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Modeling the National Power System Using Artificial Neural Networks

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Abstract. The purpose of this paper is to investigate and demonstrate the potential of modeling the National Power System (NPS) in Poland. The paper presents the results of research modeling of the NPS system using three different models based on Artificial Neural Networks. Data characterizing the NPS were implemented to build the models. The results measured by Mean Squared Error and determination coefficient were presented and analyzed. The research results and conclusions are presented in the summary.

Keywords: National Power System, modeling of the power system, power system as an intelligent system, analysis of selected sizes of the power system, Perceptron network, Recurrent network, LSTM network.

1 Introduction

One of the most important issues currently not yet fully resolved in the field of modeling systems, facilities, and processes using artificial intelligence and machine learning methods is modeling the operation of the National Power System (NPS) from the perspective of forecasting electricity production (ee) [GWh], determining the demand for total achievable capacity [MW], ee consumption (output) [GWh], ee losses in the NPS [GWh], ee export [GWh], etc. For these reasons, this issue is being addressed by all major research centers worldwide. Achieving a satisfactory method is difficult as it is one of the most complex and important issues in the global power industry, of which the Polish National Power System is a part.

In times of energy transformation in the world, including in Poland [1, 7], characterized by an increasing share of renewable energy sources (RES), growing regulatory requirements and variability of power and electricity supply, the construction of power system models is becoming a key tool for decision-makers, power grid operators, and investors in the power sector [7, 17, 30]. Power system models enable research on the correct operation of the power system, as well as, among others, forecasting the volume of electricity production following the expected demand for electricity, especially in the field of production scheduling and development of the power system [10, 30]. This publication proposes three neural models built using different architectures and different learning methods, but using the same data on the operation of the NPS, that is, perceptron ANN (MLP), classical Recurrent ANN (RNN) and Recurrent ANN preventing the disappearance of the gradient, the so-called ANN with long- and short-term memory simultaneously, the so-called LSTM [3, 21, 24, 28-29].

Therefore, the neural models obtained were trained using the same datasets of 84 measurement samples, assuming that there are 11 input quantities and four output quantities.

The following **input values** were assumed: employment [person], total installed capacity [MW], total number of turbine sets [pcs], total length of overhead lines [km], total length of cable lines [km], total hard coal consumption [thousand tons], total lignite consumption [thousand tons], total consumption of other raw materials (peat and wood, water and wind, biogas, waste fuels) [TJ], total natural gas consumption [million m^3], total nitrogen-rich gas consumption [million m^3], total electricity imports [GWh], total electricity demand [GWh].

The following **output values** were adopted: total achievable capacity [MW], total electricity production in the commercial power industry [GWh], ee export [GWh], total ee losses in power grids [GWh].

The obtained neural models were compared with each other and with respect to real data, i.e., with respect to the output values of the functioning National Power System. The comparative studies used, among others, the coefficient of determination (R^2) and the mean square error (MSE) to assess the quality of model learning. Furthermore, errors related to the effectiveness, efficiency, and robustness of forecasting were used to assess the quality of models used in forecasting [30-31]. Based on the conducted quality analysis: the process of learning ANNs as neural models of the system, the model's fit to the NPS system, the effectiveness, efficiency, and robustness of forecasting, appropriate conclusions were drawn regarding the directions of use of appropriate neural models in the context of the needs for examining the proper functioning and development of the NPS [4, 30-31].

To build the NPS operational model, monthly data from 2017 to 2023 were obtained. In the absence of open access, data from other time horizons were obtained, i.e., quarterly, half-yearly, and even annual data. The assumption was that the most important thing was to propose a good NPS operational model, and if appropriate data were available, the models could then be fine-tuned for commercial applications. The acquired data included both technical data (e.g., installed capacity, number of turbine sets, length of transmission lines) and economic data (e.g., consumption of individual fuel types, electricity import/export, etc.), which are available and regularly published by, among others, transmission system operators, ARE, URE, GUS, etc. [11-13, 23, 26]. Initial data verification was conducted to assess their completeness, time consistency, quality, reliability, etc., at this stage, which is essential for further work related to modeling the operation of the National Power System using real data, rather than test or laboratory data. Similar studies were already conducted in previous years using analytical and regression machine learning methods in the NPS and the Day-Ahead Market system operating at TGEE S.A., the results of which were published in papers [6, 8, 14-17, 19, 22, 25, 27, 30-32].

2 Neural modeling of the NPS

2.1 NPS as a modeled system

The National Power System consists of the following basic subsystems [7, 17, 30]:

1) The electricity generation system (EGS), including system producers of electricity, including utility power plants, industrial power plants, combined heat and power plants, etc., and EE prosumers (hydroelectric power plants, wind farms, solar power plants, etc., which constitute renewable EE sources (RES),
2) EE transmission and distribution systems, managed by, among others, PSE Operator and other transmission and distribution grid operators,
3) EE consumers, including industrial customers and individual customers (so-called households), a growing number of whom are becoming so-called prosumers,
4) EE system regulators, including, among others, the Energy Regulatory Office (URE),
5) EE recipient intermediaries, including, among others, TGEE S.A., etc.

2.2 Neural models of the functioning of the National Power System

So far, analytical, identification, and regression machine learning methods have been mainly used to model the functioning of the National Power System, resulting in analytical models, identification models, and regression machine learning models [6-7, 9, 14-16, 19, 30, 32]. In recent years, the demand for neural, evolutionary, and other models using other modeling methods based on artificial intelligence methods has increased [2, 21, 28-29]. This research concerns neural modeling, and various neural modeling methods will be used, i.e., based on various ANN architectures, various learning methods, and various ways of supporting learning, including the use of evolutionary methods and quantum-inspired methods [29].

The neural modeling of the National Power System in the proposed dimension differs significantly from analytical modeling using mathematical models obtained using the laws of physics or even economics, because in addition to technical, economic, climatic, etc. phenomena, other phenomena that have not yet been mathematically formulated are also taken into account, e.g. social or political ones, including the impact of strikes on energy production, or political price formation, especially in totalitarian countries, etc.

Neural modeling also differs from other types of modeling methods, such as regression machine learning [6], fuzzy systems, swarming algorithms (e.g., ant colony algorithms), evolutionary methods, or quantum computing-inspired methods, but it can be supported and inspired by these other methods, as is the case with the recently developed evolutionary methods inspired by quantum computing [29]. Therefore, the research undertaken in the field of neural modeling of the NPS system was conducted using ANNs, and in further studies, the resulting models will be improved using other artificial intelligence methods, including those inspired by quantum. This type of research has already been conducted, including our own, and the results have been published, among others, in [29]. It is also worth noting, among others, to the fact that research on modelling the power system is becoming more and more complex year by year, which is dictated by the increasing share of renewable energy, especially wind and solar energy in the energy production balance, which introduces a number of uncertainties into the system resulting from the inclusion in the model of not only technical and economic conditions, but increasingly also climatic, social and even political ones.

3 The essence of neural system modeling of NPS

Scientists and practitioners from various fields and disciplines have been modeling the operation of the National Power System since the first power system in Poland was established. This research has resulted in analytical models [9, 15-16, 19, 27, 32] as well as identification models using control and systems theory, regression machine learning [6, 17, 30], and neural learning [3-4, 17, 24-25, 29].

The research presented in this publication is part of the search for neural models of the National Power System (NPS) operation, assuming 14 inputs to the NPS system and 4-5 outputs from the NPS system. Therefore, the NPS is defined as a system composed of subsystems that can be distinguished based on the number of outputs from the NPS. Since there are four or five of them, considering conventional energy separately from renewable energy, the NPS will be a system composed of the following subsystems:

- total available capacity system [MW],
- total electricity production system in the commercial power sector [GWh],
- total electricity production system in renewable power generation (wind, solar, hydro, etc.) [GWh],
- total ee export subsystem [GWh],
- total ee losses subsystem in power grids [GWh].

The undertaken research on modeling the NPS system reduced to 4-5 subsystems with fourteen inputs is a representative enough experiment to demonstrate the method of obtaining the NPS neural model as well as the method of selecting the architecture and training method of the ANN, and even the method of improving the parameters of the obtained neural model using other artificial intelligence methods, including evolutionary and quantum-inspired ones, important in tuning the goodness of the NPS system model.

Therefore, this research attempts to encompass a comprehensive modeling of the National Power System (NPS) with its subsystems. In this respect, there are research results on modeling the development of the power system in terms of control and systems theory using identification methods, which constitute the starting point for modeling methods using regression machine learning [6, 17, 30], or conducting the analysis of long-term relationships, as well as neural models of the Day-Ahead Market system operating on the Polish Power Exchange [17, 23-25, 31], which are a tool for forecasting prices on TGEE S.A..

It is also worth mentioning an example of a system model supporting the operation of a real system to improve the reliability of the power grid, including reducing the number of failures. This application, called Predictive Maintenance, was implemented in five control centers. This application uses advanced models based on artificial intelligence techniques to analyze data from sensors installed in power grids in real time, to analyze data obtained from smart meters, resource maintenance records, and weather data to predict possible power line failures, which is important for preventing undesirable operating states of the National Power System [16, 22, 34]. A similar solution is an electricity consumption management system implemented by a Danish company for the buildings it manages. This system, supported by artificial intelligence solutions, monitors the consumption of utilities (electricity, water, heating, etc.) and detects anomalies (e.g., excessive water or electricity consumption) thanks to possible data analysis applications from multiple sources.

4 Preparation of research experiments

4.1 Selection of data for experiments

The selection of data for research experiments in the field of power system modeling is still primarily dependent on the availability of open data in Poland, due to limited access to research grants and, consequently, a lack of funds for purchasing appropriate data. After a thorough search of Internet resources, data were obtained, among others, from publications by the Energy Market Agency (ARE), Polish Power Grids (PSE Operator), and the Central Statistical Office (GUS) [11-13, 23, 26]. However, this data is not uniform and requires preliminary preparation for the research experiments. The research results published in this article used 84 validated data samples representing monthly data from 2016-2022 (7 years x 12 months = 84 samples). From the perspective of the NPS operation, these were divided into 11 quantities, classified as input quantities due to their nature and role in the NPS, and four output quantities.

Therefore, the following input quantities were adopted (with their specificity shown):

1) Total employment [person]: mean 19886.86, standard deviation (std) 1443.27,
2) Total installed capacity [MW]: mean 54533.13, std 8514.59,
3) Total number of turbine sets [pcs]: mean 86.00, std 5.30,
4) Total length of overhead lines [km]: mean 592642.86, std 2687.12,
5) Total length of cable lines [km]: mean 270128.71, std 15870.49,
6) Total hard coal consumption [thousand tons]: mean 2345.18, std 223.30,

7) Total lignite consumption [thousand tons] tons]: average 4301.14, std 548.82,
8) total consumption of other solid raw materials [thousand tons]: average 10332.01, std 3006.
9) total natural gas consumption [thousand tons]: average 67.53, std 5.69,
10) total nitrogen-rich gas consumption [thousand tons] tons]: mean 54.03, std 2.40,
11) EE import [GWh]: mean 1300.56, std 234.89,

and as output quantities (4 variables):

1) Total achievable capacity [MW]: mean 50280.83, std 7130.19 (large scale),
2) Total electricity consumption [GWh]: mean 14570.35, std 275.85,
3) Total ee export [GWh]: mean 888.64, std 373.60 (high variability),
4) Total ee losses [GWh]: mean 824.01, std 52.94 (low variability),

i.e., due to the lack of data for the period under study, electricity production was not taken into account, broken down into production by conventional energy and production by renewable energy. It is worth adding that it was assumed that the output values are delayed in relation to the input values, hence the obtained models are MIMO models [17, 24-25, 30].

Preliminary statistical studies have shown, among other things, that data on the above-mentioned 15 variables are characterized by diverse scale and variability, which poses a challenge in the modeling process, including, among others, large standard deviations of variables such as: other raw materials and ee export, which is suggested by outliers, and a small number of samples (84) increases the risk of overfitting, and the data are time series in nature, which seems to give an advantage to recursive modeling using RNN and LSTM ANNs over MLP models.

4.2 Preliminary preparation of research experiments

Neural learning of NPS system models is preceded by, among other things, data normalization, which is often crucial for the process of training ANN system models due to the differences in data scale, often amounting to several orders of magnitude.

The basic criteria for evaluating NPS system model learning were: Mean Squared Error (MSE) and RMSE, determined as the square root of the MSE, expressed as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i^s - y_i^n)^2} \tag{1}$$

wheree:

y_i^s- i-th output from system s,

y_i^n – i-th output from neural model n.

And the coefficient of determination (R^2) is expressed as follows:

$$R^2 = \frac{\sum_{i=1}^{n}(y_i^m - \overline{y})^2}{\sum_{i=1}^{n}(y_i^s - \overline{y})^2} \tag{2}$$

where:

$\overline{y}$- average value of the output quantity from the system model,
y_i^s - value of the i-th output quantity of the system,
y_i^m - value of the i-th output quantity of the model,
recently also been used in practical evaluations of ANN learning quality as the square root of the determination index, i.e., R.

The interpretation of both measures of the system model learning quality assessment, i.e., the MSE error and the R^2 coefficient of determination, comes down to a complementary assessment of the learning quality, as well as testing and validation. The MSE error is used to assess the learning quality of the system model by indicating the size of the learning error, and the R^2 coefficient of determination is used to show to what extent the model is able to explain the processes occurring in the actual NPS system. In assessing the learning quality of the system model, the aim is to obtain the lowest possible MSE value and the highest possible R^2 coefficient, i.e., close to 1. However, there is no method in the literature on the subject that would use both indicators for assessment simultaneously, hence the development of an original practical method [24-25].

5 Artificial neural networks as neural models of the PPS

5.1 Perceptron-based ANN (MLP) as a neural model of the PPS

The MLP type ANN architecture most often consists of: an input layer, one or more hidden layers, and an output layer, and in the experiment under consideration, the following elements of its structure appear:

- Number of neurons in the input layer – 11,
- Number of neurons in the output layer – 4,
- Number of hidden layers – 1,
- Number of neurons in the hidden layer – 64,
- Neural activation function in the hidden layer: tansing(),
- Neural activation function in the output layer: purlin(),
- Normalization during the training process: mapminmax and initial normalization (related to preparing the data for training) expressed as the value of a single value of the input or output variable to the sum of all values of that input or output variable.

The following conditions were adopted for the training process of the NPS system model:

- Learning method: Levenberg-Marquardt,
- Learning rate – 0.01,
- Number of training epochs – 200 (with early stopping max_fail=6).
- Training data – 70% of the training file,
- Validation data – 15% of the training file,
- Testing data – 15% of the training file.

As a result of the training, testing, and validation process, a neural model was obtained, trained on the NPS system in the form of a Perceptron ANN already in the second epoch of training, whereby:

The values of the RMSE error and the determination index regarding the quality assessment of the training and testing process of the system model in the form of an MLP ANN before denormalization were (in unitless values) as follows (Fig. 1):

1) RMSE of the training process: 0.1292,
2) RMSE of the testing process: 0.1662,
3) R^2 of the training process: 0.8686,
4) R^2 of the testing process: 0.8263,

therefore, in both cases, both measures indicated relatively good quality of the system model.

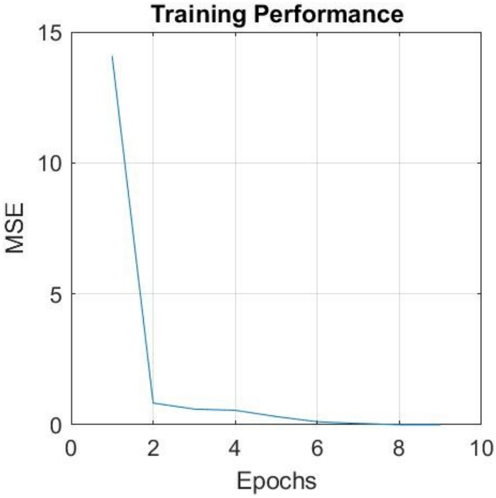

Figure 1. The MSE error curve during the learning process of the Perceptron ANN model of the NPS system. Notations: X axis – Epochs [pcs], Y axis – MSE [no titer]. Source: own study in MATLAB and Simulink using Deep Learning Toolbox [18].

1) The obtained results, broken down by individual NPS outputs, were as follows:
2) Available power: R^2=0.9820, RMSE=0.185788,
3) EE consumption: R^2=0.9820, RMSE=0.171048,
4) EE export: R^2=0.9820, RMSE=0.907958,
5) EE losses: R^2=0.9820, RMSE=0.138665.

Based on the obtained results, it can be observed, among other things, that the neural model in the form of a Perceptron ANN is characterized by fairly good knowledge generalization, while the relatively high R^2 (0.9820) indicates that the model may be too well-suited to the system. The RMSE for exports is problematic, as it shows a relatively large RMSE error of

0.907958, which requires further research, e.g., on the system model to assess the model's fit to the NPS system by examining the mean relative error or MAPE. It is also worth examining the effectiveness, efficiency, and robustness of the models and systems to verify the suitability of the resulting models for conducting forecasting, comparative, or sensitivity studies [30-31].

5.2 Neural Model as a Recurrent ANN

The Recurrent ANN (RNN) architecture, using the MATLAB function layrecnet(), incorporates temporal dependencies into its architecture and the learner's method by delaying the feedback signal from the network output to its input. In the final version, the model was characterized by the following conditions:

1) delay - 1,
2) number of neurons in the hidden layer - 64,
3) training data - 70%,
4) validation data - 15%,
5) test data - 15%,
6) learning rate - 0.01,
7) number of training epochs - 300 (with early stopping max_fail = 10), (stopping occurred after 42 epochs),
8) neuron activation function: tansing(),
9) learning function: trainbr (Bayesian Regularization),

normalization method: mapminmax. In RSSN, network parameters such as the number of hidden layers and the number of neurons in hidden layers were changed, which ultimately allowed for the selection of RSSN with the course of MSE errors (training, validation, and testing) and their values as shown in Fig. 2.

The following RMSE and R^2 values were ultimately obtained for individual grid outputs:

1) Total available power: R^2=0.9962, RMSE=0.038152,
2) Total energy consumption: R^2=0.9995, RMSE=0.041223,
3) Total energy export: R^2=0.7822, RMSE=0.229154,
4) Total energy losses: R^2=0.9988, RMSE=0.034597.

Recursive ANN proved to be a more appropriate model of the National Power System (NPS) system than MLP in modeling the dynamics of the NPS system, but it is characterized by a vanishing gradient, which limits long-term dependencies. On the other hand, a very high coefficient of determination R^2=0.9999 indicates an almost perfect fit to the training data; however, such a high coefficient on a small data set (84 samples) may result from the overfitting effect, which requires further research on the sensitivity of the obtained model of the NPS system.

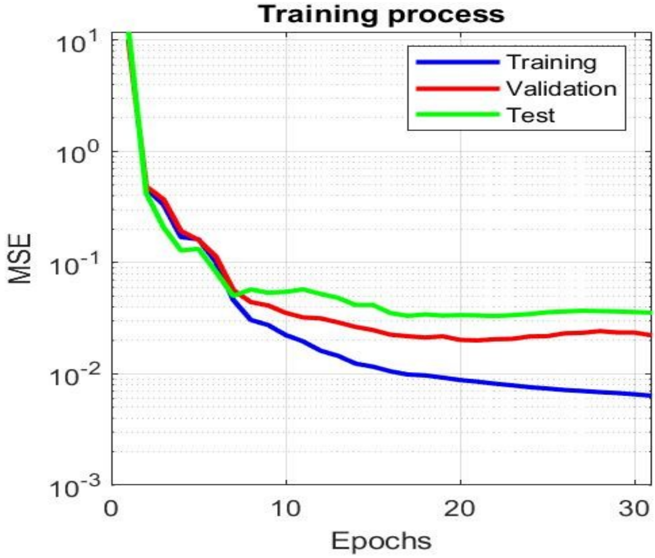

Figure 2. Perceptron network training graph. Source: own study in MATLAB and Simulink environment using Deep Learning Toolbox [18]

5.3 A neural model in the form of an LSTM-type the ANN

The LSTM architecture is based on a more advanced recurrent ANN structure with memory gates, which eliminates the vanishing gradient problem. In this case, several versions of the LSTM ANN training parameters were tested. Ultimately, the best ANN parameters were obtained, as shown in Table 1.

Table 1: LSTM ANN architecture. Source: own study in MATLAB and Simulink environment using Deep Learning Toolbox [18].

Layer Name	Layer Type	Input Size	Output Size
input	nnet.cnn.layer.SequenceInputLayer	11	N/A
lstm1	nnet.cnn.layer.LSTMLayer	'auto'	16
dropout1	nnet.cnn.layer.DropoutLayer	N/A	N/A
lstm2	nnet.cnn.layer.LSTMLayer	'auto'	8
dropout2	nnet.cnn.layer.DropoutLayer	N/A	N/A
fc1	nnet.cnn.layer.FullyConnectedLayer	'auto'	8
relu1	nnet.cnn.layer.ReLULayer	N/A	N/A
dropout3	nnet.cnn.layer.DropoutLayer	N/A	N/A
fc_output	nnet.cnn.layer.FullyConnectedLayer	'auto'	4
regression_output	nnet.cnn.layer.RegressionOutputLayer	N/A	N/A

The LSTM ANN training parameters were determined experimentally, taking into account both the learning quality of the system model and the generalization level of the system model. Ultimately, considering the nature and size of the data being processed, the following values were obtained:

1) **data processing parameters**

- Logarithmic transformation (apply_log_transform = true) stabilized the variance of the time series, which was particularly important for small data sets, as it reduced the impact of outliers, facilitating SSM training by normalizing the data distribution.
- Determining the length of the input sequence (time window seq_length = 6), with each training sample using 6 previous samples to predict the next one. This involved using 6 time steps as a compromise for small data sets and lasting long enough to capture patterns, but not too long to fragment the already small data set.
- Adding noise to the training data (data augmentation noise_factor = 0.01), which, for small data sets, was an artificial measure leading to increased data diversity. In this case, a small noise value (1%) prevented distortion of the original patterns.

2) **LSTM architecture parameters**

- The number of neurons in the LSTM layer (lstm_units/hidden_units = 16) was set relatively low to avoid the risk of overfitting, while an LSTM ANN with 16 neurons can capture basic patterns without excessive complexity.
- Regularization was performed by randomly excluding neurons and changing their values to 0 (dropout_rate = 0.05), which, for small data sets is a moderate regularization that prevents overfitting.
- For dense layers, only (dense_units = 4-8) was set, as the fc1 layer contained 8 neurons, and the number of neurons for the output layer resulted from the parameter of the number of network outputs (num_outputs), which was influenced by the size of the training data.

3) **model training parameters**

- A relatively high value (learning_rate = 0.01) was adopted for small datasets, which in this case means that faster learning compensates for the smaller number of examples.
- Very small batches were adopted for the small dataset (batch_size/miniBatchSize = 4), which resulted in more frequent weight updates (a larger number of gradient steps per epoch).
- A relatively large number of epochs (epochs = 150) was adopted to compensate for the relatively small number of samples used in the experiment, as this resulted in more passes of the learning algorithm through the training set, resulting in better pattern learning while requiring more attention and monitoring for overfitting.
- A relatively high value was adopted for the parameter (validationPatience = 20), which controlled how long the algorithm could wait for improvement in validation results before stopping training. It was expected that for relatively small datasets, the algorithm might need more time to stabilize, and thus this situation prevented premature stopping of the system model training. NPS.

The LSTM ANN architecture and learning algorithm configured in this way were used to train the NPS system model in 10.51 seconds - Fig. 3. As a result of training the LSTM ANN, the following values of the RMSE error and the determination index were obtained R^2:

Total achievable capacity: R^2= 0.9620, RMSE= 0.026313,
Total ee consumption: R^2= 0.9727, RMSE= 0.042963,
Total ee export: R^2= 0.6390, RMSE= 0.081048,
Total ee losses: R^2= 0.9653, RMSE= 0.051467.

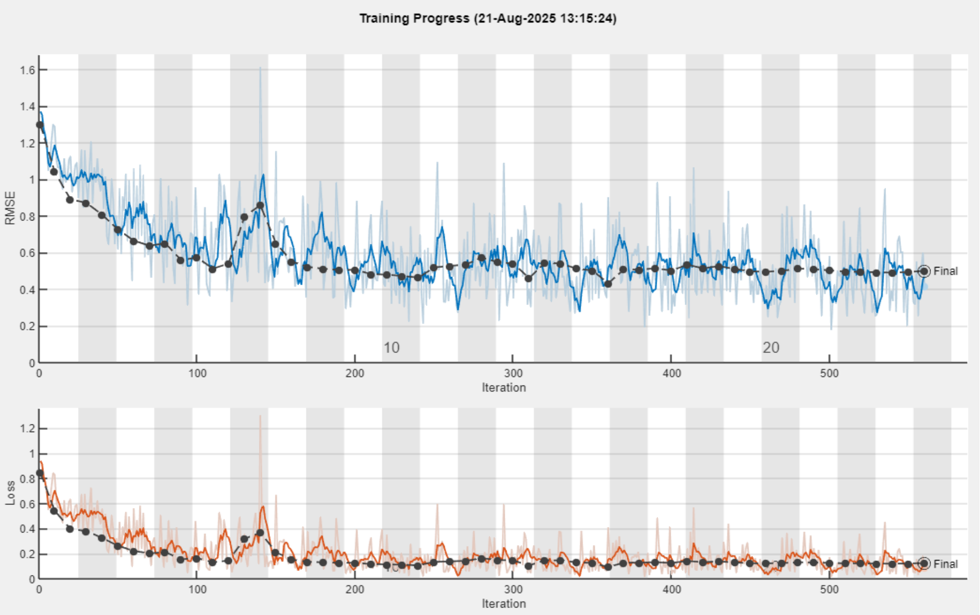

Figure 3. Training process of an LSTM ANN. Markings: at the top – RMSE error, at the bottom – Loss value. Source: own study in MATLAB and Simulink using Deep Learning Toolbox [18].

Analysis of the obtained results of the LSTM ANN shows that this ANN models the NPS system quite well, as the individual values of the coefficient of determination are relatively high, except for the R^2 value for the ee export subsystem (0.6390), indicating the need for in-depth research in further analyses.

However, the normalized root mean square error (RMSE) for all model outputs is similar, which was not the case for the other models. An advantage of the LSTM model is that the RMSE for ee export is of the same order of magnitude as the other models. In the case of the MLP and RNN networks, it was an order of magnitude larger. The LSTM model shows promising results in the context of general prediction of energy systems, achieving very high fit indices. However, significant differences in the prediction quality of individual output variables indicate the need for further tuning or, as in the case of employing other models.

6 Comparison of LMP, RNN and LSTM

The model comparison was based on the determination index for each analyzed model for each model output, shown in Table 2.

Table 2: Summary of determination indexes for each subsystem in the National Power System, taking into account the different types of neural models. Source: prepared inMATLAB and Simulink using the Deep Learning Toolbox [18].

Output / Model	MLP (R^2)	RNN (R^2)	LSTM (R^2)
Achievable Power	0.9820	0.9962	0.9664
EE Consumption	0.9820	**0.9995**	0.9631
EE Export	0.9820	0.7822	**0.6318**
EE Losses	0.9820	0.9988	0.8880

The R^2 coefficient of determination for the RNN-based ANN reached a high value (0.9999), indicating a very good fit to the training data. However, this may indicate overfitting. The R2 coefficient for the LSTM-based ANN was also high (0.9997), but the R^2 coefficient for the MLP-based ANN was slightly lower (0.8263). Therefore, it can be concluded that recurrent models generally learn general patterns better than the classic MLP-based ANN.

The LSTM-based ANN offers better neural model learning quality than the RNN-based ANN, which demonstrated somewhat moderate learning (high R^2, but significantly lower for the export ee subsystem). The MLP-based ANN, on the other hand, performed the worst in normalized metrics but achieved quite good learning results after denormalization.

7 Conclusions and directions for further research

The aim of the research was to prepare the NPS system for testing, particularly data on the NPS's operation, and to use this data to conduct neural modeling of the system. Detailed studies were conducted using three types of ANNs differing in architecture and training methods.

The study examined the learning quality of the NPS model using the R^2 coefficient of determination and the RMSE error. The analysis showed that the LSTM ANN achieved the best learning quality, as the R^2 coefficient of determination was close to 1.0 ($R^2 = 0.9997$) and the RMSE error was very small, ranging from 0.081048 to 0.026313. However, the RNN ANN achieved better learning results compared to the MLP, with both the R^2 coefficient of determination and the RMSE error being lower than those of the LSTM ANN.

The research is ongoing and covers, among other things, Assessing the quality of the neural model's fit to the National Power System (NPS) system using an ANN exported as an object to Simulink, where it was used to examine the mean relative error and the MAPE error, as well as assessing the effectiveness, efficiency, and robustness of the model and system for forecasting purposes. Further research may require expanding the dataset to include a larger number of samples so that the ANN can better capture changes occurring in the system during model training. Consideration should also be given to changing the range of output variables tested from the NPS due to the weaker results for the EE export subsystem. Models for factors such as available power, consumption, and losses model these factors relatively accurately, as evidenced by both the R^2 determination indices and RMSE errors.

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