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Neural Network Optimization of Nuclear Energy Integration for Industrial Applications and Grid Stability

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I. INTRODUCTION

The necessity of decarbonizing the energy mix has been one of the key topics in recent years and will become even more crucial in the future due to changes in the structure of the energy mix. Decarbonization efforts often focus primarily on electricity generation, while heat production is frequently overlooked. Industrial heat and heating systems are significant sectors that are currently primarily covered by fossil fuels. Achieving net-zero emissions will require a fundamental shift in the approach to the industrial sector, particularly in terms of energy sources. High-temperature processes and large industrial plants are among the largest polluters. Approximately one-quarter of total greenhouse gas emissions come from industrial applications alone [1]. Therefore, it is crucial to focus on decarbonizing industry, where nuclear facilities can play a significant role, as they are the most reliable and lowest greenhouse gas emitters. The use of nuclear facilities for industrial applications is currently being explored through several studies and projects that aim to compete with fossil fuel sources. These projects are being developed worldwide – at the European level, but mainly in the USA, China and Japan.

Most projects focus primarily on temperature requirements rather than the direct deployment of individual nuclear facilities in industrial applications. While these projects are sufficient for a high-level technoeconomic studies, real-world deployment of nuclear power in industrial applications requires advanced control strategies.

With the increasing share of renewable energy sources, ensuring grid stability is becoming an ever-growing challenge, demanding innovative approaches beyond traditional regulatory mechanisms. Neural networks offer a modern tool for optimization, enabling intelligent real-time decision-making.

Neural networks (NNs) provide a modern solution for optimizing energy systems, particularly in grid regulation and stability. As the share of renewable energy grows, power generation becomes more variable, creating new challenges for system operators. Existing control systems were not originally designed for such dynamic conditions, making it necessary to explore new approaches that can enhance flexibility and responsiveness. Nuclear power plants, as a key component of the future energy mix, will need to operate in coordination with renewables to ensure overall grid stability. This makes the development of advanced regulation strategies from the perspective of nuclear facilities essential. Modern Artificial intelligence (AI)-driven methods allow for more efficient adaptation to grid changes, improve load balancing, and support real-time decision-making. Ensuring the controllability of power grids in this evolving landscape will require innovative, data-driven, and predictive regulation strategies.

This paper explores the potential of neural networks in optimizing the operation of industrial energy hubs and nuclear facilities, particularly in their role in power grid management. Achieving grid controllability can be approached through multiple methods, from classical mathematical-physical models to innovative AI-based solutions. Many facilities operate in cogeneration mode, requiring seamless integration with the grid not only to meet industrial demand but also to support overall system stability. Advanced algorithms enable better adaptation to changing conditions and contribute to a more efficient and resilient energy ecosystem.

II. INNOVATIVE APPROACH BY NEURAL NETWORKS

Neural networks, in general, are widely used for tasks involving dynamic systems and data processing, but when dealing with time-series data, Recurrent Neural Networks (RNNs) are particularly well-suited. RNNs belong to a class of deep learning models designed specifically for sequential data processing. This type of neural network is well-suited for approximating dynamic systems-they have the ability, based on their architecture, to influence current and future outputs using previous information [2].

Long Short-Term Memory (LSTM): Since traditional RNNs generally face the vanishing gradient problem, deeply explored in this conference paper by R. Pascanu and

T. Mikolov [3], various alternative RNN models have been developed. LSTM networks effectively preserve and update critical information in long sequential data through gating mechanisms [2].

Gated Recurrent Unit (GRU): GRU represents a simplified variant of the LSTM model that also addresses the vanishing gradient problem. A key advantage of GRU over LSTM is the reduced number of parameters, leading to faster training times and making it more practical for shorter sequences. A more detailed description of the different types of recurrent neural networks can be found in the source by I.D. Mienye [2].

Temporal Convolutional Network (TCN): TCNs belong to a category of networks that leverage 1D convolutions with causality [4].

III. METHODOLOGY

In terms of the use of neural networks, for this presented study, it is necessary to develop a methodology that is very important for the following applications of neural networks for different tasks. The solution to this problem consists of three functional blocks, as illustrated in Figure 1. In the following section, the individual parts that make up the methodology will be presented.

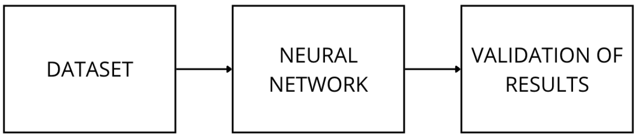

Figure 1. Methodology

A. Dataset

From the perspective of the Dataset, as illustrated in the Figure 2, it consists of three main components: Variables, Data Preparation, and Data Validation.

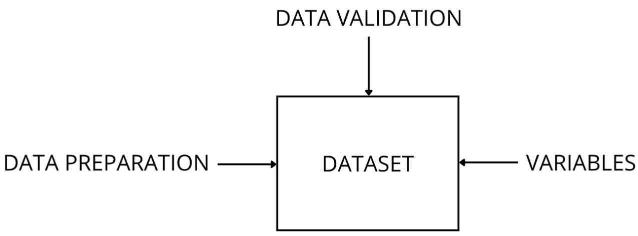

Figure 2. Dataset

Variables: The selection of individual variables influencing the predicted quantities is a crucial part of the entire system, as it directly affects all subsequent steps.

Data Preparation: In large datasets, it is common to encounter values that are not aligned in the same time step. For processing with neural networks, it is beneficial to unify the time step. This can be achieved using several methods- such as forward filling to copy previous values, linear interpolation and others.

Data Validation: Some datasets contain errors either due to data availability issues or errors introduced during data processing. Therefore, it is essential to develop a framework that validates the input data to ensure the accuracy and reliability of the predictions.

B. Neural Network

As shown in Figure 3, the key components of the neural network are type of NN, layers and hyperparameters.

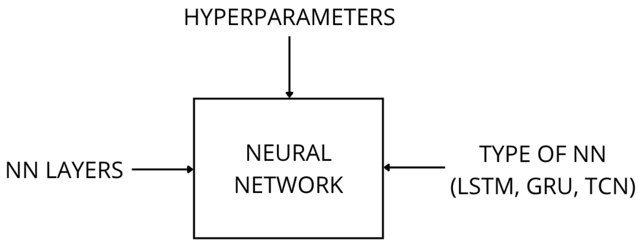

Figure 3. Neural Network

Type of Neural network: The type of neural network is closely related to the selected dataset. In our work, we use recurrent neural networks, primarily LSTM and GRU. As an alternative to RNN, we use the TCN neural network.

Neural network layers: Neural networks can also utilize individual layers. In our model, we use the feedback weighting of features that influence predictions. Physical properties of individual columns can be passed to the layers, and the predicted values can be adjusted.

Hyperparameters: In our model, the key parameters include *batchsize* – which determines the number of samples processed during one training step, and number of *epochs* – which determines how many times the model passes through the entire dataset.

C. Validation of Results

The final part of our methodology involves result validation.

MAE, RMSE: For evaluating the predictions in our model, we use these two basic parameters, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). MAE is the average of the absolute differences between the predicted and actual values:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad (1)$$

where y_i is actual value, $\hat{y}_i$ is the predicted value by neural network and n is the total number of samples.

Another commonly used parameter is RMSE, which is a more sensitive metric as it assigns greater weight to larger errors. It represents the square root of the average squared differences between the predicted and actual values.

IV. PROPOSED MODEL

The proposed model is particularly suited for long-term data with a consistent time step. In our study, we utilize data from the Czech Transmission System Operator (ČEPS) [5], which provides data from the Czech power grid. For demonstration purposes, we aim to predict the energy mix composition of nuclear power plants (NPPs), combined cycle gas turbines (CCGTs), and thermal power plants (TPPs) based on training conducted using 2024 data for specific periods, namely for 3 weeks in different parts of 2024. Since the data have different time granularities, dataset modification was necessary. In the first approach, previous available values were interpolated into the missing time slots. The proposed model for multi-criteria prediction is based on three types of neural networks: LSTM, GRU and TCN.

A. Dataset

The dataset includes power generation from all types of power plants, ancillary services for electricity grid, consumption load, frequency, and cross-border power flows. These variables are essential for analyzing grid stability, balancing supply and power demand. In total, 32 variables are used for the dataset

B. Approach of the Proposed Model

The model incorporates several key preprocessing and optimization techniques. Scaling input features ensures consistency by normalizing data to a fixed range (typically 0 to 1) using min-max normalization. Feature weighting allows the model to adjust the importance of each variable during training. To enhance stability and prevent overfitting, a trend penalty discourages undesired patterns, leading to more reliable time-series predictions. This model was computed using 30 epochs for predicting t+15 min.

C. Results

The Figure 4 presents results for nuclear electrical power generation, aiming for the lowest MAE and RMSE. The NNs were trained on minute-level data for one week and then predicted the following two days.

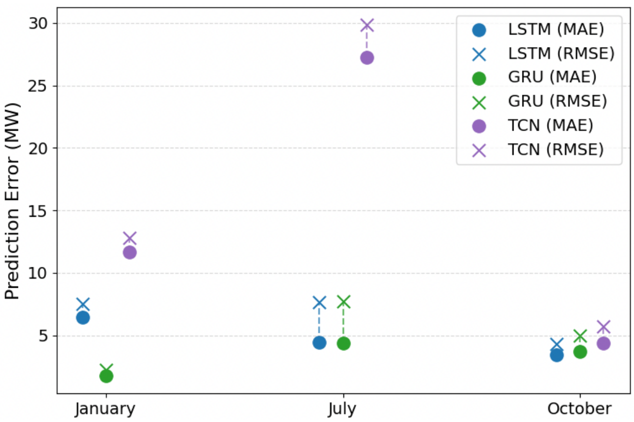

Figure 4. MAE and RMSE Evaluation for NPPs

Figure 4 presents the prediction performance of different neural network types for NPPs power generation across three different weeks in January, July, and October.

In January, GRU achieved the lowest MAE/RMSE (1.76/2.26), outperforming both LSTM (6.47/7.54) and TCN (11.66/12.82). This suggests that GRU performed the best in predicting NPPs generation during the winter month, with significantly lower error values compared to the other models.

In July, TCN showed the highest error values (27.28/29.86), followed by LSTM (4.44/7.66) and GRU (4.36/7.73). These results indicate that TCN struggled with stability during the summer months, while GRU exhibited relatively stable performance with moderate error values.

In October, LSTM achieved the best performance with the lowest MAE/RMSE (3.40/4.28), followed by GRU (3.70/4.95) and TCN (4.34/5.69). While LSTM provided the most accurate predictions in October, GRU and TCN also performed reasonably well, with GRU showing slightly higher error values than LSTM.

Figure 5 further highlights the unsuitability of the TCN neural network for predicting power generation from TPPs, CCGTs.

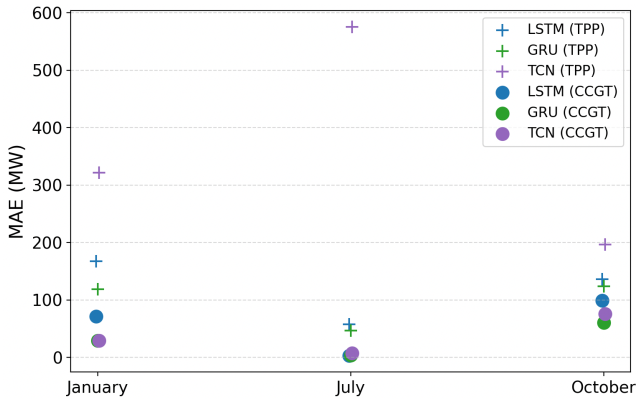

Figure 5. MAE Evaluation for TPPs and CCGTs

These results suggest that GRU delivers the most accurate predictions in January, while LSTM performs best in October. TCN shows worse results due to its focus on long-term dependencies, making it less suitable for short prediction windows such as *t+15*. It has difficulty capturing fast, short-term changes, which are more prevalent during the dynamic summer months, when temperature fluctuations and varying demand require more flexible models.

Figure 6 shows the predicted NPPs generation for two days after one week of training with a GRU (July).

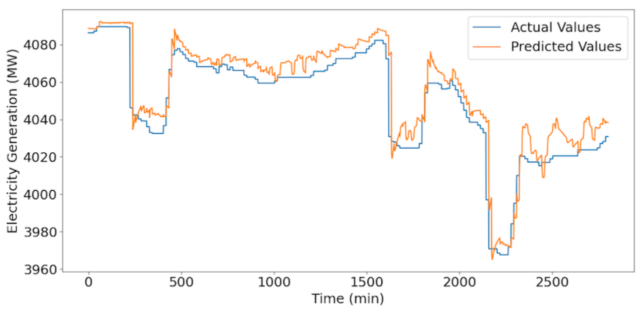

Figure 6. Comparison of Actual and Predicted Power Generation Using GRU Neural Network (July) – Results for NPPs

The presented results serve as a foundational cornerstone for the subsequent work. The choice between different types of neural networks will be the subject of future research, where an optimization method will be developed as an additional functional block in the methodology. It is the optimization of selecting the best configuration of individual neural networks for a single application that is crucial for further work. In the presented model, not much emphasis has been put on the neural network settings - setting hyperparameters, number of epochs, batchsize, configuration of weights of individual columns in more detail. The chosen multicriteria prediction also has a significant impact on the results because nowadays different types of power plants are used for different situations - mainly in terms of their regulation. CCGT and TPP are mainly used for grid balancing. To improve the model results it would be better to choose 3 different datasets for these predicted variables. However, this model was also intended to show that multicriteria prediction is also possible in today's neural networks.

Therefore, these results are highly valuable for the next steps of the work, as they offer important insights into the relative performance of the neural network models under varying seasonal conditions. They not only highlight the advantages and limitations of each architecture - LSTM, GRU, and TCN - but also set the stage for further optimization and refinement in predicting power generation. By analyzing these results, we obtain a deeper understanding of which network performs best under certain conditions. This insight helps us identify the factors contributing to optimal performance. Moreover, this knowledge can be applied to improve the accuracy and stability of predictive models in the future. Thus, these results are critical, providing both practical and methodological guidance for the next phases of the research.

The aim of this work was to validate our methodology to see if it is heading in the right direction. During the development of the different parts of the methodology, we have created flexible tools that now help us to use neural networks for different applications - a dataset preparation program has been developed where the time range, the selection of variables and how missing data will be filled in can be set. As mentioned above the development of a neural network settings optimizer is now under development, which uses various optimization methods for setting hyperparameters such as Bayesian method, Random search, Grid search, but also uses parallelization because the speed of learning and optimization are essential for future use for larger datasets. In future work, we will save trained neural networks for simulating and predicting other datasets.

After this evaluation and development of the different parts, we can clearly say that our methodology is going in the right direction, and it turns out that the flexible design of the different parts opens several possibilities for use.

V. SUMMARY

The mentioned model successfully demonstrates the potential of utilizing neural networks in power engineering, a potential that is worth further focusing on. It highlights areas where we can explore opportunities for implementation, especially given the dynamic times we are currently experiencing.

Neural networks have been studied and implemented for failure prediction and dynamic behavior modeling in various fields, including the nuclear sector. However, their adaptation in energy systems, particularly in nuclear energy, remains limited despite the vast data potential enabled by modern computational capabilities.

The developed model, along with the presented methodology, will serve as a tool for future research, as we have already prepared all the necessary components, including a framework. Future work may focus on the potential of energy storage integration in nuclear power plants, guided by neural network-based control. The most crucial aspect of these simulations and predictions is the availability of sufficient data for training neural networks. Direct implementation of data from nuclear power plants could enable neural network-based control for energy storage utilization, which will be essential. In a future energy system where NPPs must operate alongside renewables without relying on fossil-based regulation, such simulations of grid dynamics and nuclear power plant control will be critical. Additionally, the often-discussed application of nuclear facilities for industrial heat supply will require a different approach to regulation, potentially leveraging neural networks-this will be a key aspect of future work.

Future research will examine each part of the methodology separately. From the perspective of data preparation, ensuring data quality and unifying time series is a crucial and extensive topic. The neural network framework, including model architectures and hyperparameter settings, is another essential component of future research. Moreover, the evaluation and validation of results for implementing neural networks in grid control will play a critical role in the next phases of development.

VI. REFERENCES

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