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A NEURAL NETWORK APPROACH FOR PREDICTING PRODUCTION VOLUME OF BIOFUELS IN POLAND

ZASTOSOWANIE SIECI NEURONOWYCH DO PROGNOZOWANIA WIELKOŚCI PRODUKCJI BIOPALIW W POLSCE

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Abstract: This article focuses on the creation of artificial neural networks (ANN) and their use in predicting the volume of biofuel production in Poland on the basis of historical data. Artificial neural networks are extremely useful in predicting events in which it is difficult to find determinism and cause-effect relationships. For this purpose 30 artificial neural networks of different topology were created. The analysed artificial neural networks had: one or two layers, from 4 to 8 neurons on the first layer and 4 or 6 neurons on the second layer. Moreover, the effect of delayed inputs and the effect of learning set size on prediction quality were analysed. The quality of each structure was evaluated based on the coefficient of determination, mean error, and mean square error. The stability of prediction was evaluated based on the sample standard deviation of RMSE and MAE. All the presented ANN structures were simulated five times and the best individual results included in the tables. The best results were obtained for an artificial neural network with two layers, four neurons in each layer and one delay. Overall, the second layer increased the stability of the prediction.

Keywords: artificial neural networks, biofuels, prediction.

Streszczenie: W artykule skupiono się na tworzeniu sztucznych sieci neuronowych i ich wykorzystaniu do prognozowania wielkości produkcji biopaliw w Polsce na podstawie danych historycznych. Sztuczne sieci neuronowe są niezwykle przydatne w prognozowaniu zdarzeń, w których trudno doszukać się determinizmu i związków przyczynowo-skutkowych. W tym celu stworzono 30 sztucznych sieci neuronowych o różnej topologii. Analizowane

sztuczne sieci neuronowe miały: jedną lub dwie warstwy, od 4 do 8 neuronów w warstwie pierwszej oraz 4 lub 6 neuronów w warstwie drugiej. Ponadto przeanalizowano wpływ opóźnionych wejść oraz wpływ wielkości zbioru uczącego na jakość predykcji. Jakość każdej ze struktur oceniono na podstawie współczynnika determinacji, błędu średniego oraz błędu średniokwadratowego. Stabilność prognozowania była oceniana na podstawie odchylenia standardowego próby RMSE oraz MAE. Wszystkie przedstawione struktury ANN były symulowane pięciokrotnie, a najlepsze pojedyncze wyniki zamieszczono w tabelach. Najlepsze wyniki uzyskano dla sztucznej sieci neuronowej z dwiema warstwami, czterema neuronami w każdej warstwie i jednym opóźnieniem. Druga warstwa zwiększyła stabilność predykcji.

Słowa kluczowe: sztuczne sieci neuronowe, biopaliwa, predykcja.

1. Introduction

The concept of artificial neural networks arose as a result of ongoing research on the functioning and structure of the human brain. The human nervous system is constructed of interconnected neurons which is mimicked by the artificial neural network formed by artificial neurons (Lula, Paliwoda-Pękosz, and Tadeusiewicz, 2007). It was an important discovery that the complex real structure allows for simplifications and very limited processing rules while maintaining its functionality (Tadeusiewicz, Leper, Borowik et al., 2007).

The functioning of artificial neural networks can be described as follows:

- numerical data form a vector of numerical values (x from 1 to n),
- each input is assigned a weight (learning result), which together form another vector (vector of weights).

Having both vectors, the input data is aggregated. The result is used as the argument of the activation function. With the use of an activation function, the value at the output of the neuron is calculated. For the correct operation of ANN, it is required to create an appropriate learning set.

There are several important reasons indicating the validity of using artificial neural networks instead of other methods such as limited access to data (Wyrozumski, 2004, pp. 179-190), great difficulty of describing the studied phenomenon (Tadeusiewicz, 2009, pp. 200-211), besides the creation of artificial neural networks is cheap, they do not require tedious programming, and they work in parallel, so their work is efficient. Their true usefulness is proven by predicting events in which it is difficult to find determinism and cause-effect relationships (Tadeusiewicz et al., 2007). Such events are, for example, economic processes. For successful prediction, data from previous periods proved to be sufficient. Artificial neural networks have been successfully used to predict the maximum and minimum buying and selling price of consumer wheat on the Forex market (Koszela and Zaborowicz, 2014, pp. 113-122). The data collected by the authors included information about: opening and closing prices, extremes of the day, volume, day of the week, quarter, year as well as information

about the price of crude oil, corn and the EUR/USD pair rate. In the course of further work on improving the quality of forecasts, the research problem was split into parts and two neural networks were used (one with 24 variables for the highest price of the day and another with 15 variables for the lowest price of the day). Both networks had radial basis functions (RBF). The lowest value on 04/05/2012 was $599.13. The relative error was 1.52%. The other ANN performed better in the actual market, being only 0.47% wrong ($620.13 – actual price; $618.2 – forecast price).

The problem of predicting the volume of biogas produced was solved in a different way (Adamski, Pronobis, and Dworecki, 2013, pp. 26-28). The fermentation process yielded 1898 data for the learning set and thirty input variables. The network topology was as follows: two hidden layers, one hundred neurons on the first layer and twenty neurons on the next layer. Two learning algorithms were used, namely the coupled gradients algorithm and backward error propagation. The mean square error for this ANN was 0.046, with a validation quality of 0.798668.

ANNs have also been shown as helpful in selecting when to begin irrigating crops (Neugebauer, Nalepa, and Sołowiej, 2007). Due to the complexity of the phenomenon, the authors created two ANNs. The task of the first one was to predict the occurrence of rainfall. The obtained information was then used by the second network to determine the value of a binary variable (1 – irrigate; 0 – do not irrigate). The MLP network contained one hidden layer with 14 neurons and a sigmoidal activation function. The networks were correct up to 76% of the time.

Another demonstration of the remarkable versatility of ANNs is the work on the prediction of sweet potato drying kinetics parameters (Singh and Pandey, 2011). The authors obtained their data by performing drying of potato layers with thicknesses of: 5 mm, 8 mm and 12 mm, temperature range 50°C-90°C, and air velocities from 1.5 m/s to 5.5 m/s. A total of 1400 results were collected and divided into learning and test sets in the ratio 80%:20%. The purpose of the study was to establish predictions of moisture content (MC), drying rate and moisture ratio (MR). Finally, the artificial neural network explained 99.87% of the total variation in moisture content for sweet potato. For the drying rate, the coefficient of determination was 99.3%, and for moisture content index R^2 was 99.84%.

In addition, artificial neural networks have been successfully used in: yield prediction of sugar beet as well as wheat (Boniecki and Mueller, 2006, pp. 40-44), torque prediction of biodiesel-fueled engine (Cirak and Demirtas, 2014, pp. 74-80), classification of dried parsley (Koszela, 2012, pp. 87-90). Artificial neural networks have shown their usefulness in control processes (Almonti, Baiocco, Tagliaferri et al., 2019, p. 3730; Tamouridou, Alexandridis, Pantazi et al., 2017, pp. 2307), and farming (Elahi, Weijun, Zhang et al., 2019, p. 117900; Francik and Kurpaska, 2020, p. 652).

This paper focuses on the creation and testing for usability of an artificial neural network. The criterion for usability is prediction quality as measured by root mean square error (RMSE), mean error (MAE) and standard deviation for both measures.

A very popular measure of fit quality in the form of coefficient of determination (R^2) was also used. The amount of biofuel production in the future is very important, so being able to predict trends is crucial. Fossil fuels, which have been a leading source of energy, are now being depleted. The European Union has set itself the goal of developing the biofuels market due to the need to ensure its energy security (Piwowar, 2015).

2. Methodology

Artificial neural networks are built from a specific number of individual neurons. Their arrangement and the way they are connected is called the structure of the artificial neural network (Ciskowski, 2012). Layers consisting of a certain number of neurons organize the work of the whole network, which is particularly important when using programs that simulate the network which is especially important with such programs (Tadeusiewicz and Szaleniec, 2015).

Artificial neural networks having a single hidden layer can form any single--coherent convex region called a simplex from the input signals. To solve more complex problems, an artificial neural network with at least two hidden layers is required. A network with two such layers allows the space to be divided into non--convex and non-coherent sets. Adding more layers is not always a valid solution, because two and more layers form the same decisional area. Therefore, the artificial neural networks created for this paper contain one and two hidden layers. Each hidden layer contains a certain number of artificial neurons. An insufficient number of them will result in a reduction or a loss of problem-solving ability, while an excessive number will lead to network overfitting and a loss of generalization ability. The most commonly used and best activation functions are the sigmoidal function (unipolar) and the hyperbolic tangent function (bipolar). In this project, the former was used because its output signal can take a value between 0 and 1, which significantly simplifies the interpretation of results in the case of forecasting production. The implementation of delayed signals into an artificial neural network allows to create such a network which, for learning and prediction, uses only the past data of the studied phenomenon, that are the best source of information because they contain all the information about the factors affecting the level of a particular phenomenon, in this case the production of liquid biofuels. Data regarding liquid biofuels produced in Poland in the period 2007-2017 were obtained from the website of the Energy Regulatory Office (Urząd Regulacji Energetyki, n.d.).

The way a single neuron works can be described is by the formula:

$$y_n = f(u) = f\left(\sum_n^{i=1} x_n w_n\right), \tag{1}$$

where y is the signal at the output of the neuron. The result of the sum of the multiplications of inputs and weights is the argument of the activation function – $f(u)$.

For one layer, the formula takes the following form:

$$y_{n,m} = f(u) = f\left(\sum_{n,m}^{i=1} x_{n,m} w_{n,m}\right). \tag{2}$$

The calculations were done in MATLAB, which works with matrix calculations, so this equation will take the following form:

$$Y = f(u) = f(XW). \tag{3}$$

Matrix X is the input matrix of dimension $1 \times n$. This matrix in its general form presents itself as follows:

$$[x_1 \quad x_2 \quad . \quad . \quad . \quad x_n].$$

The above matrix is then multiplied by a matrix of weights of dimension $n \times m$:

$$\begin{bmatrix} w_{1,1}^1 & w_{1,2}^1 & . & . & . & w_{n,m}^l \\ w_{2,1}^1 & w_{2,2}^1 & . & . & . & w_{n,m}^l \\ . & . & . & & & \\ . & . & & . & & \\ . & . & & & . & \\ w_{n,m}^l & w_{n,m}^l & & & & w_{n,m}^l \end{bmatrix}.$$

The result of the multiplication is an output matrix of dimension $1 \times m$:

$$[y_1 \quad y_2 \quad . \quad . \quad . \quad y_m].$$

Ultimately, the operation of an artificial neural network follows the pattern:

$$Y_l = f(u) = f(X_{l-1} W_l). \tag{4}$$

To create and initialize the artificial neural network, the existing newfftd function in MATLAB was used.

In order to assess the quality of prediction the following measures were used. Coefficient of determination:

$$R^2 = \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}, \tag{5}$$

where: y_i – the actual value of variable y in period i, $\bar{y}$ – the arithmetic mean of the actual values of the explanatory variable, $\hat{y}$ – theoretical value of the explained variable (the result of the SSN).

The root of the mean squared error:

$$RMSE = \sqrt{MSE} = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2. \tag{6}$$

Mean Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|. \tag{7}$$

There is an ever-present relationship between MAE and RMSE:

$$MAE \leq RMSE. \tag{8}$$

The last statistical measure used is the standard deviation of the sample:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}{n-1}}. \tag{9}$$

3. Results and discussion

The obtained results were divided according to the number of delays and hidden layers. The tables include the following information: number of neurons, size of the learning set, $RMSE_{avg}$, σ_{RMSE}, MAE_{avg}, σ_{MAE}, R^2 – minimum and maximum, and the respective learning epochs. Selection of the best variant was based on a comparison of MAE_{avg} values (the lower the value, the better). The best variants were marked in bold and the worst variants underlined.

Table 1. Experimental ANN results for 1 delay, 1 layer, and varying number of neurons (from 4 to 8) and varying learning set size (0.5; 0.7); data in tonnes

Neurons	Learning dataset	$RMSE_{avg}$	σ_{RMSE}	MAE_{avg}	σ_{MAE}	R^2	Epochs	R^2	Epochs
4	**50%**	**1261**	**469**	**396**	**151**	**95.5%**	**278**	**90.9%**	**222**
4	70%	1871	623	593	205	93%	224	87.8%	192
6	50%	7195	4991	2455	1819	90.4%	429	53.5%	116
6	70%	5273	2590	1698	877	85.6%	259	64.6%	91
8	50%	8825	4141	3114	1545	78.6%	166	50%	130
8	70%	6545	3784	2309	1448	83.8%	239	53.7%	137
	Average	5162	2766	1761	1008				

Source: author's calculations in MATLAB.

A network with one delayed input and one hidden layer (Table 1) on average performed best for only four neurons. Teaching such a network required using half of the available data. The mean error (MAE_{avg}) was 396 t in this variant, i.e. on average the neural network was over or under-predicted by 396 t. The standard deviation of MAE (σMAE) for the series of simulations was 151 t. The root mean square error value also stood out positively compared to the other structures and was 1261 t. The more than threefold difference between MAE_{avg} and $RMSE_{avg}$ is a consequence of the calculation method of the latter which gives more weight to large errors. However,

it should be stated that in both variants these are small values in the scale of the whole phenomenon that is liquid biofuel production. This is confirmed by the very high value of the coefficient of determination (R^2) – 95.5%. The worst performing network was built with eight neurons and used 50% of the data for learning. Error parameters for such a network were significantly higher at 3114 t (MAE_{avg}), on average deviating by 1545 t; 8825 t ($RMSE_{avg}$) with a deviation of 4141 t. The fit of the model to the explanatory variable was barely 78.6%, which is below expectations. The more neurons on the hidden layer, the lower the ability of the artificial neural network to predict correctly. Although this seems illogical, it is worth noting that a larger number of neurons completes the learning process with fewer epochs, which is too fast. Another conclusion is the need to increase the learning set as the number of neurons increases. Other researchers confirm the presented thesis. The article on the description of the electrical permeability of flour using ANN (Łuczycka and Pentoś, 2010, pp. 43-48) confirms that the number of neurons can be increased if the learning set is sufficiently large. The authors of this paper had a dataset ten times larger and obtained the best results with ten times as many neurons, while the conclusion of linearity would be too far-fetched. The graphic representation for the best network structure is shown in Figure 1, where the light grey crosses show which data were used in the learning process, while the dark grey crosses illustrate the actual biofuel production in subsequent quarters. The line shows the projected production in subsequent quarters. As can be easily observed, only the values from the 39th and 40th quarters were predicted with a noticeable, although still acceptable error, the rest of the data were predicted almost without error.

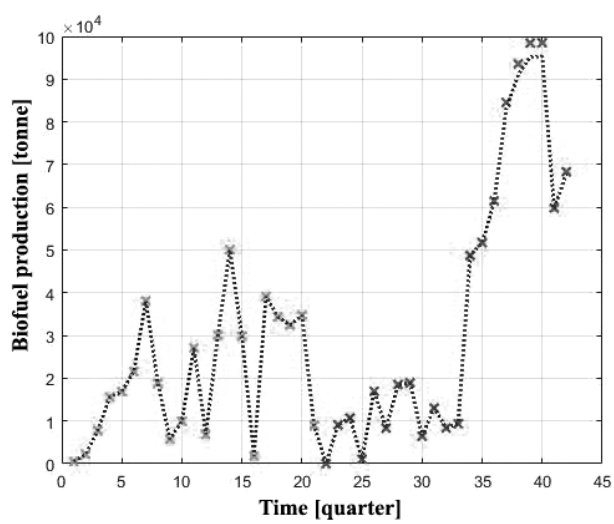

Fig. 1. Performance of an artificial neural network with 1 delay, 1 layer and 4 neurons

Source: own elaboration.

Figure 2 shows the worst variant of the artificial neural network. From the 35th quarter, one can see a clear decrease in prediction quality.

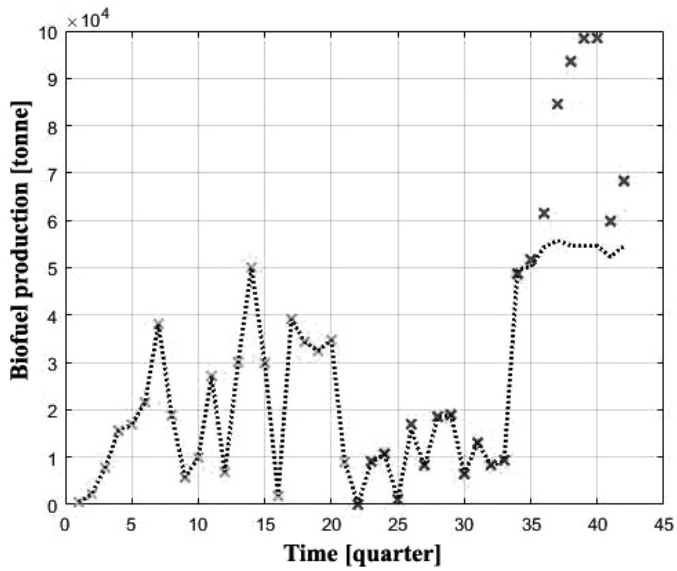

Fig. 2. Performance of an artificial neural network with 1 delay, 1 layer and 8 neurons

Source: own elaboration.

Table 2. Experimental ANN results for 1 delay, 2 layers, and varying number of neurons (from 3 to 6) and varying learning set size (0.5; 0.7); data in tonnes

Neurons	Learning dataset	$RMSE_{avg}$	σ_{RMSE}	MAE_{avg}	σ_{MAE}	R^2	Epochs	R^2	Epochs
4, 4	**50%**	**244**	**178**	**85**	**63**	**99.8%**	**793**	**98.1%**	**537**
4, 4	70%	348	294	115	98	99.7%	1000	96.5%	683
6, 3	50%	2646	4298	905	1471	99.6%	1000	65.1%	240
6, 3	70%	2411	3390	773	1074	99.7%	886	72.4%	329
	Average	1412	2040	469	676				

Source: author's calculations in MATLAB.

Based on the data in Table 2, it can be concluded that artificial neural networks with one delayed input perform best when using the minimum number of neurons (four neurons per layer), regardless of the number of layers. For a network with such parameters, the optimal amount of data was 50% of the whole set. The mean error (MAE_{avg}) was only 85 t and $RMSE_{avg}$ was 244 t. Such an insignificant difference between MAE_{avg} and $RMSE_{avg}$ means that the predictions were not subject to significant errors. Among the networks with two layers, the worst performer was the

combination of a learning set containing half of the available data with 6 neurons on the first layer and 3 neurons on the second layer. While in the best case the network achieved a coefficient of determination value of 99.6%, which is a very good result, the coefficient of determination in the worst trial fell below 70%. An important observation is that ultimately adding another hidden layer had a positive effect on the overall stability of the prediction.

Multilayer artificial neural networks were used in work on wheat kernel hardness models (Hebda and Francik, 2006). Among the structures with the lowest prediction errors, up to 70% had two layers containing artificial neurons. Moreover, the researchers identified the three most accurate ANNs (exclusively two-layer). These networks had respectively 2, 6, 7 neurons in the entry layer and 3, 7, 7 on the next layer. The mean square errors (MSE) ranged from 2 to 2.5.

Figures 3 and 4 show the networks displaying the best fit to the data, and the worst fit from Table 2.

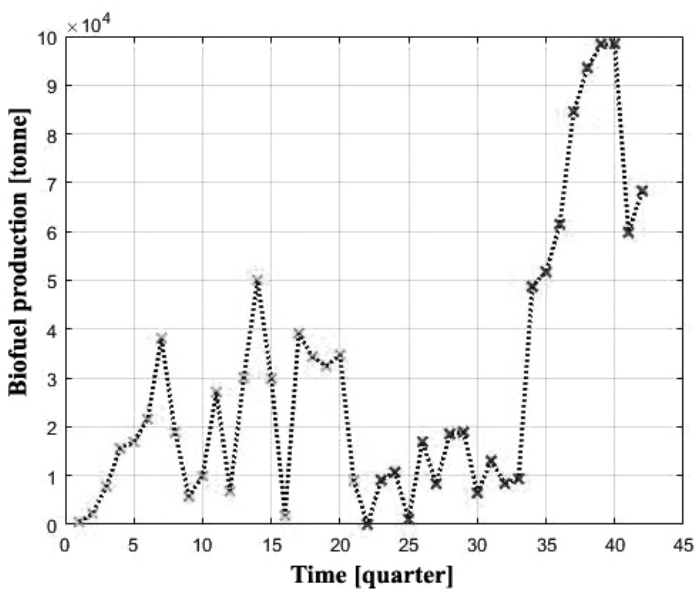

Fig. 3. Performance of an artificial neural network with 1 delay, 2 layers and 4 neurons on each layer

Source: own elaboration.

The second series of simulations (Table 4) were designed to investigate the effect of two delays on the results obtained with unchanged topology of the created artificial neural networks in relation to the previously described networks. For one layer, the best network again turned out to be the one built of four neurons. The process of learning the best network again required the use of 50% of the data. For this topology, MAE_{avg} was 663 which means that each prediction had an error

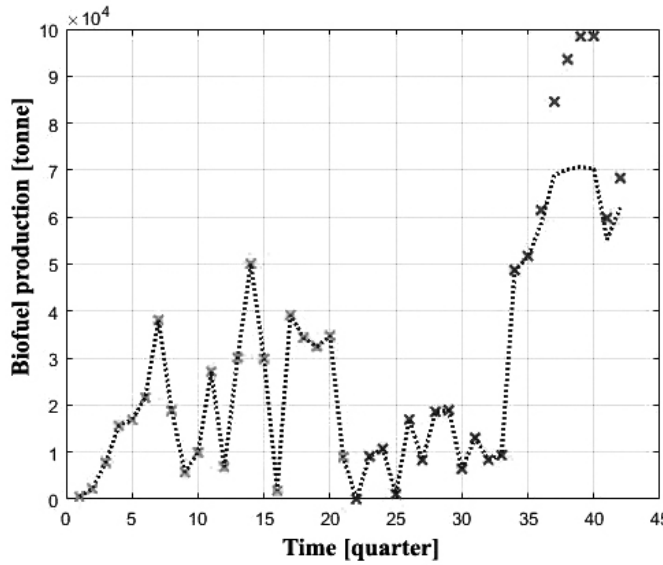

Fig. 4. Performance of an artificial neural network with 1 delay, 2 layers, 6 neurons on the first layer and 3 neurons on the second layer

Source: own elaboration.

Table 3. Experimental ANN results for 2 delays, 1 layer, and varying number of neurons (from 4 to 8) and varying learning set size (0.5; 0.7); data in tonnes

Neurons	Learning dataset	$RMSE_{avg}$	σ_{RMSE}	MAE_{avg}	σ_{MAE}	R^2	Epochs	R^2	Epochs
4	**50%**	**2045**	**1362**	**663**	**401**	**96%**	**402**	**82.6%**	**272**
4	70%	3063	1551	971	492	93.1%	143	79.4%	224
6	50%	3960	1096	1464	421	98.1%	116	75%	210
6	70%	2754	1525	887	489	90.4%	168	78.2%	121
8	50%	4867	1014	1968	356	97.3%	179	75.9%	33
8	70%	3884	3004	1242	970	96.3%	250	69.7%	61
	Average	3429	1592	1199	522				

Source: author's calculations in MATLAB.

of +/– 663. The standard deviation of MAE_{avg} shows that successive simulations had moderate repeatability and prediction accuracy, i.e. increasing the number of delayed inputs by one had a negative effect on the performance of the network with the simplest design. With two delays, the artificial neural network with the largest number of neurons again made the least accurate predictions concerning liquid

biofuel production in Poland. The average error for this network was as high as 1968 t while deviating in individual samples by only 356 t. The $RMSE_{avg}$ is 4867 t with a standard deviation of 1014 t. It is interesting to note that it was the worst network that produced the most repeatable results. To sum up, the networks with one delay were found to be worse on average than those with two delays, although the best network belongs to the first group.

Historical data were used in a paper on methods of time series forecasting using artificial neural networks (Francik, 2009). The criterion for selecting the best structures was the minimum size of the MSE error. The best neural models included historical data from the last three and four years (2 models each) and six years (5 models). The results confirm the belief that extending the period of analysis has a good effect on the quality of prediction if there are strong hysteresis relationships. Another example of ANN usage is the work on apple ripeness assessment (Górski, Kaleta, and Langman, 2008). The networks had only one hidden layer containing between 2 and 12 neurons. The optimal number was determined empirically and was from 4 to 6 neurons. The result of this study is consistent with observations on biofuels and specifically confirms the ineffectiveness of using an excessive number of neurons while maintaining a small number of learning cases.

Figures 5 and 6 show a graphical representation of the networks displaying the best fit to the data, and the worst fit from Table 3.

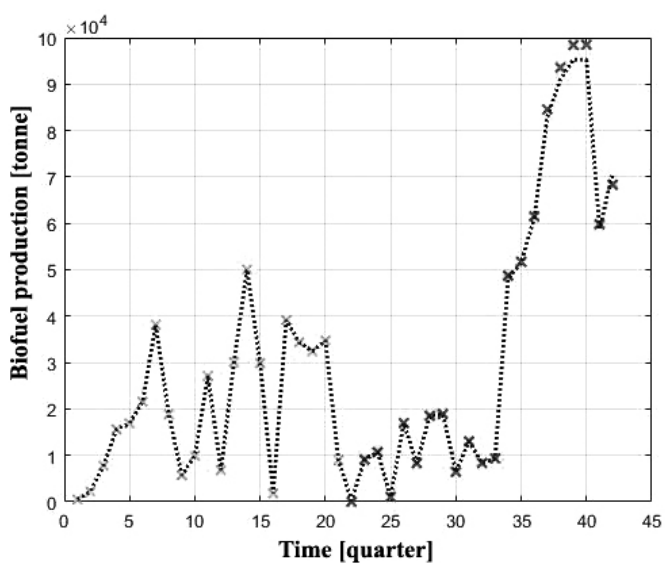

Fig. 5. Performance of an artificial neural network with 2 delays, 1 layer and 4 neurons

Source: own elaboration.

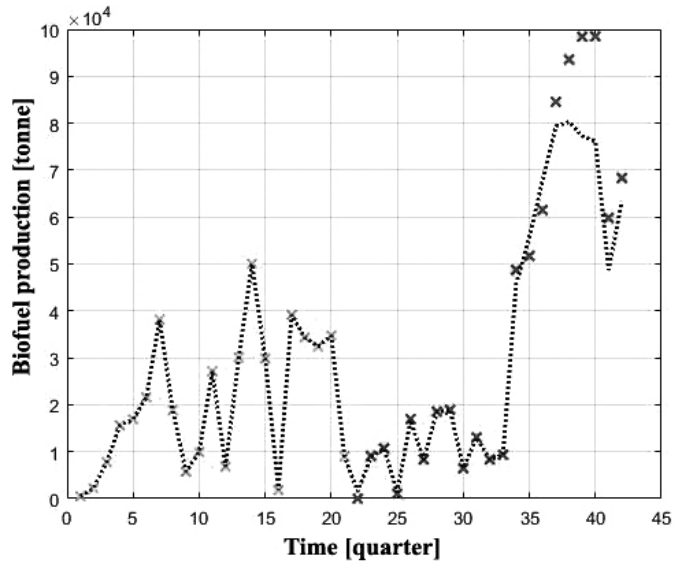

Fig. 6. Performance of an artificial neural network with 2 delays, 1 layer and 8 neurons

Source: own elaboration.

Table 4. Experimental ANN results for 2 delays, 2 layers, and varying number of neurons (from 3 to 6) and varying learning set size (0.5; 0.7); data in tonnes

Neurons	Learning dataset	$RMSE_{avg}$	σ_{RMSE}	MAE_{avg}	σ_{MAE}	R^2	Epochs	R^2	Epochs
4, 4	50%	497	379	167	126	99.5%	953	95.5%	555
4, 4	**70%**	**465**	**129**	**149**	**44**	**98.4%**	**485**	**97%**	**319**
6, 3	50%	4279	3997	1506	1473	99.6%	1000	64%	25
6, 3	70%	635	184	223	61	97.6%	980	96.1%	481
	Average	1469	1172	511	426				

Source: author's calculations in MATLAB.

Of the network architectures presented in Table 4, on average the best results were obtained for 4 neurons on each of the two layers. The network had 70% of the total data set during training. As a result, the mean error (MAE_{avg}) for the three trials was only 149 t. This is almost identical to the result obtained by using one less delay and a 20% less abundant learning set. The use of two delays improved the repeatability of the results globally, with an average standard deviation of 426 t, the best so far. The coefficients of determination of the edge variants of the optimal structure differed by only 1.4%. $RMSE_{avg}$ of the leading network – 465 t, which was the best in this aspect. as well as (σRMSE at 129 t). The error values are satisfactory but the average number of learning epochs (485) proves that there is still room

for improvement. By far the worst case is the network built with 6 neurons on the first layer, and 3 neurons on the next layer (learning with 50% of the data). This is the only case in Table 4 where errors reach several thousand t: $RMSE_{avg}$ – 4279 t (σRMSE 3997 t), MAE_{avg} – 1506 t (σMAE 1473 t). It is noteworthy that one of the trials finished only on the 1000th learning epoch, which resulted in the model fitting to the explained variable (R^2) at the level of 99.6%. However, the next attempts were much worse, although this structure has a great potential, it needs some refinement. The reason for its poor stability can be found in the learning set which turned out to be too small. Exactly the same network, which was provided with more patterns, achieved repeatable and good results.

Figure 7 shows an almost ideal prediction of biofuel production across the entire period of analysis. Only the values for the 38th and 39th quarters were slightly underestimated, which does not affect the unambiguously positive assessment of the presented SSN structure.

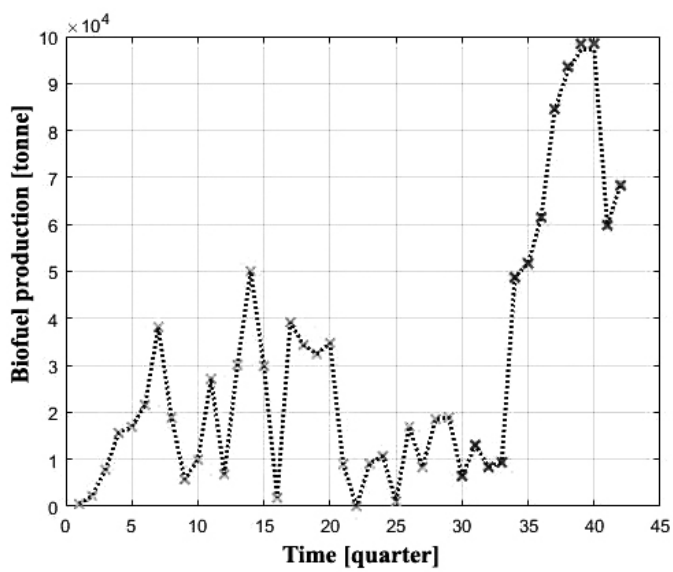

Fig. 7. Performance of an artificial neural network with 2 delays, 2 layers and 4 neurons on each layer

Source: own elaboration.

Figure 8 illustrates the mistakes made by the network with apparently the worst architecture.

The last series of tests were designed to test the hypothesis of seasonality in biofuel production, hence the jump in the number of delays from 2 to 4. Table 5 and Table 6 contain all data collected during the simulation for a given number of delayed inputs.

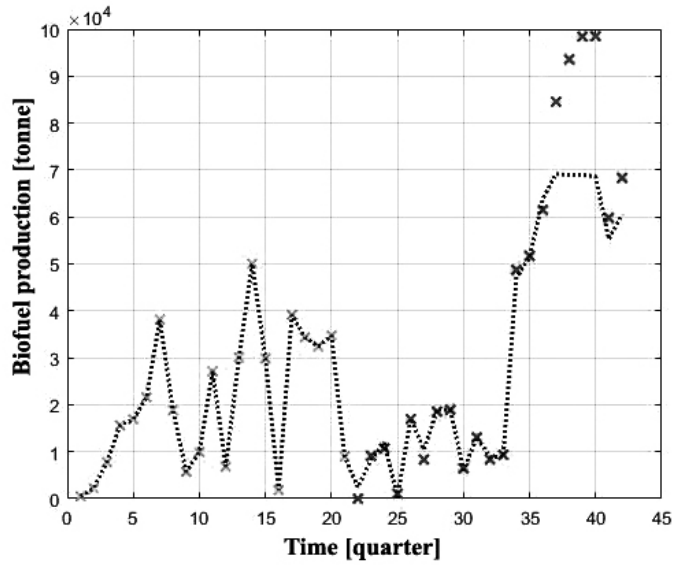

Fig. 8. Performance of artificial neural network with 2 delays, 2 layers, 6 neurons on the first layer and 3 neurons on the second layer

Source: own elaboration.

Table 5. Experimental ANN results for 4 delays, 1 layer, and varying number of neurons (from 4 to 8) and varying learning set size (0.5; 0.7); data in tonnes

Neurons	Learning dataset	$RMSE_{avg}$	σ_{RMSE}	MAE_{avg}	σ_{MAE}	R^2	Epochs	R^2	Epochs
4	**50%**	**1 737**	**513**	**626**	**238**	**93%**	**170**	**88.4%**	**96**
4	70%	3 616	1245	1138	414	85.7%	109	80%	255
6	50%	8 159	2687	3659	1046	76.0%	9	53.6%	41
6	70%	4 466	1750	1551	657	83.3%	266	68.8%	85
8	50%	13 325	2123	5591	775	51.8%	9	45%	25
8	70%	8 096	2006	2916	717	79.8%	10	59.2%	9
	Average	6 567	1721	2580	641				

Source: author's calculations in MATLAB.

The most advantageous topology was the network with 4 neurons and the learning set containing 50% of the total number of cases. Only this structure ensures the quality of the forecast not differing significantly from previous attempts. The average error (MAE_{avg}) was 626, which was not significant. The positive picture is strengthened by the satisfactory level of standard deviation for this error at 238 t. The described architecture also did not make many significant errors as proved by the value of $RMSE_{avg}$ at 1737 t. The data in Table 5 Indicate that two very significant

problems can be diagnosed. First, all ANNs learned very fast even during the 9th cycle, i.e. the MSE error for the learning set was minimized far too quickly, which consequently led to significant errors for the testing set. Secondly, only once was it possible to achieve a determination coefficient of 90% or higher. The absolute worst neural network structure was the one with 8 neurons and trained with half of the available data; MAE_{avg} reached 5591 and $RMSE_{avg}$ as high as 13325 so the error sizes awee definitely unacceptable. Forecasting with errors of this size is completely unjustifiable – as it is impossible to make rational decisions based on such uncertain economic information.

Figures 9 and 10 show the networks displaying the best fit to the data, and the worst fit from Table 5.

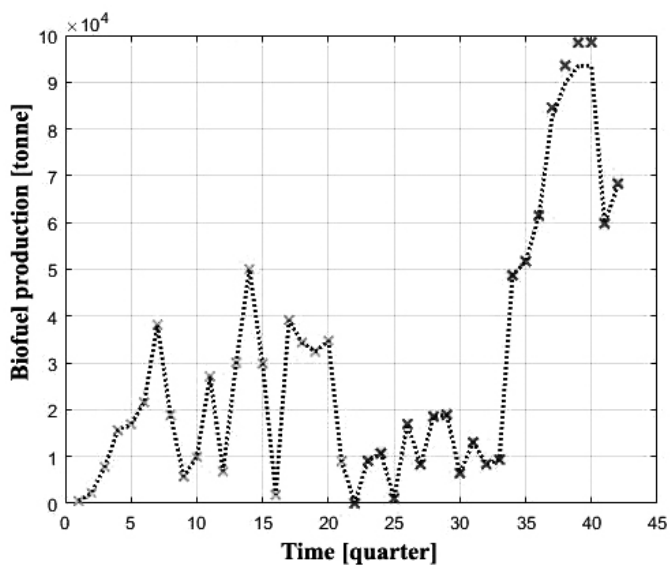

Fig. 9. Performance of an artificial neural network with 4 delays, 1 layer and 4 neurons

Source: own elaboration.

The results in Table 6 allow to conclude that dividing neurons between two layers has a positive effect on ANNs having delayed inputs. The network built from 8 neurons evenly divided between two layers was clearly the best (learning set – 70%). The most important feature of this network was its above average stability, respectively 39 t and 96 t. Two layers resulted in a longer learning process, only in two out of ten cases did the number of epochs fall below one hundred. The importance of the number of learning cycles parameter can be seen by analysing the previous table. It is not a problem to indicate the worst combination of the number of neurons and the size of the learning set (6 neurons in the first layer, 3 in the next

layer, and 50% of the entire data set). The errors made by the described network were much larger than the others (MAE_{avg} – 3946 t; $RMSE_{avg}$ – 10157 t) and its stability was also at a low level.

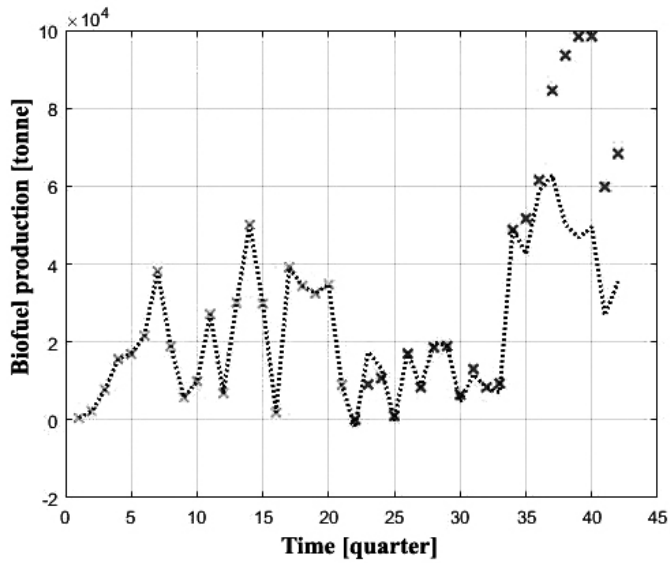

Fig. 10. Performance of an artificial neural network with 4 delays, 1 layer and 8 neurons

Source: own elaboration.

Table 6. Experimental ANN results for 4 delays, 2 layers, and varying number of neurons (from 3 to 6) and varying learning set size (0.5; 0.7); data in tonnes

Neurons	Learning dataset	$RMSE_{avg}$	σ_{RMSE}	MAE_{avg}	σ_{MAE}	R^2	Epochs	R^2	Epochs
4, 4	50%	630	484	211	162	98.7%	459	93.7%	390
4, 4	**70%**	**514**	**96**	**172**	**39**	**97.6%**	**366**	**96.6%**	**645**
6, 3	50%	10157	10391	3946	4210	82.5%	80	45.7%	210
6, 3	70%	5365	5834	1949	2007	99.7%	1000	60.5%	10
	Average	4166	4201	1569	1604				

Source: author's calculations in MATLAB.

In the paper on modelling an industrial drying process using ANN, it was noted that a linear increase in the number of neurons does not result in a linear or approximate improvement in prediction (Assidjo, Yao, Kisselmina et al., 2008, pp. 515-522). Similar observations were made in the paper on the prediction of moisture content and water activity in cassava cracker drying process using ANN (Lertworasirikul and Tipsuwan, 2008, pp. 65-74).

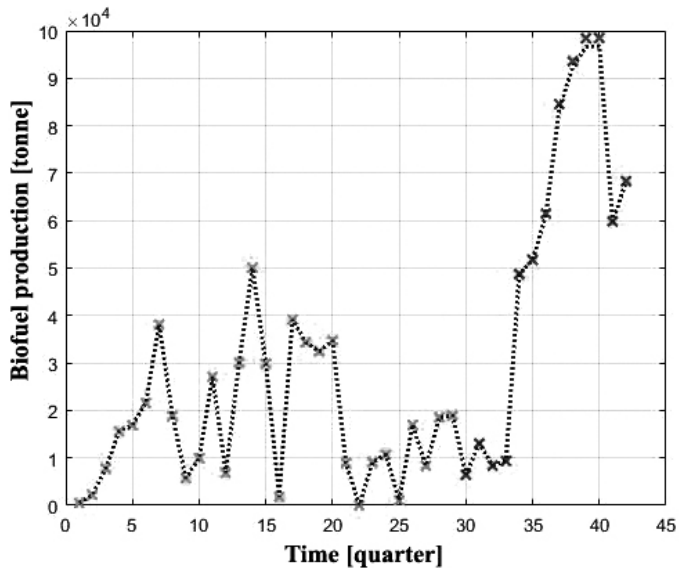

Fig. 11. Performance of an artificial neural network with 4 delays, 2 layers and 4 neurons on each layer

Source: own elaboration.

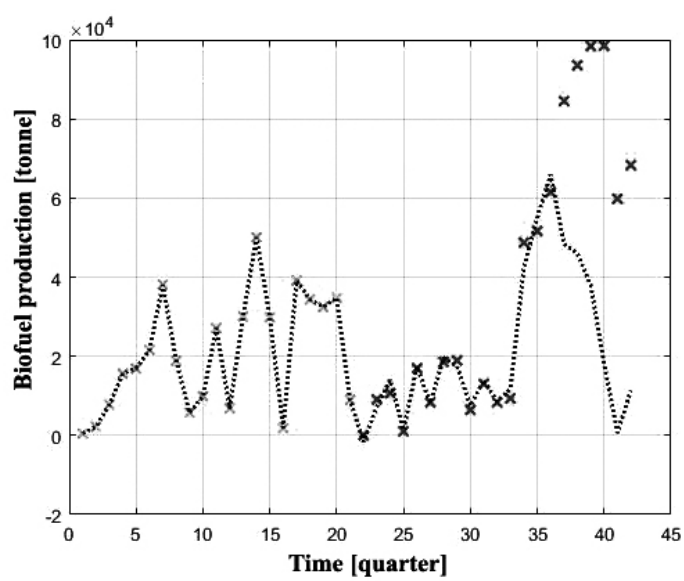

Fig. 12. Performance of an artificial neural network with 4 delays, 2 layers, 6 neurons on the first layer and 3 neurons on the second layer

Source: own elaboration.

Figures 11 and 12 show the networks displaying the best fit to the data, and the worst fit from Table 6.

4. Conclusions

Biofuels are gaining in importance every year. The share of biofuels in fuel mixtures is growing, and they are increasingly being considered by governments around the world in terms of their energy security. As a result, strategic planning is required to reduce uncertainty and thus risks. This is done by rational economic actors in biofuels and related markets. The main method is forecasting using various tools, one of the available possibilities being artificial neural networks. Their usefulness was evaluated in this paper.

In light of the presented results, the following conclusions can be drawn:

- the created and repeatedly positively verified ANN structures for the prediction of time series of biofuel production volumes confirmed the conviction expressed initially that there is a justification for using this kind of tool when solving such complex tasks,
- two-layer networks strongly improve forecasting results, the error values decrease ($RMSE_{avg}$ and MAE_{avg}), as well as the stability of these structures measured by standard deviation increases,
- the best single results ($R^2 > 99\%$) were obtained for networks learned during at least 500 cycles, four out of eight such events are associated with reaching the limit of 1000 epochs,
- based on the simulations, it can be concluded that the best network architecture for predicting liquid biofuel production was ANN with 2 layers, 4 neurons on each, and 1 delay, and the optimal size of the learning set was 50%,
- it is possible to use ANN to solve complex problems with a limited set of data,
- the modelled phenomenon is not characterized by the occurrence of seasonality, but there are indications of hysteresis (in relation to the preceding period).

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