

## FEEDFORWARD NEURAL NETWORKS AND THE FORECASTING OF MULTI-SECTIONAL DEMAND FOR TELECOM SERVICES: A COMPARATIVE STUDY OF EFFECTIVENESS FOR HOURLY DATA

Paweł Kaczmarczyk✉

The Mazovian State University in Płock, Poland

### ABSTRACT

The presented research focuses on the construction of a model to effectively forecast demand for connection services – it is thus relevant to the Prediction System (PS) of telecom operators. The article contains results of comparative studies regarding the effectiveness of neural network models and regressive-neural (integrated) models, in terms of their short-term forecasting abilities for multi-sectional demand of telecom services. The feedforward neural network was used as the neural network model. A regressive-neural model was constructed by fusing the dichotomous linear regression of multi-sectional demand and the feedforward neural network that was used to model the residuals of the regression model (i.e. the residual variability). The response variable was the hourly counted seconds of outgoing calls within the framework of the selected operator network. The calls were analysed within: type of 24 hours (e.g. weekday/weekend), connection categories, and subscriber groups. For both compared models 35 explanatory variables were specified and used in the estimation process. The results show that the regressive-neural model is characterised by higher approximation and predictive capabilities than the non-integrated neural model.

**Key words:** Prediction System, feedforward neural network, regressive-neural model, forecasting

**JEL codes:** C45, C53, D24

### INTRODUCTION

Researchers conduct scientific studies on sales forecasting for businesses in order to discover effective predictive tools. Promising results can then be used by companies as forecasting methods in their Prediction Systems (PS). In turn, an effective PS supports the operational management of an enterprise [Daft and Marcic 2011, Griffin 2015]. Operational management is an important element in achieving a company's strategic objectives. The author's research into the effectiveness of specific forecasting models can be used to provide a specific telecommunication company with a useful support structure for

price calculations, financial planning, and effective network management.

The aim of this research study was to test and compare two models, i.e. the feedforward neural network and the regressive-neural model, in terms of their effectiveness in modelling and forecasting the demand for telecom services. In the case of the second model, i.e. the regressive-neural model, the feedforward neural network was applied to reflect the variability which was received after the elimination of a deterministic component. Various methods of eliminating deterministic components from data can be found in the research literature on the subject [Makridakis and Wheelwright 1989, Box et al. 1994, Makridakis et al.

Paweł Kaczmarczyk <https://orcid.org/0000-0001-5199-6328>

✉ [p.kaczmarczyk@mazowiecka.edu.pl](mailto:p.kaczmarczyk@mazowiecka.edu.pl)

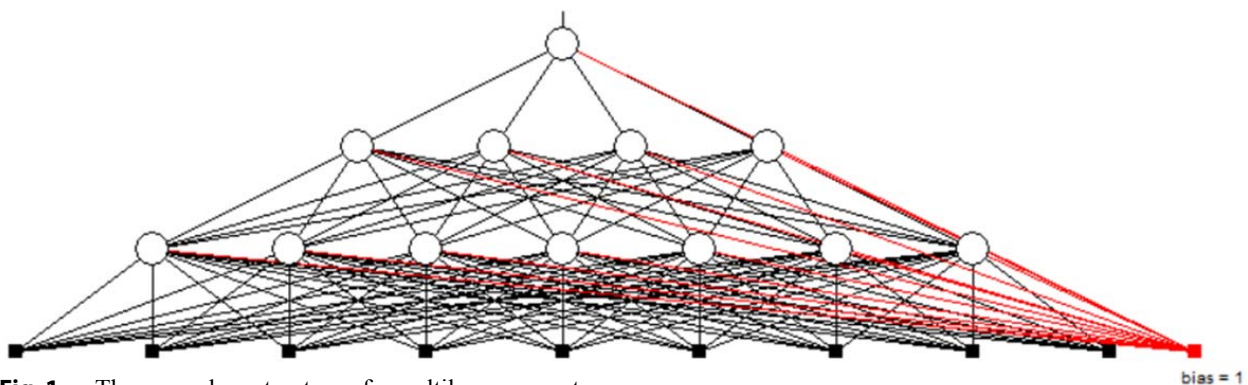
1998]. According to Masters [1993], neural networks can be better taught if deterministic components are removed from data. This enables a neural network to focus its capabilities on a nonlinear and smaller variability. This approach, according to Masters, enables researchers to obtain better results than with the use of a neural network for the modelling and forecasting of a full variability. Under Masters' approach, a regression model or other technique should be used to prepare data for a neural network model. This combination of both models is called a regressive-neural model or integrated model [Kaczmarczyk 2006, 2016].

This study undertook examination of the following hypothesis: When conducting short-term forecasting of the demand for telecom services, an integrated model allows for more accurate results than a non-integrated neural network model. The attempt to verify this hypothesis was conducted on the basis of the obtained values for the following coefficients: fit coefficients, autocorrelation coefficients, partial autocorrelation coefficients, and the average errors of expired forecasts ex-post.

The research was conducted by examining empirical material which was provided by one telecommunications network operator. The material included the number of seconds (hourly) of outgoing calls from the operator's network according to: type of 24-hour cycle, connection category, and subscriber group. The data contained a variety of analytical sections which facilitated multi-dimensional analyses to help gauge the effectiveness of the examined methods in forecasting demand.

## THE ISSUE OF FEEDFORWARD NEURAL NETWORKS

Many business applications of artificial neural networks are known [Smith and Gupta 2002, Zhang 2004]. In order to conduct this study (described in the empirical section of the article), feedforward neural networks were used [Rojas 2013]. In such networks, neurons are usually arranged in layers, and inter-neuronal connections are applied only to the neurons in neighbouring layers (Fig. 1). The typical structure of a feedforward multilayer neural network in the field of neural networks is often called a multilayer perceptron. The input layer, which consists of input buffers, is the first layer. The number of input neurons is equal to the dimension of input vector  $X$ . The input layer is characterised by the fact that signals only come out of this layer. The output layer is the last layer of the network. The number of neurons in this layer corresponds to the dimension of given vector  $d$  from the pair of training vectors  $(X, d)$ . In particular, the output layer may contain one neuron. There are no signals from the output layer to other layers. All other layers of neurons, placed between the input layer and the output layer, are called hidden layers. The number of neurons in these layers can vary. In many practical cases, one hidden layer is used. Each hidden layer receives input signals from the preceding layer and sends its output signals to the layer following it. In some applications, interlayer connections relate not only to neighbouring layers, but also to distal layers. In each case, however, there is one direction of the signal flow – from the input to the output.



**Fig. 1.** The exemplary structure of a multilayer perceptron  
Source: Author's own coverage with the use of Neuronix programme.

In the research study, the feedforward neural network was tested as the non-integrated technique and as a segment in the integrated model (i.e. the neural network worked as the tool which was integrated with the regression model). In the literature on the subject, two types of neural data representation are described: one-of- $N$  or  $N$ -in-one. In the first, the input layer of a neural network should involve the number of neurons that is equal to all possible values of input variables. It is usually implemented in the case of nominal scale. Thus, when a researcher considers, for example, the variable of “hours during the day”, he assumes 24 neurons in the input layer because the variable takes 24 possible levels and each level requires a separate neuron. When it comes to neural data representation  $N$ -in-one, a researcher assumes one neuron for one variable. So, all levels of the variable will be given to the same neuron in the learning process or testing process.

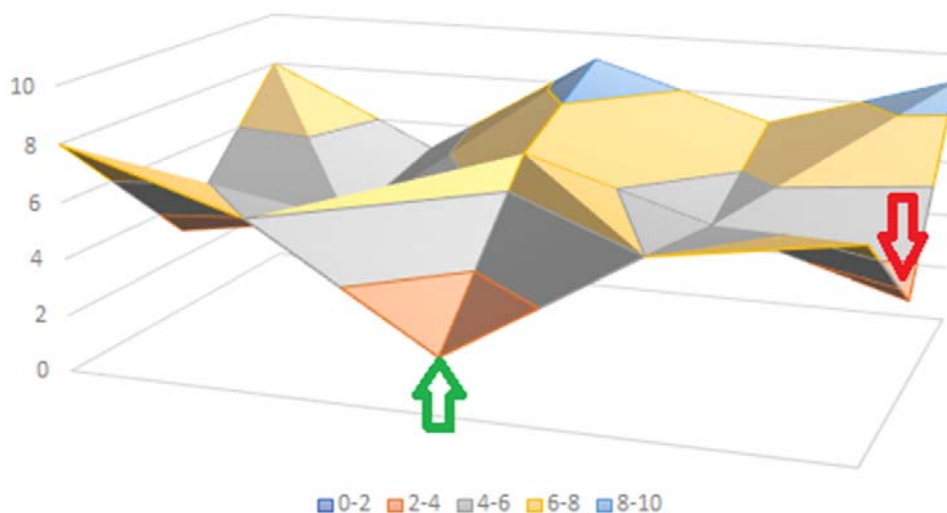
An unwanted phenomenon during the network learning process is to stop the learning at a local minimum of the error function. The learning process of neural networks is a very complex issue [Tiliouine 2007]. A simplified error function of neural networks is presented in Figure 2. The local minimum of the error function was marked in red (the arrow pointing downwards) and the global minimum of the error

function was marked in green (the arrow pointing upwards).

Research literature describes various techniques to avoid stopping the learning process of a neural network at a local minimum of the error function. Some of these techniques include: methods based on a global optimization algorithm (genetic algorithms, simulated annealing); random change in the order of giving learning samples (patterns) after each learning epoch; the multi-start method (which involves the multiple estimation of a neural network at the different, random, and initial values of weights); and the method using the momentum coefficient.

## PRESENTATION OF DATA AND RESEARCH ASSUMPTIONS

The modelled and forecasted demand (response variable  $Y$ ) was hourly counted seconds of outgoing calls within the framework of several different analytical sections. From this, the constructed models (the neural model and the regressive-neural model) can be considered as multi-sectional models [Kaczmarczyk 2016, 2017]. In order to identify the analytical sections, classification factors were specified. The classification factors were as follows: hours during 24 hours;



The red arrow (pointing downwards) indicates the local minimum of the error function, the green arrow (pointing upwards) indicates the global minimum of the error function.

**Fig. 2.** A simplified exemplification of the error function of neural networks

Source: Author’s own coverage on the basis of exemplary data.

type of 24 hours; connection categories; subscriber groups. The particular analytical levels (sections) of each classification factor were distinguished. For example, if the subscriber groups were considered as the classification factor, only two levels were taken into account (business subscribers and individual subscribers). Each assumed classification factor and its levels are presented in Table 1.

For example, 24-hour cycles of demand for outgoing calls (generated by the separate subscriber groups)

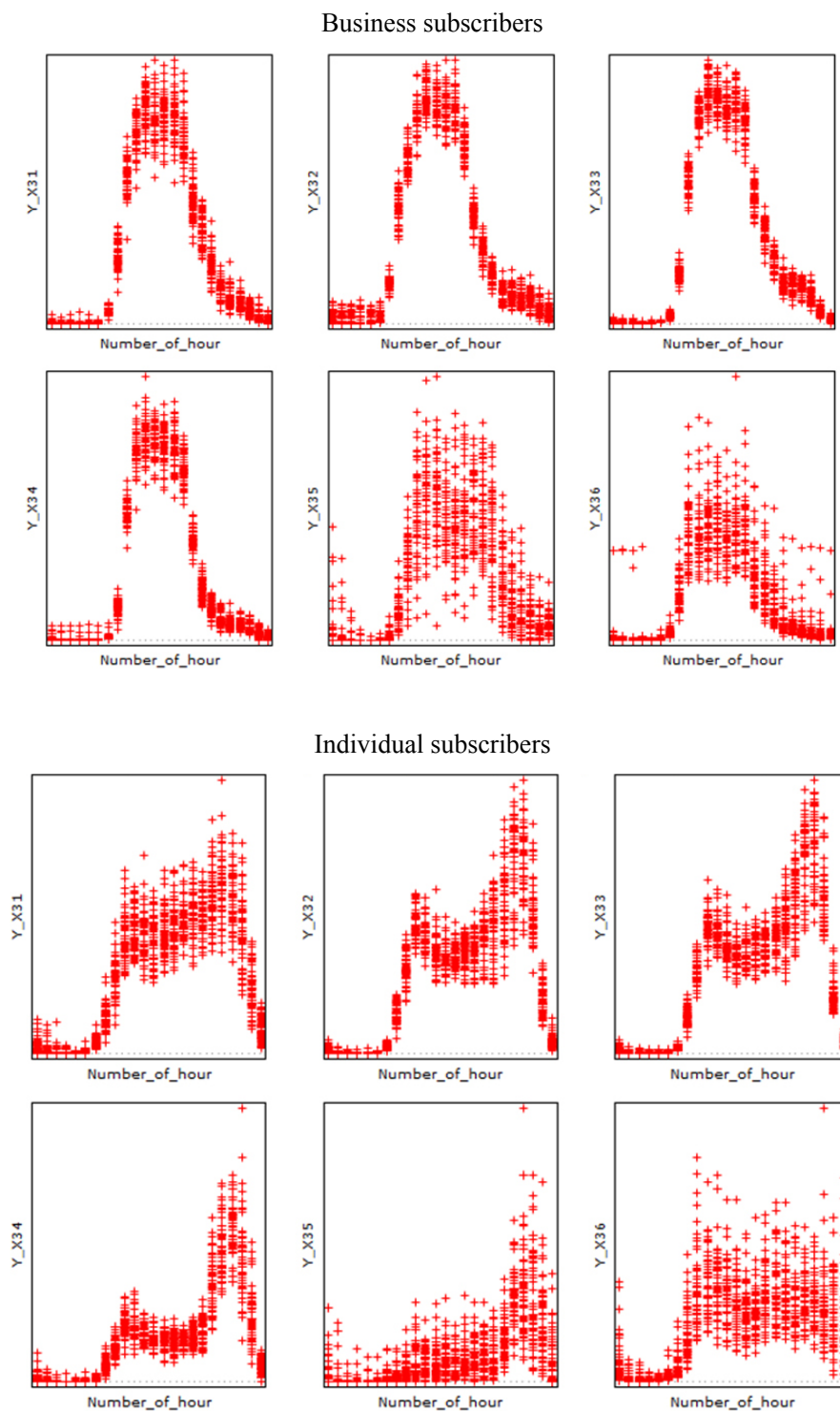
during the chosen working 24 hours (Wednesdays) in a period of one year are presented in Figure 3.

There were 35 total levels of classification factors. Within the framework of all the neural networks, one-of- $N$  was adopted as the type of neural data representation. Therefore, each of the classification factors was treated as an explanatory (independent) variable during the preparation of the neural model or the regressive-neural model. The number of explanatory variables was 35.

**Table 1.** Each classification factor and its assumed levels

Variable marking	Classification factor	Levels of classification factor	Variable marking	Classification factor	Levels of classification factor		
$X_1$	hours during 24 hours	$x_{1,1}$ – 12 am–01 am	$X_2$	types of 24 hours	$x_{2,1}$ – working 24 hours		
		$x_{1,2}$ – 01 am–02 am			$x_{2,2}$ – Saturday		
		$x_{1,3}$ – 02 am–03 am			$x_{2,3}$ – Sunday		
		$x_{1,4}$ – 03 am–04 am			$X_3$	connection categories	$x_{3,1}$ – mobile networks
		$x_{1,5}$ – 04 am–05 am					$x_{3,2}$ – local calls to the same network
		$x_{1,6}$ – 05 am–06 am					$x_{3,3}$ – local calls to other networks
		$x_{1,7}$ – 06 am–07 am	$x_{3,4}$ – trunk calls				
		$x_{1,8}$ – 07 am–08 am	$x_{3,5}$ – international calls				
		$x_{1,9}$ – 08 am–09 am	$x_{3,6}$ – other connections				
		$x_{1,10}$ – 09 am–10 am	$X_4$	subscriber groups	$x_{4,1}$ – business subscribers		
		$x_{1,11}$ – 10 am–11 am			$x_{4,2}$ – individual subscribers		
		$x_{1,12}$ – 11 am–12 pm					
		$x_{1,13}$ – 12 pm–01 pm					
		$x_{1,14}$ – 01 pm–02 pm					
		$x_{1,15}$ – 02 pm–03 pm					
		$x_{1,16}$ – 03 pm–04 pm					
		$x_{1,17}$ – 04 pm–05 pm					
		$x_{1,18}$ – 05 pm–06 pm					
		$x_{1,19}$ – 06 pm–07 pm					
		$x_{1,20}$ – 07 pm–08 pm					
		$x_{1,21}$ – 08 pm–09 pm					
		$x_{1,22}$ – 09 pm–10 pm					
		$x_{1,23}$ – 10 pm–11 pm					
		$x_{1,24}$ – 11 pm–12 am					

Source: Author’s own coverage.



**Fig. 3.** The hourly measurements of time (seconds) of outgoing calls generated by business or individual subscribers during working days

Source: Author's own coverage.

The research was carried out to compare and assess the effectiveness of the two different tools (the neural model and the regressive-neural model) in the short-term forecasting of the multi-sectional demand for telecom services. The explanatory variables were adopted as dichotomous variables in both the tested techniques. Dichotomous variables take only 0 or 1 (0 when the analysed level of a classification factor does not occur, or 1 when the analysed level of a classification factor occurs).

The non-integrated neural network model was the first analysed tool. Then, the second model, i.e. the regressive-neural model, was studied. In both cases, the effectiveness of the approximation and the forecasting of response variable  $Y$  was checked.

In the case of the regressive-neural model, the following stages were implemented:

1. The estimation of the linear (multiple) regression model. The regression model was used to capture typical demand values for telecom services that are generated in the distinguished analytical sections:

$$Y = \alpha_0 + \sum_{r=1}^{24} \gamma_r X_{1r} + \sum_{i=1}^3 \beta_i X_{2i} + \sum_{j=1}^6 \delta_j X_{3j} + \sum_{p=1}^2 \mu_p X_{4p} + Z,$$

$$y_t = \alpha_0 + \sum_{r=1}^{24} \gamma_r x_{1rt} + \sum_{i=1}^3 \beta_i x_{2it} + \sum_{j=1}^6 \delta_j x_{3jt} + \sum_{p=1}^2 \mu_p x_{4pt} + z_t, \quad t=1, 2, \dots, n,$$

$$\hat{y}_t = \alpha_0 + \sum_{r=1}^{24} \gamma_r x_{1rt} + \sum_{i=1}^3 \beta_i x_{2it} + \sum_{j=1}^6 \delta_j x_{3jt} + \sum_{p=1}^2 \mu_p x_{4pt}, \quad t=1, 2, \dots, n.$$

2. The computation of the residual values (i.e. cleaning time series of the response variable):

$$z_t = y_t - \hat{y}_t, \quad t=1, 2, \dots, n$$

3. The calculation of the demand forecast by using the regression model:

$$y_T^* = \alpha_0 + \sum_{r=1}^{24} \gamma_r x_{1rT}^* + \sum_{i=1}^3 \beta_i x_{2iT}^* + \sum_{j=1}^6 \delta_j x_{3jT}^* + \sum_{p=1}^2 \mu_p x_{4pT}^*, \quad T = n+1, n+2, \dots, n+h.$$

4. The modelling and the forecasting of residual values of the regression model by the use of the neural model:

$$Z = f(X_{1,1}, \dots, X_{1,24}, X_{2,1}, X_{2,2}, X_{2,3}, X_{3,1}, \dots, X_{3,6}, X_{4,1}, X_{4,2}, \Pi),$$

$$z_t = f(x_{1,1t}, \dots, x_{1,24t}, x_{2,1t}, x_{2,2t}, x_{2,3t}, x_{3,1t}, \dots, x_{3,6t}, x_{4,1t}, x_{4,2t}, \pi_t), \quad t=1, 2, \dots, n,$$

$$\hat{z}_t = f(x_{1,1t}, \dots, x_{1,24t}, x_{2,1t}, x_{2,2t}, x_{2,3t}, x_{3,1t}, \dots, x_{3,6t}, x_{4,1t}, x_{4,2t}), \quad t=1, 2, \dots, n,$$

or

$$z_T^* = f(x_{1,1T}^*, \dots, x_{1,24T}^*, x_{2,1T}^*, x_{2,2T}^*, x_{2,3T}^*, x_{3,1T}^*, \dots, x_{3,6T}^*, x_{4,1T}^*, x_{4,2T}^*),$$

$$T = n+1, n+2, \dots, n+h.$$

5. The correction of values obtained with the use of the regression model by the residuals obtained with the neural model, in order to construct the origin demand/correction of the prediction, as obtained with the regression model by the prognostic (neural) residuals, in order to forecast demand:

$$\hat{d}_t = \hat{y}_t + \hat{z}_t, \quad t=1, 2, \dots, n,$$

or

$$d_T^* = y_T^* + z_T^*, \quad T = n+1, n+2, \dots, n+h.$$

The conception of the regressive-neural model is that the regression model was used as the filter of demand ( $Y$ ) and the neural model was applied to construct a remain variability (i.e. regression errors) by using the same explanatory variables as in the case of the regression model.

In both the tested models (the neural model and the regressive-neural model), a selected type of neural networks was used, i.e. the feedforward neural network. The logistic function was applied as the activation function of the neurons. The chosen neural data representation (one-of- $N$ ) means that the number of all levels of classification factors is equal to the number

of neurons in the input layer of the neural network. The architecture of the tested neural network resulted from the structure of the data and the assumed neural data representation. Regarding the structure of the data and the adopted neural data representation, the input layer of the tested neural models included 35 neurons in the author's research study. Due to the fact that the forecasted variable (representing demand) was only one, the output layer of the neural networks involved only one neuron.

Both the models were estimated on the basis of the same data and the same period. This uniformity enabled the transparent comparison of the usefulness of the tested tools (which was the aim of the study).

The error backpropagation algorithm was applied in the learning process. Weights of the neural networks were corrected after each gave the learning pattern from the learning set (i.e. the learning pattern was understood as 35 values, which equalled 0 or 1, relating to the explanatory variables and a value of the response variable). As a criterion for assessing the neural models, the testing error was assumed.

The following methods were used in order to reduce the probability of stopping the learning process at a local minimum of the error function: the learning patterns mixing in each epoch; the momentum coefficient; and the multi-start method.

When it comes to the selection of the architecture of the neural network, the empirical method was used. This method consists of testing many neural networks with various numbers of hidden layers and various numbers of neurons in these layers. In both the tested models (the neural model and the regressive-neural model), the following architectures of the neural networks were tested: 35-35-1, 35-30-1, 35-25-1, 35-20-1, 35-15-1, 35-10-1, 35-5-1. Based on the number of constructs, seven non-integrated neural model experiments and seven regressive-neural model experiments were carried out. Each of these 14 experiments was based on:

- the decuple estimation of the particular neural model with the determined architecture;
- the comparison of the obtained estimation effect;
- the selection of the best-fitted neural model for each of the tested architectures.

After concluding the above-described experiments, the best-fitted model was chosen.

The basis of the comparison between the goodness of neural model fit and the goodness of regressive-neural model fit was:  $R^2$ , the autocorrelation function and the partial autocorrelation function of the residuals.

The forecast's accuracy, which was obtained by the use of both the compared techniques, was proved by means of the mean absolute error (*MAE*) and the root mean square error (*RMSE*). Both the errors related to expired forecasts ex-post. The formulas of the above-mentioned errors are as follows:

$$MAE = \frac{1}{T-n} \sum_{t=n+1}^T |y_t - y_t^*|$$
$$RMSE = \sqrt{\frac{1}{T-n} \sum_{t=n+1}^T (y_t - y_t^*)^2}$$

where:

$T$  – a forecast horizon,

$n$  – the number of observations which were used in the estimated models.

In order to compare the neural model and the regressive-neural model, the same forecasting period was adopted. This assumption enabled the clearest comparison of the two techniques.

## RESEARCH RESULTS AND DISCUSSION

Estimation of both the tested models was carried out on the basis of the data for the period from January 1 to February 20 of a selected year. Both models were estimated from data which included 14,688 cases. The period February 21–28 was assumed as the forecasting period.

The learning process characteristics of the neural networks in both models are presented in Table 2.

The values of the parameters of neural network learning and testing were selected on the basis of the conducted experiments. The higher the learning coefficient, the faster the solution search speed. The momentum coefficient affects the stability of a network's learning process. The higher the value of this coefficient, the higher the inertia of a neural network's learning process. The tolerance coefficient is used to determine the permissible error on a single network output. The tolerance coefficient is in the range of 0–1 (which is dictated by the logistic activation function whose values belong to the same range). A low tolerance coefficient means

**Table 2.** The values of the learning and testing parameters of the neural networks

Coefficient name	Value or yes/no
Learning coefficient	0.8
Momentum coefficient	0.6
Learning tolerance	0.15
Testing tolerance	0.25
Bias coefficient	yes

Source: Author's own coverage.

that only results that are very close to the pattern are acceptable. Bias determines whether an additional neuron whose output is equal to 1 is to be used. If it is used, all neurons in the hidden and output layers are connected to this additional neuron. This solution results in better stability during the learning process and is a classic example of improving network performance.

The volume of the testing set was 15% of the total data set, i.e.  $14,688 \times 15\% = 2,203$  cases. The volume

of the learning set was 85% of the total data set, i.e.  $14,688 \times 85\% = 12,485$  cases. The testing set was assumed in such a way that it contained the cases related to all tested analytical sections (e.g. categories of connections, groups of subscribers).

The criterion of stopping the learning process was understood as achieving an assumed RMSE threshold. The threshold was minimised during the learning process. The obtained value of the RMSE was the basis of the assessment of the right neural network topology and the right weights values.

When it comes to the non-integrated neural model, the best results of the learning process were obtained for network architecture 35-20-1. This learning process is shown in Table 3.

During the experiments with the use of the regressive-neural model, the best results were achieved by the use of neural model architecture 35-20-1 (Table 4).

The  $R^2$  of the neural model and the regressive-neural model amounted to 0.8112 and 0.9198, respectively. So, in the case of the regressive-neural model, the value of  $R^2$  indicated much a better fit of the model

**Table 3.** The learning process of the neural model that was chosen after all the experiments

$\varepsilon$	Epoch	Learning		Testing	
		RMSE	Out of tolerance	RMSE	Out of tolerance
0.100	4	0.0948	1 291	0.0987	0
0.090	3	0.0849	417	0.0872	0
0.080	3	0.0770	298	0.0789	0
0.070	10	0.0702	164	0.0698	0
0.060	18	0.0620	148	0.0597	0
0.050	34	0.0529	147	0.0498	0
0.045	41	0.0479	145	0.0449	0
0.040	82	0.0436	132	0.0397	0
0.035	It was not reach after caring out of 1 000 epoch				

\*Value of  $\varepsilon$  is RMSE threshold of testing set, below which the network learning process was stopped; the neural network model architecture: 35-20-1.

Source: Author's own calculations.

**Table 4.** The learning process of the neural model that was chosen as part of the regressive-neural model

$\varepsilon$	Epoch	Learning		Testing	
		RMSE	Out of tolerance	RMSE	Out of tolerance
0.100	7	0.0943	1 854	0.0979	33
0.090	2	0.0872	1 398	0.0887	6
0.080	3	0.0804	1 183	0.0797	2
0.070	4	0.0725	459	0.0685	0
0.060	18	0.0618	354	0.0599	0
0.055	27	0.0574	287	0.0548	0
0.050	53	0.0522	157	0.0494	0
0.045	It was not reach after caring out of 1 000 epoch				

\*Value of  $\varepsilon$  is RMSE threshold of testing set, below which the network learning process was stopped; the neural network model architecture: 35-20-1.

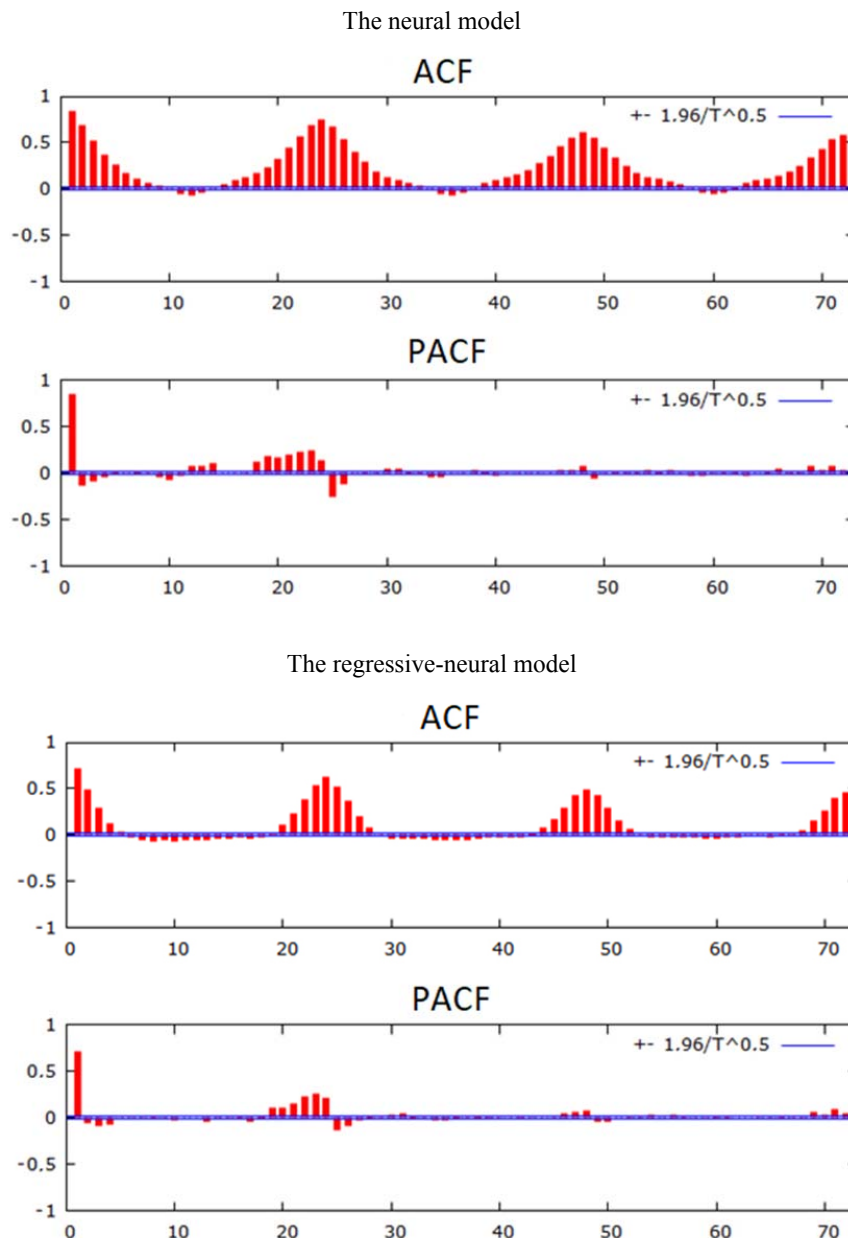
Source: Author's own calculations.



to the data. The goodness of the fit of the regression model (which was considered as a module of the regressive-neural model) was as follows:  $R^2$  0.4971, standard error of the estimate 58,177.46.

The next object of research was the autocorrelation function and the partial autocorrelation function

of the model's residuals. This research showed that repetitions are visible in the 24-hour cycle. However, in the case of the regressive-neural model, the repetitions were evidently lower in comparison to the non-integrated neural network (Fig. 4). This was because the non-integrated neural network was unable

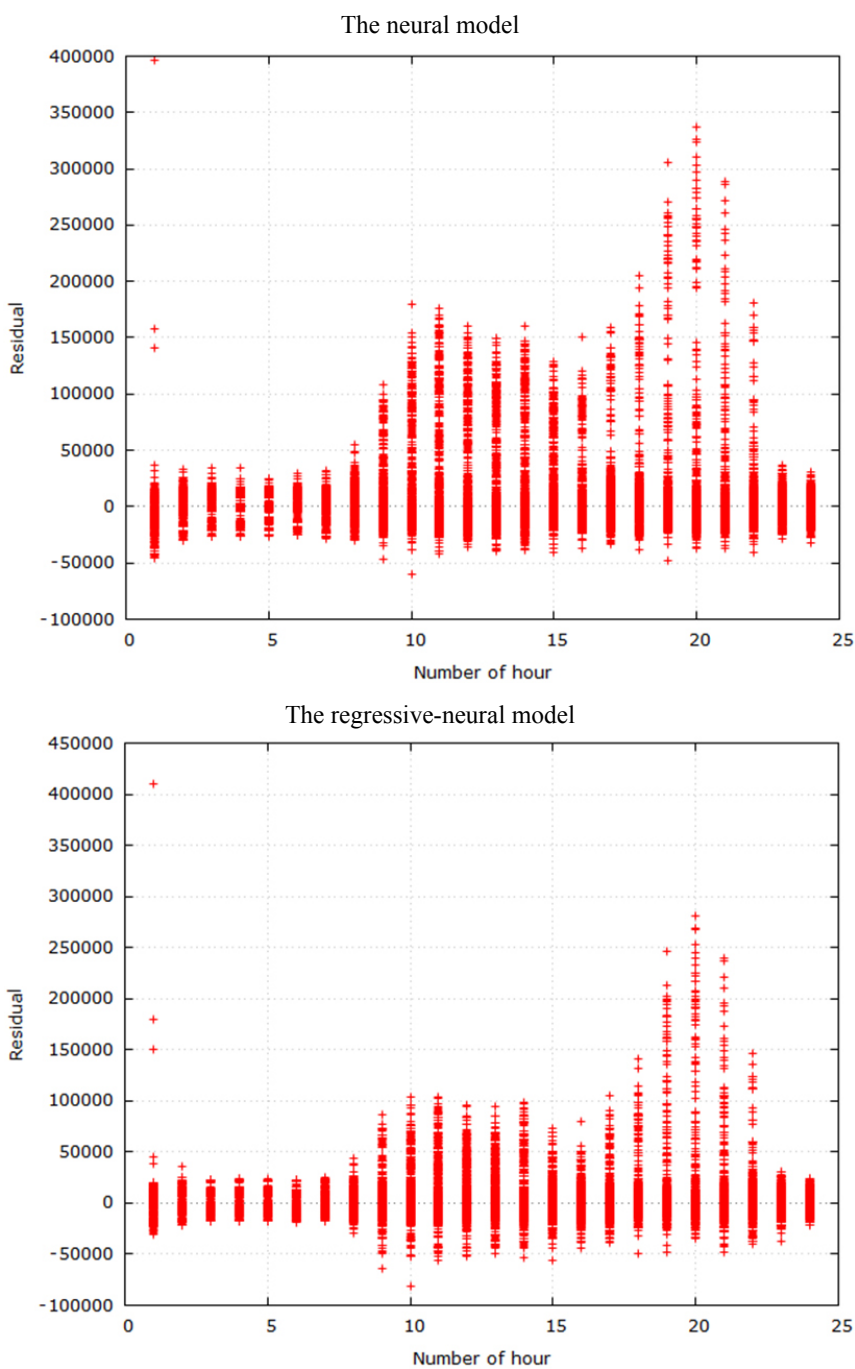


**Fig. 4.** The autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the neural model residuals and the regressive-model residuals

Source: Author's own calculation.

to effectively model so many levels of demand. The regressive-neural model was characterised by a higher effectiveness in terms of its ability to make approximations.

Unusual observations (influence observations and outliers) were recognised in the data (Fig. 5). They were confirmed with the use of calculated Cook's distances and standardised residuals. However, the unusual



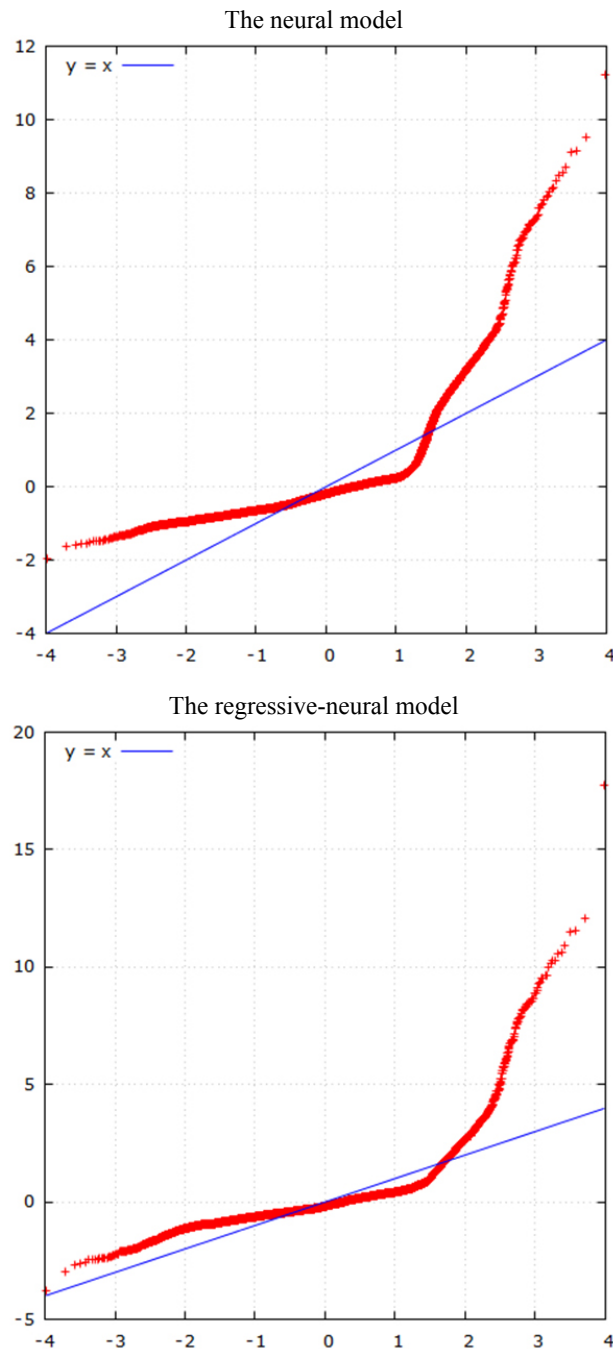
**Fig. 5.** Scatter plot of the neural model residuals and the regressive-neural residuals  
Source: Author's own calculation.

observations were left without any changes because of the risk of effacing the real patterns [Dittman et al. 2011].

The analysis of the scatter plot of the regressive-neural model residuals and the normal probability

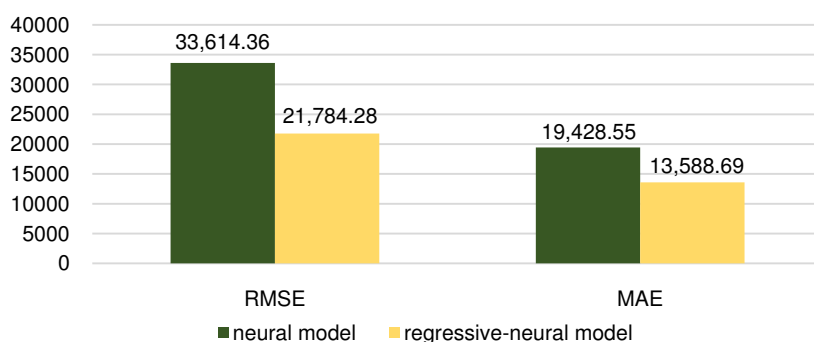
plot of these residuals (Fig. 6) confirmed the better fit of this model to the data.

In both cases, the highest values of the residuals can be observed during peak hours (which were different



**Fig. 6.** Normal probability plot of the tested models

Source: Author's own calculation.



**Fig. 7.** Comparison of the forecasting effectiveness of the neural model and the regressive-neural model

Source: Author's own calculation.

for both the subscriber groups). This analysis showed that the residuals of the second model are characterised by evidently lower values in comparison to the non-integrated model (Fig. 5). Moreover, one can differentiate the distribution of the integrated model residuals from distribution of the non-integrated model residuals through their similarity to the normal distribution (Fig. 6).

The effectiveness of the prediction for both of the tested techniques are shown in Figure 7.

The forecasting errors indicated that the predictive accuracy of the regressive-neural model is much higher in comparison to the non-integrated neural model. In the case of the integrated model, both the average errors of forecasts (the *RMSE* and *MAE*) were significantly lower than in the case of the neural network model.

## CONCLUSIONS

The obtained research results confirmed the hypothesis. They show that the regressive-neural model allows for better results in terms of the approximation and the short-term forecasting of multi-sectional demand for telecom services than does the non-supported neural model. This conclusion can be formulated on the basis of the received values of the following coefficients:  $R^2$ , the autocorrelation coefficients, the partial autocorrelation coefficients, and the average errors of expired forecasts ex-post.

Further research in this field could be based on the comparison of neural network models and regressive-neural models within the framework of a lower

number of analytical sections (e.g. only within the business group, or even only within the business group and working 24 hours). Moreover, if a regression model were to be constructed on single analytical section, the variable  $Y_{t-1}$  in the regression model would cause a better fit to the data.

A higher goodness of the model fit and the forecasting accuracy in terms of demand could also be achieved by separating particular types of 24 hours. The phases of the cycle of demand in different categories of connections within the same subscriber group and during the same type of 24 hours are very similar. So, it is possible to reduce the complexity of their approximation.

## REFERENCES

- Box, G.E.P., Jenkins, G.M., Reinsel, G.C. (1994). *Time Series Analysis. Forecasting and Control*. Prentice Hall, Englewood Cliffs.
- Daft, R.L., Marcic, D. (2011). *Understanding Management*. South-Western Cengage Learning, Mason.
- Dittmann, P., Szabela-Pasierbińska, E., Dittmann, I., Szpula, A. (2011). *Prognozowanie w zarządzaniu sprzedażą i finansami przedsiębiorstwa*. Wolters Kluwer Polska, Warszawa.
- Griffin, R. (2015). *Fundamentals of Management*. Cengage Learning, Boston.
- Kaczmarczyk, P. (2006). *Neuronowe i regresyjno-neuronowe modelowanie i prognozowanie zjawisk ekonomicznych. Empiryczna weryfikacja porównawcza*. Zeszyty Naukowe PWSZ w Płocku, Nauki Ekonomiczne, 5, 209–218.

- Kaczmarczyk, P. (2016). Integrated Model of Demand for Telephone Services in Terms of Microeconometrics. *Folia Oeconomica Stetinensia*, 16, 72–83. <https://doi.org/10.1515/fofi-2016-0026>
- Kaczmarczyk, P. (2017). Microeconomic Analysis of Telecommunication Services Market with the Use of SARIMA Models. *Dynamic Econometric Models*, 17, 41–57. <https://doi.org/10.12775/DEM.2017.003>
- Makridakis, S., Wheelwright, S.C. (1989). *Forecasting Methods for Management*. J. Wiley, New York.
- Makridakis, S., Wheelwright, S.C., Hyndman, R.J. (1998). *Forecasting Methods and Applications*. J. Wiley, New York.
- Masters, T. (1993). *Practical Neural Network Recipes in C++*. Academic Press, Inc, San Diego.
- Rojas, R. (2013). *Neural Networks: A systematic introduction*. Springer Science & Business Media, Berlin.
- Smith, K.A., Gupta, J.N.D. (2002). *Neural Networks in Business: Techniques and Applications*. PA: Idea Group Publishing, Hershey.
- Tiliouine, H. (2007). Comparative study of learning methods for artificial network. *Pomiary Automatyka Kontrola*, 4, 117–121.
- Zhang G.P. (2004). *Neural Networks in Business Forecasting*. PA: Idea Group Publishing, Hershey.

## **JEDNOKIERUNKOWE SIECI NEURONOWE W PROGNOZOWANIU WIELOPRZEKROJOWEGO POPYTU NA USŁUGI TELEFONICZNE – PORÓWNAWCZE BADANIA EFEKTYWNOŚCI DLA DANYCH GODZINOWYCH**

### **STRESZCZENIE**

Zaprezentowane wyniki badań są związane z systemem prognostycznym przeznaczonym dla operatorów telekomunikacyjnych, ponieważ są skoncentrowane na sposobie konstrukcji modelu do efektywnego prognozowania popytu na usługi połączeniowe. Artykuł zawiera wyniki porównawczych badań efektywności modelu sieci neuronowej i modelu regresyjno-neuronowego (zintegrowanego) w zakresie krótkookresowego prognozowania zapotrzebowania na usługi telefoniczne. Jako model sieci neuronowej zastosowany został model sieci jednokierunkowej. Model regresyjno-neuronowy został zbudowany na podstawie połączenia dychotomicznej regresji liniowej wieloprzekrojowego popytu i jednokierunkowej sieci neuronowej, która służyła do modelowania reszt modelu regresji (tj. pozostałej zmienności). Zmienną objaśnianą były sumowane co godzinę liczby sekund rozmów wychodzących z sieci wybranego operatora. Połączenia telefoniczne były analizowane pod względem: typów doby, kategorii połączeń i grup abonentów. Wyszczególniono 35 zmiennych objaśniających, które wykorzystano w procesie estymacji obu porównywanych modeli. Stwierdzono, że model regresyjno-neuronowy charakteryzuje się większymi możliwościami aproksymacyjnymi i predykcyjnymi niż niezintegrowany model neuronowy.

**Słowa kluczowe:** system prognostyczny, jednokierunkowa sieć neuronowa, model regresyjno-neuronowy, prognozowanie

