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Assesment of the Performance of the Neural Model of the National Electricity Demand System

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Abstract. This paper presents the results of research on the use of a neural model's capabilities for forecasting national power demand using data from the years 2019–2023. The neural model is a daily MIMO-type model with 48 hourly simultaneous inputs concerning the total electricity generation by the JWCD system and by the nJWCD system, and with 24 hourly simultaneous outputs concerning national electrical power demand shifted by one day ahead relative to the input quantities. The neural model of the National Power Demand System as well as the simulation model built on its basis for investigating model accuracy in the scope of forecasting were designed and implemented in the MATLAB and Simulink environment. Many interesting research results were obtained, particularly in the scope of model quality.

Keywords: Conventional Energy, National Power System, Neural Modeling, Recurrent Artificial Neural Network, Renewable Energy, Selection of Data for Modeling

1 Introduction

Modern power systems, including the National Power System (NPS), are characterized as intelligent systems by, on the one hand, an increasingly higher level of control, and on the other hand, an increasingly higher degree of internal system organization. This means that a system such as NPS operates from year to year in an increasingly stable and flexible manner, with the ability to employ increasingly complex controllability and observability mechanisms. In turn, due to the thus increasing complexity and internal richness of NPS as a control system, the requirements also grow, among others, with respect to the need for ever faster changes in electrical power demand, and following the growing share of renewable electricity sources in NPS, expectations also increase for the development of new methods of electrical power demand forecasting [14–15].

In response to these challenges, modern methods and their associated design methodologies are increasingly applied, including those based on artificial neural networks, which enable modeling of the electrical power demand forecasting system using data in the form of, e.g., time series, Input-Output systems, etc. [17, 20, 22–23]. The data necessary for modeling understood in this way, in the considered case of neural modeling, are obtained from the National Power System functioning as an integrated system of generation, transmission, distribution, and reception of electricity in Poland, whose fundamental task is to satisfy the demand for electricity and electrical power both in the individual sector and in the economic sector, including in particular industry [14–15, 17, 20].

The issue of satisfying demand is in turn associated with the need to ensure continuity of electricity and electrical power supply and with the necessity of maintaining appropriate quality parameters of, on the one hand, electricity as a product, and on the other hand, of NPS as a system in which electricity is generated and transmitted to consumers. In this context, the use of artificial neural networks, capable of modeling nonlinear dependencies, becomes a highly beneficial tool in the process of forecasting electrical power and energy demand.

In the contemporary approach to power system modeling, alongside neural modeling, including deep learning, various machine learning methods are frequently used, including regression-based machine learning, as well as methods such as fuzzy systems, evolutionary algorithms, ant colony algorithms and other swarm algorithms, etc. [3–7, 25–26]. In each of the aforementioned cases of applying artificial intelligence methods to NPS system modeling, one of the key aspects is the selection of an appropriate ANN architecture and the selection of its training method, which must be matched to the specifics of the problem and the available data [8–9, 12, 24–25]. In this spirit, work was carried out on the design and implementation of an electrical power demand system model in the MATLAB and Simulink environment using the library of programs called Deep Learning Toolbox, which was associated with the need to acquire data for modeling from the years 2019–2023 (a period of 5 years) [1, 13, 16].

Thus, an attempt was made to design an advanced neural model of the electrical power demand system on the basis of available numerical data, and subsequently, after obtaining the system model, to examine the correctness of this model by conducting appropriate comparative, simulation, and subsequently prognostic studies. The implementation of this model in the MATLAB and Simulink environment will also allow for its potential use in demand forecasting based on real data and may constitute a starting base for research on its integration with existing subsystems in the power engineering sector, including the NPS functioning and development system [10, 14–15, 18].

2 Related Research

Work on the need for forecasting as well as the construction of system models for these purposes is as old as NPS itself. For these reasons, within the framework of the literature review, scientific articles and research results in the most recent journals and conference proceedings concerning the methodologies and methods of electrical power and energy demand modeling were analyzed. It turns out that in recent years there is very high interest in these publications and there are also quite a number of them; therefore, the literature review was limited to purposefully defined distinguishing features from the point of view of the conducted research and, in the authors' opinion, fully showing various tendencies in the scope of building predictive models, particularly of electrical power demand.

Thus, particular attention was paid to the applied modeling methods, the type of modeled object, the type of data used for modeling, the applied computing environments and programming languages for modeling, the applied measures of model quality assessment, and the obtained results, particularly of the quality assessment of prognostic models. Selected results of the analysis of the conducted critical literature review are presented in Table 1 and Table 2, in which only the most essential information concerning the analyzed research results is shown [22–24].

The obtained research results are very interesting and extensive, and from the point of view of modeling the electrical power demand forecasting system in NPS, it is particularly worth noting, among others, that the work by R. Czapaj, J. Kamiński, M. Sołtysik [5] contains a very important review of a total of 264 models based on 47 articles concerning electrical power demand modeling, while there are no solutions among the discussed achievements in the subject literature directly concerning simultaneous electrical power demand modeling using MIMO-type modeling, which was initially proposed in the authors' works [22–24],

Table 1: Selected research results within the scope of the subject literature review. Part 1. Source: own elaboration [22–24].

Authors	Modeling method	Modeled object	Data for modeling	Environment/ Quality Ass./ Result
1	2	3	4	5
T. Ciechulski S. Osowski [3]	Hybrid modeling using an ensemble of neural networks: SVM, RBF, MLP	Electrical power demand in the NPS	Hourly electrical power demand data from the years 2014–2017 MATLAB	MATLAB MAPE 1.44%
R. Czapaj P. Benalcazar J. Kamiński [6]	10 different methods of regression machine learning, artificial neural networks, etc.	15-minute peak daily electrical power demand in NPS	time series, daily data for a period of 5 years (2010–2014) without division into weekdays and holidays	STATISTICA Mean value of: MPE, MAPE, RMSPE, Theil[3] for the best method MARSplines (10 methods were studied) 2,67%
R. Czapaj, J. Kamiński M. Sołtysik [5]	Methods of modeling electrical power demand in power systems	Review of a total of 264 models based on 47 articles concerning electrical power demand modeling	Historical data from various sources and periods (most frequently daily/hourly horizon); various quantities were used: geographical, climatic, system, as well as various learning methods	STATISTICA, SAS/ETS, and SPSS environments, GRET, R, Python languages, aa. MAPE <1%
J. Tchórzewski [22]	Methods of neural modeling of electrical power demand in the NPS	Electrical power demand system in NPS for the year 2023	MIMO model with a one-day lead, daily data from individual days of 2023, input quantities: electricity in individual hours of the day produced by JWCD and by nJWCD, output quantities: simultaneous electrical power demand with a one-day lead	MATLAB and Simulink using the Deep Learning Toolbox MSE 4,92 e -08

Table 2: Selected research results within the scope of the subject literature review. Part 2. Source: own elaboration [22–24].

1	2	3	4	5
R. Duan, X. Peng, C. Li, Z. Yang, Y. Jiang, X. Li and S. Lin [9]	Hybrid SDAE--SVR-BA method for short-term wind power forecasting	Electrical power generated by wind turbines	MIMO model using deep learning. Historical data and NWP data with hourly resolution: from 1 July 2009 to 1 Feb. 2011	MATLAB with the Deep Learning Toolbox Normalized Root Mean Square Error 11,54%
S. Al-Dahidi, M. Louzazni, N. Omran [8]	Neural modeling of electricity production prediction in photovoltaic systems	Electricity production by photovoltaic (PV) systems	Hourly data from 2015–2018 for a PV installation. Input-Output approach, input: weather conditions and hours) are transformed into PV power output values using a trained neural network model.	MATLAB RMSE improvement of approximately 25% RMSE, 30% MAE, 22% WMAE
M. Madhiarasan [12]	Recursive Radial Basis Function Neural Network	Wind speed	Input-Output method, data from the years 2016–2018. Input data: wind direction, temperature, wind speed. Output data: wind speed.	MATLAB MSE 1,62 e-12
T-J. Chang, S. Lee J. Lee, C-J. Lu [7]	model using: Support Vector Regression, Extreme Learning Machine, etc.	Forecast of electricity generation	Interval-Valued Time Series. Hourly generation data for the period from 2017/2/1 to 2019/10/31 (45,264 data points)	not specified MSEI 3440,23 MRIE 7,5%
T. Ciechulski, S. Osowski [4]	Method of forecasting 24-hour electrical power demand in NPS using ensembles of fuzzy systems	Electrical power demand in NPS	Power demand data cover the time period from 1 January 2014 to 31 December 2018, The total number of days is 1,826, which constitutes 43,824 hours [MW].	MATLAB MAPE 3,04%

and is discussed more broadly in the present article with the presentation of modeling results based on numerical data from the years 2019-2023 [16].

It is worth noting that out of nine research results presented in Table 1 and Table 2, in as many as six cases the MATLAB and Simulink environment with its toolboxes was used in the implementation of electrical power demand forecasting system models, while in the remaining published studies such environments as STATISTICA, SAS/ETS, SPSS and Gretel were used, as well as two programming languages, namely R and Python, while in one case the environment used in the implementation was not specified.

As modeling methods, machine learning methods, neural learning methods, and even fuzzy system methods were used, while hybrid methods were also applied, combining different types of artificial neural networks as ensembles, or machine learning methods with neural learning methods and fuzzy systems. Hybridization generally led to an improvement in model quality, which was associated with improved accuracy of electrical power demand forecasting using such measures as primarily MAPE errors, but also MAE, MSE, RMSE, or the R index, as well as other measures purposefully adapted to a given type of research, including normalized measures (Table 1). The obtained MAPE error research results are shown in an illustrative manner in Figure 1.

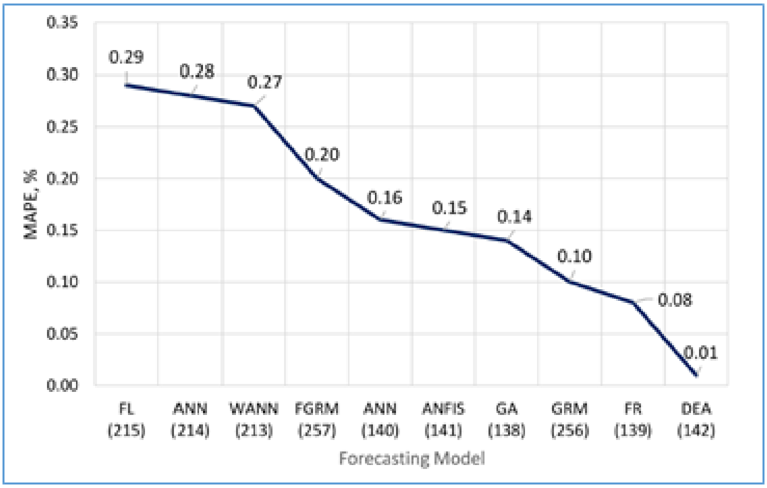

Figure 1: The effectiveness of forecasting models in the Top 10 set from a group of 264 models. Source [5].

As for the manner of using data for modeling, time series were most frequently applied, and less frequently Input-Output models, including MIMO-type models. The objects of research were generally electrical power demand systems, although forecasts of wind power in wind farms or forecasts of electricity production were also sought.

It is also important to note that an effort was made to show the most recent research results in the literature review; therefore, the review covers the last 15 years, i.e., the years 2009–2024, in which period the values of measures were already presented as very low, and they were differentiated depending on the forecast horizon, the number of factors taken into account, the type of models, and the type of data considered (time series, or Input-Output, etc.).

3 Methodology and applied models for electrical power demand modeling

Due to the increasing speed of information circulation, including in particular financial means and precision in electricity trading, the necessity of adapting the electrical power and energy demand forecasting system to this also increases [10]. For these reasons, new, more effective and efficient methods for forecasting electrical power demand are being sought. Among these methods, apart from analytical methods, artificial intelligence methods begin to play a fundamental role, including in particular regression-based machine learning methods as well as neural methods and fuzzy systems [3, 26]. In the research presented in this article, neural models were used, which, after training the electrical power demand forecasting system model, the ANN was employed in a simulation model built in Simulink [1, 13, 22].

In the research presented in this article, the methodology of control theory and systems as well as automation [2, 11, 19, 26] was used, obtaining Multi Input Multi Output (MIMO) type models [22–24, 26], in which hourly quantities were adopted as output quantities, and hourly total JWCD and nJWCD generations delayed by one day relative to the output quantities were adopted as input quantities [16]. Thus, by adopting artificial neural networks as the modeling method [21, 25, 27-28] and selecting as the modeling tool the MATLAB and Simulink environment with the Deep Learning Toolbox library [1, 13, 22–23], a neural model of the electrical power demand system was obtained both in the form of a mathematical model and an object-oriented model with the possibility of using it, e.g., in Simulink.

The algorithm for creating the Artificial Neural Network (ANN) was associated with many design and programming activities, including, among others: the selection of a training, testing, and validation file of learning pairs, i.e., pairs of input quantities and their associated output quantities; the selection of the ANN architecture and its parameters for research experiments, i.e., determining the number of ANN layers and the number of neurons in individual layers, as well as the type of connections between neurons, including assigning them appropriate parameters such as weights and biases as well as neuron activation functions, etc.

Therefore, the research experiments using data from the entire investigated period concerned the years 2019-2023 (a five-year period). As input quantities, 48 data points regarding electricity production by the NPS system in the JWCD scope and in the nJWCD scope were adopted, whereas as output quantities, 24 data points concerning the national electricity demand were adopted. In this way, a MIMO model with 48 input quantities and 24 output quantities was obtained. When designing the Perceptron Artificial Neural Network, one hidden layer was adopted, and research experiments were conducted for a different number of neurons in the hidden layer, ultimately adopting the optimal structure of the ANN as 48-33-24.

The next design stage was the equally important selection of the learning method for the modeling experiment in order to achieve a sufficiently high learning quality, which ultimately was the Levenberg-Marquardt method, etc. In this regard, among other things, the learning rate, the learning accuracy measure, the forgetting method, the learning inertia method, etc., were also established, while the learning process was repeated until the ANN learning quality measure was satisfied, i.e., the expected degree of accuracy of the neural model was obtained, i.e., in particular the fitting of outputs from the system model relative to the expected data at the output of the electrical power demand forecasting system [22–23].

Thus, conducting experimental research was associated, among others, with the preparation of appropriate data, including annual data and data from a five-year period, from which it follows, among others, that artificial neural network models exhibit varying effectiveness depending on the data range; for example, in the research results presented in this article for annual data and for the entire studied five-year period, the MAPE error (years 2019–2022) is decidedly low. Obtaining neural models was associated with the design and implementation of appropriate artificial neural networks as neural models of the electrical power demand forecasting system, which involved their training, testing, and validation. In this case, learning errors (MSE) were obtained reaching values of the order of $1.5916 \cdot 10^{-8}$, thus decidedly very low, and coefficients of determination R^2 of the order of 0.935, thus decidedly very high.

Furthermore, comparative and simulation studies were conducted to assess the quality of the obtained models, which was associated with the need to build a simulation model in Simulink using the system model exported to Simulink in the form of an ANN, which enabled, among others, the comparison of results obtained from artificial neural network models with real data, as well as the analysis of the influence of various input parameters on forecast accuracy and the assessment of model quality in various scenarios.

Verification studies and sensitivity analyses of the neural models of the electrical power demand system were also conducted, which consisted of analyzing the model's response to changes in input parameter values and assessing the influence of various factors on the stability and accuracy of the forecast. Within the presented research, the trained Perceptron ANN model was therefore exported to Simulink as an m-file of a Simulink block. Subsequently, using it, a simulation model was built meeting comparative requirements in order to compare outputs generated by the model with analogous outputs generated by the electrical power demand forecasting system.

In such a simulation model, the inputs are common and concern the total JWCD and nJWCD generation on an hourly basis (48 inputs), and the divergence, absolute error, relative error, and MAPE error between the output from the model and from the electrical power demand forecasting system are examined. Thus, the neural model of the electrical power demand system as an ANN has at its output 24 hourly values of the forecasted electrical power demand (one for each hour of the day), and at its input 48 quantities concerning the electricity produced by JWCD and nJWCD units. In parallel, hourly data on actual electrical power demand are collected, which enables comparison of the forecast with observations. In this situation, first the divergences between corresponding outputs are sought, and on their basis the absolute error, relative error, mean relative error, and MAPE error. An example of the simulation model is shown in work [23].

4 Research results regarding the quality of the obtained models

4.1 Annual periods from the years 2019–2023

The training data used for training the neural model of the electrical power demand system covered the period of the years 2019–2022, and the data used for model verification covered the period of the years 2020–2023. As a result of simulation studies using artificial neural network models, results were obtained concerning, among others, the percentage MAPE error, which are presented in Table 3 with waveforms as shown in Figs. 2–5 [1, 13, 22–23].

Table 3: MAPE error values [%] concerning the forecasted electrical power in NPS for the years 2020–2023 using neural models trained on data from the preceding year. Source: Own elaboration using the MATLAB and Simulink environment [1, 13, 22-23].

Houer	**MAPE [%]**			
	2020	**2021**	**2022**	**2023**
1	0.008	0.011	0.007	0.155
2	0.010	0.019	0.010	0.064
3	0.010	0.007	0.010	0.216
4	0.009	0.024	0.008	0.274
5	0.003	0.010	0.003	0.135
6	0.003	0.021	0.003	0.143
7	0.022	0.010	0.022	0.120
8	0.003	0.018	0.003	0.160
9	0.006	0.013	0.005	0.013
10	0.009	0.035	0.008	0.017
11	0.001	0.014	0.001	0.025
12	0.019	0.022	0.019	0.211
13	0.011	0.033	0.010	0.005
14	0.014	0.027	0.013	0.078
15	0.002	0.025	0.002	0.016
16	0.002	0.013	0.001	0.269
17	0.008	0.018	0.007	0.066
18	0.006	0.015	0.005	0.221
19	0.027	0.020	0.026	0.051
20	0.023	0.049	0.022	0.112
21	0.052	0.035	0.053	0.002
22	0.012	0.053	0.012	0.088
23	0.032	0.040	0.031	0.155
24	0.009	0.037	0.008	0.104

The results of simulation studies indicate a high quality of the obtained neural models of the electrical power demand forecasting system trained on annual data (years 2019–2022) and

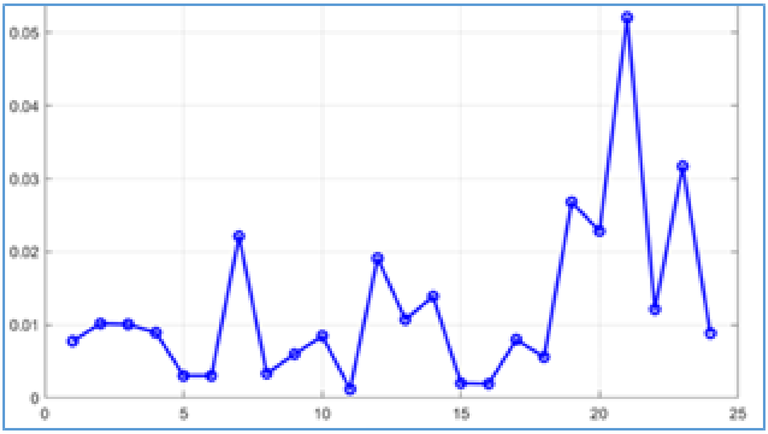

Figure 2: MAPE error results [%] for the forecast of electrical power demand in 2020 in individual hours of the day obtained from a model trained on data from 2019 in relation to actual data from 2020. Designations: X-axis – hours of the day [h], Y-axis – MAPE error [%]. Source: Own elaboration using the MATLAB and Simulink environment [1, 13, 22–23].

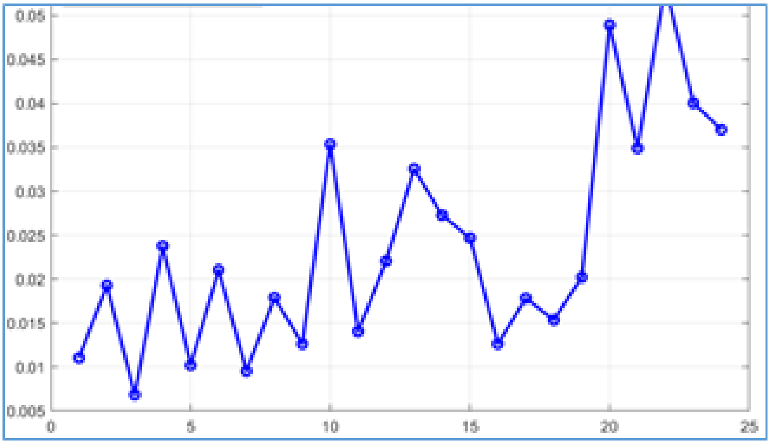

Figure 3: MAPE error results [%] for the forecast of electrical power demand in 2021 in individual hours of the day obtained from a model trained on data from 2020 in relation to actual data from 2021. Designations: X-axis – hours of the day [h], Y-axis – MAPE error [%]. Source: Own elaboration using the MATLAB and Simulink environment [1, 13, 22–23].

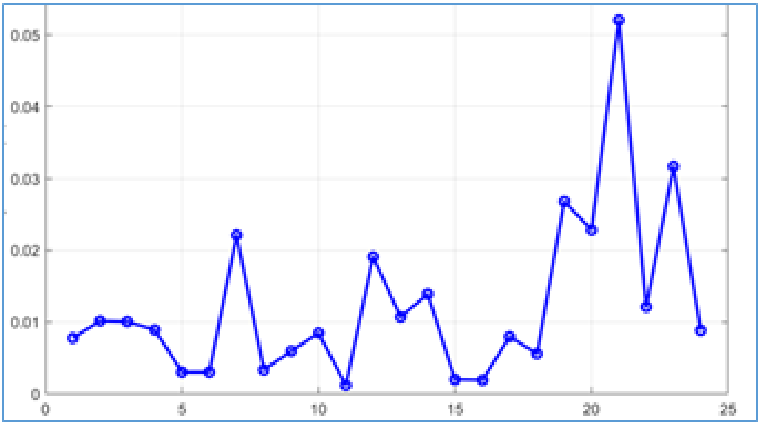

Figure 4: . MAPE error results [%] for the forecast of electrical power demand in 2022 in individual hours of the day obtained from a model trained on data from 2021 in relation to actual data from 2022. Designations: X-axis – hours of the day [h], Y-axis – MAPE error [%]. Source: Own elaboration using the MATLAB and Simulink environment [1, 13, 22–23].

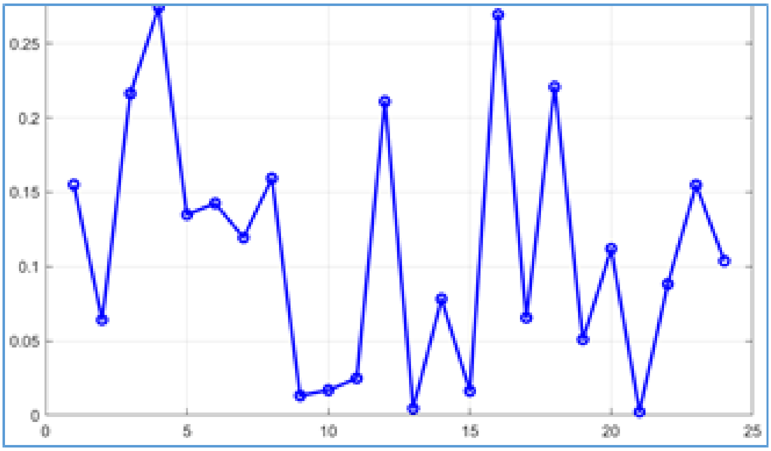

Figure 5: MAPE error results [%] for the forecast of electrical power demand in 2023 in individual hours of the day obtained from a model trained on data from 2022 in relation to actual data from 2023. Designations: X-axis – hours of the day [h], Y-axis – MAPE error [%]. Source: Own elaboration using the MATLAB and Simulink environment [1, 13, 22–23].

the model trained on four-year data (years 2019–2022), as the obtained MAPE forecast errors were contained in the intervals respectively for the forecasting model in the year:

2020: from 0.% - for 11:00 AM to 0.052%, - for 9:00 PM,

2021: from 0.007% - for 03:00 AM to 0.053%, - for 10:00 PM,

2022: from 0.001% - for 11:00 AM to 0.053%, - for 10:00 PM,

2023: from 0.005% - for 01:00 PM to 0.274%, - for 04:00 AM.

which demonstrates a very high capability of the ANN for data generalization and accurate forecasting of electrical power demand under typical operating conditions of the NPS. Due to the fact that the proposed forecasting method using a Perceptron Artificial Neural Network trained with the Levenberg-Marquardt algorithm is characterized by high quality and may find practical application in the process of power forecasting in the National Power System.

The results of simulation studies confirm that the majority of the obtained electricity demand forecast errors fall within the range from 0.01% to 0.274%, which demonstrates an excellent capability of the artificial neural network for data generalization and accurate estimation of demand under typical operating conditions of NPS. The presented forecasting method using an artificial neural network is characterized by high effectiveness and may find practical application in the planning process of the National Power System operation.

4.2 Five-year period covering the years 2019–2023

In the research, data from the years 2019–2022 were subsequently used for training the Perceptron ANN of the neural model of the electrical power demand forecasting system, adopting 48 hourly input quantities concerning the volume of electricity production by the NPS system within the scope of the so-called JWCD units and within the scope of the so-called nJWCD units, and 24 output quantities concerning the forecast of electrical power demand for each hour of the day [14–15, 22–23]. For checking the quality of the neural model, data from 2023 were used, which enabled the assessment of model quality by means of the MAPE error. As a result of training artificial neural networks using numerical data from the years 2019 - 2023, results were obtained concerning, among other things, the courses of MSE errors and determination coefficients R, which are presented respectively for the entire studied period in Table 4 and Table 5. The courses of MSE errors, on the other hand, are shown respectively for the entire studied period in Figure 6. The analysis of the obtained results shows, among other things, that the training error MSE decreased by as much as five orders of magnitude, that is, from 0.00344 to 1.5910^{-8}. Meanwhile, the coefficient of determination R for training, testing, and validation was shaped as follows: 1.0000, 0.9999, 0.9999, thus at a high level of accuracy.

The results of simulation studies confirm that the obtained MAPE forecast errors concerning electricity demand fall within the range from 0.003% for 18:00 to 0.242% for 12:00, which demonstrates a very high quality of the obtained electrical power demand system model, which

Table 4: Results of training the Perceptron ANN for data concerning the entire study period. Notations: Epoch - number of epochs, specifically 0, 38, 1000; Elapsed Time - training time; Performance - measure of model fit quality to the data (MSE error); Gradient - size of the error function gradient; Mu - coefficient regulating the rate of weight changes in the network; Validation Checks - number of stops in improvement after which the training process is halted; Unit - specification (concerning the name of individual parameters); Initial Value - initial value; Stopped Value - value at the time of stopping; Target Value - target value. Source: Own study using DLT in MATLAB and Simulink based on data concerning the National Electricity Demand in the NPS [1, 13].

Specification	Initial Value	Stopped Value	Target Value
Epoch	0	38	1000
Elapsed Time	-	00:03:03	-
Performance	0.00344	1.59e-08	0
Gradient	0.00353	9.91e-08	1e-07
Mu	0.001	1e-10	1e+10
Validation Checks	0	0	6

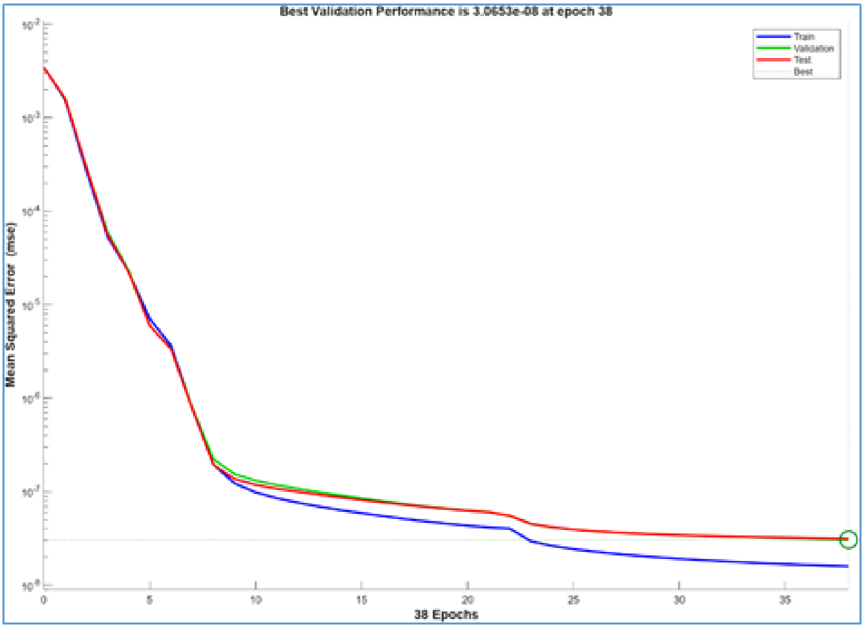

Figure 6: Learning performance of the Preceptor SSN for data concerning the year 2019. Source: Own elaboration using DLT in the MATLAB and Simulink environment based on data concerning the National Electricity Demand in the NPS [1].

Table 5: Summary of the Preceptor ANN learning model for data covering the entire study period. Notations: Training – training, Validation – validation, Test – testing, Observation – number of observations, MSE Mean Squared Error – Mean Squared Error, R – coefficient of determination. Source: Own elaboration using DLT in the MATLAB and Simulink environment based on data concerning the National Electricity Demand in the NPS [1, 13].

Specification	Observation	MSE	R
Training	1279	1.5916e-08	1.0000
Validation	273	3.0653e-08	0.9999
Testing	273	3.1580e-08	0.9999

can be successfully used for forecasting electrical power demand in the NPS system. Simulation studies were carried out based on a block diagram built in Simulink shown in work [23].

After completion of the learning process, the Perceptron Artificial Neural Network was exported to Simulink, in which, similarly to that described in section 4.1, the divergence between the forecasted data and the actual data concerning electrical power demand was determined, and on this basis the absolute error, relative error, and MAPE error, while 48 hourly quantities concerning electricity generation by the JWCD system and by the nJWCD system were connected to the model input.

As a result of simulation studies using artificial neural network models trained for forecasting on data from the years 2019–2023, results concerning the percentage MAPE error were obtained, which are presented in Table 6.

5 Discussion of the obtained research results and conclusions

On the basis of data concerning electricity production by JWCD system units and nJWCD units in individual hours of the day [kWh] adopted as input quantities, and data concerning electrical power demand in NPS in individual hours of the day [MW] adopted as output quantities, neural system models in the form of Perceptron ANNs were designed and trained.

The generated neural models of the electrical power demand system in NPS were implemented in the MATLAB and Simulink environment using the Deep Learning Toolbox.

After checking the quality of the neural system model by comparing its outputs with outputs from the real system, MAPE errors were obtained, which amounted in individual hours of the day for annual models from 0.01% to 0.27%, and for the four-year period from 0.003% for 18:00 to 0.242% for 12:00, for experiments conducted in the years 2020–2023; thus, the presented forecasting method using artificial neural networks is characterized by high quality (very small MAPE errors) and may find practical application in the process of power demand forecasting in the National Power System.

Furthermore, the results indicate the necessity of further improvement of neural network architectures and consideration of other optimization methods that may improve model accuracy. This research may constitute a basis for the development of more advanced predictive systems in the area of electrical power demand forecasting in NPS.

Table 6: MAPE error values [%] concerning the forecasted electrical power in NPS for the year 2023 using neural models trained on data from the years 2019–2022. Source: Own elaboration using the MATLAB and Simulink environment [1, 13, 22–23].

Hour	MAPE [%]
1	0.190
2	0.066
3	0.078
4	0.060
5	0.117
6	0.119
7	0.078
8	0.112
9	0.202
10	0.237
11	0.144
12	0.242
13	0.196
14	0.096
15	0.205
16	0.151
17	0.144
18	0.003
19	0.141
20	0.019
21	0.093
22	0.161
23	0.130
24	0.014

Depending on the time horizon (from annual to four-year), very low MSE error values (of the order of 10^{-8} to 10^{-7}) % and high coefficients of determination R (most frequently exceeding 0.7–0.9) were obtained, which indicates the capability of the applied model for very good forecasting of electrical power demand in NPS. It was also noted that the Levenberg–Marquardt learning algorithm ensures a fast and stable learning process, and it was established that the ANN should have one hidden layer with 33 neurons.

It can also be indicated that high values of the determination index R demonstrate the high accuracy of forecasts obtained from neural models, which is of significant importance in the context of ensuring stable and balanced operation of NPS. In turn, low MSE error values, maintained within a narrow range even across different time ranges, confirm that the applied model effectively captures the characteristics of demand variability.

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