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Food demand prediction using the Nonlinear Autoregressive Exogenous Neural Network

K. Lutosławski[1], M. Hernes[1], Member, IEEE, J. Radomska[2], M. Hajdas[3], E. Walaszczyk[1] and A. Kozina[1]

[1]Department of Process Management, University of Economics and Business, Komandorska 118/120, 53-345 Wrocław
[2]Department of Strategic Management, University of Economics and Business, Komandorska 118/120, 53-345 Wrocław
[3]Department of Marketing Management, University of Economics and Business, Komandorska 118/120, 53-345 Wrocław

Corresponding author: Marcin Hernes (e-mail: marcin.hernes@ue.wroc.pl).

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ABSTRACT Food demand prediction is a significant issue for both businesses processes improvement and sustainable development issues. The data science methods, including artificial intelligence methods, are often used for this purpose. The aim of this research is to develop the models for food demand prediction based on the Nonlinear Autoregressive Exogenous Neural Network. The research focuses on the processed food, such as bread or butter. Developed models' architectures differing in the number of hidden layers and the number of neurons in the hidden layers, as well as with different sizes of the delay-line, were tested for a given product. Results of the research show that depending on the type of product, prediction performance slightly differed. The results of the R^2 measure ranged from 96,2399 to 99,6477 depending on particular products. The proposed models can be used in a company's intelligent management system for rational control of inventories and food production. It can also lead to reducing food waste.

INDEX TERMS food industry, sustainable development, neural networks, machine learning, demand forecasting.

I. INTRODUCTION

Food demand prediction is one of the critical issues for both businesses and sustainable development. The business aspects are mainly related to improving the manufacturing, logistics and supply chain processes, inventory cost reduction and customers satisfaction. Sustainable development issues are mainly related to food loss and waste, and they have been drawing much attention in recent years. Food and Agriculture Organization of the United Nations estimates that up to one-third of food produced globally, amounting to 1,3 billion tons of food per year, is lost and wasted [1]. Food loss occurs along the food supply chain from harvest to the retail level, and food waste occurs at the retail and consumption levels [1]. In the whole food chain, beginning from direct production on farms through processing, ending with retail and wholesale, consumer food waste is the largest. It is estimated at 40-60%, while retailer waste is evaluated at the level of 10% [2], [3], [4]. The prevention of food waste is one of the most important issues today worldwide, especially in the context of sustainable development. The amount of food wasted is not geographically specific but correlates with the country's development [5]. Food waste is responsible for economic, environmental, and social problems in many countries, and the strategies for its reduction are crucial [2], [6], [7]. The United Nations, in its Agenda for Sustainable Development, included a target number 12.3 considering food waste reduction of 50% by the year 2030 [8]. The European Commission is committed to fighting food waste and has included the target 12.3 in its European Circular Economic Action Plan [9].

Wasted food is defined as food unconsumed or discarded by the retailer because of its colour or appearance [10]. Some products delivered to the store are never sold because of the expiration date on the label, time spent on the shelf, or damage. Store managers expect a certain loss rate and monitor its level. Food whose expiration date is close is distributed as an ingredient of ready-to-eat products, discounted, or donated to food donation organisations. However, little is known about the implementation of food waste reduction activities and policies within stores. Managers indicate customer demands and legal and logistics issues as barriers to reducing food waste [10]. Such food waste levels and cited limitations indicate that modern food systems should be developed to determine and prevent food over-production, over-abundance, and waste [4]. One of the functions of these systems is food demand prediction. There are two types of prediction methods: qualitative (based, among others, on the opinions of process specialists predicting the demand) and quantitative (based on mathematical models, which use historical data of demand volume). However, the quantitative methods, including data science methods, present a better performance of prediction [68]. The predictive data science methods are very helpful for performing the demand prediction process. These methods automatically analyse the relationships and trends in data and make future predictions based on current observations [66].

Traditional data science forecasting models,such as multiple regression, exponential smoothing, the Holt-Winters model (also called seasonal exponential smoothing), ARIMA, supervised regression & classification models, random forest, gradient boosting, stochastic optimisation are often applied in food demand prediction [11], [12], [13]. However, several limitations of traditional methods should be mentioned: e.g., they include a relatively short "life cycle", they do not have the ability to learn, and the food market is very turbulent, as a result of which historical data becomes less valuable for forecasts [14]. In addition, traditional methods do not have the ability to generalisation. The prediction is proper only in a given time period. When the characteristics of the food market change, new models must be developed. To overcome the limitations of traditional models, the machine learning approach is applied, including deep learning models.

The aim of this paper is to develop the models for food demand prediction based on the Nonlinear Autoregressive Exogenous Neural Network (NARXNN). We focus on the processed food in the research (e.g. bread, butter). To the best of our knowledge, such a model has not been yet developed; therefore, it is the main contribution of the research presented in this paper. The NARXNN as a special type of RNN (Recurrent Neural Networks), i.e. many-to-one RNN, usually provides better predictions than the traditional RNN (i.e. one-to-one RNN) because it uses the additional information contained in the series of interest that has already been output before a given period [15]. The research put the main focus on data science applications issues related to food demand predictions. The supply chain management theory is treated as a supplementary issue.

The rest of the paper is divided as follows: the next part presents the state of art in the considered field. Then, the materials and methods are presented. The last part presents the results of experiments, conclusions, and future works.

II. BACKGROUND

A. PREMISES FOR FOOD DEMAND PREDICTION

The food demand prediction is critical for both businesses (in terms of optimising their strategies and processes) and societies (in terms of economic, environmental, and social policies). Moreover, demand prediction is an essential tool for increasing the speed of the decision-making process and lowering the risk observed in it [16]. For organisations operating in the foodservice industry, demand estimation impacts production effectiveness and resource planning [17]. As shown by [18], the inaccuracy of sales forecasts in the retail food industry is the main cause of wasted products and stockouts. Many scholars have investigated the problem of managing the inventory of perishable products [69], especially considering the growing number of perishables in retailing that are disposed of due to spoilage, which is reported to be even around 15% [70]. According to [19], more accurate forecasts in the fresh food sector result in a reduction in both losses from products that reach their expiration dates and the costs of transportation and storage of refrigerated products. Food sales prediction is also extremely important in the case of products facing seasonal changes in demand, which may depend on many hidden contexts, not always easily recognised [13]. At the same time, food demand prediction relates to the effectiveness of a supply chain management challenged by several shifts such as the growing urbanisation level, accompanied by an increasing consumer demand for organic products but also the growth of the e-commerce distribution channel [20]. All those aspects are considered by many retail companies that decided to concern waste reduction not only in the operational targets but also the performance indicators [71].

Predicting food demand is crucial also from societal and environmental standpoints. The world population is estimated to reach 9.7 billion people in 2050 [21]. Feeding the rising population requires developing sustainable agricultural, economic, and conservation policies which would respect the environment [22] and manage food waste [23]. According to [24], prevention is the most favourable option in terms of food waste management. This option includes avoiding surplus food generation through food production and consumption. It is postulated by some currently emerging movements against food waste, to take the responsibility for this problem by the food chain actors, especially the retailers [73]. More accurate food demand forecast methods could significantly contribute to this issue in both perspectives - the economic and managerial challenges observed by retailers, and the social and environmental impact the food waste impose. As reported by

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[72], the data on the ability of food waste prevention measures is still scarce and that is the gap we want to address.

B. METHODS FOR FOOD DEMAND PREDICTION

Scholars distinguish different forecast models, including both linear and nonlinear methods for quantitative demand forecasting [25]. They also share a similar understanding that none of them is universal enough to be used for all situations and circumstances [26], [27]. Although food demand traditionally was perceived as remaining stable on many occasions [28] and influenced by factors such as seasonality and perishability, nowadays we may witness an increasing demand volatility caused by a variety of factors, such as changing lifestyle choices [29], [30], blooming foodie culture [31], or social media influencers [32]. All those issues make predicting food demand more challenging. They open up research streams devoted to the comparisons and evaluations of traditional models [26] as well as the development of machine learning models.

Among the existing traditional models used for food demand forecasting, we may distinguish multiple regression, exponential smoothing, and the Holt-Winters model (also called seasonal exponential smoothing), ARIMA, supervised regression & classification models, random forest, gradient boosting, and stochastic optimisation.

The Holt-Winters model has been proven to be effective in the case of short-lifecycle dairy products [11], but also the ARIMA model has been effectively applied and tested, proving that it could be utilised to model and forecast the future demand for the purposes of manufacturing this type of food [33]. When the two models were compared for dairy products with a short lifecycle, the HW model obtained better results (higher accuracy of prediction) [26].

Due to some limitations of single forecasting models, researchers try to use a mixed approach to obtain better results. As shown in [34], a mixed-method combining three different models (4-week moving average, exponential smoothing, and ARIMA) is efficient in exploring demand prediction in the food industry. To provide a more advanced multi-region and multi-commodity analysis of food consumption in the long term, a partial equilibrium model was proposed [35] and solved using the dynamic recursive technique [36].

The need to provide more accurate forecasts encouraged researchers to develop alternative approaches, such as a judgmental-based approach where traditional mathematical forecasts were considered as a basis and developed further with the structured knowledge of the experts, which enables the adjustment of the initial forecasts but also provides better initial data cleaning and outlier identification [12]. Another one is the ensemble learning approach aimed at using the dynamic integration of classifiers reflecting seasonal changes and fluctuations in consumer demands, which has been proven to perform better than the currently used baseline [13].

Researchers share a view that, in general, Machine Learning models result in better demand predictability than the use of traditional ones [19], [20]. The main advantages mentioned in previous research are better predictions and more flexibility, which is relevant when the estimation models are built not just on the basis of historical sales series but also when new variables are added, which increases data volume and analysis complexity [19].

Several researchers have investigated the advantages of Machine Learning models over traditional ones in the food industry context. Such advantage was discussed by Tsoumakas [37], who proved that Machine Learning techniques for sales prediction are reliable and efficient for accurate short-term forecasting, which enables inventory level minimisation, expired products reduction, and the lost sales drop. Among the main benefits, the reduction of human bias, a higher degree of forecast precision, and the flexibility to change variables were observed [19].

One of the methods used for food demand forecasting was the Artificial Neural Network (ANN) prediction model developed by Agrawal and Schorling [38]. The model's efficiency was tested for a perishable and refrigerated food convenience store chain. The results proved that although the ANN may suffer from interpretability problems, it is more accurate than the traditional estimation method (multinomial logit model). The ANN model is aimed at using previous data and a predefined demand estimate [17].

Another method used in demand forecasting is the Support Vector Machine (SVM) [39]. In combination with other techniques, it brought a reduction in losses from unsold dairy products after their expiration date.

The Heterogeneous Mixture Learning technology was developed by Ochiai [40] based on algorithms useful in the demand estimation performed for a short-term food grocery store chain and presented a significant reduction in unsold items.

A model that aggregates Machine Learning for demand forecasting and price-optimisation techniques was presented by Fujimaki [41] and further tested in beverage retailing. It has shown greater reliability for decision-makers, and, as a result, a revenue increase estimated at 16%.

Deep learning models have been tested and confirmed for forecasting crude oil prices [42], photovoltaic power [43], and on-demand ride services [44]. Research results related to the food industry mention deep learning methods (Convolutional Neural Network (CNN)-based food image recognition algorithm) used to derive food information (food type and portion size) from food image [45] or to propose an assistive calorie measurement system [46]. In [47] proposed a time-dependent food distribution model and a weight optimisation algorithm aimed at adapting the user's data to their eating habits. Deep learning has also been imposed in the waste sorting process to automate some of the waste handling tasks [48].

C. NARXNN APPLICATIONS

Taking into consideration the research related to the NARXNN, there are many areas of implementation of this type of neural network. For example, it has been used for the prediction of water consumption [49], traffic condition prediction and monitoring on motorways [50], and also energy forecasts [51].

The DL applications in agriculture employing the NARXNN model were analysed in [52] and [53]. The leaf area index (LAI) estimation has been performed. . In [54], a NARXNN model was applied to predict the LAI of rubber.

To estimate time-series, the LAI used a NARX model called the NARXNN. The NARXNN proved to be a promising tool for time-series LAI estimation [55]. The authors of the paper [56] present weather prediction using three models: an RNN-based model named NARXnet, a case-based reasoning model (C.B.R.), and a segmented CBR model. The structure of the input of the NARXnet meant that the NARXnet could not only learn from historical data but also previous predictions. The NARXnet had an accuracy of 93.95%, outperforming the other two models significantly. Soil moisture (SM) estimation successfully used a simplified NARXNN model, whose input was only the current features and the prediction it had given in the last time step [57].

In [58], a NARXNN model was used (called DLNN) to predict soil moisture on an hourly basis. The predictions were compared with ground measurements. The experiments showed that the model was a promising tool for the task.

The article [59] predicted wheat yields using historical wheat data and related plantation area, rainfall & temperature. The Spatial NN model gave better results in terms of forecasting yield when compared to the temporal Nonlinear Autoregressive Neural Network and the NARXNN model. The same study with the same result was also conducted in [60].

In [61] used single-layer NARXNN models, which were designed for forecasting sesame yield in the dry zone of Sri Lanka. The NARXNN was used as a useful tool for addressing future climate changes through forecasting weather variables in the study area [62].

Two AI-based prediction models of a single variate MLFNN and multivariate NARXNN were developed to provide 1- to 7-day ahead offer price forecasts for a certain type of strawberry in Canada. The series-parallel NARXNN architecture with one hidden layer and ten neurons was used for the multivariate model. The results demonstrated the usefulness of including California's commodity yield variable as an additional predictor, which resulted in up to 39% improvement in future price forecasts obtained by the NARXNN multivariate model compared to the univariate MLFNN model [63].

Although we may find works where the demand forecasting model using the deep learning approach was used for the supply chain [64], to the best of our knowledge, it has not been tested in the food industry. Therefore, it is the first study to combine the NARX Neural Networks with food demand forecasting.

III. MATERIAL AND METHODS

A. DATA

The data supplying the decision-making process was collected by ProLogistica Soft company, which deals with modelling inventory management and demand forecasting systems for producers and distributors. They represented the volume of demand for food products within the chain of stores located in the Lower Silesian Voivodeship (Poland). The basic statistical features (minimum and maximum value, daily average and its deviation) of the food demand data for each product are presented in Table 1. The company has not agreed to publish products' names, therefore they are marked with numerical identifiers. The samples were recorded over approximately 2 years (04.2017-06.2019) or 3.5 years (01.2016-06.2019) with an irregular time steps. The average daily demand was characterised by different variability expressed by the standard deviation. Depending on the product, it ranges from 42.0 (product id=1272) to 103.4 (product id=492) (Tab. 1).

TABLE I
STATISTICAL ANALYSIS OF DEMAND VOLUME FOR FOUR SELECTED FOOD PRODUCTS

Product ID	**Observations**		**Min**	**Max**	**Mean**	**SD**	**Kolmogorov-Smirnov test: exponential distribution, α=0.01**			
	Date	n					p-value	K-S stat.	c-value	H
492	19.04.2017-27.06.2019	339	10	820	94.5	103.4	0.0020	0.1003	0.0879	1
1272	05.01.2016-18.06.2019	451	-23	298	43.3	42.0	0.0772	0.0597	0.0762	0
1325	11.01.2016-11.06.2019	296	0	700	24.4	45.8	0.1168	0.0687	0.0940	0
1347	05.01.2016-28.06.2019	617	-44	410	60.1	61.5	0.0947	0.0494	0.0652	0

The demand data profile of most products was characterised by an exponential distribution, which was confirmed by the Kolmogorov-Smirnov test. Only in the case of the product ID=492, at the significance level alpha=0.01, the obtained p<alpha was the basis for rejecting hypothesis 0, assuming that the empirical and theoretical distributions are equal (Tab. 1). The daily variability of demand data under investigation is shown in Fig. 1. The input data were first extracted and then aggregated (for each product separately) within a day. Subsequently, for the use neural network approach, the normalisation was required to train and test the prediction model. Finally, the output had to be de-normalised to reflect the volume of demand.

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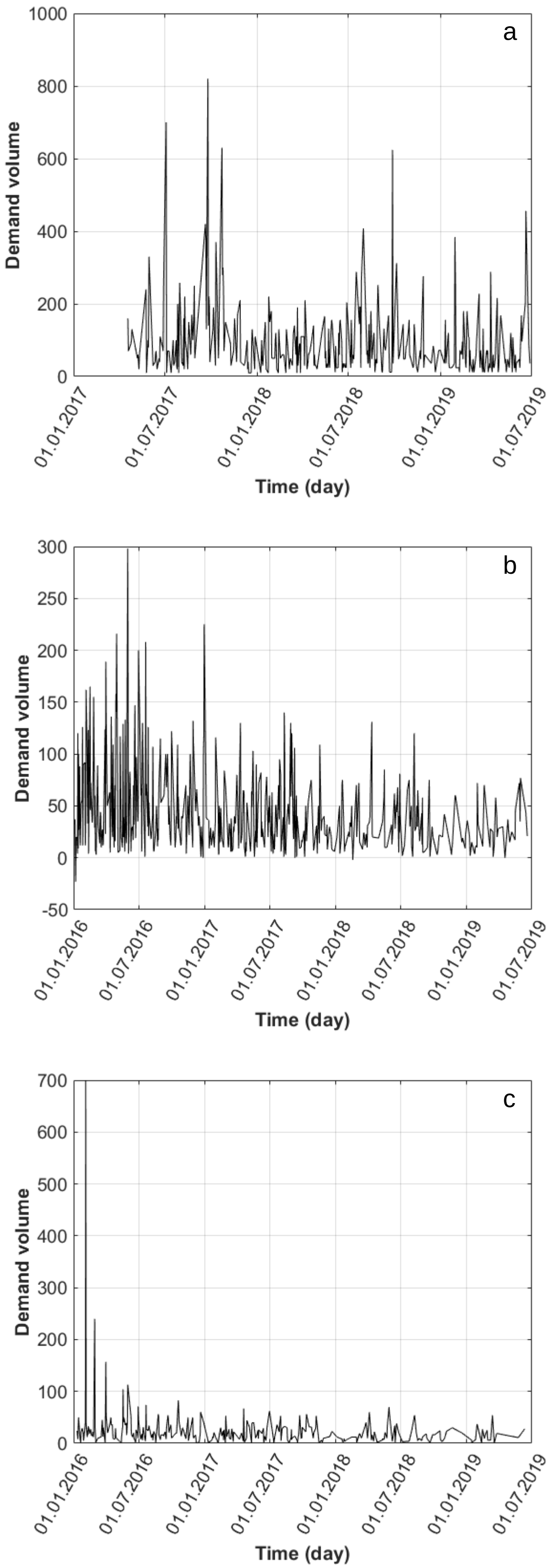

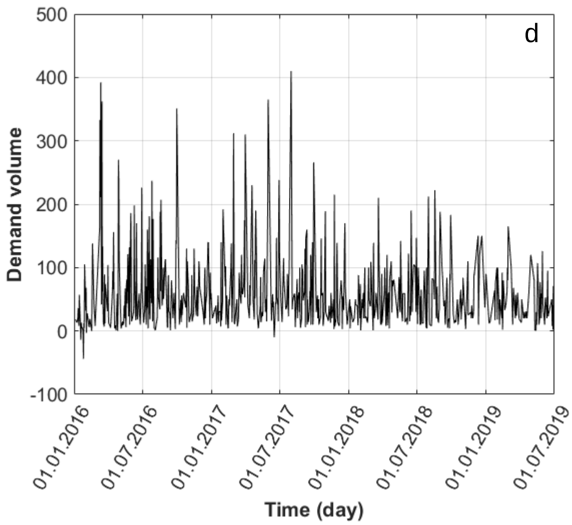

FIGURE 1. **Variation in demand volume for four selected food products: (a) product id=492, (b) product id=1272, (c) product id=1325, and (d) product id= 1347.**

B. PREDICTION SYSTEM

Models for describing a dynamic stochastic process in a discrete-time domain take various forms of difference equations. One of the interesting concepts in time series forecasting is a hybrid model, i.e. a nonlinear autoregressive exogenous model in combination with neural networks (NARXNN). It is a recurrent dynamic network due to the feedback loop between the output and input. The value of the dependent output (y) is estimated based on the past values of y and the past values of the independent (exogenous) input (x). The NARXNN model equation is as follows $y(n) = f\big(y(n-1), y(n-2), \dots, y(n-d); x(n-1), x(n-2), \dots, x(n-d)\big)$. In this study, it was assumed that *x(n)* denotes the discrete-time sequence, *y(n)* denotes the demand values in these time sequences, and *d* is the size of the tapped delay lines (TDLs). In this way, the ability of the NARXNN model to predict the value of the demand time series on the basis of its past values was ensured. Past values were supplied from TDLs in which the past sequence values of *x(n)* and *y(n)* were stored. A three-layered network was used, consisting of a sigmoidal activation function in the first and second hidden layer and a linear activation function in the third output layer. Learning was performed based on the Levenberg-Marquardt backpropagation algorithm.

C. EXPERIMENTS

The research consisted in developing an accurate NARXNN demand forecasting model for each product analysed in this study. Accordingly, model architectures differing in the number of hidden layers and the number of neurons in the hidden layers, as well as with different sizes of the delay-line were tested for a given product. Neural network topologies were first trained and then simulated for demand prediction. So, two separate datasets (time series) were necessary: one for training and the other for simulation (prediction testing).

The training dataset was a time series with demand values (in-sample period) that were shown to the neural network during its training. The testing dataset, not previously shown to the neural network, represented only the time series for multi-step prediction testing (out-of-sample period). The model simulation for each product was carried out both in the short and long prediction period defined by the ratio. The ratio was calculated as the percentage of the number of testing samples to the number of complete data samples. Two of its values were considered: 4% as the low ratio (short prediction period) and 10% as the high ratio (long prediction period). Thus, the ratio determined the number of steps ahead in the multi-step forecast.

D. PERFORMANCE PREDICTION MEASURES

The best topology of the demand prediction model (at low and high ratio) for each product was determined first on the basis of the minimum value of mean absolute error (MAE), mean absolute percentage error (MAPE) and root-mean-square error (RMSE), and then on the basis of the highest value of the determination coefficient (R-squared). R^2 measures the percentage of variation in the response variable Y explained by the explanatory variable X. MAE, MAPE, RMSE, and R-squared are defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \quad (1)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\% \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \quad (3)$$

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \times 100\%$$

where n is the number of out-of-samples; y_i and $\hat{y}_i$ are the observed (actual) values and fitted values of the dependent variable Y for the ith case, respectively; and $\bar{y}$ is the arithmetic mean of Y.

IV. RESULTS AND DISCUSSION

A. TRAINING PROCESS

The effects of training various nonlinear autoregressive exogenous neural network (NARXNN) models on the in-sample period dataset with low and high ratio were presented in Tables 2 and 3, respectively. The number of hidden layers, number of neurons in the hidden layers, different sizes of the delay-line were tested to find the best network architecture for each product data demand. These tables summarise the best results obtained after repeating the training process of each NARXNN architecture 20 times. The number of epochs needed to achieve them ranged from 6 to 177 with a low ratio of 4% (Tab. 2) and from 8 to 181 with a high ratio of 10% (Tab. 3).

TABLE II
PERFORMANCE OF DEMAND VOLUME PREDICTION AT THE LOW RATIO FOR SELECTED FOOD PRODUCTS BY DIFFERENT NARX NEURAL NETWORK MODEL ARCHITECTURES.

Food product ID	TDLs of input data	Neurons in hidden layers	Min. MSE during network training	Epochs	RMSE	MAE	MAPE (%)	R^2 (%)
492	1-4*	7 3	7784.9	13	176.5	142.9	0.454	95.9654
	1-4**	**14 6**	**25800.1**	**11**	**215.4**	**138.4**	**0.436**	**96.2399**
	1-6	7 3	15751.3	10	221.7	162.7	0.515	93.8579
	1-6	14 6	15100.6	8	244.1	170.5	0.539	91.8534
	1-8	7 3	13785.9	77	214.3	194.0	0.620	91.6632
	1-8	14 6	10196.4	8	273.1	170.7	0.538	93.5866
1272	1-4	7 3	1033.3	12	77.3	65.3	0.339	98.2828
	1-4	14 6	1967.6	12	39.7	33.7	0.176	98.7997
	1-6	**7 3**	**1257.8**	**54**	**37.1**	**31.1**	**0.161**	**98.9632**
	1-6	14 6	1622.5	117	62.8	46.5	0.242	95.9914
	1-8	7 3	1501.6	57	43.6	31.4	0.163	98.5197
	1-8	14 6	2264.1	66	49.1	44.0	0.229	97.5744
1325	1-4	7 3	575.5	35	46.6	36.0	0.503	97.4634
	1-4	**14 6**	**821.3**	**6**	**25.3**	**24.7**	**0.347**	**97.5620**
	1-6	7 3	10023.0	20	27.9	25.2	0.355	96.7378
	1-6	14 6	11248.5	8	39.8	37.7	0.531	97.9493
	1-8	7 3	781.0	14	49.3	43.2	0.605	98.5877
	1-8	14 6	3575.9	12	35.0	30.3	0.425	92.9236
1347	1-4	7 3	3230.4	82	78.5	71.6	0.196	98.6145
	1-4	14 6	6715.6	7	88.9	69.3	0.189	97.9142
	1-6	7 3	3469.1	177	75.6	61.4	0.167	98.9170
	1-6	14 6	4200.1	97	141.9	105.8	0.287	97.1736
	1-8	7 3	3666.3	46	87.8	71.8	0.195	98.6994
	1-8	**14 6**	**3563.0**	**12**	**43.7**	**38.6**	**0.105**	**99.6477**

*denotes the last past samples from y_{-1} to y_{-4} in steps of 1
** values for the best performance are highlighted in bold

Thus, the fewer samples were used in the training process (or otherwise, the more in the prediction process), the more epochs were needed for the tested model to obtain satisfactory results of data generalisation. Not only the number of samples influenced the learning process length, but also model architecture complexity determined by the number of neurons or delayed inputs. It involved learning experiments conducted with the use of an in-sample dataset in both low and high ratios. For example, regarding the number of neurons, training with 4% or 10% dataset of the model for product ID=1347 with 20 neurons and 4 delays required 11 times (Tab. 2) or 21 times (Tab. 3) fewer epochs, respectively, than the model with 10 neurons. A decrease in learning time after an increase in the number of neurons was observed in most of the trained models (excluded for the

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product ID=1272) at a 4% ratio (Tab. 2). For example, regarding the number of delays, training using 90% dataset of the model for the product ID=492 with 20 neurons and 8 delays required 8 times fewer epochs than the corresponding model with 4 delays (Tab. 3).

TABLE III
PERFORMANCE OF DEMAND VOLUME PREDICTION AT THE HIGH RATIO FOR SELECTED FOOD PRODUCTS BY DIFFERENT NARX NEURAL NETWORK MODEL ARCHITECTURES.

Food product ID	TDLs of input data	Neurons in hidden layers	Min. MSE during training network	Epochs	RMSE	MAE	MAPE (%)	R^2 (%)
492	1-4*	7 3	9019.8	15	169.0	137.1	0.445	97.4717
	1-4	14 6	9076.0	83	165.4	142.7	0.465	97.4107
	1-6**	**7 3**	**6925.3**	**44**	**169.5**	**133.4**	**0.431**	**97.3525**
	1-6	14 6	15637.0	12	231.5	147.4	0.475	96.5301
	1-8	7 3	19218.3	27	200.1	163.8	0.532	96.5066
	1-8	14 6	13787.3	10	205.8	134.6	0.434	97.1524
1272	1-4	7 3	2233.5	92	126.0	111.9	0.596	96.7720
	1-4	14 6	1401.2	15	61.1	52.9	0.281	98.9538
	1-6	7 3	1157.5	62	326.6	241.9	1.265	93.7499
	1-6	**14 6**	**3624.5**	**12**	**61.6**	**46.6**	**0.248**	**98.8526**
	1-8	7 3	2287.6	61	173.2	133.0	0.698	97.5482
	1-8	14 6	2857.1	13	103.2	73.0	0.383	97.7506
1325	1-4	7 3	1702.1	9	33.4	24.9	0.354	96.5167
	1-4	14 6	915.2	19	36.7	28.0	0.398	95.9722
	1-6	7 3	1749.0	20	32.8	26.4	0.376	96.8585
	1-6	**14 6**	**1876.2**	**14**	**24.5**	**18.5**	**0.263**	**98.6790**
	1-8	7 3	3616.4	9	28.2	26.0	0.373	98.5432
	1-8	14 6	330.0	19	26.6	19.6	0.278	97.9625
1347	1-4	7 3	2775.4	175	212.0	170.9	0.481	98.2207
	1-4	14 6	2958.9	8	192.9	161.6	0.454	97.7791
	1-6	7 3	4721.2	36	170.6	127.0	0.351	99.0980
	1-6	14 6	5884.0	18	164.3	137.7	0.386	98.8652
	1-8	**7 3**	**4365.6**	**12**	**164.6**	**120.9**	**0.335**	**99.0908**
	1-8	14 6	3006.3	181	210.4	156.8	0.437	98.7703

*denotes the last past samples from y_{-1} to y_{-4} in steps of 1
** values for the best performance are highlighted in bold

However, it should be emphasised that too low a number of epochs usually did not succeed in providing good learning outcomes. This is because only in one case, i.e. for the product 1272 with the use of 90% in-sample dataset, the minimum number of epochs resulted in the achievement of the lowest MSE error value (1033) (Tab. 2). Overall, depending upon the product, the lowest values of the minimum MSE error were reached from 575 (ID=1325) to 7785 (ID=492) at a 4% ratio (Tab. 2) and from 330 (ID=1325) to 6925 (ID=492) at a 10% ratio (Tab. 3). On their basis, it should be noted that in both ratios, there is a clear difference in the achieved MSE error values between the product ID of 492 and the other ones.

B. PREDICTION PERFORMANCE

The results of the prediction performance of the demand volume for the product under investigation was measured using RMSE, MAE, MAPE and R^2. The NARXNN models trained at the low and high ratio were also included in Tables 2 and 3, respectively. Based on their analysis, it can be concluded that with both ratios, the lowest values of the minimum error MSE obtained in the learning process did not appear in equally good values of the above-mentioned indicators obtained in the testing (prediction) process in the case of all food products without ID=492. However, during the training, as well as during the forecasting, an influence of the tested neural network structures on the demand forecast accuracy of all the analysed products in both the short and long period was observed.

In the short period of the demand volume prediction, both according to MAE, MAPE and RMSE, the best results were achieved by the model for product ID=1272. This optimal model consisted of 10 neurons (7 in the first and 3 in the second hidden layer) and 6 delay inputs. For the other products, these were models with 20 neurons (14 in the first and 6 in the second hidden layer) and 4 delays (IDs of 492 and 1325) or 8 delays (ID of 1347). All optimal models provided forecasts with the lowest MAE, MAPE and RMSE values ranging from 24.7 (ID=1325) to 138.4 (ID=492), 0.105% (ID=1347) to 0.436% (ID=492) and from 25.3 (ID=1325) to 215.4 (ID=492), respectively, with the best simultaneous fit expressed by the R^2 determination coefficient, ranging from 96.2% (ID=492) to 99.6% (ID=1347) (Tab. 2). It follows therefore that the deviations of the estimated demand values by the network from the actual values are relatively small and the generalisation capability is quite satisfactory. For each product, the error values between MAE and RMSE did not differ very much, which indicated that errors with very large values did not occur in the forecast period. It can also be confirmed by analysis (for all products) the plots presented in Fig. 2 regarding the actual (X) and predicted values of demand (Y), as well as the error plots ($E=X-Y$). For the product ID=1347, the NARXNN model trained on the past demand data executed an almost flawless forecast ($E<0.3\%$) throughout the low out-of-sample period (Fig. 2d). For the other products, the forecasts were equally accurate, but already in a slightly limited time interval, i.e. without the time interval corresponding to the last 3 samples (Figs. 2a, 2b and 2c). However, during this period, the most marked increase in the E value was only observed for product ID=492, but it did not exceed 1.6% (Fig. 2a). Finally, the error values in the last 3 forecast moments for IDs of 492, 1272, and 1325 contributed to the increase in both the MAE, MAPE and RMSE values. The values of MAE and RMSE in the demand prediction for the product ID=492, several times higher than the other ones, were additionally affected by the wide range of values as well as the large variation of demand data for this product. Nevertheless, for each product, a fairly good fit of the model

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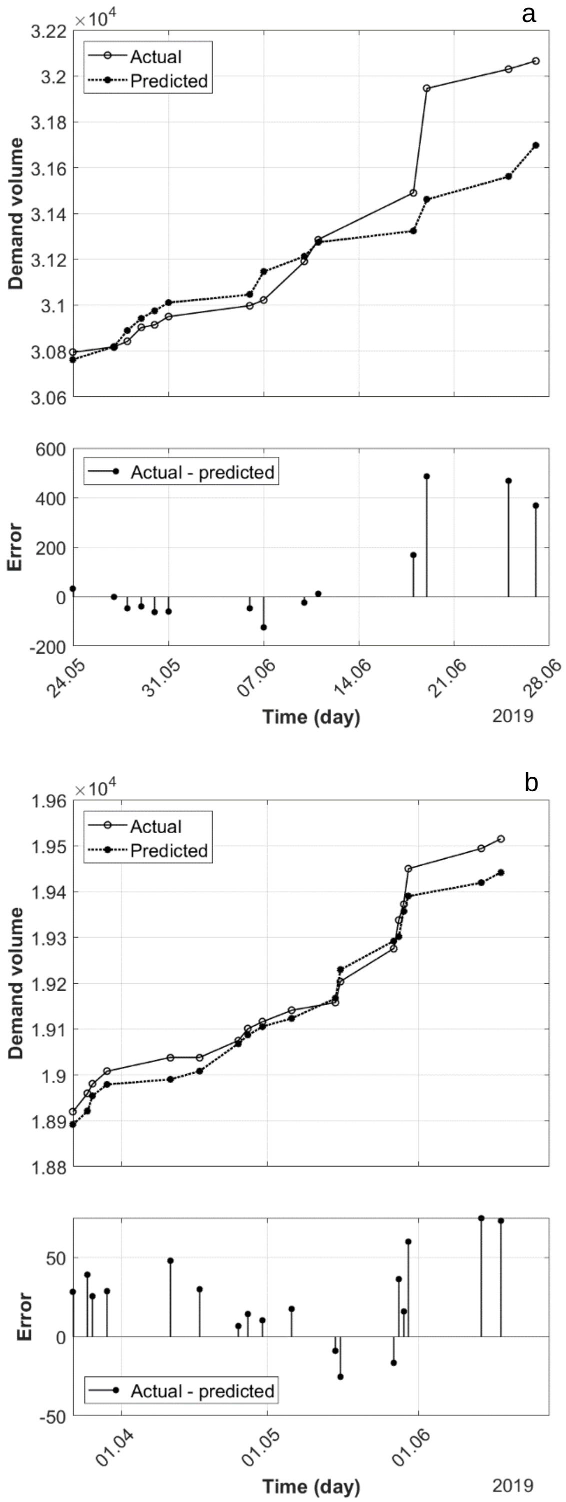
data to the actual demand data was reached. It was best reflected by the linear regression presented in Fig. 3.



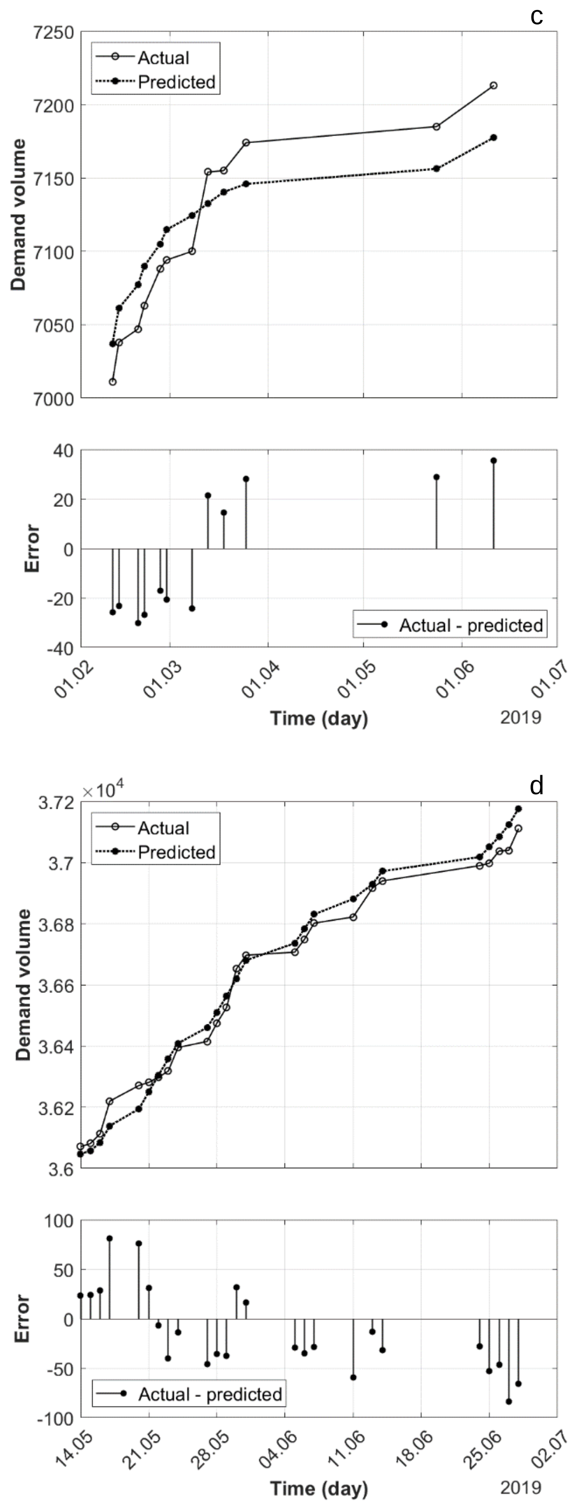
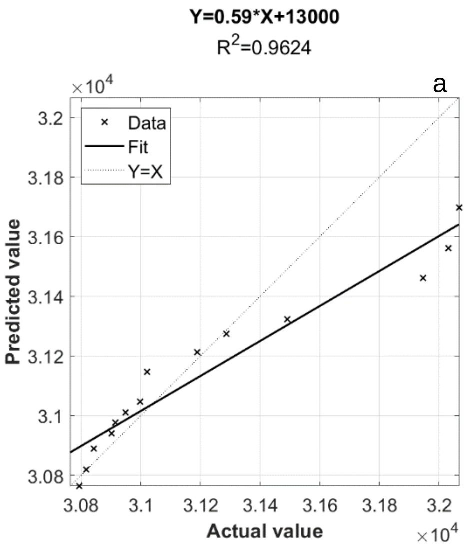
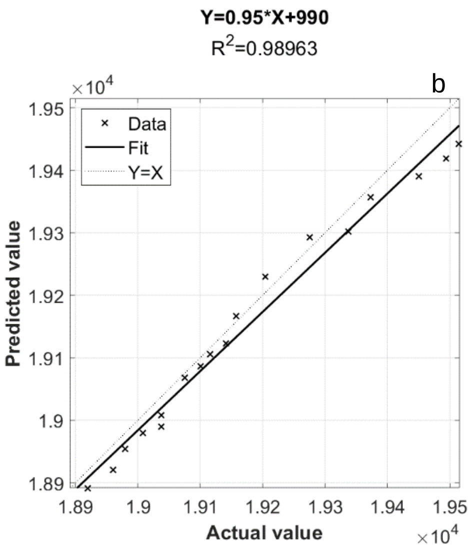


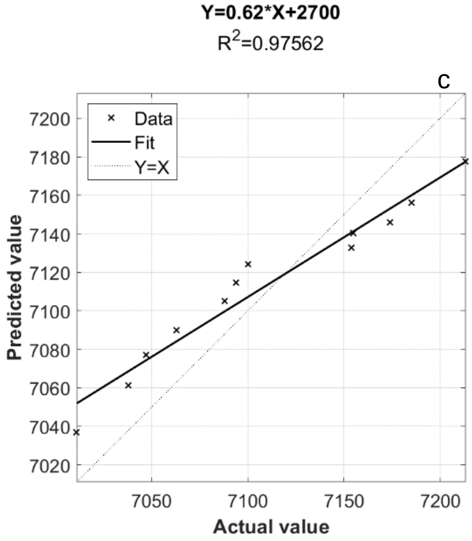
FIGURE 2. Demand volume prediction with error prediction at the low ratio obtained by the best NARX neural network model architectures for four food products: (a) products id=492, (b) products id=1272, (c) product id=1325, and (d) product id=1347.

Very low values of MAE, MAPE and RMSE allowed for an almost perfect fit (R^2> 0.989) of the model to the independent variable for the product ID=1272 (Fig. 3b) as well as ID=1347 (Fig. 3d). Larger deviations of the forecast from the ideal realisation of the explained variable (*Y*=*X*) were observed for the other two products, i.e. ID=492 and ID=1325.

The prediction performance in MAE, MAPE, RMSE, and R^2 obtained on the high ratio can be considered very satisfactory (Tab. 3). Taking into account the first 3 indicators, the best results were achieved with the models containing 10 neurons and 6 (ID=492) or 8 (ID=1347) delay inputs. Compared to these models, the most effective structure of the neural network for another product (ID=1272 and ID=1325) demand predictions required twice as many total neurons, with sufficient 6 delays.







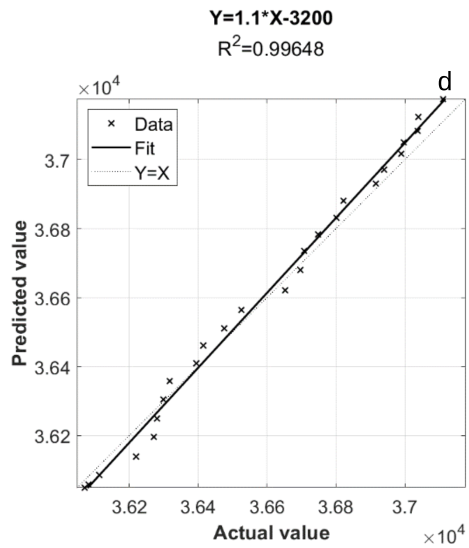


FIGURE 3. Comparison between actual values and NARX neural network model predictions at the low ratio for four food products: (a) product id=492, (b) product id=1272, (c) product id=1325, and (d) product id=1347.

MAE, MAPE and RMSE values for these models were ranged from 18.5 (ID=1325) to 133.4 (ID=492), 0.248% (ID=1272) to 0.431% (ID=492) and from 24.5 (ID=1325) to 169.5 (ID=492), respectively, with the degree of fit expressed by R^2 ranging from 97.4% (ID=492) to 99.1% (ID=1347) (Tab. 3). Thus, there were slight differences between MAE and RMSE, which indicates that no large-scale errors occurred also at the high ratio prediction. Nevertheless, in the long period, these differences were higher than in the shorter period for most products (IDs of 1272 1325 and 1347) of the prediction demand.

The plots of the observed and forecasted demand data, as well as the plots of forecast errors for all researched products at a high ratio, are presented in Fig. 4. They show that all of the developed NARX neural models underestimated or

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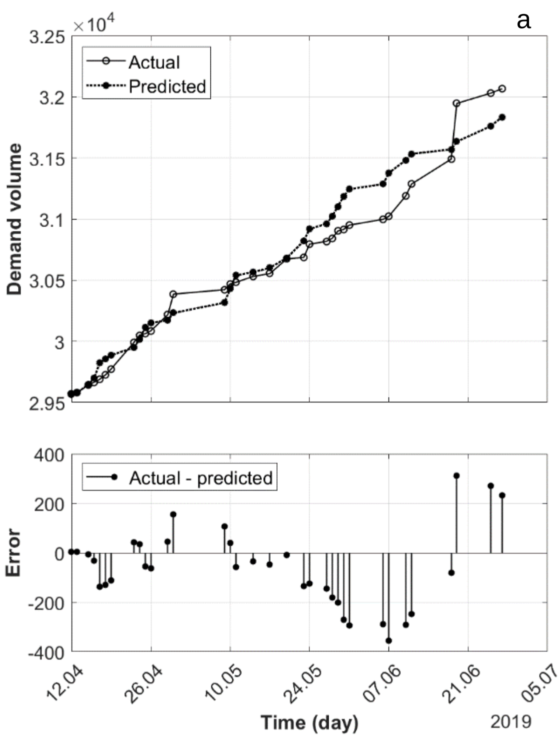
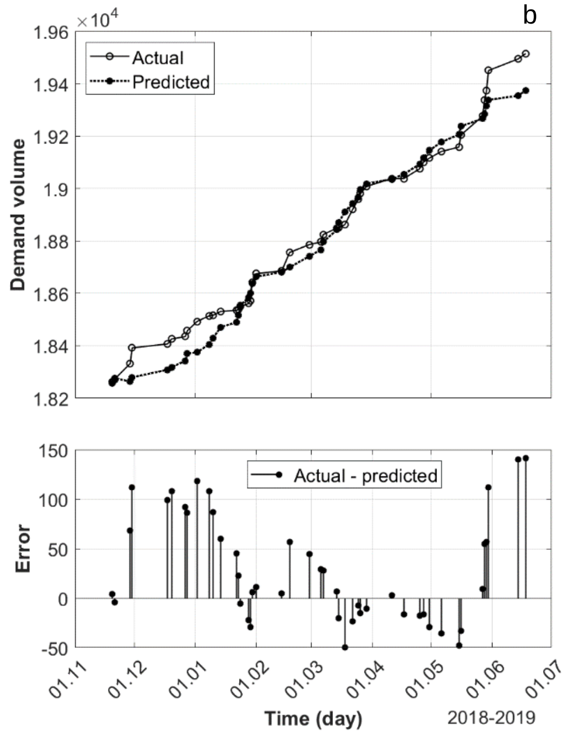
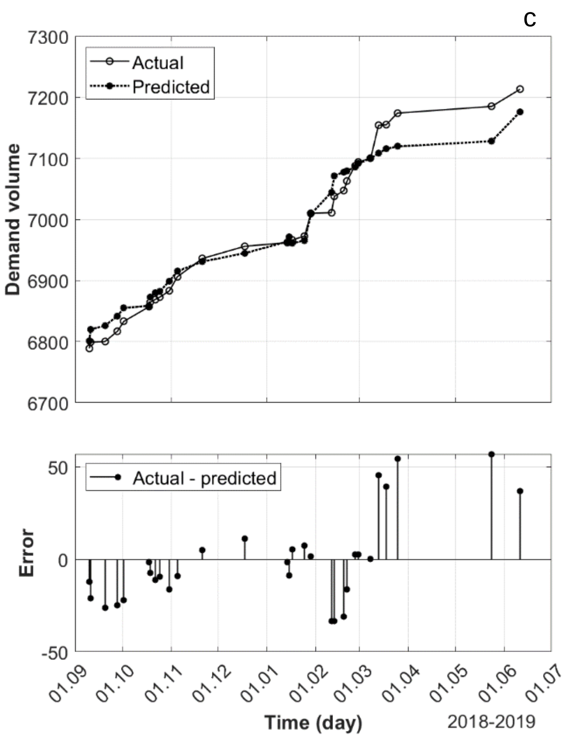
overestimated the demand volumes in most of the analysed time moments. However, in the worst case, it was, depending on the product, with an error E of no more than 0.7% (ID=1325) to 1.3% (ID=492). The maximum values of E were noticed only at the end of the forecast period for ID=492 (Fig. 4a), ID=1325 (Fig. 4c), and ID=1347 (Fig. 4d), and additionally in the initial forecast period for ID=1272 (Fig. 4b). However, in the latter case, an almost flawless prediction was observed in the middle period of March 2019 - June 2019.

Apart from the product demand forecast ID=492, higher values of the maximum errors E in the long than in the short prediction interval were recorded. Nevertheless, the extension of the period from low to high did not result in a drastic deterioration of the overall prediction performance for all products. There were no regular relationships between the prediction effects at high and low ratios. Compared to the low ratio, at the high ratio, on the one hand, there was even a decrease in MAE and RMSE by 3.6% and 21.3%, respectively, for the product ID=492 and by 25.1% and 3.2%, respectively, for the product ID=1325. On the other hand, an increase in these errors was recorded by 49.8% and 66%, respectively, for the product ID 1272 and by 213% and 277%, respectively, for ID 1347 (Tables 2 and 3).







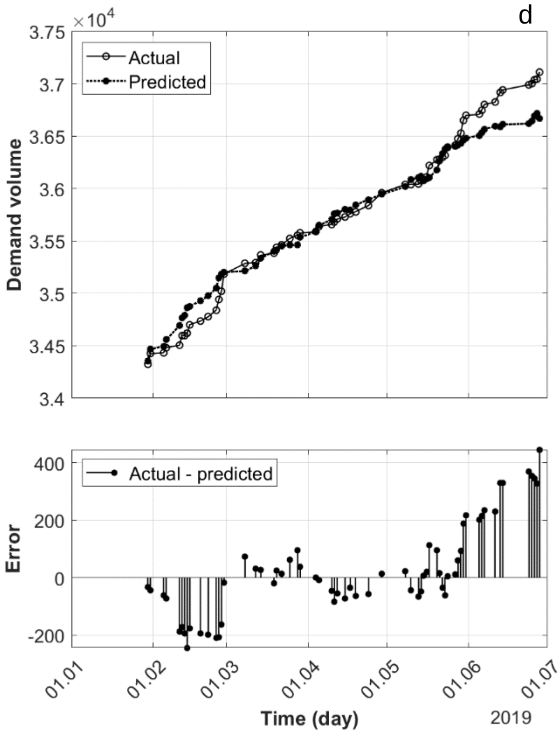
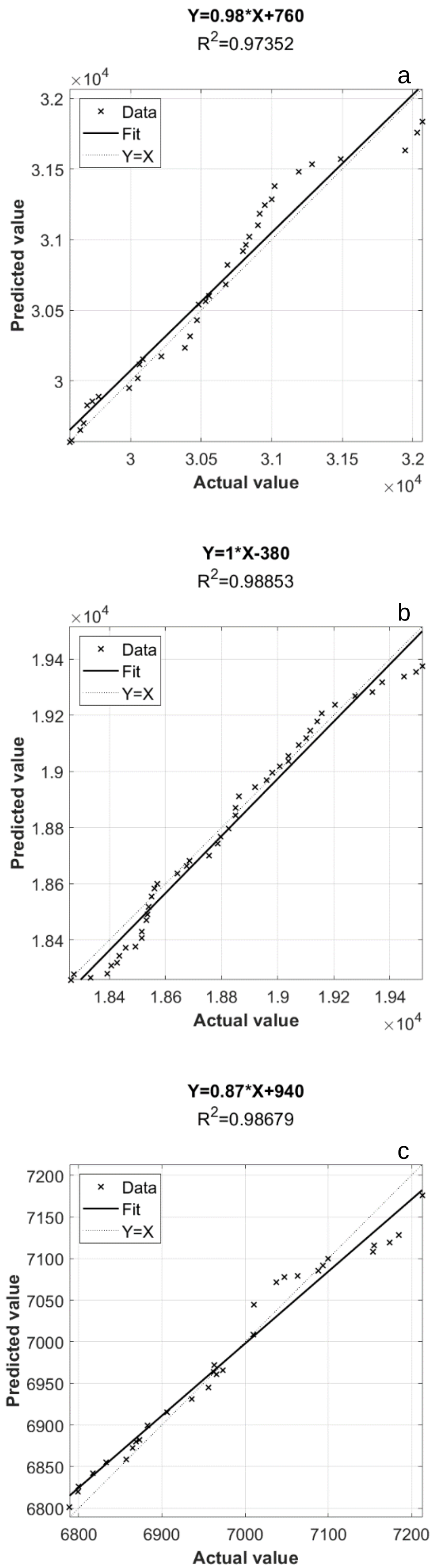


FIGURE 4. Demand volume prediction with error prediction at the high ratio obtained by the best NARX neural network model architectures for four food products: (a) product id=492, (b) product id=1272, (c) product id=1325, and (d) product id=1347.

The plots of the observed demand volumes versus the NARXNN simulated values for all samples on a high interval are shown in Fig. 5. Comparing them with those obtained at a low ratio (Fig. 4), it can be concluded that in all cases, good fits of the model data to the actual data were also achieved. Similar to the low ratio, the high ratio with the best effect of the correlation coefficients (R^2>0,988) for products IDs of 1272 (Fig. 5b) and 1347 (Fig. 5d). Thus, contrary to MAE, MAPE and RMSE, the extension of the forecast period of these two products did not worsen the R^2 score. For the other two products, i.e. ID=492 (Fig. 5a) and ID=1325 (Fig. 5c), even an improvement in the NARXNN realisation of the demand variable was noted, whereby R^2 increased to a slight extent, not exceeding 0.012% (Tab. 3). Moreover, for these two products, the noticeable deviations of some of the predicted samples from the determined regression line did not decrease the prediction accuracy assessed also by MAE, MAPE as well as RMSE.



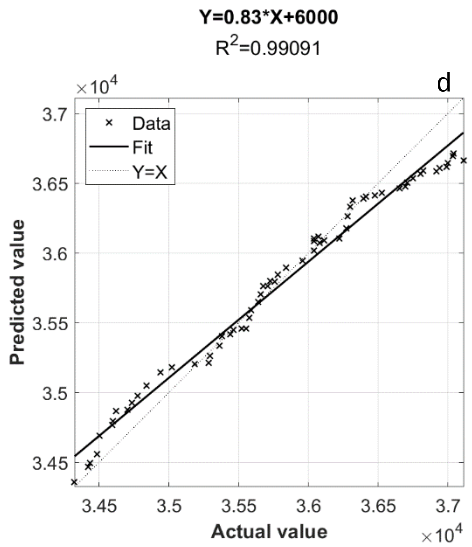


FIGURE 5. **Comparison between actual values and NARX neural network model predictions at the high ratio for four food products: (a) product id=492, (b) product id=1272, (c) product id=1325, and (d) product id=1347.**

Taking into account the results of all measures, the developed models were provided with the most accurate forecasts of demand for products with IDs of 1347 and 1272, and then for products with IDs of 1325 and 492, regardless of the number of steps ahead tested. It can be assumed that it was caused by a smaller number of samples for product IDs of 1325 (n=296) and 492 (n=339) (Tab. 1) than for the other ones (n>450). Moreover, in the case of the last one, the overall data samples that showed the highest standard deviation of the mean and failed the one-sample Kolmogorov-Smirnov test to establish a normal distribution (Tab. 1) resulted in inferior forecast accuracy. The factors mentioned above negatively affected the data generalisation already in the training process.

Overall, we obtained very satisfactory predictive results for all of the NARXNN models assessed. However, depending on the type of product, its prediction efficiency in RMSE, MAE, MAPE and R^2 indices differed slightly. Nevertheless, comparing them with the results of other works, the NARXNN has an advantage over some other models. In one study on sales forecasting in the fashion industry using various shallow techniques [72], i.e. decision trees (DT), random forest (RF), support vector regression (SVR), artificial neural networks (ANN) and linear regression (LR), as well as deep learning (DL) approaches, the results of the R^2 coefficient ranging from 0.568 (LR) to 0.756 (RF) with MAPE ranging from 0.451 (LR) to 0.345 (RF). On the other hand, in predicting the time series of footwear sales at the out of sample period [73], using the ETS and ARIMA models obtained minimum MAPE error values of 12.5% and 14%, respectively.

By relying on the results obtained in this study, it can be concluded that the developed NARX models based on artificial intelligence can be used to create highly accurate food demand forecasts. It is crucial when managing short shelf-life products, such as fresh food. In consequence food retailers can effectively reduce food waste [67]. Also, it may have a positive impact on the research on sustainable development. However, lack of supply volume data does not allow for the assessing the influence of food demand prediction on the food waste reducing, in this research.

V. CONCLUSIONS

The hybrid concept combining Nonlinear Autoregressive Exogenous with the Neural Network (NARXNN) is an effective technique for building prediction models of time series. This article has presented a novel application of NARXNN to accurately forecast the demand for selected foods. The proposed approach can be practically applied as a component of a company's intelligent management system. It can support the rational control of food inventory and production while reducing waste and costs in the supply chain. The main limitation of the developed models is the lack of possibility of analyzing small data sets (below 100 rows of data).

Future research works can concern using stacked autoencoder pretraining in the developed models [65] to process small datasets. Also, the research using demand and supply data aggregated to shop level should allow for verification of the developed models with respect to the prediction of demand in other areas (such as drinks or fuel).

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KRZYSZTOF LUTOSŁAWSKI received the MSc degree in the field of control engineering and robotics with specialisation in computer-based control networks from Wroclaw University of Science and Technology, Poland, in 2003, the MSc degree in the field of computer science and engineering with specialisation in data processing systems engineering from Wroclaw University of Science and Technology, Poland, in 2007, and PhD degree in the discipline of nutrition and food technology from Wroclaw University of Economics and Business, Poland, in 2014. Currently, he is an assistant professor at the Department of Process Management at the Faculty of Management at Wroclaw University of Economics and Business. He has authored peer-reviewed publications in international indexed journals and has authored conference reports. He has conducted research on the food quality, process optimisation and applications of machine learning.

MARCIN HERNES received the MS degree in computer science from Wroclaw University of Science and Technology, Poland, in 2004, the Ph.D. degree in economics from Wroclaw University of Economics and Business, Poland, in 2011, and D.Sc. in management from Wroclaw University of Economics and Business, Poland, in 2019. He is an associate professor, head of Department of Process Management and chairman of Center for Intelligent Management Systems at Wroclaw University of Economics and Business. His research has been in artificial intelligence, knowledge management, decision support systems, management systems, cognitive architectures. He has authored over 150 peer-reviewed publications in international journals and conferences. He is a member of IEEE, The Polish Artificial Intelligence Society and Scientific Association of Business Informatics. He was awarded the Rector's of Wroclaw University of Economics and Business award for scientific achievements, several times. Marcin Hernes is also a practitioner in the scope of management systems, coordination and automation of production processes and multi-agent decision support systems and author of dozen computer applications in industrial companies and public administration entities.

JOANNA RADOMSKA is an associate professor and Vice-Dean of the Faculty of Business and Management at Wrocław University of Economics and Business. Her research interests cover areas of open strategy, strategy implementation, risk in strategic management, behavioral strategy, creative industries and relations as a source of competitive advantage. She authored and co-authored 85 book chapters and articles. In 2017 she was awarded Santander Universidades scholarship. She serves as a reviewer at several journals (i. e. International Business Review, Benchmarking, Journal of Organizational Change Management) and conferences (EMAC, EURAM). She has been engaged in several research projects in the field of strategic management, strategy implementation, employee engagement and change management.

MONIKA HAJDAS is a professor at Wrocław University of Economics and Business. Her research interests include brand management, cultural branding and marketing innovation. She authored and co-authored over 50 articles, book chapters and three books. She has published her work in Journal of Retailing and Consumer Services, Journal of Brand Management and International Journal of Management Education. She combines scientific work with business practice. For the last 15 years she has advised in dozens of projects for global and local companies from various industries: finance, pharmaceuticals, retail, FMCG, education, HoReCa, luxury goods, interior design, building materials, oil industry, local government.

EWA WALASZCZYK received the MS Eng. degree in industrial management from Wroclaw University of Economics and Business, Poland, in 2004, and the Ph.D. degree in food technology from Wroclaw University of Economics and Business, Poland, in 2016. She is an associate professor, working in the Department of Process Management and is a member of the Center for Intelligent Management Systems at Wroclaw University of Economics and Business. She is also a member of the Polish Society of Food Technologists. Her research concerns food biotechnology, food production and technology, production process management and environmental costs of product life cycle. She has authored over 50 peer-reviewed publications in international journals and conferences.

AGATA KOZINA received an engineering degree in Management and Production Engineering in 2018 and a Master's Degree in Production and Service Management in 2019 at the Wrocław University of Economics and Business. From 2019, she attends the Doctoral School of the Wrocław University of Economics and Business. She is a Ph.D. student in the Department of Process Management at the Faculty of Management. She is the author of publications in prestigious magazines, which actively presents research results at international conferences. Her research concerns artificial intelligence, decision support systems, management systems, deep learning, data augmentation, and transformation in machine learning. Her interests also include the Internet of Things, Quality management standards, management systems, cognitive architectures, and enterprise resource planning software.