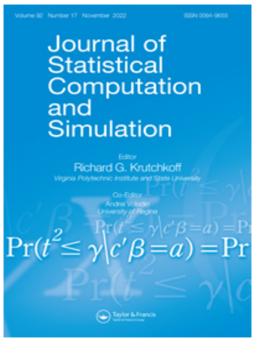

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Evaluation performance of time series methods in demand forecasting: Box-Jenkins vs artificial neural network (Case study: Automotive Parts industry)

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ABSTRACT
Production planning is a vital activity for manufacturing companies in managing any kind of organizational operations. One of the most important and vital tools that are considered necessary in production planning is forecasting future production demand. One of the most widely used approaches in demand forecasting is time series analysis. Also, two widely used methods in time series analysis are Box-Jenkins and Artificial Neural Network (ANN) approaches. In this study, the performance of these two methods to the types of errors and based on the concepts of multi-criteria decision making (MADM) has been investigated. These two methods are implemented for a product family in the automotive industry, and then the findings are compared and analyzed. The results showed that the Box-Jenkins method (Arima) provided much better predictions, which means that this method presented better results for 6 out of 8 products.

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Arima; Artificial Neural Network (ANN); Box-Jenkins; demand forecasting; seasonal Arima (Sarima); time series

1. Introduction

In the last few decades, time series analysis has become a popular research topic and has attracted a lot of attention. Time series analysis has established as a powerful tool for describing complex systems from observed data, andresearchers have used time series analysis in many fields such as clustering [1], pattern recognition [2], classification [3] and prediction [4,5]. As a branch of time series analysis, time series prediction plays a vital role in practical applications [6]. Time series prediction is one of the most important types of quantitative models in which past observations of variables are collected and analyzed to describe a model of what theirfundamentalrelationship is [7]. This modelling approach is beneficial when little knowledge of the production process is available, or there is no satisfactory explanatory model that relates the prediction variable to other explanatory variables [8].

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The purpose of forecasting is to estimate the circumstances and events that will occur in the future. Not only does it reduce unexpected costs, but also provides useful information for decision-makers. More accurate forecasting of future demand helps to ensure that development activities are appropriatelyplanned. Medium-term and long-term forecasting of demand based on realistic indicators is a necessary condition for becoming an industrial country and having high living standards [9]. The purpose of demand forecasting is to match supply and demand with each other [10]. Many studies on demand forecasting methods and different types of classification are also presented in the literature review. In general, forecasting methods are divided into two basic types of quantitative and qualitative methods according to the data and the type of analysis used in it. Kahraman et al. [11] also divided the forecasting methods into four groups. This classification is based on the kind of information available and the factors that affect the forecast.

The most comprehensive popular statistical model used to predict time series over the past four decades is the Box–Jenkins method. The Box–Jenkins model is just a class of linear models [12] that can only consider the linear feature of data time series [13], while many time series are often non-linear and irregular, for this reason, Artificial Neural Networks (ANNs) due to their non-linear, non-parametric, data-driven and self-adaptive nature have attracted much attention in the field of time series modelling and prediction [14,15].

ANNs are one of the most accurate and widely used forecasting models that have benefited from fruitful programmes in social, economic, engineering, currency and stock forecasting [16]. Several distinctive features of ANNs make them valuable and attractive for prediction. First, unlike traditional model-based methods, ANNs are self-adaptive and data-based [17] since there are a few prior assumptions about the models under consideration [14]. Second, ANNs are generalizable. After learning the datapresented to them (a sample), ANNs can often correctly infer the neglected part of a population, even if the sample data contains noisy information. Third, ANNs have a global performance approximation [18–20].

There are different types of learning functions in artificial networks, the most important of which is network training function. This function works on input vectors in consecutive training courses and updates the network. The operation continues until one of the grounds for stopping the learning process is provided. Among the grounds for stopping the learning process is reaching the top courses, reaching the minimum slope of error or reaching the desired goal. The second learning function is the adaptation function [21], which simulates a network and updates the network after each step. The third learning function is the performance function, which is used to score network behaviour. Performance functions are helpful for many learning algorithms (such as post-publication, which operate by adjusting network weights and biases) and improve their performance [22,23]. The last learning function is the transfer function that calculates the output vector of each layer [24,25].

Due to the great importance of forecasting in different parts of the organization, various researches have been conducted in this field. Some researchers have used the ANN model [14] and some researchers have used the Box–Jenkins method [26,27] to predict time series. Meanwhile, some researchers have used both methods in their research to predict [28–34]. This study aimed to compare the two methods of Box–Jenkins and Artificial Neural Network with the learning algorithm of colonial competition in predicting time series using measurement error measurement criteria.

2. Theoretical background

2.1. Literature review

Many different studies have been done on Box–Jenkins and Artificial Neural Networks. For this reason, Box–Jenkins research, Artificial Neural Networks, and hybrid research related to both methods were reviewed. Oshadi et al. [31] conducted a study on 'Comparing univariate techniques for tender price index forecasting: Box–Jenkins and neural network model'. The purpose of this study was to investigate the reliability of using univariate models to predict the tender price index because they had concluded in the past literature that uncertainty in project cost is one of the reasons for the poor performance of construction projects. They used both Box–Jenkins and artificial neural network models in their study, but the results showed that the neural network model performed better than the Box–Jenkins model in terms of accuracy. In addition, the neural network model offers a reliable forecast of the tender price index for the next 12 months. On the other hand, another study showed that the Box–Jenkins model provides better results than the artificial neural network. Safeeand Ahmad [32] conducted a survey on 'Comparing the Univariate Modelling Techniques, Box–Jenkins and Artificial Neural Network (ANN) for Measuring of Climate Index'. The purpose of this study was to determine the most appropriate method for producing forecasting models using data from the Climate Index Collection in Sitiawan, Perak. In this study, two models of Box–Jenkins and artificial neural network were investigated. Also, time series data from 1961–2012 (monthly) were used, but there were also data that had missing values, so the MSE was calculated for both models. After data analysis, the most appropriate model for forecasting the climate index was the seasonal Box–Jenkins (SARIMA) model. Also, some research indicates that both methods are better for research. Yip et al. [34] conducted a study on 'Predicting the maintenance cost of construction equipment: Comparison between general regression neural network and Box–Jenkins time series models'. This study aimed to conduct a comparative research on the applications of general regression neural network (GRNN) model and typical Box–Jenkins time series models to predict the maintenance cost of construction equipment. The results show that time series approaches can only be used to complement the current method, and both Box–Jenkins and GRNN models are the best approximation for their maintenance time. Also, most of the model parameters are through trial and error based on the scientific method. In addition, some other researchers have used a hybrid model, the Box–Jenkins combination with an artificial intelligence network, for research. BuHamra et al. [28] conducted a study on 'The Box–Jenkins analysis and neural networks: prediction and time series modelling'. In this study, they used the Box–Jenkins approach and the artificial neural network (ANN) approach to model time series data on water consumption in Kuwait; in fact, they combined the two methods. The Box–Jenkins method was used to predict unregistered water consumption data from May 1990 to December 1991. Then the neural network was used to monitor water consumption modelling and forecasting from January 1980 to December 1999 through the publication of a controlled counter. The results showed that when the input layer variables in ANN network are selected more than traditional methods based on Box–Jenkins method, the average relative error for training and test data sets is reduced by 24% and provides a superior and reliable alternative to traditional methods. Gairaa et al. [29] conducted a study on 'Estimation of the daily global solar radiation based on Box–Jenkins and ANN models: A combined approach'. They aimed to examine the new ARMA-ANN hybrid approach to global daily forecasting. Using these two models in combination had the advantages of both methods. In this study, data recorded during two years (2012-2013) in global solar radiation were used. The results showed that using the combined approach has better results than the use of each method alone.

Reviewing the literature, the results of some studies indicate that the Box–Jenkins method is better than the artificial neural network, while some studies show the opposite. Other research suggests that combining both models in research improves results. Therefore, in this study, a comparison of both Box–Jenkins and artificial neural network methods for the automation component industry was investigated.

2.2. Demand forecasting methods

There are many studies on demand forecasting methods. Different types of classification are also presented in the subject literature. For example, Kahraman et al. [11] have divided forecasting methods into four groups, and Hayedeh Mottaqi (2009) has divided demand forecasting methods into two categories in terms of nature: qualitative methods and quantitative methods. In general, the forecasting methods are divided into two basic types of quantitative and qualitative methods according to the data and the type of analysis used in it. Qualitative methods are approaches that do not use quantitative and mathematical models for predictionwhile quantitative methods are also divided into three kinds of time series, causal and meta-heuristic techniques. In time series, the relationship between demand and time variable is examined, while in the causal method (causal model), the relationship between demand and other factors (except time) is reviewed. In fact, in causal models, first, the variables that are related to the predicted variable are identified, and then the prediction is performed. Among the methods used in causal methods are linear and nonlinear regression, each of which can be a univariate or multivariate form. Meta-heuristic approaches mimic phenomena, physical objects, and living things that have been developed since the 1970s. These algorithms have been developed to solve optimization problems. Optimization is a mathematical problem that literally means finding the best possible and desirable solution.

In this study, by reviewing the literature on demand forecasting, forecasting techniques are divided into two main groups of qualitative and quantitative methods according to Table 1.

With the studies that have been done in the field of demand forecasting and also the review of recent trends in the use of various forecasting techniques, it can be seen that new studies have moved towards the use of more advanced techniques such as Meta-heuristic methods. In this research, the Box–Jenkins method, which is a linear method, is compared with the nonlinear method of ANN with colonial competitive training algorithm, and the efficiency of each method is evaluated in the case study.

2.3. Box–jenkins prediction method

Box–Jenkins Prediction Method is divided into two general modes of Arima and seasonal Arima (SARIMA) [35,36], which Arima model has three parameters p (self-regressive order), d (differentiation order), q (moving average order) and in addition to

Table 1. Demand forecasting methods based on researcher collection.

	Demand forecasting methods			
	Quantitative methods			
Qualitative methods	Time series methods	Causal models	Meta-heuristic methods	
Survey of sellers	Naive Method	Simple linear regression	Single technical approach	Combined approach of new and meta-heuristic techniques
Collective agreement	Simple Average	nonlinear regression	Genetic *algorithm*	Artificial Neural Networks (ANN) and Fuzzy Logic
Consumer expectations	Moving Average		Artificial Bee Colony (ABC) *Algorithm*	Support *Vector* Machines and Particle Swarm Optimization
Delphi method	Weighted Moving Average			Support *Vector* Machines and Genetic Algorithm
	Single Exponential Smoothing		Particle Swarm Optimization (PSO) Algorithm	Artificial Neural Networks and Particle Swarm Optimization
	Adjusted Exponential Smoothing		Gravitational Search Algorithm (GSA)	Radial Basis Networks and Particle Swarm Optimization Algorithm
	Least Square		Harmony Search Algorithm	Radial Basis Networks and Genetic Algorithm
	Seasonal Index		And …	And …

the mentioned parameters, the seasonal Arima (SARIMA) model has the parameters Ps (seasonal autoregressive order), Ds (seasonal differentiation order), Qs (seasonal moving average order). If seasonal trends are observed in the data, we use the seasonal Arima; otherwise, we use the Arima method. One of the primary needs of the Jenkins box statistical model is to identify and determine the exact parameters of the model, because if these parameters are not well identified, the determined coefficients will not be correct and as a result, the predictions will be incorrect. On the other hand, a suitable method for determining d and Ds minimises of time series variance. Therefore, by adopting different values for d and Ds and comparing the variance of the differentiated series for these values, it is possible to determine the degree of difference for the seasonal and non-seasonal levels. In other words, the values of d and Ds are chosen so that the differential variance is at its lowest. Then, the appropriate Box–Jenkins model is fitted to the differentiated time series. Other coefficients, namely the parameters p and q, are obtained from the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).

The relationship of an Arima (non-seasonal) model is as follows [37].:

$$ARIMA(p, d, q) : \phi(B)(1 - B)^d X_t = \theta(B) Z_t$$

And the relation of a seasonal Arima model is as follows [38]:

$$SARIMA(p, d, q)(P, D, Q)_s = \phi(B)\Phi_p(B^S)\nabla^d \nabla_S^D X_t = \theta_q(B)\Theta_Q(B^s) Z_t$$

2.4. Predictive method of Artificial Neural Networks

Artificial Neural Networks are systems based on computational intelligence that attempt to model the neuro-synaptic structure of the human brain. These intelligent systems, based on calculations on numerical data or examples, learn general rules; that is, they are able to extract patterns from observed data without having to make assumptions about the type of relationships between variables (Delgado, 2005). In general, an artificial neural network is a machine that models a desired function or action with useful computations during a learning process. The artificial neural network derives its computational power from its extensive parallel structure and its ability to learn, which means producing reasonable outputs for inputs not used in education (Waz, Alsinga, Van Salek and Brito; 2016). The more data input to the network, the more network training will be provided.

ANNs are used in various fields such as pattern recognition, classification, speech of visual systems, modelling and process control [39], and generally wherever a linear or non-linear mapping is required. Neural networks are nonlinear, while real-world systems are often nonlinear. In general, there are three types of neural layers in neural networks:

1. The input layer receives the basic information given to the network.
2. Hidden or intermediate layer in which the performance of these layers is determined by the inputs and the weight of the connection between them and the hidden layers.
3. And the output layer, the performance of which depends on the activity of the hidden unit and the weight of the connection between the hidden and output units.

In multi-layer networks, each layer matrix has its own weight, bias, input and output. In neural network literature, instead of the term coefficient estimation, the term learning or training is used to find the values of network weights. To teach artificial neural network, a kind of classification of learning algorithm is proposed by Lip Mann, which is divided into two categories: Supervisedlearning and Unsupervisedlearning.

Different types of neural network architecture define a network based on the number of layers, the number of neurones in each layer, the transmission function of each layer, and how the layers are connected. Among the neural networks with Supervised algorithm, the structure of some models such as backpropagation, perceptron models, probabilistic, time-delay neural network and advanced cascade post-emission have been accepted, but in the meantime, some of these models were not selected because of their disadvantages, and finally, the multilayer Perceptron model was selected for analysis because of its more significant advantages and more minor disadvantages. This model is also helpful in predicting time series.

2.5. Colonial competitive algorithm

The Colonial Competitive Algorithm is a population-based evolutionary algorithm inspired by the human political and social process and first proposed by Atashpaz-Gargari and Lucas [40]. In the genetic algorithm, a bunch of chromosomes, the optimization of the cluster of particles, and in the colonial competition algorithm, a group of countries encode the parameters of the problem [41] and seek to solve it. In this algorithm, random answers are first generated with the names of the countries and the initial empire is formed. In the first step, how countries are coded is defined as a one-dimensional array of length n, and the suitability of the answers is assessed based on the evaluation function (cost function) and the power of an empire is calculated based on the merits of countries, and in this empire, one country is defined as a colonizer (best value) and the rest as its colonies. The second stage, known as the equation stage, in any empire, the colonized countries move towards the colonizing country. This movement can be direct, which is a random number between zero and one (β) or with or with an angle (θ). In the third stage of the algorithm, a colony may be recognized as a colonizer as its power increases (to reach a more optimal answer). In the fourth stage, the total power of the empire, as mentioned in the first stage, is determined by the colonial power and a coefficient such as ζ of the colonies. The fifth stage or stage of colonial rivalry between different empires is to weaken the colonies of the empire, one of which will eventually win; in this competition, the strongest empire wins. In the sixth stage, an empire that has gradually lost all its colonies will be conquered.

3. Research process

The research has a statistical basis and is based on the use of time series models. This analysis is usually related to data that are not independent and are sequentially interrelated. After prediction by Box–Jenkins model and ANN, the accuracy of the predicted model is examined through four parameters: Mean Square Deviation (MSD), Root Mean Squared Error of Prediction (RMSE), Mean Absolute Deviation (MAD) and Mean Absolute Percent Deviation (MAPD). Then, the score of each of these methods was obtained by considering the four mentioned parameters as well as the weight, importance and value obtained by Shannon's entropy model. Finally, using a simple weighting model, the total value of each method for the product family is obtained and finally the optimal model is selected for forecasting. In data analysis, mini-tab statistical software was used in Box–Jenkins method and MATLAB software was used for Perceptron Artificial Neural Network using colonial competition algorithm. The research process has 5 main steps, which are shown in Figure 1.

3.1. Phase 1: identify and collect data on the actual monthly demand of each product

Data were collected from Automotive Parts Industryduring a 6-year period of 187-Y compound family products. In this study, statistical data of the last year were not included to evaluate the amount of prediction error in the studies. An example of the data is shown in Table 2.

3.2. Phase 2: modelling and forecasting product demand

At this stage, before modelling and forecasting demand through two methods Box – Jenkins and ANN with the colonial competitive algorithm, the measurement criteria were examined and then the forecasting errors of each method were presented separately. In the last step, a comparative comparison was made between the two methods and the two prediction methods were evaluated using graphs.

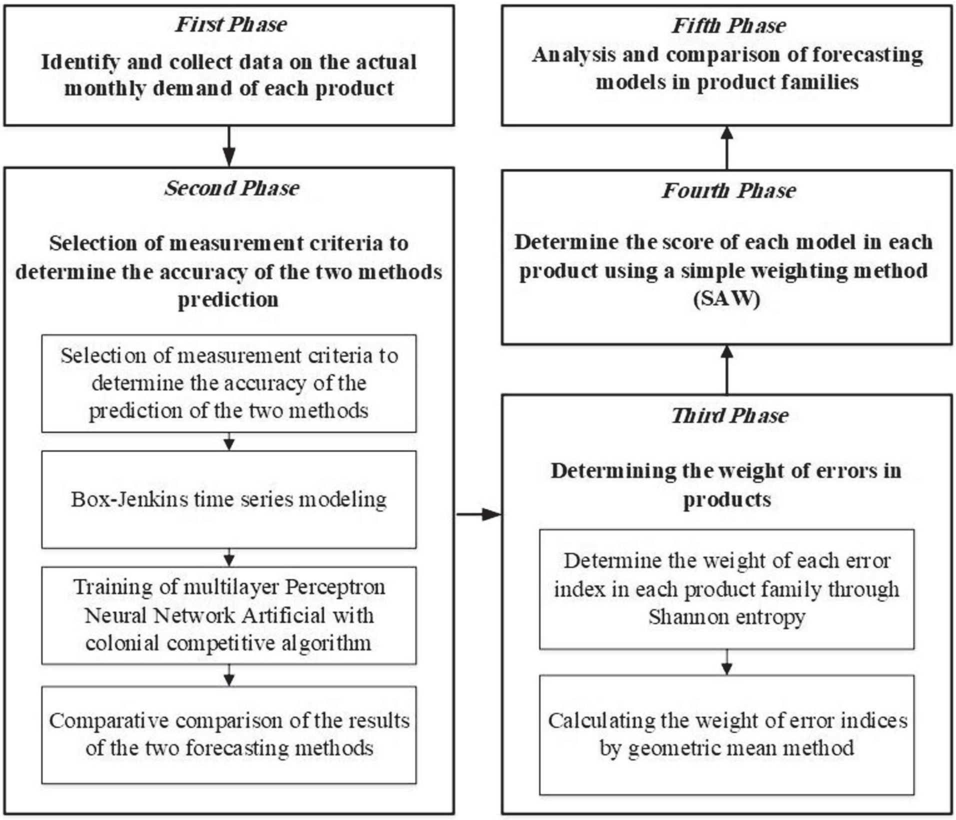

Figure 1. Research process.

Table 2. Sample of collected data.

Year	Month	PR060	PR069	PR127	PR128	PR129	PR190	PR191	PR134
First	1	10620	11250	9900	6300	11400	0	0	0
	2	15450	11250	12400	14950	15600	0	0	0
	3	12450	18900	8400	8750	9600	0	0	100
	4	19500	13500	9600	8700	12000	40	40	1520
	5	9600	7000	6400	12500	9600	0	0	760
	6	10000	11500	13400	12050	12000	0	0	1800
	7	15000	13050	11400	9000	14400	0	0	1520
	8	10320	13800	12300	14000	19742	0	0	2100
	9	12720	9300	8100	9500	9600	0	0	1178
	10	4680	9750	10300	9350	8400	0	0	1330
	11	10320	9270	9000	11500	4800	0	0	760
	12	10800	11550	8400	4500	8640	0	0	0
Second					…				
Third					…				
Fourth					…				
Fifth					…				
Sixth					…				

3.3. 2-1- Selection of measurement criteria to determine the accuracy of the prediction of the two methods

Predictions are always accompanied by error. It is important to keep the forecast error to a minimum. The accuracy of the predicted model is examined through four parameters: Mean Square Deviation (MSD), Root Mean Squared Error of Prediction (RMSE), Mean Absolute Deviation (MAD) and Mean Absolute Percent Deviation (MAPD).

MSD is a method of estimating the amount of error, which is actually the difference between the estimated values and what is estimated. MSD is a method of estimating the amount of error, which is actually the difference between the estimated values and what is estimated [42]. MSD is positive almost everywhere (not zero), one because it is random, and the second because the estimator does not count the information that can produce a more accurate estimate. So this index, which always has a negative value, the closer the value of the index is to zero, the lower the error rate.

$$MSD = \frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n}$$

RMSE is the difference between the value predicted by the model or statistical estimate and the actual value [43]. RMSE is a good tool for comparing forecast errors by one data set and is not used to compare multiple datasets.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n}}$$

Absolute mean deviation (MAD) is a robust measure of the variability of a sample whose data is univariate and quantitative. Because the MAD test is more robust than the standard deviation or variance, it works better with distributions that do not have a mean or variance, such as the Cauchy distribution.

$$MAD = \frac{\sum_{t=1}^{n} |A_t - F_t|}{n}$$

The mean absolute deviation percentage (MAPD) or (MAPE) is also used to predict accuracy in statistics.

$$MAPE = \frac{\sum_{t=1}^{n} |A_t - F_t|}{\Sigma A_t}$$

3.4. 2-2-Box–Jenkins time series modelling

In Box–Jenkins time series modelling, first the time series for each product was drawn and homogeneity test was performed on the series and the series was determined to be non-random. To create homogeneity of variance in the monthly demand series, the natural logarithm of the series is used. If an instability is observed in any product, the instability was eliminated using a delayed difference of 12 for the monthly forecast. Then the model was

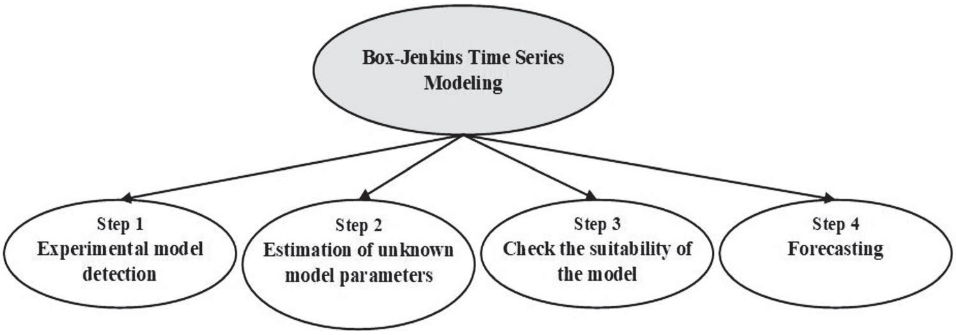

Figure 2. Box-Jenkins time series modelling.

Table 3. Box-Jenkins (Arima) prediction errors.

Product	MAD	MSD	RMSE	MAPE
PR060	1534.991	3328205	1824.337	0.310486
PR069	2875.469	13037483	3610.745	0.315653
PR127	1564.056	3850249	1962.205	0.493912
PR128	1977.356	7129809	2670.17	0.411592
PR129	1091.497	2579504	1606.083	0.674805
PR134	199.1722	75132.82	274.1037	0.574535
PR190	132.5296	22999.15	151.6547	0.729855
PR191	118.6252	39634.91	199.0852	0.918389

static in terms of variance and mean and the order d was determined. After eliminating the seasonal trend and behaviour, to identify the appropriate model after differentiation,Self-correlation diagrams andPartial series autocorrelationwas drawn to identify the original time series model through them. A correlogram in which values break relatively quickly or decline relatively quickly indicates stagnation, and a correlogram in which values do not approach zero at a reasonable rate indicates instability. If a time series has seasonal variations, the correlogram shows fluctuations. In this study, because no seasonal trend was observed in the data, a non-seasonal Arima model was used to predict the behaviour of each product. In the next step, p and q were also obtained. In the next step, the suitability of the fitted model was examined through two residual analysis and a more comprehensive fitting. Finally, after confirming the suitability of the models for the products, the demand forecast for each product was made. Box–Jenkins time series modelling is shown in Figure 2 and Box–Jenkins (Arima) method prediction errors are shown in Table 3.

3.5. 3-2- Training of multilayer Perceptron Neural Network Artificial with colonial competitive algorithm

Demand for products in the product family is the input parameters of the artificial neural network time series. The number of inputs in this model is the demand of the previous 15 periods. The number of intermediate layers is also considered as one and the number of hidden layer neurones is determined by the error test method due to the fact that they do not yet follow a single pattern. This means that the model is first trained with a secret neurone and its MSE value is calculated. A unit is then added to the secreted neurones

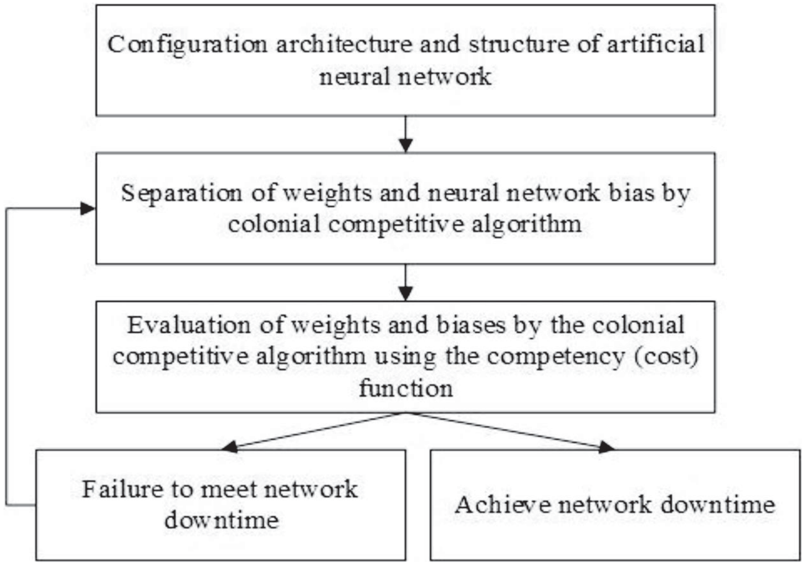

Figure 3. Training of the multilayer perceptron neural network with the colonial competition algorithm.

Table 4. Prediction errors by the artificial neural network method.

Product	MAD	MSD	RMSE	MAPE
PR060	1382.17	2766752	1663.356	0.279575
PR069	3823.549	21636807	4651.538	0.419728
PR127	2897.904	10908997	3302.887	0.915128
PR128	2440.148	10931647	3306.304	0.507923
PR129	1660.697	4854798	2203.361	1.026706
PR134	1443.964	4791159	2188.872	0.892714
PR190	191.9808	67462.62	259.7357	0.553791
PR191	139.2016	28210.61	167.9602	1.07769

and the MSE value is compared to the previous value. This process is continued to obtain the appropriate number of neurones. In this study, to make the assessment more accurate, 1–15 neurones in the hidden layer were considered and each was compared using MSE. The training of the multilayer perceptron neural network with the colonial competitive algorithm is shown in Figure 3 and the prediction errors by the artificial neural network method are shown in Table 4.

3.6. 4-2- Comparative comparison of the results of the two forecasting methods

The multilayer perceptron artificial neural network model for product 060, 069 and 127 is a feed network with a hidden layer with 8 neurones and sigmoid tangent activation (transmission) and linear functions for the middle and output layers. The algorithm of colonial competition also starts with 400 primary countries and 8 empires and the number of repetitions (decades) is 100. Also, the values of β, $\theta$and ζ are considered 0.3, 2 and 0.05, respectively.

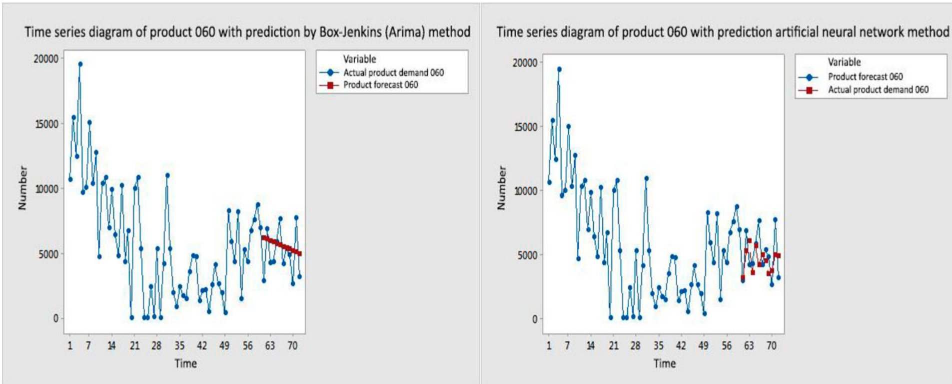

Figure 4. Real values and 12 months forecast of product demand 060 using ANN method and Box-Jenkins (ARIMA).

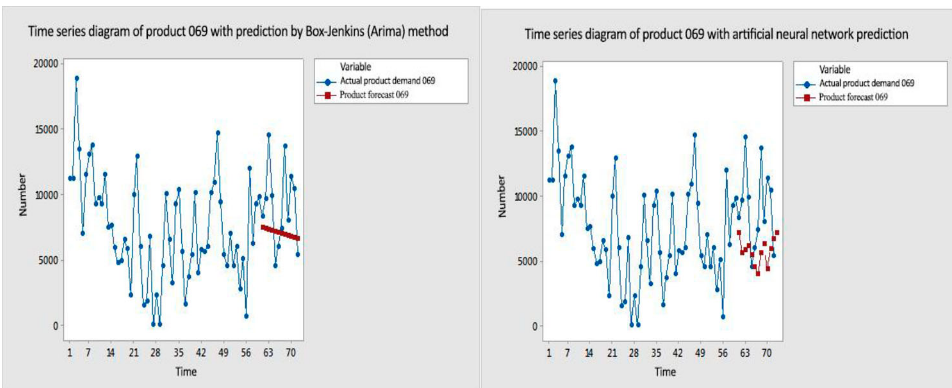

Figure 5. Real values and 12 months forecast of product demand 069 using ANN method and Box-Jenkins (ARIMA).

Also,the multilayer perceptron artificial neural network model for product 128, 129, 134 and 190 is a feed network with a hidden layer with 5 neurones and sigmoid tangent activation (transmission) and linear functions for the middle and output layers. The algorithm of colonial competition also starts with 300 primary countries and 30 empires and the number of repetitions (decades) is 40. Also, the values of β, $\theta$and ζ are considered 0.3, 2 and 0.05, respectively.

And finally, the multilayer perceptron artificial neural network model for product 191 is a feed network with a hidden layer with 6 neurones and sigmoid tangent activation (transmission) and linear functions for the middle and output layers. The algorithm of colonial competition also starts with 300 primary countries and 40 empires and the number of repetitions (decades) is 40. Also, the values of β, θ and ζ are considered 0.3, 2 and 0.05, respectively.

Box–Jenkins (Arima) method model for product 060 (1, 1, 1), product 069 (1, 1, 0), product 127 (4, 0, 0), product 128 (4,1,2), product 129 (2,0,0), product 134 (2,0,1), product 190 (1,0,0) and for product 191 (0,0,3). (Figures 4–11).

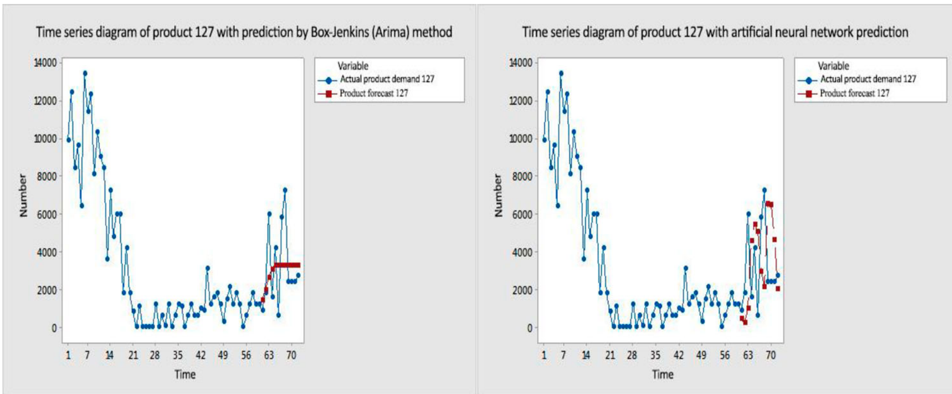

Figure 6. Real values and 12 months forecast of product demand 127 using ANN method and Box-Jenkins (ARIMA).

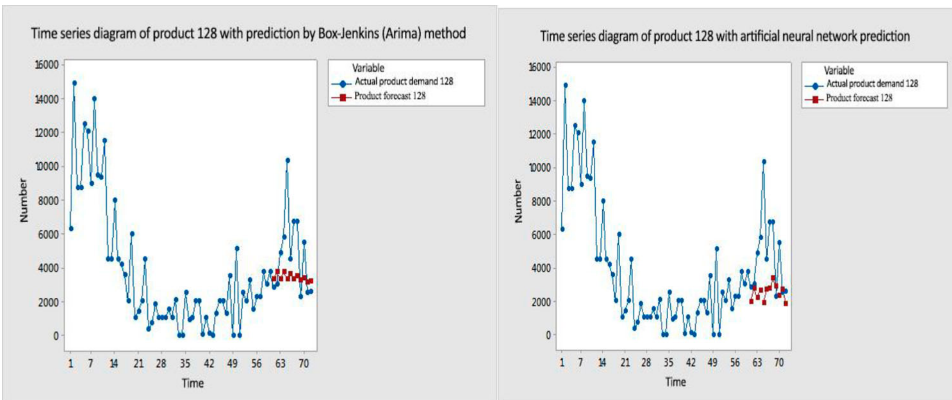

Figure 7. Real values and 12 months forecast of product demand 128 using ANN method and Box-Jenkins (ARIMA).

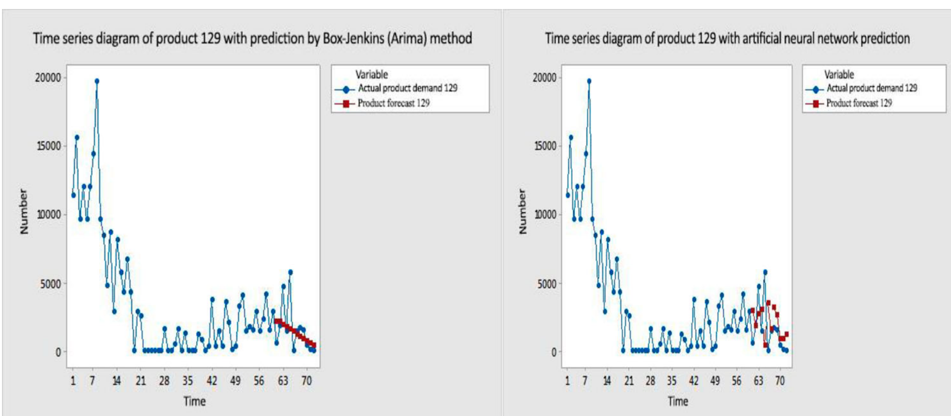

Figure 8. Real values and 12 months forecast of product demand 129 using ANN method and Box-Jenkins (ARIMA).

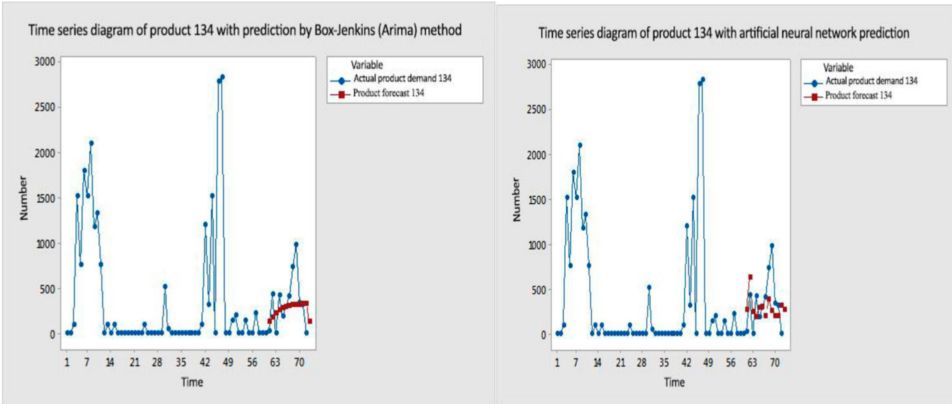

Figure 9. Real values and 12 months forecast of product demand 134 using ANN method and Box-Jenkins (ARIMA).

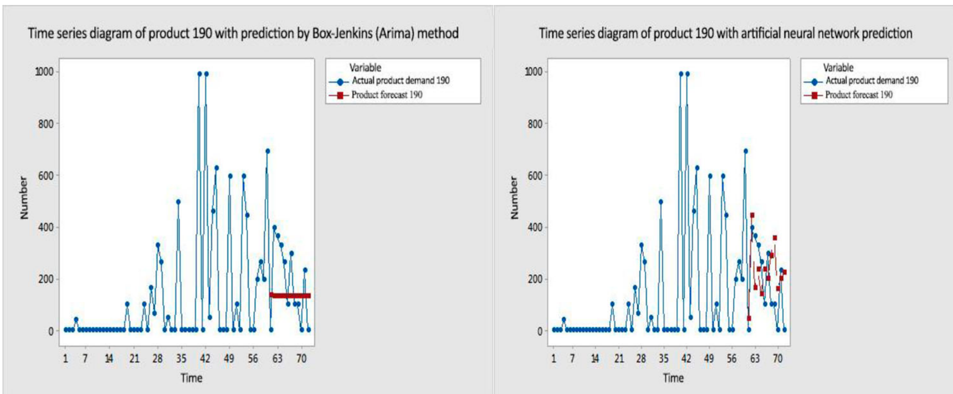

Figure 10. Real values and 12 months forecast of product demand 190 using ANN method and Box-Jenkins (ARIMA).

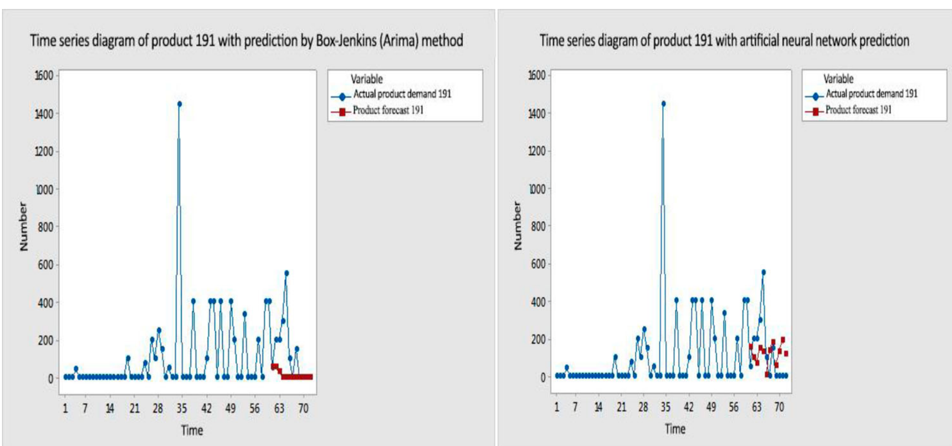

Figure 11. Real values and 12 months forecast of product demand 191 using ANN method and Box-Jenkins (ARIMA).

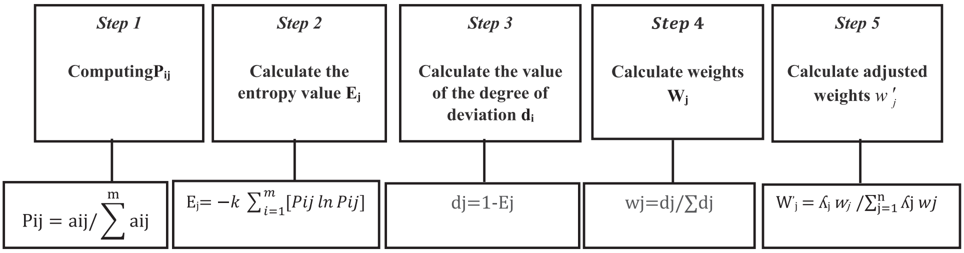

Figure 12. steps for calculating Shannon entropy.

Table 5. Calculate Shannon entropy weight for product 190.

	PR190			
	MAD	MSD	RMSE	MAPE
Weight obtained from Shannon entropy	0.090042	0.673309	0.186305	0.050344
Artificial Neural Network	191.9808	67462.62	259.7357	0.553791
Box – Jenkins	132.5296	22999.15	151.6547	0.729855

3.7. Phase 3: determining the weight of errors in products

In this step, to determine the weight of error indices, first the weight of each error in each product family is calculated through Shannon entropy and then the geometric mean of the weights obtained for each error index in the product families is calculated.

3.8. 1-3- determine the weight of each error index in each product family through Shannon entropy

Once the data of a decision matrix is fully specified, the entropy method can be used to evaluate the weights. Entropy is a very important concept in social sciences, physics as well as information theory. The basic idea of this method is that the higher the scatter in the values of an index, the more important that index is. The entropy method calculates the weight of the criteria. In fact, this method is often combined with methods such as TOPSIS, VIKOR or SAW. The steps for calculating Shannon entropy are shown in Figure 12.

The weight of each error index in each product family via Shannon entropy is shown in Table 5 for a sample of 190 products. For the other 7 products, the mentioned steps have been done.

3.9. 2-3-Calculating the weight of error indices by geometric mean method

Basically, the use of geometric mean is also for data that are relative and percentage. For example, in pairwise comparisons, because there is an inverse state and some numbers are relative and inverse, the simple arithmetic mean is not responsive and the geometric mean must be used. To calculate the geometric mean of n numbers, the numbers must be multiplied and then the root of the nth number must be calculated.

$$\left(\prod_{i=1}^{n} a_i\right)^{\frac{1}{n}} = \sqrt[n]{a_1 a_2 a_3 \ldots a_n}$$

Table 6. The total weight of each error in the product family.

The total weight of each error in the products	MAD	MSD	RMSE	MAPE
PR060	0.170322	0.527148	0.132208	0.170322
PR069	0.169943	0.525571	0.134543	0.169943
PR127	0.186944	0.491055	0.135057	0.186944
PR128	0.140999	0.572447	0.145556	0.140999
PR129	0.209103	0.461991	0.119804	0.209103
PR134	0.248151	0.470104	0.263582	0.018163
PR190	0.090042	0.673309	0.186305	0.050344
PR191	0.131622	0.588131	0.148624	0.131622
Weight of each error in products (geometric mean)	0.161778	0.534864	0.153345	0.108496
Total weight of each error in products (Normalized)	0.168785	0.558032	0.159987	0.113196

Table 7. Determine the score of each model in each product using a simple weighting method.

Product	Method	MAD *0.168785	MSD *0.558032	RMSE *0.159987	MAPE *0.113196	Score
PR060	ANN	1	1	1	1	1
	Box-Jenkins	0.900442	0.831305	0.911759	0.900442	0.863672
PR069	ANN	0.752042	0.60256	0.776248	0.752042	0.672499
	Box-Jenkins	1	1	1	1	1
PR127	ANN	0.53972	0.352943	0.59409	0.53972	0.444191
	Box-Jenkins	1	1	1	1	1
PR128	ANN	0.810343	0.652217	0.8076	0.810343	0.721665
	Box-Jenkins	1	1	1	1	1
PR129	ANN	0.657252	0.531331	0.728924	0.657252	0.598451
	Box-Jenkins	1	1	1	1	1
PR134	ANN	0.137934	0.015682	0.125226	0.643583	0.124918
	Box-Jenkins	1	1	1	1	1
PR190	ANN	0.690327	0.340917	0.583881	1	0.513369
	Box-Jenkins	1	1	1	0.758768	0.972694
PR191	ANN	0.852183	1	1	0.852183	0.958318
	Box-Jenkins	1	0.711762	0.84366	1	0.814142

* The weight of each product in the product family

The geometric mean was calculated for different products whose weight of error indices had been obtained in the previous step. The results of the total weight of each error in the product family are shown in Table 6.

3.10. Phase 4: determine the score of each model in each product using a simple weighting method (SAW)

At this stage, the total weight of each error in the products was calculated using the geometric mean method and then the total score of each method in each product was obtained based on the simple weighting method. The results obtained in Table 7 shows that the artificial neural network model is the best model for predicting product demand 060 and 191 and also the best method for products 069, 127, 128, 129, 134 and 190 is the Box-Jenkinsmodel.

Table 8. Final score of each method in the product family

Method	PR060 *0.151	PR069 *0.114	PR127 *0.07	PR128 *0.157	PR129 *0.173	PR134 *0.153	PR190 *0.033	PR191 *0.148	Final score
ANN	1	0.672499	0.444191	0.721665	0.598451	0.124918	0.513369	0.958318	0.653476
Box-Jenkins	0.863672	1	1	1	1	1	0.972694	0.814142	0.957148

*The weight of each product in the product family

3.11. Phase 5: analysis and comparison of forecasting models in product families

Finally, after reviewing the optimal method and model to predict the demand for each of the products of the 187-Y compound product family, according to the amount of consumption of each product from the compound material in the product family, the Box–Jenkins method was selected as the optimal model. The final score of each method in the product family is shown in Table 8.

Discussion and ConclusionThis study was conducted to predict the demand for 187-Y compound family products with statistical data over 6 years. The prediction was made by the best model of artificial neural network models as well as the best model of Box–Jenkins models. Finally, after examining the optimal method and model to predict the demand for each of the product family products, the Box–Jenkins method was selected as the optimal model in the 187-Y compound product family.

Since in this study a nonlinear method (artificial neural network) and a linear method (Box–Jenkins) are used and according to the results obtained and the choice of linear method, it can be concluded that short-term demand follows a linear model. Also, artificial neural network cannot be used as a better model in predicting short-term demand.

Various studies have been performed comparing Box–Jenkins and artificial neural network methods. In some studies, the Box–Jenkins method works better than artificial neural network, and vice versa. Singhand Mishra [44] conducted a study on 'Application of Box–Jenkins method and Artificial Neural Network procedure for time series forecasting of prices'. The results showed that ANN performed better than the ARIMA models in forecasting the prices. A study was also conducted by Işığıçok and Tarkun [45] on 'Forecasting and technical comparison of inflation in Turkey with box–jenkins (ARIMA) models and the artificial neural network' which showed that obtained from both techniques were close to each other. Other research also includes Safeeand Ahmad [16] research on 'Comparing the Univariate Modelling Techniques, Box–Jenkins and Artificial Neural Network (ANN) for Measuring of Climate Index'. Results show that Box–Jenkins is the most suitable model for forecasting. The results of the research are consistent with the latest research and show that Box–Jenkins prediction is better than artificial neural network.

At present, many domestic research centres and research centres of organizations, as well as offices of strategic studies that are required to predict, use structural models for forecasting. Although very accurate forecasting may not be important in some cases, short-term accurate forecasting is certainly important for policymakers for many variables. As a result, other meta-heuristic and more accurate combination methods can be used as a competitor alongside conventional and traditional methods. For example, the combination of perceptron neural network and other learning algorithms can be used to predict time series and compare with the proposed method. Other independent variables such as inflation rate, car demand, fuel price (gasoline), etc. can also be used as input data for forecasting. Comparing the efficiency of old forecasting methods with other newer techniques and various combinations of meta- heuristic methods can be considered as future research topics.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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