributors in the case of the textile industry. Achieving performance in an industrial sector is inherently correlated with a high degree of customer satisfaction, and the textile industry is no exception. The implementation of CRM software can significantly contribute to the development of certain businesses in the textile industry by providing optimal and intelligent solutions. Moreover, in the case of the textile industry, a very important role is played by the supply chain network. The textile industry includes certain main categories such as upstream, intermediate stream and downstream industrial clusters.

Customer lifetime value is defined as the total revenue from the organization's customers during the life of their transaction with the organization, minus the total costs of attracting, selling and customer service. Used for different groups of customers. By estimating the value of customers, it is possible to identify customers who create high value for the company and to communicate with them in a motivational way. This relationship can increase loyalty and thus increase the life expectancy of beneficial customers and increase the profits obtained from these customers [4]. Customer value refers to the total present and future value of the customer and includes three dimensions of customer attraction, retention and development and can be divided into two categories: customer desired value and perceived customer value [5]. Predicting the value of customer longevity and consequently identifying profitable customers for organizations is a special priority. Statistical models and neural networks are a new generation of data mining techniques that have been greatly developed in the last two decades. Is. And it has always been questioned which one performs better in forecasting. On the other hand, the main purpose of modelling is to determine the relationships between variables, determine the effective variables and predict. The neural network model is a simulation of the human nervous system and is in fact an imitation of the human brain and neural network [6, 7]. Learning in the neural network is done by minimizing the mean squares of the output error and by applying the error post-learning learning algorithm using numerical repetition methods [8, 9]. The number of middle layer neurons is very important because if they are small, the network will lack learning resources to solve complex nonlinear problems, and if it is large, it will cause two problems, the first being training time. Enhanced network and secondly that the network may also learn the errors in the data and act poorly in forecasting [10]. Therefore, the purpose of this study is to predict the value of customer longevity by neural network and ARIMA model and compare the results obtained in industrial organizations and identify profitable customers.

LITERATURE REVIEW

Recently, Chalaki and Bazdar have used the beta geometric model to predict the lifetime value of customers of the Tehran Stock Exchange and have increased the accuracy of predicting the lifetime value of customers by creating a correlation between the number of transactions and profits earned by each customer. They have also shown through numerical comparisons that the dependent BG model is superior to the BG/NBD model and has better performance than the Pareto model and the NBD model [11, 12]. The most accurate method for estimating customer lifetime value for large companies is the probabilistic modelling method. Although there are several techniques for modelling LTV, two methods are more common: Pareto/NBD and BG/NBD.) Many retailers today are losing customers due to the increase of e-commerce and its benefits. Yang and Chiang conducted research to predict customers' future buying patterns as well as to calculate their current lifetime value. They collected information about customers in a small store in Hong Kong and clustered customers based on RFM model parameters using the Means-K algorithm and then calculated the value of each customer's life using the weight RFM method(Recency, frequency, monetary value (RFM) a marketing analysis tool used to identify a firm's best clients, based on the nature of their spending habits). They have also used the Crisp algorithm(CRISP-DM stands for a cross-industry process for data mining. The CRISP-DM methodology provides a structured approach to planning a data mining project. It is a robust and well-proven methodology. We do not claim any ownership over it. We did not invent it. We are however evangelists of its powerful practicality, its flexibility and its usefulness when using analytics to solve thorny business issues. It is the golden thread that runs through almost every client engagement)to predict the value of customers' future lives, and finally proposed strategies that affect customer loyalty and increase profits and revenue [13].

Kaigeni et al. have proposed a new hybrid algorithm called the LLM model. The LIBOR market model, also known as the BGM Model (Brace Gatarek Musiela Model, in reference to the names of some of the inventors) is a financial model of interest rates. It is used for pricing interest rate derivatives, especially exotic derivatives like Bermudan swaptions, ratchet caps and floors, target redemption notes, auto caps, zero-coupon swaptions, constant maturity swaps and spread options, among many others. The quantities that are modelled, rather than the short rate or instantaneous forward rates are a set of forwarding rates (also called forward LIBORs), which have the advantage of being directly observable in the market, and whose volatilities are naturally linked to traded contracts in order to calculate the likelihood of a telecom company losing customers. This algorithm is a combination of decision tree and logistic regression and includes two stages of segmentation and prediction. They first identify the customers of each department using decision rules and then provide a model to calculate the probability of customers losing each department [14].

In 2018, Kavdar et al. conducted research on modelling the longevity of airline customers. They first modelled the customer lifespan based on a basic model that included only flight-related factors such as flight date, flight number, etc., and then predicted their lifespan using multiple linear regression methods. Customers have developed the model by integrating social media information with flight-related parameters. Finally, by analysing the data, they have shown that adding information related to social networks to the basic model has increased the accuracy and ability to predict [15]. In 2018, Yen et al. divided the third-party insurance clients of one of the insurance companies and determined their life value based on the RFM model and using fuzzy theory. In this research, based on the RFM model and adding a customer risk assessment index to this model, customers are divided into four groups, for each group, the value of customer life is calculated and the characteristics of each group of customers are described qualitatively [16].

Other research elaborated studies on maintaining and increasing customer satisfaction based on the quality of products and services have been done, among which we can refer to the inhibitory and active research in 2017. In this case, the chain changes test the key characteristics of product quality of connecting rods and The source of the error was identified, after which, by eliminating the causes of the error and reducing the quality characteristic changes, it is possible to improve the quality and increase customer satisfaction, and as a result, maintain and maintain its loyalty in purchasing and receiving after-sales service [12]. Moreover, some researchers [17] examined in a research study the value of customer longevity and the use of neural networks to predict membership in banks' telephone networks. They stated that one of the benefits of customer relationship management is identifying customers with more profitability. One of the important results of this research, which is for the telephone call centre to communicate with the customer, was that even without additional information, the performance of the organization can be predicted and improved.

Other researchers [18] have conducted a study to establish a computational framework for customer lifetime value for a car maintenance company in Taiwan. They stated that the value of the customer's lifetime is composed of the present and future value of the customers, which includes the estimation of longevity, future buying behaviour and the profit associated with each behaviour. They used three techniques to estimate customer lifetime value using a customer trading database. Logistic regression model and decision tree model to estimate customer turnover probability and predict customer lifespan. Then regression analysis to identify important variables affecting buying behaviour. Customers and the Markov chain, which expresses the probability model of changing customer behaviour. And finally, neural networks predict the profit offered by the customer under different buying behaviours.

Other researchers [19], while pointing to the importance of recognizing profitable customers for each organization, examined the types of CLV calculation models, then surveyed 5,000 customers for three consecutive years and after collecting and comparing customer information, customer retention and customer value creation after applying targeted advertising policies based on the results of CLV calculation were compared with 3 years ago. In this way, the effect of the programs that were used to increase customer loyalty in the organization was determined. Moreover, [20] have studied the value of customer lifetime value by RFM analysis based on customer buying behaviour. In their study based on the RFM model, they calculated the value of customers' lifespan in the end, valuable and profitable customers. The organization was divided into 8 clusters based on the value of the life cycle and using the RFM model and their characteristics were analysed. [21] have considered the importance of recognizing the value of customer life in segmenting customers based on this value and then explaining the appropriate strategies for each segment.

In this paper, a new model of customer lifetime value and customer segmentation based on customer value and side sales opportunities is examined. Several researchers [22] analysed the value of customers of industrial equipment manufacturing companies using the RFM model and the clustering method. The characteristics of customers in the form of clusters were analysed using the value analysis of the customer life cycle. It was also presented to use appropriate promotion programs with different customer segments. By comparing and reviewing the research that has been done in the field of predicting customer behaviour, most of these methods have used different data mining methods in comparison with statistical forecasting methods, also among the various data mining methods, the most predictive method is Customers' behaviour has been using neural networks for this purpose. On the other hand, Qaiser Gillani et al. investigated the role of ecological consumption considering the importance of sustainability issues [23].

RESEARCH METHODOLOGY

Research questions

Some of the questions that can be considered in the present study are as follows:

1) What are the effective factors in measuring the value of customer longevity?

2) Is the neural network model suitable for predicting customer lifetime value?

3) Is ARIMA model suitable for predicting customer longevity value?

4) Which model has more efficiency and performance?

Realm of time

The period of this research is the first half of 2021 (April) and the data related to the analysis are also related to the initial period of 2021 (April).

Expert Group

The group of experts in this study includes 10 managers, experts and decision-makers in the field.

RESEARCH VARIABLES

The main variables of the research include: Exchange recently, Number of exchanges, repetitions, Exchange volume, The length of the customer relationship, Net present value and customer revenue. In the following, an overview of each of the variables is given:

Exchange recently: It is a method of trading in which goods or services are exchanged directly and without any intermediary with other goods or services and no means of exchange are used. For example, no money is received. This type of exchange has a bilateral mode, but there is also the possibility of being trilateral and multilateral. And in developed countries, it is similar to the monetary system of that country. Of course, this is usually the case and its use is limited.

Number of exchanges: The number of times goods or services are exchanged between people.

Repetitions: Repetition can mean one of the following:

– Iteration;

– Repetitive literary array;

– Repetitive and incremental development, a project management method and in particular, software development.

There are also used the following: exchange volume, the length of the customer relationship, net present value and customer revenue.

DATA COLLECTION AND RESEARCH METHODOLOGY

After collecting the data, the required variables were first identified by the Delphi method and then the data were analysed using the artificial neural network method and the Arima model, for which MATLAB software was used. The Delphi method is a structured communication method or technique that was originally developed and developed for the purpose of systematic and interactive prediction based on the thinking of experts. This method, which is used in future research, mainly pursues goals such as discovering innovative and reliable ideas or providing appropriate information for decision making. The Delphi method is a structured process for collecting and classifying the knowledge available to a group of experts which is done by distributing questionnaires among these people and controlled feedback on the answers and comments received. In this study, the mean absolute value of error percentage (MAPE) and MSE and R as well as the effect of the new trend predictor variable have been used as indicators to select the final estimator model more accurately.

$$MSE = \frac{\sum_{J-=0}^{P} \sum_{i=0}^{N} (d_{ij} - y_j)^2}{N \times P} \tag{1}$$

In the above relation, the output number of processed elements, and the number of samples in the data set. The network output for instance i in the processed element j is the output for instance i in the processed element j. The mean square of the errors shows the difference between the observed value and the calculated values. The lowest mean square of the errors indicates the highest accuracy of the prediction. Also, the correlation coefficient indicates the amount of network efficiency, which is presented as follows:

$$r = \frac{\frac{\sum_j (x_i - x)(d_i - d)}{N}}{\sqrt{\frac{\sum_j (d_i - d)^2}{N}}\sqrt{\frac{\sum_j (x_i - x)^2}{N}}} \quad (2)$$

is the network output, d_i is the desired output, the average network output and the average desired output. The best answer for the model will be created when the correlation coefficient and the mean square of the errors tend to be one and zero, respectively.

Mean Absolute Percentage Error (MAPE) =

$$= \frac{100}{n} \sum_{t=1}^{n} \left| \frac{At - Ft}{At} \right| \quad (3)$$

EMPIRICAL ANALYSIS

There are some factors affecting the value of customer longevity. Delphi method was used to determine the effective factors in measuring the value of customer longevity. In order to achieve the effective factors in measuring the value of customer longevity in Iran, using experts and research literature related to this field, the existing criteria were extracted. In the next step, the decision group was asked to identify the most important criteria in the field of value. To determine the customer life expectancy, collecting their opinions according to the factors that scored above 0.8, is considered an effective factor in measuring the value of Iranian customer life expectancy. Finally, by confirming the figures obtained by experts, the data to perform the calculation operation, as described in table 1.

Table 1

PROBLEM VARIABLES		
Symbol	**Variable name**	**Score**
A1	Exchange recently	0.86
A2	Exchange length	0.75
A3	Number of exchanges	0.91
A4	The ratio of product sales to total purchases from the same product	0.63
A5	Money exchange value	0.83
A6	The amount of capital return per customer	0.62

As can be seen, the variables of the freshness of exchange and number of exchanges and monetary value of exchange have been identified as effective variables in measuring the value of customer lifetime. These variables are related to RFM model, which is one of the most common models for measuring length value. Are customer life. Therefore, in this research, RFM model has been used to measure customer lifespan.

CALCULATION OF CLV INDEX

Normalization of indicators

Due to the difference in the unit of each indicator, it is necessary to normalize the values of these indicators based on the same unit. These indices are normalized using the relations 4, 5 and 6 between the numbers 0 to 1.

$$R = \frac{R\max - R}{R\max - R\min} \quad (4)$$

$$F = \frac{F - F\min}{F\max - F\min} \quad (5)$$

$$M = \frac{M - M\min}{M\max - M\min} \quad (6)$$

Weighing the indices

To obtain the relative weights of the indices, the Hierarchical Analysis Course of the Hierarchical Analysis Process has been used. Finally, the weights of each of the variables *R*, *F*, and *M* are denoted by *WM*, *WF*, and *WR*, respectively, and the sum of these relative weights is equal to one.

Determining the value of indices for each customer

The value of each index of RFM model is determined by multiplying the normalized value of the index by its weight. The values of these indices are indicated by "M, "F and "R.

The calculated weights of the variables can be seen in table 2.

Table 2

WEIGHT OF VARIABLES				
Variable	**R**	**F**	**M**	**Final weight**
R	1	33/0	33/0	13/0
F	3	1	25/0	28/0
M	3	4	1	59/0

Determining the average value of indices

The average value of each of these indices is determined by dividing the total value of that index in all customers by the total number of customers.

$$R'' = W_R * R' \quad (7)$$

$$F'' = W_F * F' \quad (8)$$

$$M'' = W_M * M' \quad (9)$$

Calculating the value of customers' life cycle

The value of the customer life cycle is calculated from the total average value of RFM indices:

$$CLV = R_t + F_t + M_t \quad (10)$$

ARIMA MODEL

At this stage, after entering the data in the software, in order to initially analyse and review the data graph related to the customer's lifetime value was drawn.

This data can be identified by the symbol f in the variables. According to some authors [24] ARIMA model represents a category of time-series analysis based on prediction algorithms.

Static test and estimation of ARIMA model

As can be seen, the trend in parts has regular fluctuations and an increasing pattern. This issue should be analysed by examining the correlation diagram. Using the logarithm of data in the form of rates or ratios is not recommended. In this section, the root test of the Dickey-Fuller unit is used to determine whether the variable is meaningful. Dickey-Fuller test In statistics, the Dickey-Fuller test tests the null hypothesis that a unit root is present in an autoregressive model. The alternative hypothesis is different depending on which version of the test is used but is usually stationarity or trend-stationarity. It is named after the statisticians David Dickey and Wayne Fuller, who developed the test in 1979 [25]. The Dickey-Fuller test is one of the most widely used tests in order to determine stationary. The use of the OLS estimation method in experimental work is based on the assumption that the time series variables used are constant.

The first step in determining the meaning of a variable is to observe its time-series diagram. It is possible to detect the existence of a random trend in a time series simply through a single root test.

Consider the following first-order explanation process:

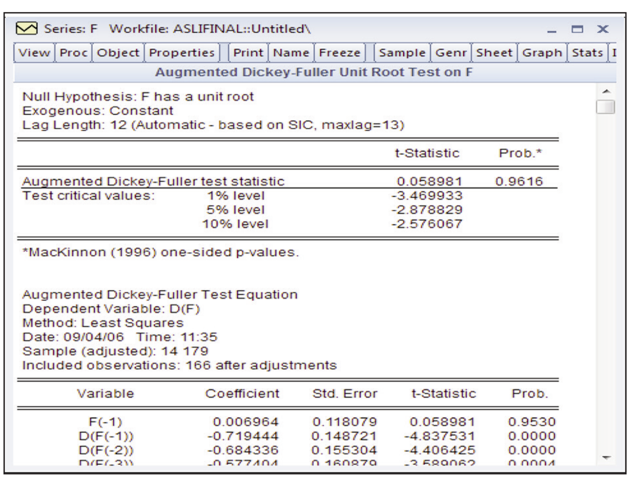
$$y_t = p\,y_{t-1} + u_t \quad t = 1,2,\dots \qquad (11)$$

To test whether the time series has a single root, or in other words is anonymous, we test the following hypothesis:

$$H_0 : p = 1 \qquad (12)$$

$$H_1 : p < 1 \qquad (13)$$

The test results are presented in figure 1.



Series: F Workfile: ASLIFINAL::Untitled\

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Augmented Dickey-Fuller Unit Root Test on F

Null Hypothesis: F has a unit root
Exogenous: Constant
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.058981	0.9616
Test critical values:	1% level	-3.469933	
	5% level	-2.878829	
	10% level	-2.576067	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(F)
Method: Least Squares
Date: 09/04/06 Time: 11:35
Sample (adjusted): 14 179
Included observations: 166 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
F(-1)	0.006964	0.118079	0.058981	0.9530
D(F(-1))	-0.719444	0.148721	-4.837531	0.0000
D(F(-2))	-0.684336	0.155304	-4.406425	0.0000
D(F(-3))	-0.577404	0.160879	-3.589062	0.0004

Fig. 1. Dickey-Fuller test

As can be seen, the model has a single and meaningless root. In figure 1, the absolute value of the Dickey-Fuller statistic is less than the critical values, so there is a single root. At this stage, the data are differentiated. The difference diagram is shown in figure 2.

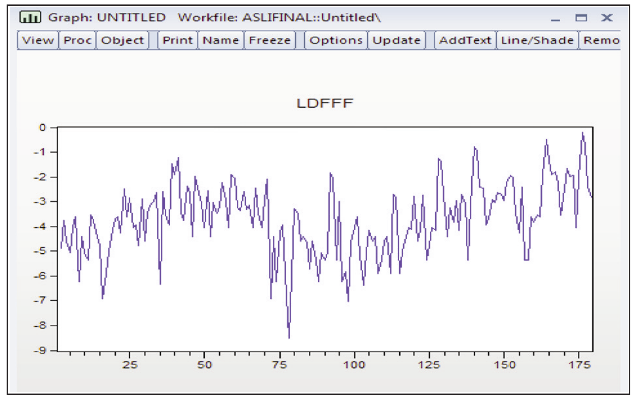
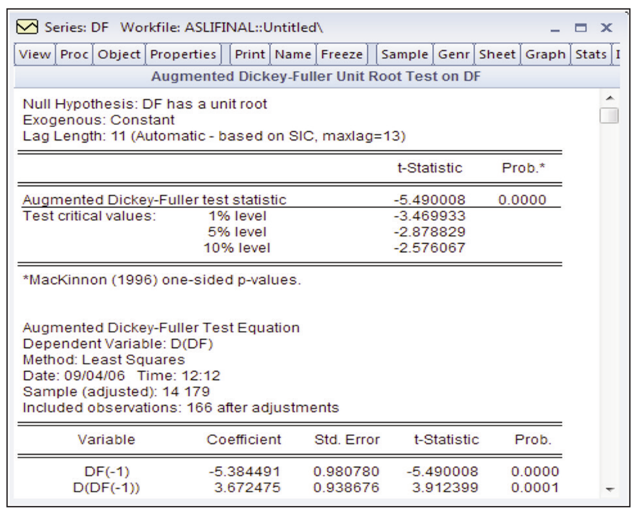


Fig. 2. Differentiation diagram

The Dickey-Fuller test is run again. As can be seen and shown in figure 3, once the absolute value of the Dickey-Fuller statistic was differentiated, it was greater than the critical values, which indicates that the unit root problem is solved.



Series: DF Workfile: ASLIFINAL::Untitled\

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Augmented Dickey-Fuller Unit Root Test on DF

Null Hypothesis: DF has a unit root
Exogenous: Constant
Lag Length: 11 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.490008	0.0000
Test critical values:	1% level	-3.469933	
	5% level	-2.878829	
	10% level	-2.576067	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DF)
Method: Least Squares
Date: 09/04/06 Time: 12:12
Sample (adjusted): 14 179
Included observations: 166 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DF(-1)	-5.384491	0.980780	-5.490008	0.0000
D(DF(-1))	3.672475	0.938676	3.912399	0.0001

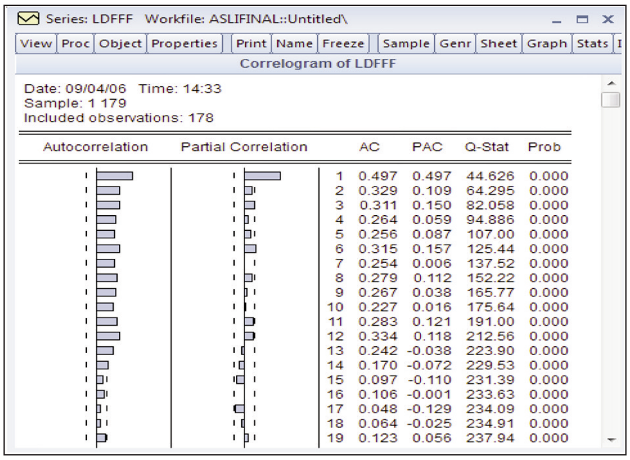
Fig. 3. Dickey-Fuller retest

As can be seen, by differentiating 1, the problem of variance anonymity is solved. Now the data self-correlation diagram is examined. The self-correlation diagram is presented in figure 4.

According to the data in figure 4, it can now be concluded based on the PACF and ACF columns that this model has AR (1), and according to the partial PC MA (2), MA (1) can be added to the model. After testing the model with equation 14, in figure 5, all MA and AR coefficients are significant and Watson camera statistic is close to 2, which indicates the absence of autocorrelation, and the value of F-STATISTIC indicates significant regression.

$$\text{LDFFF C AR (1) MA (1) MA (2)} \qquad (14)$$

Figures 6 and 7 show the forecast and actual graphs as well as the calculated errors.

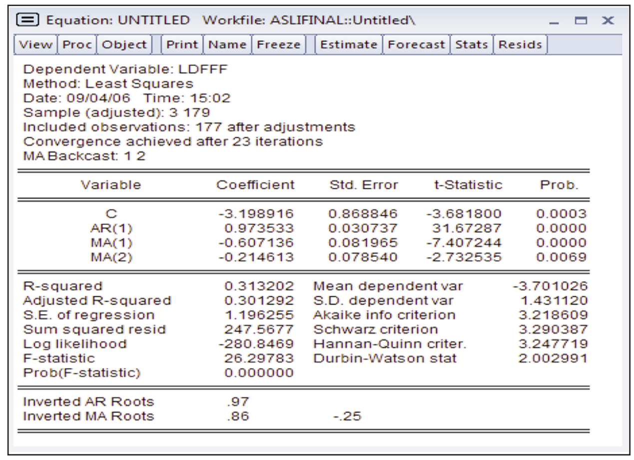

Series: LDFFF Workfile: ASLIFINAL::Untitled\

Correlogram of LDFFF

Date: 09/04/06 Time: 14:33
Sample: 1 179
Included observations: 178

	AC	PAC	Q-Stat	Prob
1	0.497	0.497	44.626	0.000
2	0.329	0.109	64.295	0.000
3	0.311	0.150	82.058	0.000
4	0.264	0.059	94.886	0.000
5	0.256	0.087	107.00	0.000
6	0.315	0.157	125.44	0.000
7	0.254	0.006	137.52	0.000
8	0.279	0.112	152.22	0.000
9	0.267	0.038	165.77	0.000
10	0.227	0.016	175.64	0.000
11	0.283	0.121	191.00	0.000
12	0.334	0.118	212.56	0.000
13	0.242	-0.038	223.90	0.000
14	0.170	-0.072	229.53	0.000
15	0.097	-0.110	231.39	0.000
16	0.106	-0.001	233.63	0.000
17	0.048	-0.129	234.09	0.000
18	0.064	-0.025	234.91	0.000
19	0.123	0.056	237.94	0.000

Fig. 4. Self-correlation graph after differentiation


Equation: UNTITLED Workfile: ASLIFINAL::Untitled\

Dependent Variable: LDFFF
Method: Least Squares
Date: 09/04/06 Time: 15:02
Sample (adjusted): 3 179
Included observations: 177 after adjustments
Convergence achieved after 23 iterations
MA Backcast: 1 2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.198916	0.868846	-3.681800	0.0003
AR(1)	0.973533	0.030737	31.67287	0.0000
MA(1)	-0.607136	0.081965	-7.407244	0.0000
MA(2)	-0.214613	0.078540	-2.732535	0.0069

R-squared	0.313202	Mean dependent var	-3.701026
Adjusted R-squared	0.301292	S.D. dependent var	1.431120
S.E. of regression	1.196255	Akaike info criterion	3.218609
Sum squared resid	247.5677	Schwarz criterion	3.290387
Log likelihood	-280.8469	Hannan-Quinn criter.	3.247719
F-statistic	26.29783	Durbin-Watson stat	2.002991
Prob(F-statistic)	0.000000		

Inverted AR Roots	.97	
Inverted MA Roots	.86	-.25

Fig. 5. Fit test of ARIMA model

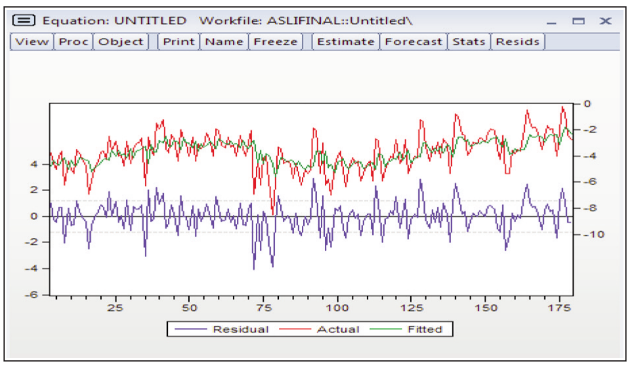


Fig. 6. ACTUAL and FITTED charts to compare actual and predicted values

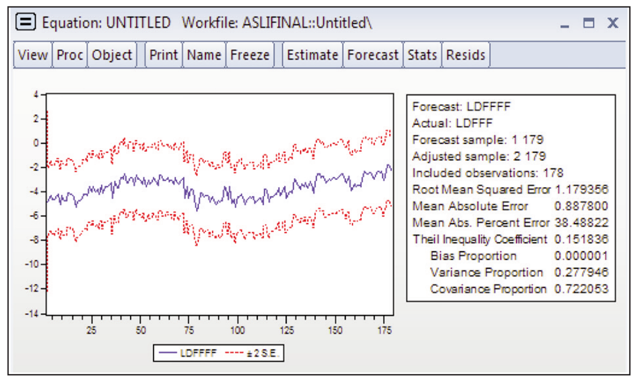


Fig. 7. Model output diagram and forecast error

NEURAL NETWORK MODEL

The neural network returns the error due to the difference between the network output and the actual value to the network and adjusts the parameters to provide a more accurate output with the next similar input pattern and reduce the error. The more training, the better the neural network performance and the less error. Mathematically, the neural network implements the extension of the desired unknown function in terms of the basic functions, which are the activity of neurons. Expansion weights are the same as network weights. Artificial neural networks are made up of simple processor parts that are interconnected by weight ratios and have the ability to learn the relationships between a set of variables. The contents of 4 important factors in the structure of neural network architecture are important in this research are as follows:

- Number of input and output variables: In the present study, the variables of exchange value, exchange volume and recent exchange were used as input variables of the forecast model and customer lifetime value data as the output variable of the forecast model and the number of 180. The customer is selected as the sample.
- Number of hidden layers: In this study, the hidden layers are two layers.
- Activation functions: The activation function of hyperbolic tangent and sigmoid tangent in hidden and linear layers have been used for transfer in the output layer.
- Learning algorithm: The number of these algorithms is very large, but the most widely used ones that have been used in this research are: the momentum algorithm, Lonberg-Marquardt algorithm, descending gradient algorithm, step algorithm, delta bar delta algorithm and Conjugate rotation algorithm.

Among the various networks, multilayer perceptron networks with error propagation algorithms are used more than others in engineering, which are usually made of three layers of neurons (input layer, hidden layer, output layer). Determining 90% of them for training and 10% of them for testing, we have changed the number of neurons from 1 to 50 and the two-layer neural network has been used. Also, the results of different neural network models are presented separately. The data of the mentioned variables are collected from the information provided by the company.

The neural network error rates in training mode using different arrangements and models are given in table 3.

Examination of previous table shows that the best state of artificial networks is when the first hyperbolic

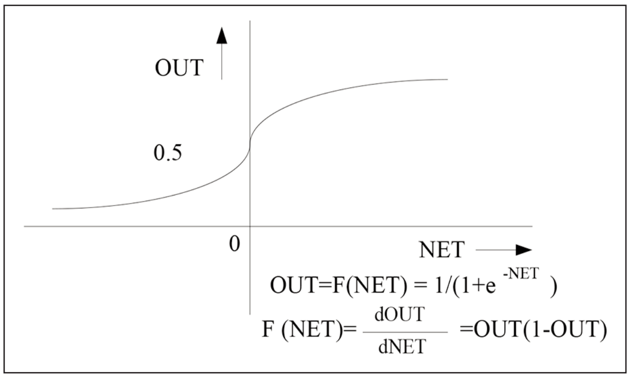


Fig. 8. Sigmoid tangent excitation function

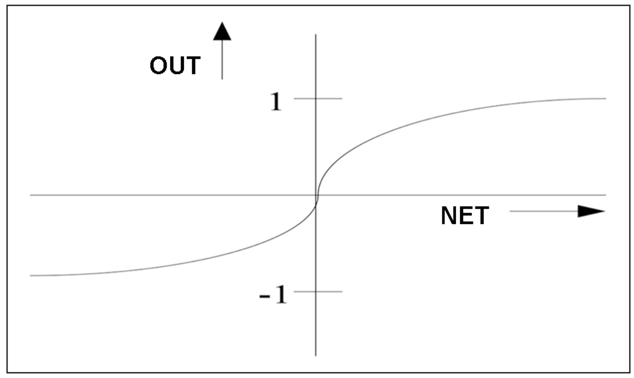


Fig. 9. Hyperbolic tangent stimulation function

Table 3

NEURAL NETWORK ERROR RATE IN TRAINING MODE

Model type	The number of repetitions	Training algorithm	Arrangement	Transfer function			MAPE	MSE
				The first layer	The second layer	Output layer		
Perceptron 1	1000	Lonberg Marquat	3–4	Hyperbolic tangent	Sigmoid tangent	Linear	159/0	134/0
Perceptron 2	1000	Descending gradient	10–12	Hyperbolic tangent	Sigmoid tangent	Linear	153/0	156/0
Perceptron 3	1000	Descending gradient	9–11	Hyperbolic tangent	Sigmoid tangent	Linear	142/0	138/0
Perceptron 4	1000	Lonberg Marquat	12–8	Hyperbolic tangent	Sigmoid tangent	Linear	138/0	141/0
Perceptron 5	1000	Lonberg Marquat	16–5	Hyperbolic tangent	Sigmoid tangent	Linear	141/0	151/0

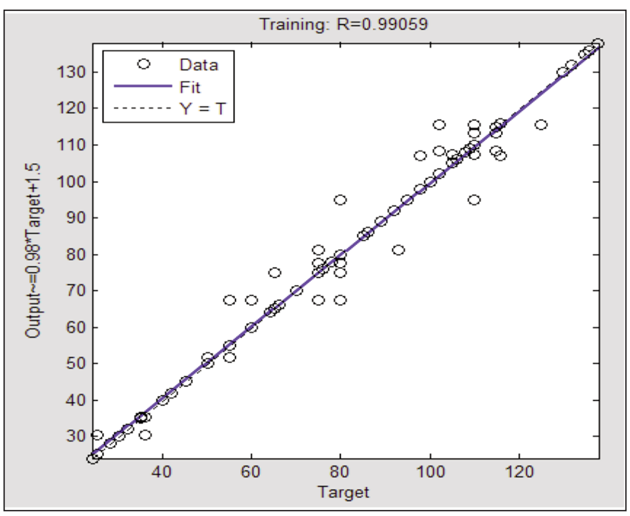


Fig. 10. Data distribution in training mode

tangent transfer function and the second sigmoid tangent transfer function and the output layer are linear and the Levenberg-Marquat learning function and the number of neurons in the first hidden layer 8 and the second hidden layer 12. In this case, the error rate of the best network is 13.8%.

The neural network error rates in training mode using different arrangements and models are given in table 4.

Examination of previous table shows that the best state of artificial networks is when the first hyperbolic tangent transfer function and the second sigmoid tangent transfer function and the output layer are linear and the Levenberg-Marquat learning function and the number of neurons in the first hidden layer 8 and the second hidden layer 12. In this case, the error rate of the best network is 10.3%.

Figure 11 shows the relationship between the predicted values and the actual values in the training mode. As can be seen, the variable *R* indicates a simple correlation between the two variables, in other words, the intensity of the correlation between the two variables. As can be seen from the value of *R* (Pearson correlation between the two variables), there is a very strong correlation between the two dependent variables and all the independent variables. As can be seen, the value of *R* is equal to 0.936, which indicates a strong relationship. It is between two variables, which indicates that independent variables are suitable for predicting the dependent variable.

Is ARIMA model suitable for predicting customer longevity value? As seen in the results, ARIMA model has been able to predict the value of customer longevity, in which the MAPE error values are 38.4%, which is acceptable and shows the efficiency of this

Table 4

NEURAL NETWORK ERROR RATE IN TEST MODE								
Model type	**The number of repetitions**	**Training algorithm**	**Arrangement**	**Transfer function**			**MAPE**	**MSE**
				The first layer	**The second layer**	**Output layer**		
Perceptron 1	1000	Lonberg Marquat	3–4	Hyperbolic tangent	Sigmoid tangent	Linear	128/0	123/0
Perceptron 2	1000	Descending gradient	10–12	Hyperbolic tangent	Sigmoid tangent	Linear	113/0	142/0
Perceptron 3	1000	Descending gradient	9–11	Hyperbolic tangent	Sigmoid tangent	Linear	108/0	123/0
Perceptron 4	1000	Lonberg Marquat	12–8	Hyperbolic tangent	Sigmoid tangent	Linear	103/0	116/0
Perceptron 5	1000	Lonberg Marquat	16–5	Hyperbolic tangent	Sigmoid tangent	Linear	116/0	123/0

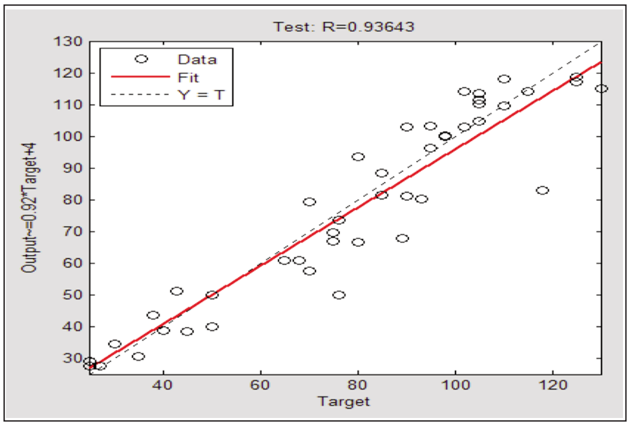


Fig. 11. Data distribution in test mode

model. Which model has more efficiency and performance? According to the issues raised, it can be seen that the artificial neural network model has a better ability to predict the lifetime value of the customer and by comparing the MAPE of each of the two models, which is shown in table 5, the model presented using the neural network. In this study, it has a better performance in predicting customer lifetime value than ARIMA model.

Table 5

COMPARISON OF NEURAL NETWORK AND ARIMA MODEL RESULTS	
Model	**APE**
Neural Network	3/10
ARIMA	4/38

CONCLUSIONS

Predicting the value of customer longevity and consequently identifying profitable customers for organizations is a special priority. Statistical models and neural networks are a new generation of data mining techniques that have been greatly developed in the last two decades. Is. And it has always been questioned which one performs better in forecasting.

What are the factors influencing the value of customer longevity? In this sense, certain optimal variants are provided, such as exchange recently, the number of exchanges and money exchange value. Is the neural network model suitable for predicting customer lifetime value? As can be seen, the neural network model has the conditions and assumptions to predict the value of customer life expectancy, so the neural network model can be used to predict the value of customer life expectancy. Also, the results show that for prediction the customer life expectancy value can be used by neural networks of the variables of recent exchange, the number of exchanges and monetary value of exchange. In total, the values of MAPE error are 10.3% and MSE error is 11.6% for the neural network model. The neural network model is acceptable.

On the other hand, the supply-chain activity is essential in the dynamics of the textile industry. CRM is primarily used for obtaining an important competitive advantage [26]. The purchase behaviour of the consumer of textile products and services can be influenced by the implementation of sustainable CRM-based strategies.

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