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Selection of Data for Modeling the Development of the Power System Using a Recurrent Artificial Neural Network

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Abstract. The National Power System in Poland is now already an intelligent system, and the changes increasingly have a hybrid character, that is, structural-parameter in nature. The uniform National Power System is increasingly being supplied with electricity not only from conventional sources but also from renewable sources: solar, wind, and hydro. In addition to producers and consumers of electric power and energy, prosumers are also appearing. The power system in this diversity is equipped with various types of automated devices, which make it increasingly intelligent. In Poland, the total installed capacity of all electricity sources, both conventional and renewable, reached 72.9 GW in April 2025, of which as much as 34.8 GW comes from renewable sources (over 47.7%), while the rapidly growing number of prosumers makes the NPS system increasingly complex at the system level. The growing complexity and diversity of the National Power System means that controlling the development of the system intelligently involves the necessity of building development models. Thus, there exists a specific research gap between the need to obtain development models of the National Power System for the purpose of development control and the possibilities of obtaining such models using artificial intelligence methods, such as neural methods. In line with research within this research gap, this study attempted to obtain a development model of the National Power System using annual statistical data on the operation of the National Power System from 1990 to 2024. This formulation of the research problem involves, among other things, the selection of data for research experiments in the area of modeling the development of the National Power System, as well as the selection of architecture and learning methods for ANNs. In the present publication, in particular, the research methodology for modeling the development of the National Power System and the obtained research results using Recurrent ANN for modeling are presented.

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

1 Introduction

The National Power System (NPS) in Poland is currently undergoing dynamic changes, which on one hand result from the increasing integration of renewable electricity sources into the NPS and increasingly environmentally friendly methods of electricity generation in conventional power plants, as well as changing requirements of electricity consumers and producers, and prosumers on the other hand. In addition, increasingly complex market mechanisms are being introduced, and the NPS system is being equipped with increasingly intelligent devices, which makes it, in a sense, an unmanned system [32-34, 37].

The changes occurring in the NPS system are both parametric and structural. The NPS system is developing, and as it develops, it increasingly becomes an intelligent system, that is, among other things, a system with an ever higher level of control and an ever greater degree of internal organization. To study the development of the NPS system, development models are necessary, obtaining which was a fundamental goal of the conducted research. Among various types of modeling methods, the authors considered two groups of methods, namely regression machine learning methods and neural learning methods. In this publication, the neural learning method using Recurrent ANN was utilized.

In this context, artificial intelligence methods play a key role as tools enabling not only the technical optimization of power systems, such as smart grids and energy consumption forecasting [5, 35], but also in terms of using them to build new system models and making real-time decisions with their use [5, 7].

It is worth noting that the KSE system in Poland is a system in which the total installed capacity of all electricity sources amounted to 72.9 GW in April 2025 (conventional energy and RES), of which 34.8 GW was accounted for by renewable energy sources (over 47.7%) [39-41], and the growing number of prosumers made the NPS system increasingly complex at the system level [39].

Such actions make neural models built using Artificial Neural Networks, trained on the NPS system, a convenient tool for studying the behavior of the NPS system model [7]. Therefore, obtaining neural models is not only an important task for predicting selected output quantities from the NPS system, but also for studying to what extent the NPS system is intelligent and, consequently, to what extent the NPS system is developing towards greater autonomy as a unmanned factory. In light of these requirements imposed on NPS development models, comprehensive analysis of the data needed for modeling requires in-depth research, which in this article has been limited to the essential [11].

This publication in this area fits into the direction of research on seeking development models of the NPS system in the context of intelligent systems, that is, systems with flexible control systems. Therefore, after reviewing the relevant literature, data for modeling were selected, and then, using the data, a neural model of the development of the NPS system was designed and implemented in the MATLAB and Simulink environment based on the architecture of the Recurrent ANN, and the quality of the model was examined.

2 Overview of Selected Models of Power System Development

The construction of NPS system models, and in particular the construction of NPS system development models, is the subject of research at many scientific centers around the world, including in Poland [32]. There are advanced systems using artificial neural networks, regression machine learning models, alongside analytical models, etc. [1, 6, 8-10, 14]. Increasingly, hybrid models and simulation models are also being built [19, 26].

It is worth noting at the beginning models of this type, such as, among others, those occurring under the names:

1) GridMind, which was developed by DeepMind and National Grid, in which reinforcement learning assisted by graph networks was used to model a complex power system, also taking into account fuel supply, the geographic location of power plants, and consumers, etc. [42],
2) PSSE-ML (Power System Simulator for Engineering with the addition of Machine Learning), which is an extension of the classic PSSE simulator with machine learning capabilities taking into account fuel transport infrastructure [35],
3) GridLAB-D + DNN, which was created as a combination of the open-source GridLAB-D simulator with deep neural networks for load forecasting and system resilience modeling [7, 17],
4) PowerTAC (Power Trading Agent Competition), which is a type of framework using agents based on artificial neural networks to model energy markets and their impact on the physical infrastructure of the power system [43].
5) HELICS (Hierarchical Engine for Large-scale Infrastructure Co-Simulation), which is a kind of co-simulation platform from PNNL and NREL that uses, among other things, elements of machine learning to model interdependencies between power, transportation, and telecommunication systems [13],
6) ResilNet, which is a system using Recurrent Artificial Neural Networks to predict cascading failures in power systems, taking into account geographical dependencies [17].

In Poland, research is also being conducted on the use of artificial intelligence methods for modeling the National Power System, including, among others:

1) The Polish Energy System Simulator (NCBR) as a tool that enables simulation of various configurations of the power system, including analysis of the impact of renewable energy sources on system stability and efficiency,

2) ENERGA Living Lab as a project conducted by the ENERGA group, using elements of artificial intelligence to simulate consumer and energy infrastructure behavior on a local scale, with the first laboratory in Poland being an experiment carried out on 300 households in Gdynia, in which innovative energy solutions were tested,
3) Systematic developments aimed at obtaining metamodels of the power system development in Poland [19, 32].
4) Examples of forecasting the demand for power and electricity on the scale of the National Power System (NPS), but also concerning elements of the KSE system such as e.g., in energy enterprises, in field transformer stations, for an individual consumer from the G11 group, spatial forecasting, or forecasting electricity generation in generating units, etc. [3],
5) Using analytical methods to carry out calculations of switching processes in the power system [30],
6) Mathematical modeling of various elements of the power system, such as synchronous generators, excitation systems, turbines and generators, wind farms, photovoltaic power plants, elements of the power network, including transmission lines and transformers [18, 38].

It can be noticed that Polish system models are usually more specialized and focus on specific aspects (e.g., energy consumption prediction or modeling of specific infrastructure elements) rather than on a comprehensive representation of the power system; nevertheless, the development direction is more oriented towards comprehensive solutions.

It is worth adding that the referenced models of the power system were created for various purposes, ranging from studying the stability of the power system, performing switching process calculations, forecasting the demand for power and electricity, to various types of safety system studies, reliability, etc. In the context of the aforementioned modeling methods, the neural method proposed in this paper relates to modeling the development of the National Power System, rather than its operation, and in this respect it fits into this type of modeling methods [19, 32].In this spirit, Table 1 presents example data considered in the modeling of power systems and their development [2, 15, 31,35, 42].

3 Neural Modeling of the Development of the NPS system

So far, various attempts have been made to build a model of the power system, ranging from mathematical modeling by constructing models of synchronous generators, excitation system models, turbine and governor models, wind farm models, photovoltaic power plant models, or models of power system components such as transmission line models or transformer models using circuit theory or control and systems theory [15-16, 18, 38], to attempts to create models using artificial intelligence methods such as regression machine learning methods or neural methods [35]. In this publication, an attempt was made to build a neural model of the development of the National Power System using a Recurrent ANN.

The development model of the National Power System is mainly built to use it, among other things, to conduct studies of the future states of the NPS system, so that on the basis of model simulations, appropriate development strategies can be adopted in terms of implementing

Table 1: A summary of input and output data used in selected models. Source: own elaboration based on [2, 15, 31,35, 42].

Model	Input Data	Output Data
GridMind	**data from network sensors, (phasor measurement units, SCADA, WAMS), historical consumption and production profiles, weather data, power plant locations, fuel deliveries to consumers, multimedia data (optional)**	**forecasts of energy supply and demand, recommendations for network control, warnings about threats, efficiency and emissions reports CO_2**
PSSE-ML	**network topology, parameters of nodes, lines, transformers, data of generators and consumers, dynamic data of machines and protections, data on fuel transport infrastructure, historical and weather data**	**voltage profiles and phase angles, power flows in the network, dynamic and stability analyses, safety indicators, data optimizations and failure forecasts**
GridLAB+DNN	**historical consumption profiles at the node level, measurement data from sensors, weather data, network parameters and topology, synthetic load profiles**	**load forecasts and 'loads wings', system resilience analyses, results of remedial actions simulations, prediction efficiency statistics**

parametric changes and structural changes, which is very important under conditions of frequent changes being implemented without properly examining the effects in the near and long-term perspective.

The monthly data from the years 2017–2023 [39-40] were used to build the electric power system model, including both technical data (e.g., installed capacity, number of turbo units, length of transmission lines) and economic data (e.g. fuel consumption, energy import/export), which are available and regularly published, among others, by transmission system operators, ARE, URE, GUS, etc.[29, 36, 39-41]. Data availability is crucial here to ensure future possibilities for using the model. Preliminary data verification allows for assessing their completeness, temporal consistency, and quality, which is essential for further work related to modeling the electric power system defecting the operation of the NPS system, such as employment, installed capacity, raw material consumption, electricity import and export, and network losses, as well as variables characterizing the power infrastructure, such as the number of turbo units, the length of power lines, etc.

The use of Artificial Neural Networks as a method for building the power system model will allow capturing dependencies and dynamic connections within the system. At the same time artificial neural networks themselves will undergo a separate analysis to assess their usefulness and efficiency in energy market modeling, which will enable the optimization of their architecture and parameters [21, 23, 28].

This type of approach, applied to modeling the development of the power system using the machine learning regression method, is contained in the work [32], and when applied to modeling the DAM system operating on the Power Exchange, in the work [19, 24-27, and other energetic system [22]. Both of the aforementioned works are based on control and systems theory, which allows for the introduction of an assessment of the functioning and development of systems in terms of, among others, their stability, controllability, observability, level of control, and degree of internal organization [15-16, 32-33].

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Before starting the construction of the neural model, an analysis of the collected data was carried out, including, among other things [43]:

1) correlation analysis related to identifying dependencies between variables in order to select the most important features affecting the system's functioning,
2) data normalization concerning the standardization of their values to ensure comparability and stability of the artificial neural network training process,
3) aggregation and completion of missing data through the use of interpolation methods to minimize the impact of data gaps on model quality.

Properly prepared data were then used for training, testing, and validating artificial neural networks in order to obtain neural models of the National Power System. These models can be further used for prediction, which involves prior assessment of their quality by obtaining relative error or other errors such as MSE and MAPE. Such a comparison especially leads to the evaluation of the obtained models in terms of the accuracy of output quantities from the model in relation to the corresponding output quantities from the system represented by the existing data used to build the neural models, as well as represented by data that can be used to predict the expected power quantities.

4 Selection of data for neural learning experiments

The data used in the neuronal modeling conducted within the framework of this study consists of 15 variables obtained on a monthly basis from 2017 to 2023 (12 x 7 = 84 observations for each variable). Due to the nature of the functioning of the National Power System, the following were adopted for modeling:

input variables: employment [number of people], installed capacity [MW], number of turbo units [pcs.], length of overhead lines [km], length of cable lines [km], consumption of hard coal [t], consumption of lignite [t], consumption of other fuels (peat and wood, biogas, waste fuels, etc.) [TJ], natural gas consumption [million m^3], nitrogen-ed gas consumption [million m^3], electricity import [GWh].

output variables: achievable power [MW], electricity consumption [GWh], electricity export [GWh], electricity losses [GWh].

Thus, the basic input data and output data constitute sets of complex data arrays respectively: for input variables: 84x11 and for output variables: 84x4. Depending on the problem being modeled, they will be appropriately taken from these matrices or, if necessary, extended. The results of their basic analysis are shown respectively for input variables in Table 2 and for output variables in Table 3.

Table 2: Results of the preliminary statistical analysis of the input data. Source: own elaboration in the MATLAB and Simulink environment [4, 20].

Variable	Mean	Max Value	Min Value	Standard Deviation	Cross-sample
Employment	19 886.86	22 230.00	17 322.00	1 443.27	0.10
Installed capacity	54 533.13	70 210.57	43 330.23	8 514.59	0.30
Number of turbine sets	86.00	92.00	78.00	5.30	0.69
Overhead line length	592 642.86	596 685.00	589 060.00	2 687.12	0.32
Cable line length	270 128.71	294 308.00	246 757.00	15 870.49	0.00
Hard coal consumption	2 345.18	2 558.60	1 957.56	223.30	-0.75
Lignite consumption	4 301.14	5 040.62	3 331.58	548.82	-0.40
Natural gas consumption	67.53	73.86	55.15	5.69	-0.64
Nitrogen-rich gas consumption	54.03	61.42	50.86	2.40	0.6
Other raw material consumption	10 332.01	18 013.50	7 573.15	3 006.22	1.04
EE imports	1 300.56	1 828.10	806.94	234.89	0.48

Table 3: Results of preliminary statistical analysis of the output data. Source: own study in MATLAB and Simulink environments [1, 23].

Variable	Mean	Max Value	Min Value	Standard Deviation	Cross-sample
Achievable Power	50 280.83	66 308.00	41 291.50	7 130.19	0.77
EE Consumption	14 570.35	15 043.25	14 243.92	275.85	0.41
EE Export	888.64	1 839.93	325.79	373.60	0.64
EE Losses	824.01	876.58	741.17	52.94	-0.75

4.1 Data aggregation and interpolation

Due to the different time intervals in which data are published, e.g., hourly, monthly, yearly, in order to unify them, it was decided to analyze them in monthly time intervals by summing the appropriate data published in intervals shorter than a month and by interpolating data published in longer intervals (e.g., yearly), such as employment or the number of turbo units. Data aggregation is a simple problem, whereas data estimation methods are a more complex issue. There are many methods, from the simplest linear interpolation, through polynomial interpolation, to more complex ones, e.g., Lagrange or Hermite. Due to the nature of the data (a relatively small set) capturing existing trends, the polynomial method was chosen for interpolation [25]. The polynomial method is implemented in the Matlab environment and is executed by the function polyfit(), which fits a polynomial using the least squares method, finding the coefficients of a polynomial of degree n that best describes the relationship between the independent variables x and their corresponding y values. For a polynomial of degree n, it is presented as follows:

$$P(x) = p_1 \cdot x^n + p_2 \cdot x^{n-1} + ... + p_{n+1} \cdot xn + 1, \quad (1)$$

where its essence lies in minimizing the sum of the squares of deviations:

$$min\Sigma_{i=1}^{n} [y_i - P(x_i)]^2. \quad (2)$$

It is worth noting that some data concerning the NPS system, such as the number of turbo units or the length of overhead lines, change in a 'stepwise' manner, hence it was assumed that the monthly data for a given year would be the values shown in the reports for that year.

4.2 Data Normalization

In the process of data normalization, that is, in the process of transforming data to a common scale so that different variables become comparable and none of them dominates the analysis due to their range of values, many normalization methods are used. For the purposes of the conducted research in the field of modeling, two of them were adopted, namely:

1) Z-Score Normalization (Standardization), in which the data are calculated according to the formula:

$$z = \frac{X - \mu}{\sigma}, \quad (3)$$

where:
X - the value of the original quantity,
μ - the arithmetic mean,
σ - the Standard Deviation.

As a result of such normalization, the data are transformed to a distribution with a mean equal to zero 0 and a standard deviation equal to 1, while maintaining the shape of the original distribution, and in a situation where positive values indicate points above the mean, and negative values indicate points below the mean. An example of normalization results for the original values is shown in Fig. 1.

2) The min-max normalization method, in which data are determined according to the formula:

$$X_{norm} = \frac{x - \min(x)}{\max(x) - min(x)}, \quad (4)$$

where:
X - original data vector,
min(x) - minimum value in the vector,
max(x) - maximum value in the vector,
x_{norm} - normalized vector with values in the range [0, 1].

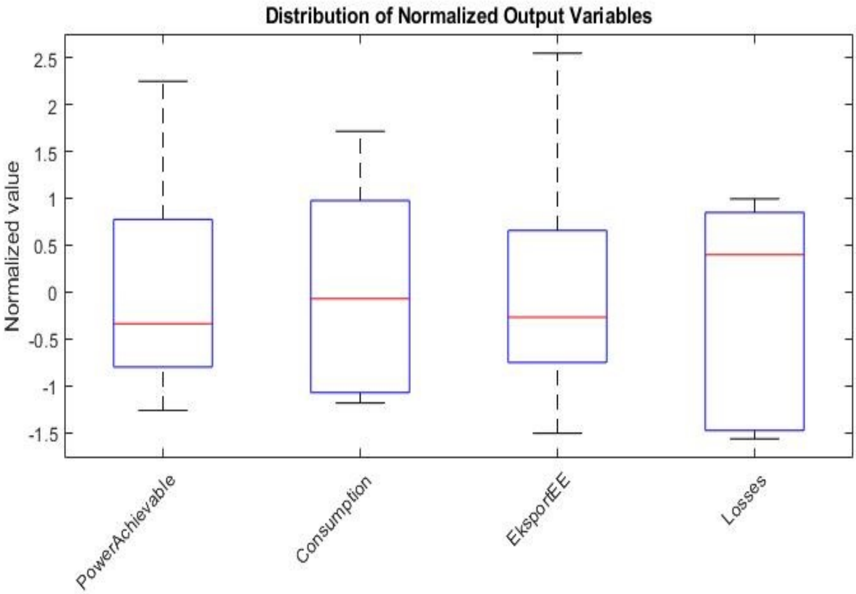

Figure 1: Output values after Z-score normalization. Source: own study in the MATLAB and Simulink environment [4, 20].

This type of normalization is characterized by certain features that may be useful when implementing them in models, i.e., it preserves relative distances between data points, enabling the establishment of a normalization range, values that fit within a specific, predetermined range (in this case [0, 1]). An example of normalization results for the output values is shown in Fig. 2.

4.3 Analysis of correlations occurring between data

Correlation analysis is used to study the strength and direction of relationships between variables. It allows understanding of how variables affect each other or whether they change in a similar way. It identifies which variables are related to each other and how strong that relationship is. The matrix of the obtained correlation between the input variables and output variables is shown in Table 4, while the relationships between individual variables are illustrated in Fig. 3.

The strongest, but negative, correlation was found between the variables Employment and Achievable Power (r = -0.963), which from the point of view of organizational changes, is a reason to note that over the studied period, work efficiency increased, hence the large number of employed persons. A high, but positive, correlation also occurs between the variables Consumption of other raw materials and Achievable Power, which indicates an increase in the use of renewable sources in the energy mix.

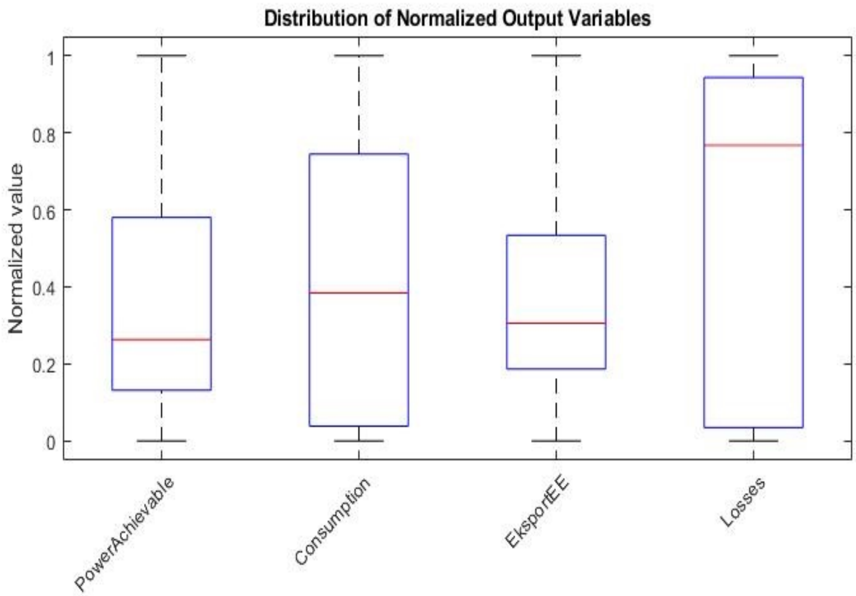

Figure 2: Output values after min-max normalization. Source: own elaboration in the MATLAB and Simulink environment [4, 20]

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Table 4: Input-output correlation matrix. Source: own elaboration in the Matlab environment 20.

Variable	Power Achievable	Consumption ee	Eksport ee	Losses
Employment [number of people]	-0.963	-0.096	-0.409	-0.678
Installed power [MW]	0.976	0.080	0.443	0.718
Number turbine units [pcs]	-0.890	-0.080	-0.384	-0.460
Length of overhead lines [km]	0.384	0.705	0.481	0.439
Length of cable lines [km]	0.935	0.100	0.383	0.685
Hard coal consumption [t],	-0.589	0.663	0.188	-0.379
Lignite consumption [t],	-0.681	0.446	0.094	-0.378
Consumption of other raw materials (peat and wood, biogas, waste fuels, etc.) [TJ],	0.989	-0.073	0.405	0.683
Natural gas consumption [million m^3],	-0.262	0.394	-0.158	-0.242
Nitrogen-rich gas consumption [million m^3],	0.150	-0.537	-0.381	-0.371
Import ee [GWh]	0.046	-0.203	-0.229	0.031

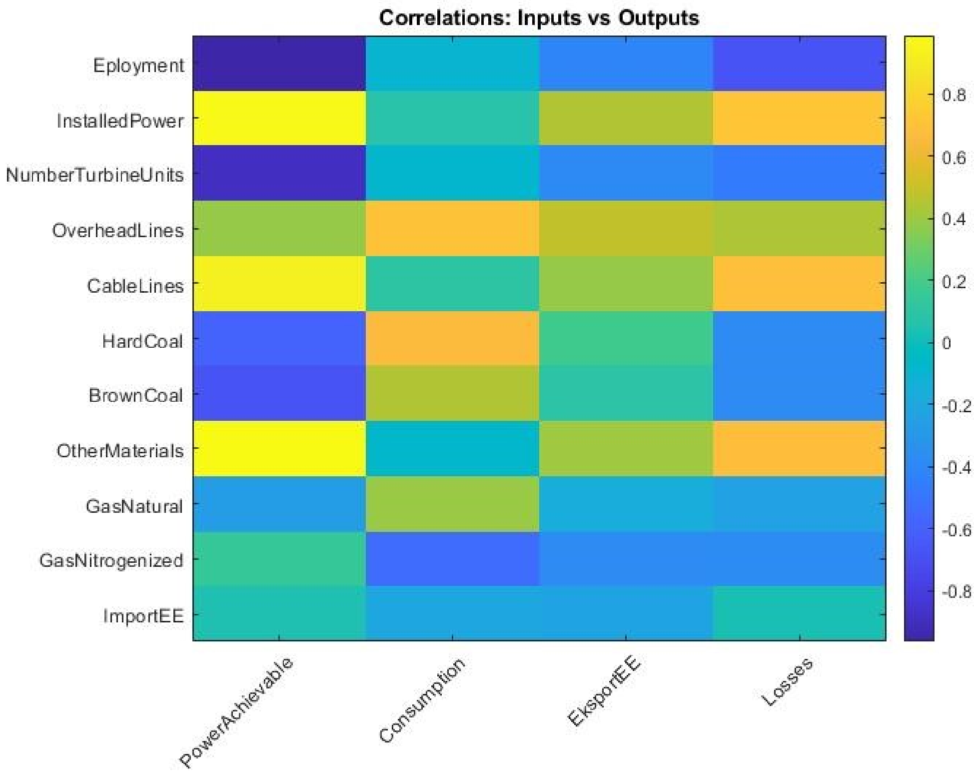

Figure 3: Correlation between the input quantities and the output quantities of the NPS system. Source: own study in the MATLAB and Simulink environment [1, 23].

5 Implementation of the NPS system Neural Model using Recurrent ANN

After conducting a data analysis to verify their suitability for modeling the NPS system, they were subjected to neural modeling using Recurrent ANN in order to later use the model for predicting key system quantities. In the design and implementation, 84 data samples were used, characterizing various aspects of the NPS system's functioning, from human resources to quantities characterizing technical infrastructure and energy resource consumption. In the process of designing the architecture and training the NPS system model using Recurrent ANN, a dataset consisting of 11 input variables and 4 output variables was prepared. The designed and trained NPS system Recurrent ANN model is shown in Fig. 4.

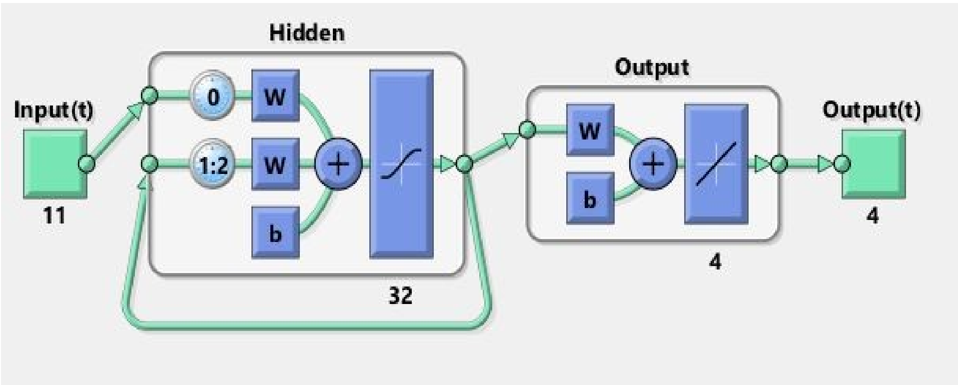

Figure 4: Architecture of the Recursive ANN as a model of the neural NPS system. Source: Own elaboration in the MATLAB and Simulink environment [4, 20]

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The following parameters of the Recurrent ANN were selected for training, testing, and validation: one hidden layer with 32 neurons, learning function as Bayesian Regularization, data split: 70% training, 15% validation, 15% testing. The ANN training process was characterized by high efficiency, reaching convergence after 26 epochs in 30.21 seconds, with the best validation result of $1.61 \cdot 10^{-2}$ after the 16-th epoch (Fig. 5).

Trained with the neural model of the NPS system, the Recurrent ANN demonstrated satisfactory prediction quality, achieving (Fig. 6):

- a coefficient of determination (R^2) at the level of 0.99822, which indicates a high ability of the model to learn the system based on the training data,

- indicators for the validation data at the level of 0.95155 and for the test data at the level of 0.96983, indicating high quality of the obtained model,

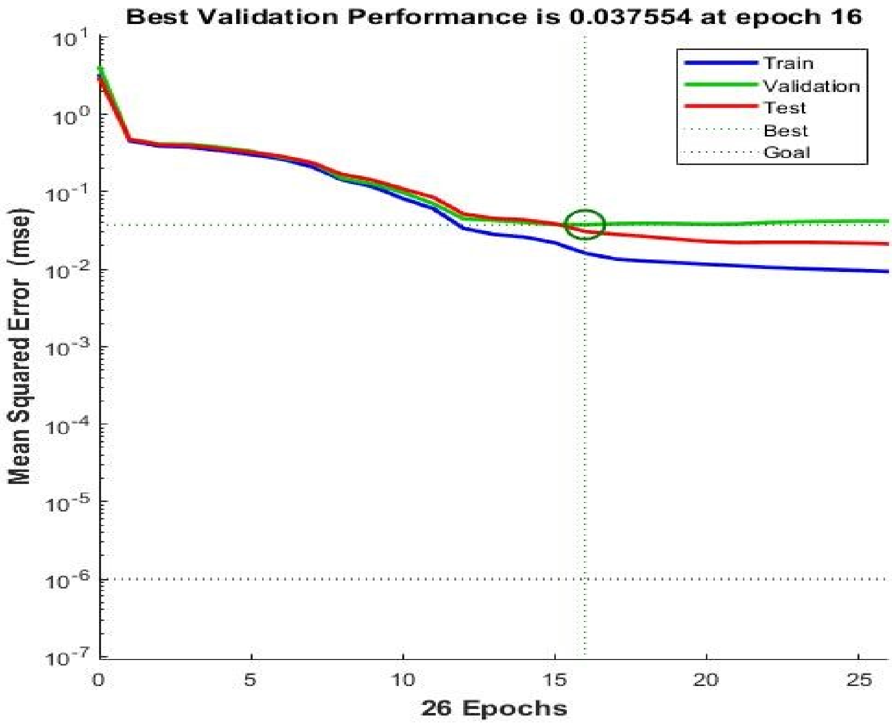

Figure 5: MSE error courses: training, testing, and validation for the Recurrent ANN. Source: own study in the MATLAB and Simulink environment [4, 20]

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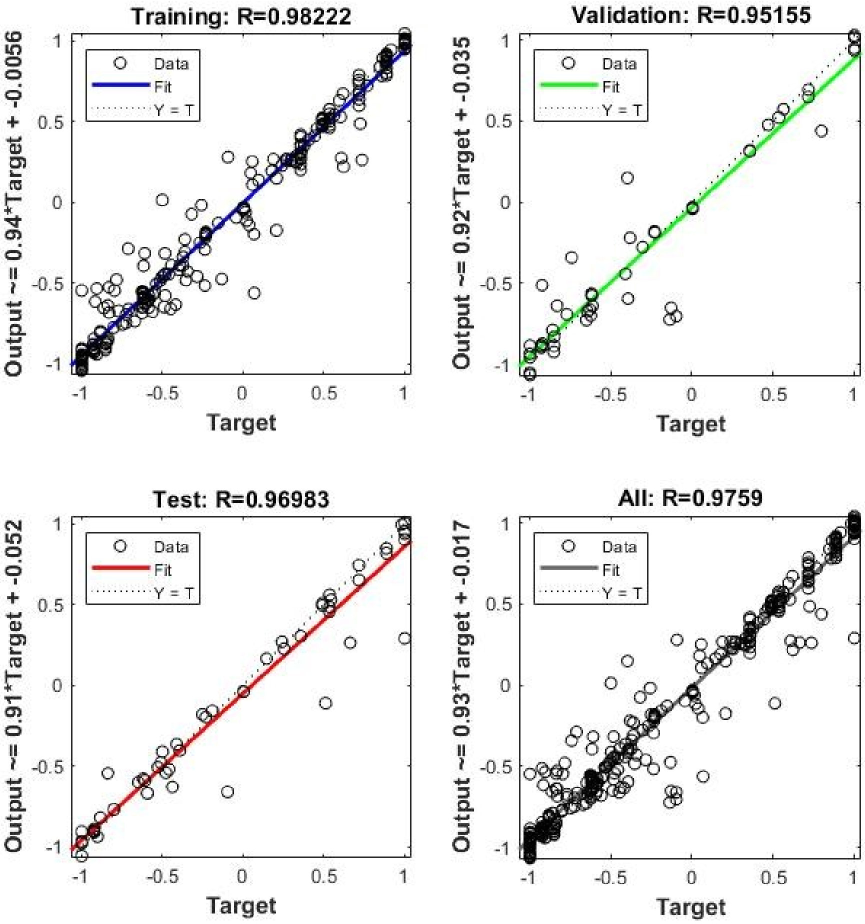

Figure 6: Regression index for the trained model. Source: own elaboration in the MATLAB and Simulink environment [4, 20]

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- the mean absolute percentage error (MAPE) of 5.89% is also acceptable as an error level for practical applications.

Analysis of Individual Output Variables

Achievable Power (R^2 = 0.9955, MAPE = 0.84): The model shows excellent ability to predict available power in the system, which is crucial for operational planning.

Energy Consumption (R^2 = 0.9970, MAPE = 0.08): The best predicted variable, characterized by the smallest relative error, indicating stable energy consumption patterns.

Electricity Export (R^2 = 0.6642, MAPE = 22.24): Variable with the lowest predictability, which may indicate the influence of other external factors, such as price fluctuations in international markets or changing demand in neighboring countries. This value indicates analysis towards building a network that would better model this subsystem based on an extended set of input data or analyzing the possibility of implementing a different type of neural network.

System Losses (R^2 = 0.9948, MAPE = 0.38): High accuracy of system loss prediction enables effective energy efficiency management.

6 Conclusions, practical implications, and directions for further research

The research objective was achieved, as a preliminary data analysis was conducted to select the architecture and parameters of the ANN for training the neural model of the NPS system as an intelligent system. The strengths of the model include, among others:

- high overall accuracy, as the NPS system neural model shows an exceptionally high ability to map complex dependencies in the power system, confirmed by an R^2 value of 0.9998,

- very good computational efficiency characterized by a very short training time of 30 seconds, which, combined with achieving high prediction quality, makes the model a practical tool for system operators in the prediction process,

- convenient differentiation of accuracy, as the model best predicts parameters directly related to technical infrastructure (power, consumption, losses), which is particularly important in operational planning when using the model for prediction.

There are certain limitations and areas for further work and analysis, including in the field of the output variable of energy exports, which is characterized by a low coefficient of determination R^2 value of 0.6642, indicating the need to consider additional external variables, such as, for example, prices on international markets or the energy policy of neighboring countries.

A method for preliminary analysis and selection of architecture and learning method for training the ANN neural model of the NPS system was proposed. Particularly significant results include, among others:

- increased efficiency, as the obtained correlation of -0.945 between employment and achievable power shows that the NPS system significantly improved productivity in 2017-2023,

- the presence of high-quality data, as only 4.8% of anomalies occur, which confirms the high reliability of the analysis,

- the possibility of simplifying the model, as 88% of the information can be retained using only 3 principal components instead of 11 variables.

The following practical implications result from the analysis:

- the NPS system has become more intelligent (unmanned), as increasingly fewer employees are needed to achieve the same power,

- the data are suitable for building AI-based models, particularly on artificial neural networks,

- the power infrastructure and the structure of electricity consumption are key variables affecting system performance.

The conducted analysis of the selection of the artificial neural network and its parameters, as well as the learning method, confirms the high effectiveness of using Recurrent ANN for modeling the NPS system. The obtained neural model demonstrates excellent ability to predict key operational parameters, making it a valuable tool supporting decision-making in the management and control of the NPS system.

Further research directions can include, among others: 1) the possibility of expanding the data set, including the incorporation of additional external variables, particularly for the purpose of improving energy export prediction, 2) conducting a time analysis on models with a larger number of delay time constants in order to better capture the system dynamics, 3) implementing operational execution to demonstrate that the obtained neural model of the KSE system can be effectively used for short-term operational planning, particularly in terms of power management and electricity consumption forecasting.

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