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FORECASTING OF THE DAILY DEMAND FOR NATURAL GAS IN RURAL HOUSEHOLDS USING THE METHODS OF ARTIFICIAL INTELLIGENCE PART I. FORECASTING USING ARTIFICIAL NEURAL NETWORKS

Summary

The paper determines daily forecast demands for natural gas using artificial neural networks (MLPs). The influence of network structure, the type of activation function and the training process used on the quality of prediction were studied. It was found that the quality of forecasts was highly influenced by the network training algorithm. The smallest errors of the expired forecasts (MAPE 5-6%) were obtained using the BFGS algorithm.
***Keywords**: natural gas, short-term forecasts, artificial neural networks*

PROGNOZOWANIE DOBOWEGO ZAPOTRZEBOWANIA NA GAZ ZIEMNY WIEJSKICH GOSPODARSTW DOMOWYCH PRZY WYKORZYSTANIU METOD SZTUCZNEJ INTELIGENCJI CZĘŚĆ I. PROGNOZOWANIE PRZY WYKORZYSTANIU SZTUCZNYCH SIECI NEURONOWYCH

Streszczenie

W trakcie badań wyznaczano dobowe prognozy zapotrzebowania na gaz ziemny z wykorzystaniem sztucznych sieci neuronowych MLP. Przebadano wpływ struktury sieci, rodzaju funkcji aktywacji oraz zastosowanego procesu uczenia sieci na jakość predykcji. Stwierdzono, że na jakość prognoz duży wpływ ma algorytm uczenia sieci. Najmniejsze błędy prognoz wygasłych (MAPE rzędu 5-6%) uzyskano stosując algorytm BFGS.
***Słowa kluczowe**: gaz ziemny, prognozy krótkookresowe, sztuczne sieci neuronowe*

1. Introduction

Natural gas, as well as electricity and district heating networks, is a specific commodity for which the efficiency of market mechanisms is limited. Despite the fact, extensive measures were taken to liberalize the gas market. Liberalization of the gas market is modeled on the solutions implemented in the electricity market.

In line with the assumptions of the European Parliament and of the Council [4], a unified market for natural gas is expected to start functioning in the European Union in 2015. Ultimately, this is to result in the creation of a harmonized and barrier-free natural gas market, covering all EU Member States, acting on the basis of the principle of full competition. Network codes are the tools to implement a unified energy market, in particular those regarding balancing the gas in transmission networks. The Balancing Code will come into force in Poland in October this year [11]. In the code, much attention is paid to the problems of forecasting of demand for natural gas, indicating the entities responsible for this or specifying the requirements for the forecasts. The basic forecast is a forecast of daily consumption of natural gas, which is a short-term forecast. It is to support the operational management of a natural gas company in the planning of daily gas purchases.

In Polish literature, few publications in the field of forecasting demands for natural gas in short-time horizons can be found [3, 5, 7, 10]. In contrast, the number of foreign publications in this field is growing quite fast, especially in the countries advanced in the liberalization of their gas market [9]. The methods commonly used in recent years for short-term forecasting of demands for natural gas include the methods of artificial intelligence and, in particular, artificial neural networks [1, 2, 6, 8, 12, 14]. Their suitability for short-term forecasts has already been demonstrated in the electricity market.

2. Aim and scope of the paper

The aim of this study was to develop daily forecasts of the demand for natural gas with the use of artificial neural networks, with different ways of processing and comparison in this respect.

Calculations and analyzes were performed on the example of rural households as characteristic gas customers.

3. Material and methods

Prior to the construction of a neural network allowing to solve a specific problem, one shall decide on various stages of preparation and operation of the network. First, the network architecture must be defined, in particular, the type of network, the number of hidden layers and the number of neurons in each layer. At this stage, activation functions of neurons must also be chosen. The next step is to choose a training method, training networks and verification of the obtained results.

The best known and most widely used network architectures include one-way multilayer networks (Multi-Layer Perceptrons), *MLPs*. And such a network was built for the needs of predicting demands for natural gas. By varying the number of hidden layers, the number of neurons in each layer and the type of activation function, the impact of these factors on the quality of the forecasts was determined. The impact of the network training algorithm used on the prediction quality was also analyzed.

Quality of predictions was assessed on the basis of prediction error values estimates ex-post, basing on:

$$APE = \frac{\left|G_t - G_t^P\right|}{G_t} \cdot 100 \qquad (1)$$

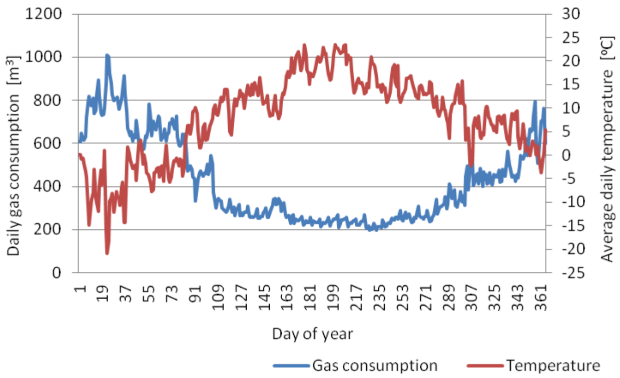
$$MAPE = \frac{1}{n} \cdot \sum_{t=1}^{n} \frac{\left|G_t - G_t^P\right|}{G_t} \cdot 100 \qquad (2)$$

where:
APE – absolute percentage error,
MAPE – mean absolute percentage error,
G_t – actual daily gas consumption,
G_t^P – daily prediction of gas consumption.

For calculations, *Statistica 10.0* was used. Calculations and analyzes were performed basing on the results of measurements of daily gas consumption for the Klodzko rural municipality, powered via I degree low-pressure reducing stations. Data from four years were used, whereas data for the first three years was the training set, and the last year was the test set.

4. Results

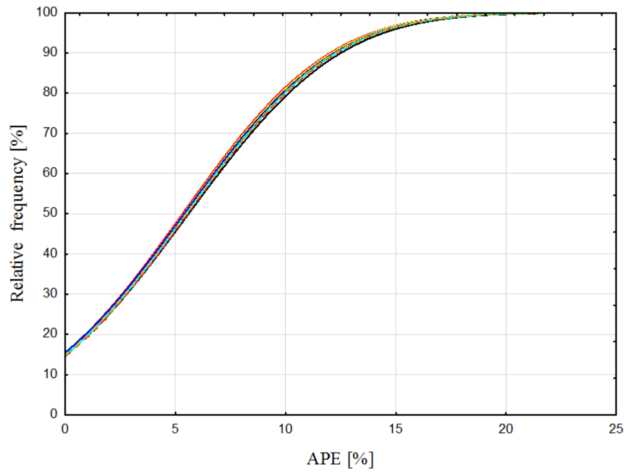
In accordance with the requirements of the Balancing Code, forecasting of demands for natural gas should take into account factors that affect its size, i.e. meteorological and time factors. The authors studied the correlation of daily gas consumption and such meteorological factors as temperature, humidity and air pressure, wind speed and direction; and time factors: daily gas consumption in earlier periods and days of the week [7]. It was found that the value of daily gas consumption of rural consumers was most affected by the value delayed in time of day, the average temperature of the previous day and day of the week. These figures were taken as input for the network. Figure 1 shows the course of daily gas consumption by the consumers surveyed against average daily temperatures in the selected year.



Source: Own work / Źródło: opracowanie własne

Fig. 1. The course of daily natural gas consumption by rural households against changes of the average daily air temperatures
Rys. 1. Przebieg dobowego zużycia gazu ziemnego przez wiejskie gospodarstwa domowe na tle zmian średniej dobowej temperatury powietrza

Searching for the optimal network structure, numbers of neurons in the hidden layers 3 to 13 were changed, functions of hidden layers and output activations were used: linear, logistic, tangential, exponential and sinusoidal. Calculations were repeated for three network training algorithms: the method of the steepest descent, the *BFGS* algorithm and the conjugate gradient algorithm. Tables 1 and 2 and Figure 2 show the assessment of the quality of predictions calculated on the basis of the *MLP* network with 12 electrons in the hidden layer, as considered optimal for individual activation functions and training algorithms.



Source: Own work / Źródło: opracowanie własne

Fig. 2. Empirical cumulative distributions of prediction errors based on the network *MLP* for each activation function in individual network training algorithms
Rys. 2. Dystrybuanty empiryczne błędów prognoz wyznaczonych w oparciu o sieć MLP dla poszczególnych funkcji aktywacji przy poszczególnych algorytmach uczenia sieci

Tables 1 and 2 show that, although the type of activation function of layers has no significant impact on the quality of predictions, the training network algorithm already has a big impact. In the case at hand, the best quality of predictions was obtained using the *BFGS* algorithm. The *BFGS* (Broyden-Fletcher-Goldfarb-Shanno) is an effective, high-speed neural network training algorithm. However, it requires the use of the Hessian matrix and more calculations in each iteration, as compared with the method of conjugate gradients.

Table 1. Assessment of the acceptability of the forecasts (based on the training set)
Tab. 1. Ocena dopuszczalności prognoz (na podstawie zbioru uczącego)

Functions of hidden layers and output activations	*MAPE* [%] for the network training algorithm:		
	steepest descent	*BFGS*	conjugate gradients
linear	74.73	5.52	6.91
logistic	50.96	5.40	6.50
tangential	85.58	5.61	6.87
exponential	87.02	5.51	6.98
sinusoidal	49.62	5.56	7.08

Source: Own work / Źródło: opracowanie własne

Table 2. Assessment of prediction accuracy (based on the test set)

Tab. 2. Ocena trafności prognoz (na podstawie zbioru testowego)

Functions of hidden layers and output activations	*MAPE* [%] for the network training algorithm:		
	steepest descent	*BFGS*	conjugate gradients
linear	73.85	5.72	7.11
logistic	50.39	5.43	6.23
tangential	84.94	5.77	7.06
exponential	86.45	5.68	7.18
sinusoidal	48.13	5.74	7.25

Source: Own work / Źródło: opracowanie własne

In the case of this method of network training, errors of expired forecasts were at the level of 5-6%. And despite them not being good predictions [13], for the purpose of predicting daily demands for natural gas, they could be considered acceptable and accurate, especially that of the cumulative distribution of errors indicates that 80% of the predictions obtained had errors below 10%.

5. Conclusions

In the paper, the multilayer perceptron (*MLP)* was used to build a predictive model of daily demands for natural gas. The constructed model has three input variables: the value of daily gas consumption on the previous day, the average air temperature from the previous day and the day of the week.

It has been found that the neural model predictive value depends significantly on the used network training algorithm. The *BFGS* algorithm proved to be the most effective way of training, because of the quality of predictions. In the case of this way of training, the developed daily demand predictions for the natural gas used by rural households may be considered acceptable (5.40% $\leq$ MAPE $\leq$ 5.61%) and accurate (5.43% $\leq$ MAPE $\leq$ 5.77%).

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