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The Effectiveness of Using Fuzzy Neural Networks in Predicting the Sales Volume of Perishable Products

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Abstract: This article discusses methods for predicting the sales volume of perishable products to identify the best method that provides the most accurate forecast value of the indicator under study. The initial data for forecasting are the volumes of daily perishable products that we sell. For a trading company, the volume of products purchased for retail sale must match the volume of demand. Therefore, the presence of product residues at the end of the trading day is unacceptable. That is especially true for products with a short shelf life (chilled meat, dairy products, fruits, vegetables, etc.). We must write off the products as losses if the sale period has expired. Therefore, identifying the most accurate forecasting method in this area is a significant task. Solving this problem will reduce losses from trading activities. For comparison, the following three methods were used: alignment of the obtained dynamics series according to the Fourier series, forecasting using a two-layer neural network, and forecasting using a neuro-fuzzy network. We determined the accuracy of each method by calculating the average approximation error. The prediction method using a neuro-fuzzy network showed higher efficiency. The discrepancies between the actual and theoretical values of the implementation volume were minimal. Therefore, the developed neuro-fuzzy model can be used to predict the sales volume of perishable products. We are further testing the neuro-fuzzy model on new sales data.

Keywords: sales volume, demand, forecasting, dynamics series, neural network, neuro-fuzzy network, average error

1. Introduction

Currently, the solution to the practical problems of the analysis and forecasting of time series is used in various fields of human activity. Obtaining forecast values based on the initial data of a time series is relevant for solving planning problems in economics, trade, and management when assessing the risks of information security and building intelligent decision support systems [1]. The accuracy of forecasts is critical in areas related to the quality of life and the preservation of human health [2, 3]. Various modeling methods have been used to solve such problems, including correlation and regression analysis [4–6], trend analysis [7–10], and artificial neural networks [11–14], developed based on the principles of both distinct and fuzzy logic.

This study examines the problem of identifying a method for the most accurate forecasting of sales of perishable products. By knowing the projected sales volume, a manager makes an objective decision regarding the volume of products purchased for sale in a retail store. That will prevent the products from reaching their expiration dates and reduce store losses.

As practice shows, a single method suitable for any forecasting task does not exist. The technique choice often depends on the conditions of forecasting and the characteristics of the predicted indicator [15]. Therefore, this study aims to identify the best method that provides the most accurate forecast value of sales of perishable products in a retail store and its application to reduce unreasonable costs. The significance of the study is to prevent purchases of goods for sale in a retail store over the volume that the store can sell.

2. Literature Review

As mentioned above, the problem of modeling and forecasting sales volumes has been addressed in many papers. Their common goal is to optimize the activities of a trading company. These and other publications differ in research objects, industry specifics, and modeling methods. Some researchers focus on building time series models [7, 9, 10] and using them in forecasting, another group of authors believes that artificial neural networks have better effectiveness in solving forecasting problems [16, 17], and the third group of researchers "promotes" correlation and regression analysis [6, 18]. In some studies [19–21], several approaches were applied to forecasting , but depending on the specifics of the initial data, the best method is not determined. There is no consensus on which method is better.

The technique choice depends on the problem area and the object of forecasting. There are very few publications on forecasting of sales volume of perishable products. The most significant studies are those reported by Firyago et al. [22], Yigit and Esnaf [23], Hendrix et al. [24], and Li et al. [25]. In almost all such works, they use only one forecasting method. Review articles also exist, e.g., studies reported by Kaizer et al. [26] and Seyedan and Mafakheri [27]. They discuss the possibilities of various forecasting methods, but no specific examples are provided. Comparative analyses of the effectiveness and accuracy of forecasting methods based on the same source data are not yet available. Therefore, the author of this article found it important and beneficial to perform a comparative analysis of the effectiveness of several methods for

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forecasting sales volume using the example of selling chicken meat in one of the small retail stores in Tver.

2.1. Setting the task

For retailers of perishable food products, one of the most critical problems is determining the product volume purchased from a wholesaler with a short shelf life. Perishable food products are those that require cold storage (at a temperature of 4 °C ± 2 °C) and are intended for consumption within 24–48 h [28]. Therefore, when determining the volume of purchase of perishable products, a retailer must remember the following conditions:

1) It is hard to sell a large volume of products in a short period. An entrepreneur is forced to write off the unrealized goods for losses.
2) Small volumes of orders can also result in a loss in the form of lost profits.

Mistakes are inevitable in this case, especially for a novice entrepreneur. Therefore, at the beginning of the retailer's activity, it is recommended to record the daily sales volumes of all types of perishable food products. That is the solvable task at the current level of information technology development. Through forecasting, an entrepreneur can purchase only the quantity of goods that can be sold in a trading day.

Table 1 and Table 2 present data on purchases of goods and sales in one of the retail stores in Tver selling chilled meat, respectively.

Purchases of chilled meat are from a wholesale supplier in quantities determined by the owner of the retail store based on his own experience and intuition. As a rule, the daily delivery of goods and their sale do not coincide. There is almost always a surplus of goods or a shortage. Figure 1 shows graphs of the volume of purchases and sales over 97 days of observations.

Unsold refrigerated products had to be frozen at the end of the trading day, which negatively affected their organoleptic properties. In addition, the price of frozen products is lower. The disadvantage is determined by surveys of regular customers. They talk when they come to the store, but the product is out. Thus, the retailer loses the profit that he could have made.

Thus, 96 observations were for predictive models. The goal is to determine the forecast value of sales of chilled meat on the 97th day of trade and subsequent days for each model. It is assumed that the demand and the pricing policy will not change.

3. Research Methodology

Modern methods based on machine learning and big data analysis are for predicting the volume of perishable products. These approaches

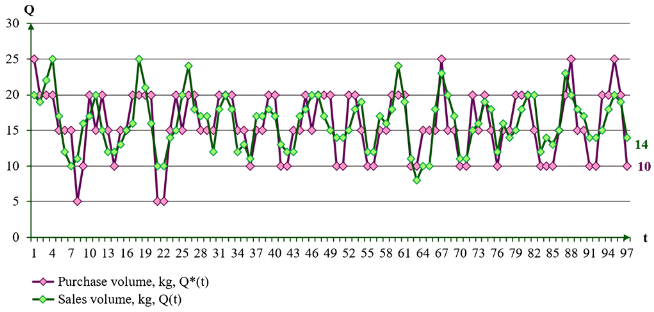
Table 1
A fragment of data on purchases of chilled meat from a wholesaler

Date	Day of the week	Purchase volume, kg, Q(t)	Date	Day of the week	Purchase volume, kg, Q(t)	Date	Day of the week	Purchase volume, kg, Q(t)
01/05/24	Wed	25	10/05/24	Fri	20	19/05/24	Sun	20
02/05/24	Thu	20	11/05/24	Sat	15	20/05/24	Mon	20
03/05/24	Fri	20	12/05/24	Sun	20	21/05/24	Tue	5
04/05/24	Sat	20	13/05/24	Mon	15	22/05/24	Wed	5
05/05/24	Sun	15	14/05/24	Tue	10	23/05/24	Thu	15
06/05/24	Mon	15	15/05/24	Wed	15	24/05/24	Fri	20
07/05/24	Tue	15	16/05/24	Thu	15	25/05/24	Sat	15
08/05/24	Wed	5	17/05/24	Fri	20	…	…	…
09/05/24	Thu	10	18/05/24	Sat	20	04/08/24	Sun	20

Table 2
A fragment of the initial data for forecasting

Date	Day of the week	Sales volume, kg, Q(t)	Date	Day of the week	Sales volume, kg, Q(t)	Date	Day of the week	Sales volume, kg, Q(t)
01/05/24	Wed	20	10/05/24	Fri	17	19/05/24	Sun	21
02/05/24	Thu	19	11/05/24	Sat	20	20/05/24	Mon	16
03/05/24	Fri	22	12/05/24	Sun	15	21/05/24	Tue	10
04/05/24	Sat	25	13/05/24	Mon	12	22/05/24	Wed	10
05/05/24	Sun	17	14/05/24	Tue	12	23/05/24	Thu	14
06/05/24	Mon	12	15/05/24	Wed	13	24/05/24	Fri	15
07/05/24	Tue	10	16/05/24	Thu	15	25/05/24	Sat	20
08/05/24	Wed	11	17/05/24	Fri	16	…	…	…
09/05/24	Thu	16	18/05/24	Sat	25	04/08/24	Sun	19

Figure 1
The volumes of purchases and sales of chilled meat in the retail store



allow us to identify patterns in the data and make accurate forecasts, which is crucial for inventory management and minimizing losses.

Table 3 shows the main ones.

Table 3
Modern methods used for forecasting

Machine learning methods		Methods of big data analysis	
Neural networks	They model complex dependencies in data and identify hidden patterns.	Time series methods	They use historical sales data to predict future values and take into account seasonal fluctuations and trends.
Decision trees	They help in identifying the key factors influencing demand and create predictive models that take these factors.	Casual models	They take the influence of external factors on demand, such as price, promotions, seasonality, and economic indicators.
Cluster analysis	Divides data into subgroups based on similarity, which allows you to predict demand for individual product categories.	Hybrid models	Several methods, for example, combine time series methods to predict an underlying demand and then adjust it to take external factors.

The method choice depends on the specifics of the forecasting object and the available data regarding it. In this case, Table 2 shows a moment row of the dynamics of the sales volume of chicken meat at the end of the trading day, containing 96 levels. To predict time series, the method of alignment using analytical formulas (if we can match analytical formulas to the source data), as well as artificial neural networks, is often employed. Different architectures of neural networks are suitable for forecasting in machine learning tasks, which differ in data processing features and the ability to model complex relationships. Multilayer perceptrons (MLPs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers have their advantages and recommended architectures for forecasting. To solve this problem, when choosing, we were guided by two factors: the ability to display nonlinear dependence and adaptability to different types of data by configuring the architecture (i.e., number of layers and neurons per layer). For comparison, we chose a dynamic Fourier series model, a two-layer neural network, and a neuro-fuzzy network to predict the sales volume of chilled meat. These methods are in this section.

3.1. Analytical Fourier row alignment

The essence of alignment according to analytical formulas is that on empirical data, a trend equation is found, according to which theoretical levels are determined, considered as a function of time $\hat{y}_t = Q(t)$. If the empirical row of dynamics is a periodicity of changes in levels, which are sinusoidal oscillations, then alignment using a Fourier series is acceptable for such a series [29].

In the Fourier series, the levels are a function of time, as shown in the following Equation [30]:

$$\hat{y}_t = a_0 + \sum_{k=1}^{m}(a_k cos(kt) + b_k sin(kt)), \tag{1}$$

where k is the number of harmonics (sinusoids) and the fluctuations of the levels of the series are the sum of several sinusoids superimposed on each other.

Therefore, for $k = 1$, the function will have the form:

$$\widehat{_1y}_t = a_0 + a_1 cos(t) + b_1 sin(t). \tag{2}$$

For $k = 2$:

$$\widehat{_2y}_t = a_0 + a_1 cos(t) + b_1 sin(t) + a_2 cos(2t) + b_2 sin(2t). \tag{3}$$

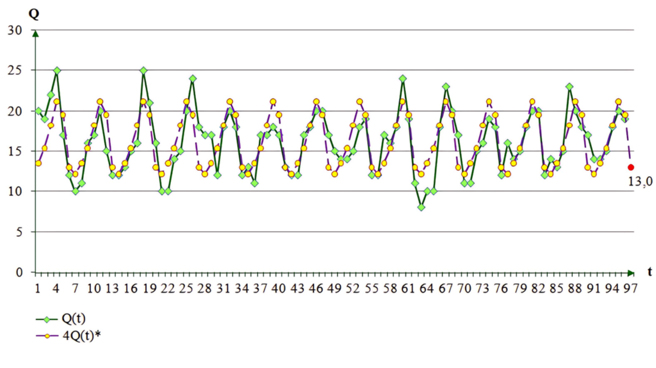
Usually, the number of harmonics is assumed to be no more than four. The parameters of this equation are shown in the following formulas:

$$a_0 = \frac{\sum y}{n}; \quad a_k = \frac{2\sum y cos(kt)}{n}; \quad b_k = \frac{2\sum y sin(kt)}{n}. \tag{4}$$

Successive values of t are usually from zero with an increment equal to $\frac{2\pi}{n}$, where n is the number of levels of the empirical series.

In this case, sales of chicken meat increased on weekends and decreased at the beginning of the week. According to the survey of customers, on Saturday and Sunday, there is free time for shopping and cooking for several upcoming working days (Monday, Tuesday, and Wednesday). Therefore, the demand for chilled meat products increases by the weekend, and that on weekends (usually on Sunday) is a maximum. Figure 2 shows the initial series $Q(t)$ of dynamics and a series aligned with the Fourier row $4Q(t)^*$.

Figure 2
Fourier row alignment



The aligned series is at k = 4. The increase was calculated as $\frac{2\pi}{7} \approx 0.898$ because there are seven days in a week. The parameters of the predictive equation obtained using formula (4) were the following: $a_0 = 16.125$, $a_1 = -3.695$, $a_2 = 1.326$, $a_3 = -0.121$, $a_4 = -0.121$, $b_1 = 2.374$, $b_2 = -0.120$, $b_3 = -0.143$, and $b_4 = 0.143$.

The forecast value of sales volume on the 97th day (Monday) was 13.0 kg. The actual value on this day was 14 kg.

3.2. Application of a two-layer neural network

A two-layer neural network predicts sales volume (Figure 3).

Figure 3
A two-layer neural network

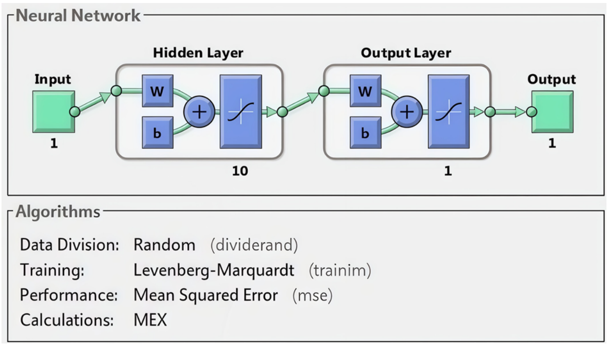
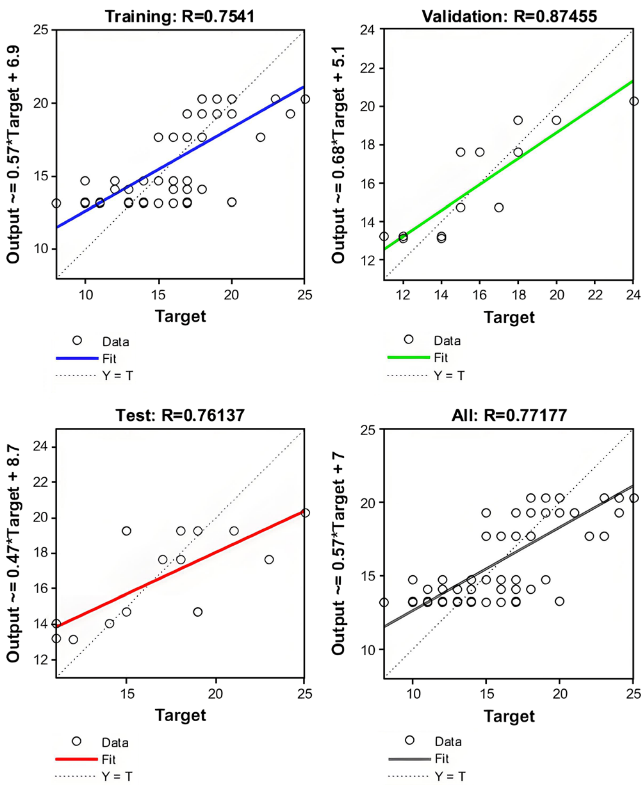


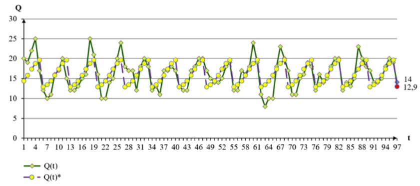
Figure 4 shows the results of the training of this network.

Figure 4
Learning outcomes of a two-layer neural network



Because the correlation coefficient after training the network was 0.7541 (the connection was noticeable), this network was used for forecasting. Figure 5 shows the initial and forecast values.

Figure 5
Theoretical and predictive values obtained using a two-layer neural network



As shown in Figure 5, the deviation of the forecast value from the actual value was 1.1 kg.

3.3. Application of the neuro-fuzzy network

The neuro-fuzzy network is in MatLab, as in the previous paragraph. Its structure is shown in Figure 6.

The days of the week are encoded here with a sequence of numbers. The number "1" means "Monday," the number "2" is "Tuesday," etc. The results of the system are shown in Figure 7.

As shown in Figure 7, the deviation between the actual and predicted values was only 0.1 kg (Q(1)=14, Q(1)^*=13.9), which can be considered a real result. The remaining experiments also showed sufficient proximity to the actual and estimated sales volumes of chilled chicken meat. The results of the neuro-fuzzy network on the remaining days of the week are as follows: Tuesday, 12.6 kg; Wednesday, 13.4 kg; Thursday, 15.0 kg; Friday, 17.8 kg; Saturday, 20.9 kg; and Sunday, 18.9 kg. In practice, it is impossible to purchase such volumes of goods from a wholesaler. Thus, the forecast values were rounded up according to the rule:

$$\begin{gathered} If\ Q(t)^* < Q(t),\ Then\ ROUNDUP\left(Q(t)^*;\,0\right), \\ Else\ ROUNDDOWN\left(Q(t)^*;\,0\right). \end{gathered} \tag{5}$$

Rule (5) was also applied when establishing the values recommended by the Fourier series and two-layer neural network models. The simulation results were analyzed and evaluated in MS Excel. Table 4 shows a fragment of the initial data (columns A–E), simulation results (columns G–I), absolute (columns J–L), and approximated deviations.

Figure 6
The structure of the neuro-fuzzy network

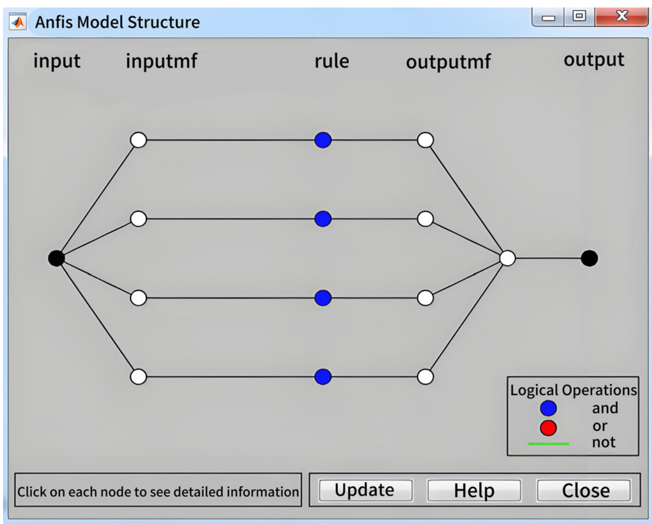
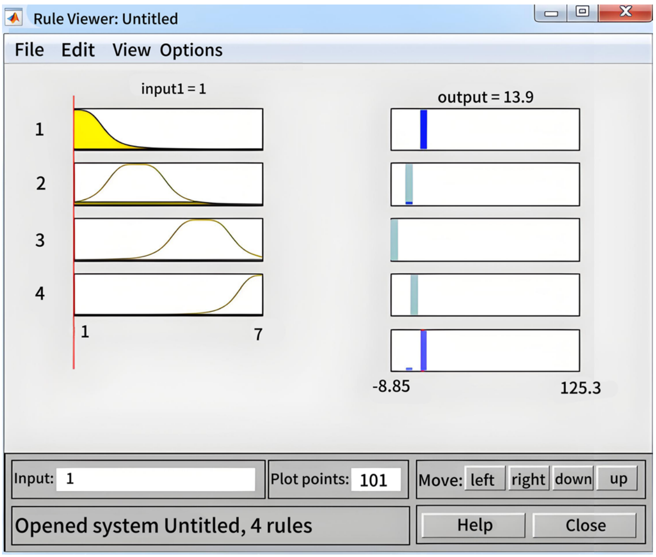


Figure 7
The results of the neuro-fuzzy network



The approximated deviations were calculated using the formula:

$$\widehat{a_i} = \left|\frac{Q(t)^* - Q(t)}{Q(t)^*}\right|. \tag{6}$$

A detailed analysis of the results is presented in the fourth section of the article.

4. Discussion of the Results and Limitations in the Application of the Methods

4.1. Evaluation of the effectiveness of the considered forecasting methods

In column "F" in Table 4, the deviations of the daily sales volumes from the volume of purchases of chilled meat are calculated. Table 5 shows the calculations of the total negative deviations (total shortage of goods) and positive deviations (total excess of goods) for 97 trading days. The correspondence of these values was observed for only 5 days out of the entire period.

The total values of the deviations were from the models (lines 101–103 in columns "J"–"L") and absolute and relative reductions in excess and shortage of goods compared to the original version (column "F"). The model based on a neuro-fuzzy network showed the best results. Here, that is the highest percentage reduction in excess production and the highest number of coincidences between the quantities of products purchased and sold in one day. The average approximation error (9.3%) also indicates further application of the neuro-fuzzy network. Models based on a Fourier series and a two-layer neural network exhibit a higher average approximation error.

Table 6 shows the effectiveness of the considered forecasting practices and the constructed predictive models.

Thus, the neuro-fuzzy network shows the best results. Therefore, it is used to solve the problem of obtaining the most accurate forecast of the sales volume and purchases of perishable products. Many studies have rightly pointed out that we must use several sets to test the performance of predictive models. For example, Qin et al. [2] presented the results of the experiments on the classification and segmentation of research objects in three sets. In this article, the operation of the three models is on a dataset obtained in 2024. However, in 2025, we analyzed sales of chilled meat at the same retail store. The sales dynamics have not changed. It was that sales decreased by the middle of the week and increased by the weekend this year. The neuro-fuzzy model shows better results on new datasets when factors such as demand and the level of competition are constant.

4.2. Limitations in the use of forecasting methods

Fourier row alignment often gives good results in series containing a seasonal wave. However, if frequent "outliers" are observed, smoothing over the Fourier series is ineffective because a high error in forecasting is formed.

To adequately make an artificial neural network, you spend a lot of time on experiments with changing weights (reconfiguring the network), the number of layers, neurons in the hidden layer, etc. That is a more time-consuming job than using the neuro-fuzzy editor ANFIS.

The obtained estimates showed the effectiveness of the neuro-fuzzy model and its suitability for solving the task. Using the graphical tools of the MatLab system, you can control and configure the parameters of the membership functions of input variables and the rules of fuzzy productions. You can use the Membership Function Editor to perform the appropriate operations. However, before checking the adequacy of the constructed fuzzy model, it is not recommended to change the parameters of the membership function.

The most significant limitation when choosing a forecasting method will be the initial information: its type, accessibility, processing capability, uniformity, formalization capability, and volume. The main limitation is the inability to take the likely changes in the conditions that determine the market situation in the future. At the same time, any forecast, as a prediction of the future, is based on information obtained in the past. Many market processes have some inertia. That is especially evident in short-term development. It justifies the considered forecasting methods in the presence of appropriate prerequisites.

5. A Comparative Study with Recent Existing Methods

A significant part of the study is the comparison of the applied approaches and other modern forecasting methods. Such a comparative analysis makes it possible to identify the advantages and limitations of different methods and justify the choice of a method for solving a specific forecasting problem or a combination of methods, as in this article.

The following methods were used:

1) Alignment of the time series according to the Fourier series. This method allows you to take periodic fluctuations in the data for forecasting. The original time series is a sum of harmonics superimposed on each other. The number of harmonics is using the least squares method. Prediction using the Fourier series is an analysis of the frequency characteristics of the data. That is how it differs from other methods. Unlike other Fourier series forecasting methods, it does not assume that the past values of the series are independent. On the contrary, it is that they contain information regarding the behavior of data in the future.
2) Artificial intelligence technologies, particularly artificial neural networks, are increasingly being used to predict time series. The difference between this approach and traditional methods is that it allows you to make the system self-learning. Due to the ability to work with "noisy" data, the system is flexible, although it usually does not solve the problem with 100% accuracy. Artificial neural networks are capable of extracting hidden patterns from the data stream. However, the data may be incomplete, contradictory, or deliberately distorted. If there is some connection between the input and output variables that is not detectable by traditional correlation methods, the artificial neural network can automatically

Table 4
Data for analyzing the effectiveness of the models

A	B	C	D	E	F	G	H
Date	**Day of the week**	**t**	**Purchase volume, kg, Q*(t)**	**Sales volume, kg, Q(t)**	**Q*(t) - Q(t)**	**Purchases based on the Fourier series model**	**Purchases based on a two-layer neural network (TLNN) model**
01/05/2024	Wednesday	1	25	20	5	**14**	**15**
02/05/2024	Thursday	2	20	19	1	**16**	**16**
03/05/2024	Friday	3	20	22	-2	**19**	**18**
04/05/2024	Saturday	4	20	25	-5	**22**	**19**
05/05/2024	Sunday	5	15	17	-2	**19**	**19**
06/05/2024	Monday	6	15	12	3	**13**	**12**
07/05/2024	Tuesday	7	15	10	5	**12**	**13**
08/05/2024	Wednesday	8	5	11	-6	**13**	**14**
09/05/2024	Thursday	9	10	16	-6	**16**	**16**
10/05/2024	Friday	10	20	17	3	**18**	**17**
11/05/2024	Saturday	11	15	20	-5	**21**	**19**
12/05/2024	Sunday	12	20	15	5	**19**	**19**
13/05/2024	Monday	13	15	12	3	**13**	**12**
14/05/2024	Tuesday	14	10	12	-2	**12**	**13**
15/05/2024	Wednesday	15	15	13	2	**13**	**14**
16/05/2024	Thursday	16	15	15	0	**15**	**15**
17/05/2024	Friday	17	20	16	4	**18**	**17**
18/05/2024	Saturday	18	20	25	-5	**22**	**19**
19/05/2024	Sunday	19	20	21	-1	**20**	**20**
20/05/2024	Monday	20	20	16	4	**14**	**13**
21/05/2024	Tuesday	21	5	10	-5	**12**	**13**
22/05/2024	Wednesday	22	5	10	-5	**13**	**14**
23/05/2024	Thursday	23	15	14	1	**15**	**15**

(Continued)

tune in to it with a given degree of accuracy. A two-layer neural network allows you to model complex dependencies that cannot be done using linear models. The network adapts to the task by compiling an input–output correspondence table based on the training sample.

3) Forecasting using neuro-fuzzy networks differs from other methods in several features. Neuro-fuzzy networks make it possible to integrate decision-making rules and factual information. They take uncertainty and expert knowledge. Such networks are effective in missing or noisy data and recognize chaotic behavior. They are good at modeling nonstationary and nonlinear multifactorial processes. Neuro-fuzzy systems can adapt to new data, improve forecasting results, and self-learn. The net results of the work are from a practical point of view, which gives rise to confidence in the correctness of the model, which is on a neuro-fuzzy network.

The forecasting method choice depends on the specific task and the nature of the available data.

6. Conclusion

The success of using neuro-fuzzy models is due to the advantages of neural networks (the possibility of adaptive self-learning) and fuzzy systems (the simplicity of linguistic interpretation of the result obtained with their help). That is proven by the example of a neuro-fuzzy model for predicting the sales volume of perishable products.

Correct forecasting of the demand for perishable products allows the following:

1) Determination of the optimal order as the volume in one trading day.
2) Reduction of the losses of the trading company.
3) Reduction of the risks associated with fluctuations in demand and taking them during supply chain management.

This article offers solutions for forecasting consumer demand for products with a limited shelf life for each day of the week. A neuro-fuzzy model with a hybrid learning method is most suitable for this type of forecasting. This model is used to obtain prediction results with the lowest error level before alignment according to analytical formulas and a two-layer neural network. Using that model in the retail store mentioned in the article reduces unproductive costs. The neuro-fuzzy model predicted various types of perishable products in other retail stores in Tver and the Tver region. We performed a comparative analysis of models to predict the sales volume of perishable products, e.g., chilled meat. That refers to any perishable products with a sales period of one trading day. The models have passed both internal and external checks. The models are tested on the data used for their development

Table 4
(Continued)

I	J	K	L	M	N	O
Purchases based on the neuro-fuzzy network (NFN) model	**Variations according to the Fourier series model**	**Variations according to the TLNN model**	**Variations according to the NFN model**	**Fourier model approximation**	**Approximation according to the TLNN model**	**Approximation according to the NFN model**
14	**-6**	**-5**	**-6**	0,429	0,333	0,429
15	**-3**	**-3**	**-4**	0,188	0,188	0,267
18	**-3**	**-4**	**-4**	0,158	0,222	0,222
21	**-3**	**-6**	**-4**	0,136	0,316	0,190
18	**2**	**2**	**1**	0,105	0,105	0,056
13	**1**	**0**	**1**	0,077	0,000	0,077
12	**2**	**3**	**2**	0,167	0,231	0,167
13	**2**	**3**	**2**	0,154	0,214	0,154
15	**0**	**0**	**-1**	0,000	0,000	0,067
17	**1**	**0**	**0**	0,056	0,000	0,000
20	**1**	**-1**	**0**	0,048	0,053	0,000
18	**4**	**4**	**3**	0,211	0,211	0,167
13	**1**	**0**	**1**	0,077	0,000	0,077
12	**0**	**1**	**0**	0,000	0,077	0,000
13	**0**	**1**	**0**	0,000	0,071	0,000
15	**0**	**0**	**0**	0,000	0,000	0,000
17	**2**	**1**	**1**	0,111	0,059	0,059
21	**-3**	**-6**	**-4**	0,136	0,316	0,190
19	**-1**	**-1**	**-2**	0,050	0,050	0,105
14	**-2**	**-3**	**-2**	0,143	0,231	0,143
12	**2**	**3**	**2**	0,167	0,231	0,167
13	**3**	**4**	**3**	0,231	0,286	0,231
15	**1**	**1**	**1**	0,067	0,067	0,067

Table 5
Calculations for evaluating the effectiveness of the predictive models

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
97	04.08.2024	Sunday	96	**20**	**19**	1	**19**	**19**	19	***0***	***0***	***0***	0,000	0,000	0,000
98	05.08.2024	Monday	97	**10**	**14**	-4	**14**	**13**	14	***0***	***-1***	***0***	0,000	0,077	0,000
99	**Total**			**1540**	**1562**	**-22**	**1576,0**	**1544,0**	1538,0	***14,0***	***-18,0***	***-24,0***	**9,1**	**9,6**	**9,0**
100	**Average approximation error, %**												**9,4**	**9,9**	**9,3**
101	**Total shortage of goods, kg**					**-151**				**-64**	**-83**	**-80**			
102	**Total excess of goods, kg**					**129**				**78**	**65**	**56**			
103	**Total matches, days**					5				30	37	37			
104	***Reducing the shortage:***		***kg***							***87***	***68***	***71***			
105			*%*							***57,6***	***45,0***	***47,0***			
106	***Reducing excess:***		***kg***							***51***	***64***	***73***			
107			*%*							***39,5***	***49,6***	***56,6***			
108	***Increasing matches:***		***days***							***25***	***32***	***32***			
109			***in several times***							***6,0***	***7,4***	***7,4***			

Table 6
Criteria for the effectiveness of the predictive models

Model	The teaching method	Average approximation error, %	Deviation from the actual value, kg
Fourier row	–	9.4	0.0
A two-layer neural network	Backpropagation of the error	9.9	−1.0
Neuro-fuzzy network	Hybrid	9.3	0.0

(the second part of the data) and on other independent data. The second sample was data on sales of chilled beef. We performed a sensitivity analysis of the models by changing their parameters. Changing the parameters allows you to assess how much the model remains adequate as a result of the work. The development of sales forecasting models for other types of products is a future research topic. A significant effect was in economics, expressed in the cancellation of losses from the write-off of unsold products and due to a shortage of goods during the trading day.

Recommendations

The results obtained during the study showed that the neuro-fuzzy model demonstrated the greatest accuracy in predicting the volume of demand for perishable products. Retailers are recommended to use it to avoid losses from both purchases of excess products and shortages.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that she has no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Nataliya Mutovkina: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration.

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