An Artificial Intelligence Approach for Predicting Hydropower Production in the Nordic Power Market

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Abstract. Hydropower has historically had an important role in the Nordic power market. In the Nordic power market, hydropower accounts for around 60% of the electricity generated (2010–2019). The share of variable renewable energy sources (VRES) has grown considerably in recent years. Because of the growing awareness about climate change, this tendency is likely to continue in the future. In this paper, an artificial intelligence-based model to forecast hydropower production in different bidding areas in the Nordic power market was developed. Furthermore, the effects of spatial characteristics of VRES production on short-term hydropower production planning are analysed at bidding area level. As predicted, the AI model revealed that inflow and reservoir level are critical for the model's performance prediction. The findings showed that residual demand within the bidding region alone is insufficient to estimate hydropower generation. The model's forecast can be greatly improved by including residual demand for the other bidding areas as an input parameter. The forecast performance of the AI model for hydropower deteriorated as the percentage of non-dispatchable generation increased. However, the model demonstrated its ability to estimate hydropower in the face of the growing amount of variable renewable energy generation in the Nordic power market.

Keywords: Artificial intelligence; Hydropower; Nordic power market; Machine learning; Renewable energy

1 Introduction

Hydropower plays a pivotal role in the Nordic power generation, with the exception of Denmark [1]. It is a renewable, efficient, and stable energy source for power generation that is widely employed throughout the Nordic nations [2]. Hydropower accounts for more than half of the electricity generated in the Nordic countries. It demonstrates that this energy infrastructure plays a critical role in meeting the Nordic nations' electricity needs. Hydropower provides both energy and rapid and easy regulation to the market. Typically, hydropower is used partly to provide baseload power and partly to respond to the hour-to-hour variations in demand. Increasing the use of intermittent energy sources like solar and wind in the power system creates several challenges for the grid. We can address the problem with efficient and reliable balancing, as well as reserve markets. As a result, markets that are cleared after the day-ahead market, such as intraday or balancing power markets, may become increasingly significant for market participants' profitability [3]. Producers can benefit from more flexible hydropower output by increasing their profit margins. This flexible hydropower planning adds to the complexity of a hydropower producer's decision-making process, since decisions in one market may limit options in other markets [4]. From a technical point of view, all of the subsequent markets should be considered before bidding in the first market. Fast and reasonable decisions for hydropower producers on their bids is needed since trading of energy in intraday market and balancing power market is continuous [5]. Therefore, developing a model to predict the hydropower production in the Nordic power market can help hydropower producers to make the best decisions. Additionally, variable renewable energy sources (VRES) have increased their share in the production portfolio. It is important to know if increasing share of VRES production has affected hydropower planning and does the magnitude of this effect vary between different bidding areas? What implications this might have in the future?

Several optimization strategies for dealing with optimum system planning challenges have been published in the literature [6], [7]. These are often based on the traditional methods, such as classical mathematical programming methods (e.g., linear programming, dynamic programming, etc.) or heuristic algorithms. However, the aforementioned model-based methods can often be limited in a way that they cannot adapt to the continuously time-varying condition since they must solve the problem at each time step. This may hinder their usefulness for real-time decision making [8]. In recent years, data driven modelling has emerged as a method to simulate the behaviour of complex systems [9]. Actually, a dataset is used as a source of information for developing model. The model is trained based on the dataset and learns how to predict targets. Artificial intelligence methods such as fuzzy inference systems, artificial neural networks (ANNs) and support vector machines (SVMs) are increasingly employed as soft computing techniques to extract the complex hidden patterns between input(s) and output(s) parameters [10]. Simulating accurately the behaviour of the Nordic power market needs to implement an extensive and gigantic model. In this study we use AI to predict the hydropower production in the Nordic power market. The key contribution of this study is to use an AI model to answer the following research questions: (1) Can residual demand be used to (relatively accurately) estimate hydropower production in different bidding areas in the Nordic region? (2) Should other parameters such as inflow and reservoir level be added? (3) Has wind power production in Germany become a more significant factor for hydropower planning in Norway?

2 Material and methods

2.1 Case study

Nord Pool power market consists of different bidding areas in the Nordic (Finland (FI), Sweden (SE), Norway (NO) and Denmark (DK)) and the Baltic countries (Estonia (EE), Latvia (LV) and Lithuania (LT)). In the recent years, the power market area has expanded also to central European countries. Hydropower has historically had an important role in the Nord Pool power market. For example, in the Nordic countries, the share of hydropower is about 56 percent (2015–2019) of the electricity demand [11]. However, the share of hydropower in production mix varies significantly between the countries in the Nordic power market. Most of the hydropower capacity is located in Norway and in Sweden. In this paper, we concentrate on predicting hydropower production planning in the bidding areas in Norway, Sweden and Finland. In this regard, hydropower production planning is analysed at aggregated level within the bidding area. The analysis is limited to bidding areas located in the Nordic and the Baltic countries, Germany (DE), Poland (PL) and Netherlands (NL). Time series data used for deriving individual variables include electricity demand, wind power production, solar power production, hydropower production and reservoir level. Time series data is obtained from ENTSO-E transparency platform [12].

2.2 Multilayer perceptron model (MLP)

To estimate hydropower output in the Nordic power market, a three-layer neural network structure is designed. The input vectors are in the first layer; the hidden layer is in the second layer (this layer contains two nonlinear transfer function with 25 neurons for which *tansig* is used); and the third layer (output layer) has a linear function (*purelin* is selected for this layer), more details of the model in [13]. The statistical indicators (root mean square error (RMSE) and correlation coefficient (R)) are used to evaluate the method's prediction performance.

2.3 Scenario descriptions

Figure 1 illustrates different scenarios for each bidding area. To address the research question 1, the residual electricity demand is considered to be the input parameter. Figure 1 is divided into 10 different segments, representing the case study bidding areas in Finland, Sweden and Norway. Each segment includes 8–9 scenarios where we analyse the effect of system boundaries on the prediction accuracy. In the first one, we considered 8 different scenarios for Finland. In scenario 1, the RD for FI is the input parameter. Scenario 2 contains RD of FI and EE as inputs, and the same goes for the other scenarios. As mentioned before, the hydropower production is the target for the scenarios. The hourly residual demand $d_{r,h}$ is determined as follows in (1).

$$d_{r,h} = d_h - (p_{w,h} + p_{p,h}) \; \forall \; h = 1 \ldots 8760 \tag{1}$$

In (1), d is electricity demand, p_w is wind power production and p_p is photovoltaic production. The Electricity demand and the RES production time series for each bidding area in the Nordic power market are from ENTSO-E Transparency platform database [12]. Aggregated weekly reservoir level and hourly hydropower generation data for each bidding area was obtained from ENTSO-E Transparency platform database [12]. Furthermore, reservoir inflow data was not readily available, and thus it was estimated using weekly reservoir level data and hydropower generation data. The weekly inflows i_w is determined as follows in (2)

$$i_w = h_w + r_w - r_{w-1} \; \forall \; w = 1 \ldots 52 \tag{2}$$

In (2) h_w is the aggregated weekly hydropower generation and r_w is the aggregated reservoir level at the end of the week. Weekly reservoir inflow data is converted to hourly values using linear interpolation by preserving the entire reservoir inflow over the course of each week.

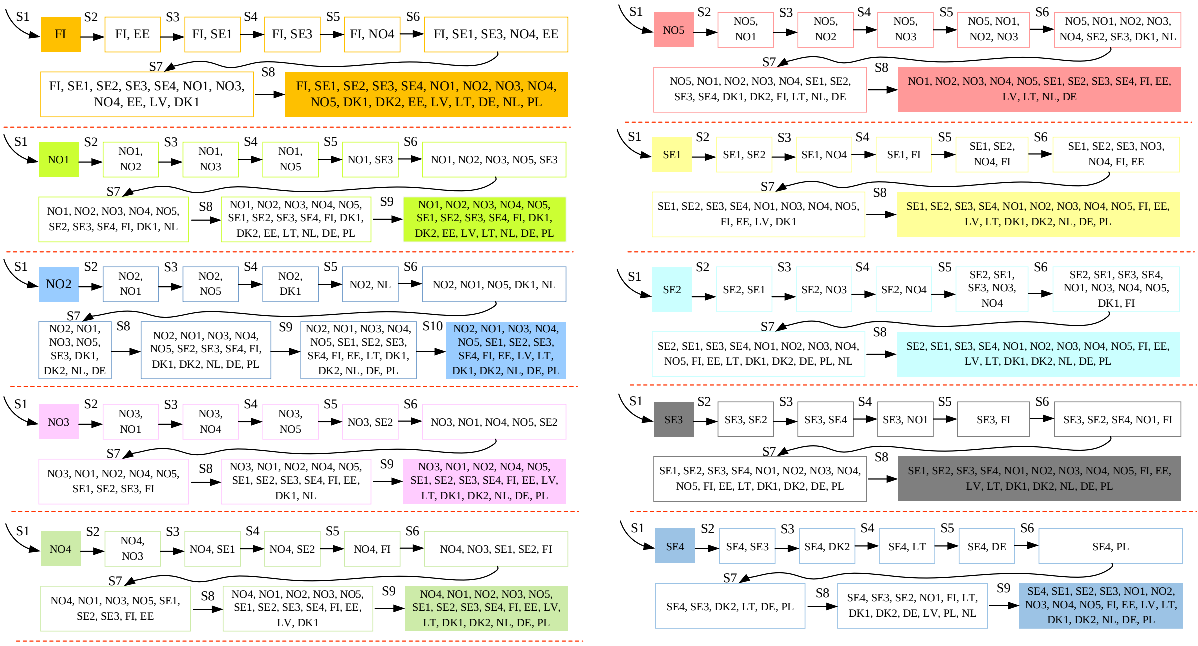


Figure 1 Various scenarios for different regions of Finland, Norway and Sweden. The ten segments. represent the case study bidding areas in Finland, Sweden and Norway. Each segment includes 8–9 scenarios where we analyse the effect of system boundaries on the prediction accuracy.

3 Results and discussion

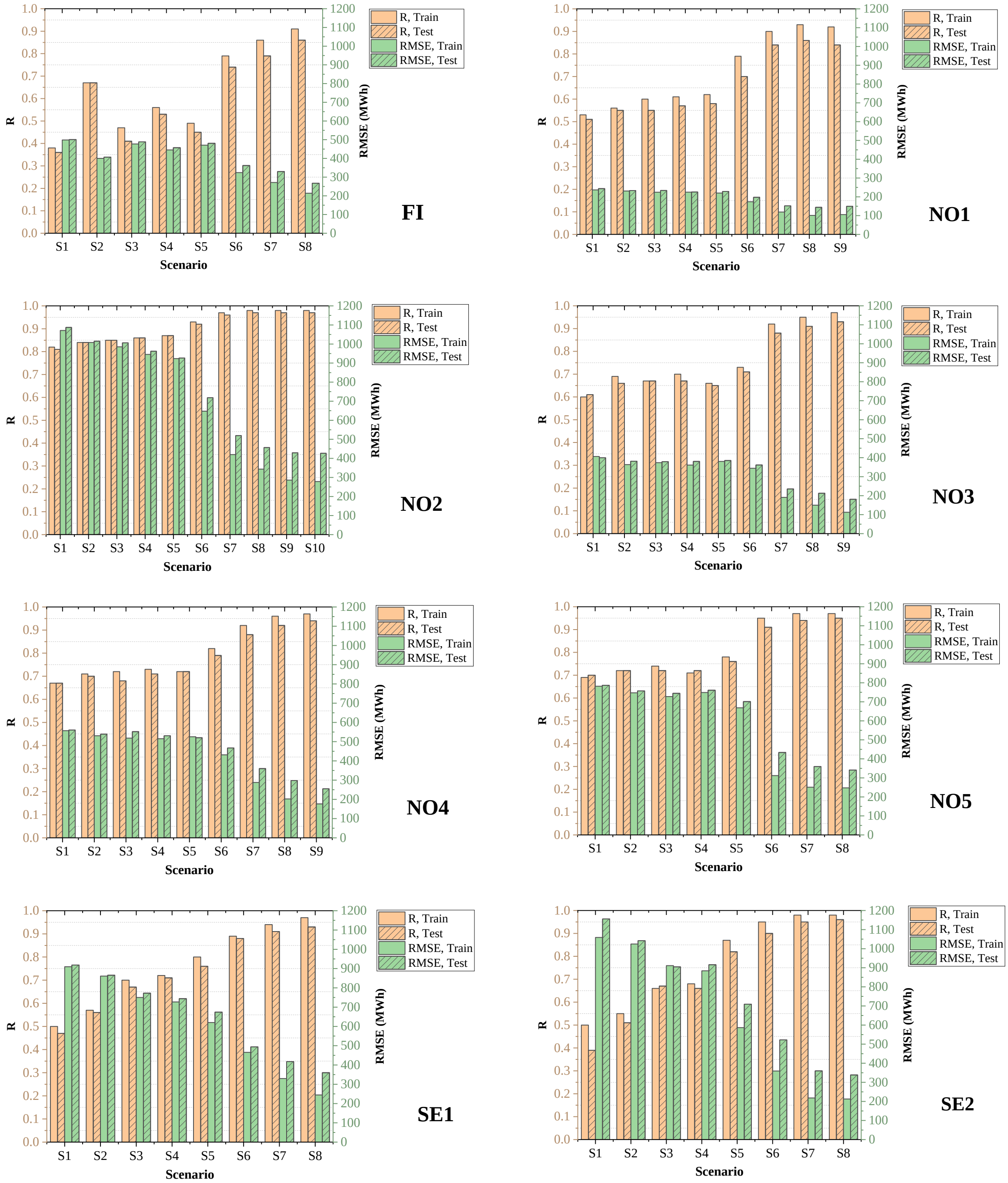
3.1 Can residual demand be used to (relatively accurately) estimate hydropower production in different bidding areas in the Nordic region?

We utilized residual demand (RD) (given in Eq. (1)) as an input parameter to forecast hydropower output in the Nordic power market to answer this research issue. We defined different scenarios for each bidding area, as presented in Figure 1. For FI, if we just utilize RD of FI as input parameter, R_{test} and $RMSE_{test}$ are 0.36 and 500.66 MWh, respectively, as presented in Figure 2. In scenario 2, we consider the RD of EE and FI as input parameters, and as presented in the figure, the model's performance prediction improves, R_{test}= 0.67 and $RMSE_{test}$= 406.89 MWh. This shows that the electricity exchange between bidding areas will affect the results, as Finland and Estonia have a strong interconnection. We can improve the model's performance prediction by include the RD of the other bidding areas, such as scenarios 6 and 7. Taking into account the RD of all bidding regions can significantly improve the model's performance prediction, R_{test}= 0.86 and $RMSE_{test}$= 267.25 MWh, scenario 8. Returning to the research question, the figure shows that by taking into account the RD of the other bidding areas, we may reasonably anticipate hydropower output in the Nordic power market, see the results for NO1-S9, NO2-S10, NO3-S9, NO4-S9, SE1-S8, SE2-S8, SE3-S8 and SE4-S9. Model’s performance varies between different bidding areas. Generally, including more individual variables (i.e. data from bidding areas) improve prediction accuracy. However, for some bidding areas (e.g. NO1) fewer individual variables are needed to improve prediction accuracy. This could mean that most of the hydropower production is used within that bidding area. Furthermore, export/import is less significant factor in hydropower planning in that bidding area. On the other hand, the model performs better for some regions than for some others. The reason is that for some regions (such as Finland and Sweden) run-of-river hydropower (RoR) and hydropower with storage were combined together. This may affect the results, since RoR is not as flexible, and hence the correlation with demand is not as strong.

3.2 Should we add other parameters such as inflow and reservoir level?

This research question was investigated by considering RD, inflow and reservoir level as input parameters of the MLP model. Figure 3 depicts the model's forecast accuracy for various bidding areas. As shown in the diagram, including inflow and reservoir level in the model can significantly aid in recognizing the nonlinear hidden pattern between parameters and predicting hydropower generation. For example, for FI-S1, R_{test}= 0.917 (for RD as input parameter R_{test}= 0.36) and $RMSE_{test}$= 216.61 MWh (for RD as input parameter $RMSE_{test}$= 500.66 MWh). For FI, the best scenario is S8, in which the MLP model can predict the hydropower generation with R_{test} and $RMSE_{test}$

as 0.973 and 124.42 MWh, respectively. Prediction performance of the model for the other bidding areas also demonstrates inflow and reservoir level have a pivotal role to predict the hydropower production. With residual demand we can have a good prediction for the timing of the hydropower production. However, by including inflow and reservoir level parameters, the model is able to produce better prediction for how much electricity is generated each hour. The best prediction is for the last scenario in each bidding region, when we have RD, inflow, and reservoir level for all bidding areas as input factors, as shown in the graph, see the results for NO1-S9, NO2-S10, NO3-S9, NO4-S9, SE1-S8, SE2-S8, SE3-S8 and SE4-S9. Again, there are differences between bidding areas. For some bidding areas just inflow and reservoir level are sufficient individual variables (NO1, SE3) for the MLP model to produce valid prediction accuracy for hydropower production. Furthermore, for some bidding areas (e.g. NO2) including individual variables from the whole market area will improve the model accuracy. This could mean that export/import is a significant factor for hydropower planning within that bidding area.



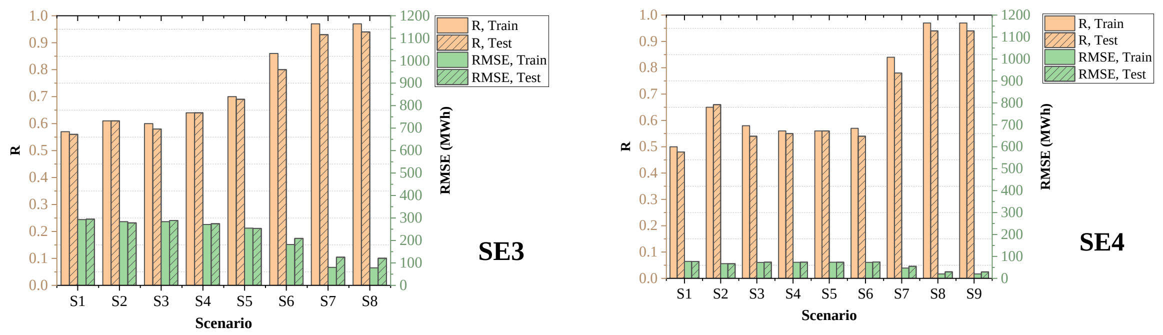
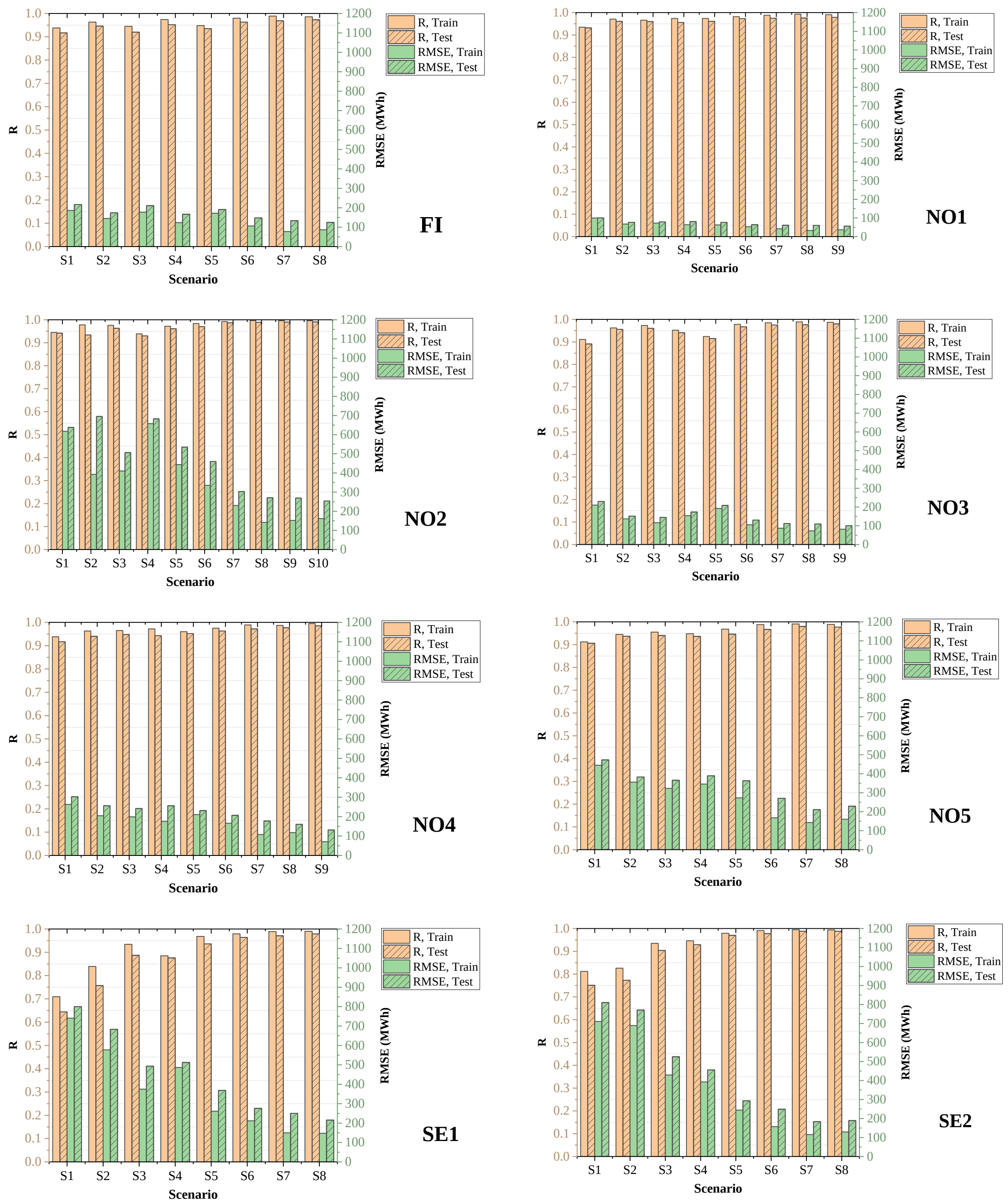


Figure 2 Research question 1-performance prediction of each scenario in different bidding areas.



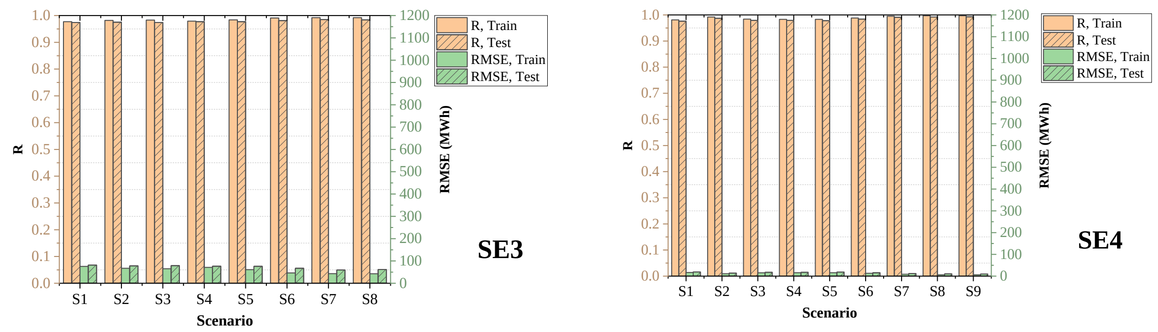


Figure 3 Research question 2, performance prediction of the model for each scenario.

3.3 Has wind power production in Germany become a more significant factor for hydropower planning in Norway?

This study issue is explored by two different scenarios: S1 is hydropower prediction in NO regions by RD of other bidding areas except Germany (DE), {'NO1'; 'NO2'; 'NO3'; 'NO4'; 'NO5'; 'SE1'; 'SE2'; 'SE3'; 'SE4'; 'FI'; 'EE'; 'LV'; 'LT'; 'DK1'; 'DK2'; 'NL'; 'PL'}. S2 also takes DE's RD into account as an input parameter. Figure 4 denotes the result of this simulation and compares two scenarios for different years. The statistical indicators show a higher accuracy for this prediction by considering RD of DE as input parameter. The results in NO2 are better than the other Norway bidding areas. This is due to the interconnection between NO2 and DE.

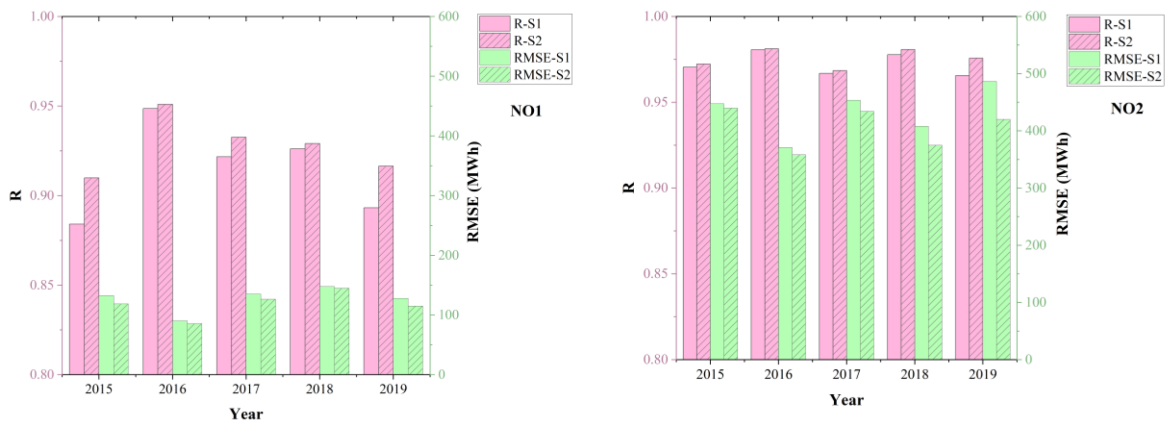


Figure 4 Performance prediction of the MLP model for hydropower planning in Norway, Scenario 2 (S2) includes RD of Germany (DE) as the input parameter.

4 Conclusions

In comparison to the rest of the EU, the Nordic nations have a larger percentage of renewable power production. Hydropower accounts for more than half of all electricity generation. In the current study, we developed an intelligent model (MLP) for predicting the hydropower generation in the Nordic power market. This research was carried out to attentively address the research questions. The following are the study's main findings: The residual demand (RD) by itself was discovered to be insufficient for hydropower planning in the Nordic power market. However, taking into account the RD of other bidding areas can greatly improve the model's performance prediction. It is noteworthy to mention that considering the RD as input parameter merely somewhat describes the state of the market. However, hydropower is a finite resource on annual level, and thus input from the production-site is necessary to accurately plan production. Therefore, we reconstructed the model by the RD, reservoir level and inflow as input parameters. The statistical indicators revealed that the model's accuracy in forecasting hydropower generation improved significantly. In addition, the impact of wind energy generation in Germany on hydropower planning in Norway was studied. The model had a better accuracy for hydropower forecast in Norway when the RD of DE was used as an input parameter. The NO2 results are better than for the other bidding areas in Norway, as NO2 and DE are interconnected. Robustness of the model to forecast the hydropower in confronting the increasing amount of variable renewable energy production in the Nordic power market was another contribution of this study. As the share of non-dispatchable generation increased (2015-2019), the model showed promising performance to predict the target. But the results showed that as the percentage of non-dispatchable generation increases, the model's forecast performance decreases.

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