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Estimating the value of power losses forecast in the transmission system by comparing different electricity procurement strategies

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***Abstract*—One of the main roles of the transmission system operators (TSOs) is to predict and plan the procurement of the active power losses in transmission systems. TSO can reduce operating cost using power losses forecasts and, in principle, the higher the power losses forecast accuracy is the lower are the TSO's operating cost. The paper continuous on our previous work where we describe the newly designed machine learning based tool forecasting power losses that has been implemented at the Croatian TSO. After more than a year of continuous everyday operation of the tool we now evaluate its real world performance and use its results in further analysis. To reap the benefits of accurate power losses forecast, the TSO has to choose a good strategy for procurement of those losses on the electricity markets. In this work we present an analysis of hypothetical procurement strategies. Electricity markets that consider in the analysis are Croatian day-ahead, intraday and balancing markets. The baseline procurement strategies are procurement on single markets, while advanced strategies combine all three markets for lowest cost. Special attention is given to the imbalance market, as the differences between maximum and minimum price are very large. The use case for the presented analysis is Croatian TSO, but most of the analysis should generalise well to other TSOs. Our analysis shows that the value of forecast is greatly influenced by the market rules. The value of a forecast is much larger in two-price imbalance systems as compared to one price imbalance systems.**

***Index Terms*—forecast, power losses, energy markets, transmission system operator**

I. Introduction

In many countries, the Transmission System Operator (TSO) is responsible for covering the cost of power losses in the Transmission System (TS). This type of regulation is also valid in Croatia, where the Croatian Transmission System Operator - HOPS (Croatian: Hrvatski Operator Prijenosnog Sustava) is obligated by Croatian "Law of electricity market" [1] to purchase all power losses that occur in the Croatian transmission system in electrical energy markets. Exactly what strategy they employ to achieve that goal is not specified in the regulation except that it should be done transparently and without bias. It is generally assumed that having accurate forecasts reduces the financial costs as well as the uncertainty of the financial costs. The real data driven research on developing a prognostic tool that would automatically create short term power losses forecasts for HOPS began in 2019 and resulted in development of a machine learning based tool production implementation in HOPS everyday operations. At the time we could only use simulations to predict how useful the tool would ultimately be. Now, after almost two years of the tool continuous everyday operation and usage in HOPS, we evaluate real-world usefulness of the tool. We explore two aspects of usefulness: forecast error and financial savings. The forecast errors are straightforward to calculate, but financial savings are not. Financial savings depend on the forecast error, but also on other parameters: different electricity market prices and HOPS procurement strategy, but also Croatian rules and regulation. Intuitively one would expect to calculate financial gains coming as a result of the new and superior losses forecast tool. We found, however, that in current Croatian market price setup there is little to no financial gain of accurate forecasts, even if one would have access to perfect forecasts. Despite no direct financial gain, it is an obligation by Croatian law [1] that the effort has to be invested in order to reduce the imbalances. In that respect, having accurate forecasts has benefits, but they are not easy to quantify. In order to try to quantify those benefits, we introduce a simulated and hypothetical framework that has a two-price imbalance system, like those of Nordic countries [2]. That is, we calculate financial benefits in a demonstration regulatory system as if Croatia did not have one-price but two-price imbalance system. This type of system is shown to stimulate well thought out participation in balancing markets [3].

The rest of the article is divided as follows: In Chapter II, we describe data sources we used for our analysis along with the methods we used for data cleaning. In Chapter III-A we analyse losses forecasts errors for baseline forecasts and for our own forecast. In Chapter III-B we propose several trading strategies and calculate the financial benefit each strategy would yield. In Chapter IV we conclude the paper and propose future work.

II. Input data

To create the presented research, 5 data sources were needed. In this chapter we describe all data sources and data cleaning methods used where it was necessary. All data reading and manipulation was done in programming language python [4], using the pandas package [5].

A. Losses measurements

This is the central data source from which all the described research started. HOPS has an internal data warehouse where all historical hourly losses measurements are stored. The available historical data is stored from 1.1.2018. till present. This data was considered as the ground truth for training our machine learning (ML) tool. With the exception of a few data points in the first year, this data source is very clean and reliable. The first two years were used for baseline strategy average persistence in Chapter III-B. The second two years were used as a ground truth to estimate errors of our tool. Total losses in Croatian transmission system are indirectly measured as the difference between all generation/import and all consumption/export. Since there were no errors or missing values in the last two years, no data cleaning was used for this data source.

B. Cropex market data

This data source is official day-ahead (DA) prices and intraday (ID) prices from Croatian Power Exchange (CROPEX) [6]. This data source is publicly available. For the intraday prices the volume weighted average price was used. The data source is without missing values and outliers, so no cleaning of data was used.

C. Imbalance price data

The data for imbalance prices in Croatia was obtained from Transparency platform of ENTSO-e [7]. This data source is publicly available (only the registration on the webpage is needed). The data source is without missing values and outliers, so no cleaning of data was used.

D. Currency exchange rates data

The day-ahead and intraday prices are expressed in Euros (EUR), but imbalance prices are expressed in Croatian kuna (HRK). To compare the two, we converted imbalance prices to Euros. Because the exchange rate varies, daily exchange rates were obtained from the webpage [8]. The data is publicly available and no cleaning of data was needed.

E. Losses forecast data

This data source is the result of everyday losses forecast generation of our tool [9] that uses only the historical losses measurements as input. The observed forecast is generated once per day in the morning, in time for that information to be used on the day-ahead market (that closes by noon every day, for tomorrow) It should be noted that this is real-world data. If there was some technical error with any part of the data pipeline, the resulting forecast is of high error or even nonexistent. This degrades the forecast performance. Although we could have run the prognostic algorithm again and improve the performance, we have kept the errors, because they represent real-life performance. The only improvement of the forecasts that are done, are available to the HOPS operator in everyday operations. We employ two data cleaning techniques. The first is filling missing values with week-persistence values. That is, if there is a missing value in the forecast, we use measurement from the last week as a forecast. This technique is one of the baseline forecasts described in Chapter III-A and one of the baseline strategies described in Chapter III-B. This method was used mostly from 1.1.2020. to 1.8.2020. when our tool was in the testing phase so many days were missing from the dataset. Second data cleaning technique we employ is outlier detection. The property of losses time series is that it does not have sudden jumps or falls. If the jump/fall in one hour is by 25 MW different from the average of the last 5 hours, we declare it an outlier and delete the value. The value is then again filled with the first data cleaning technique. This method is relevant only for the February of 2020 when there were such outliers. To conclude, datasource quality is good from August of 2020 onward, and before we did a lot of data cleaning.

III. Results and Discussion

A. Forecast accuracy

Our forecast accuracy is assessed in comparison with two baseline forecasts. The first baseline forecast is the most naive average persistence. Average of measured losses is calculated for the period of 1.1.2018. - 1.1.2020. The resulting value of 57.55 MW is used as a forecast for all hours. Second baseline forecast is week persistence. For each hour the forecast is equal as the measurement in the same hour of the previous week. For example, if we want to forecast losses for this Wednesday at 19:00, we will use the value of the measured losses on previous Wednesday at 19:00. This is a more advanced baseline because it incorporates regularities in weekly losses. Perhaps surprisingly, it is even better baseline than the day persistence baseline (in which we always use yesterday's measurement as a forecast). Since we are interested in financial value of the forecast, we want to use linear error metric. MAPE error [10] is used, because it is a standard linear metric used internally in HOPS. Figure 1 shows comparison of our forecast with the two baseline forecasts. All graphs are made in matplotlib package [11]

The error is calculated for each hour, and then averaged for each month of the observed time interval. The first conclusion

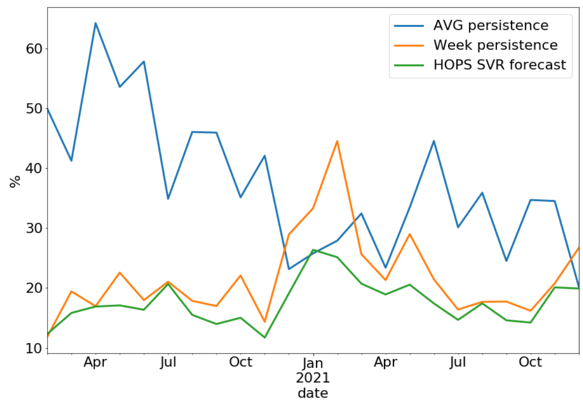

Fig. 1: Comparison of MAPE between baseline power losses forecasts and tested machine learning based power losses forecast for each month.

is that our forecasting strategy outperforms both baselines. The second conclusion is that both week persistence and our forecast has higher errors in late 2020 and early 2021. This high error corresponds with high power transits through Croatia. In these months our prognostic model has an error that is unacceptably high, and in the other months, our prognostic model is sufficiently accurate. It is noteworthy that the forecast error is slightly higher in this real-world test than it was in our simulations [9]. One of the reasons can be considered a lesson learned: the losses measurement database was not designed as a real-time database. This results in unreliable data for the first few hours after real time. When we performed the machine learning training, we treated the database as a real-time database. So the data-driven model learned to rely on the last hour measurement that was available to it in the simulations, but in the real-world the input data was unreliable.

B. Trading strategies

Besides reduction of MAPE, we are interested in how much value does our forecast provide. The value is not depended only on forecast accuracy, but also on the trading strategy, so we explored multiple strategies. The markets considered are Day-ahead market, Intraday market (with volume weighted average prices) and imbalance "market". Long-therm markets are out of scope of this paper, primarily because of lack of available public data on the prices. For the imbalance "market", quotations are used, because no imbalance markets with varying prices exist in Croatia yet. Instead, the price is calculated based on day-ahead price. If caused imbalance is in the same direction as the total system imbalance, price paid is 30-40 % higher than Day-ahead market price. Conversely, if caused imbalance is in the opposite direction as the total system imbalance, price paid is 30-40 % lower than Day-ahead market price. Exact percentage varies between hours and it depends on the ratios of types of reserves activated. All strategies explored in the paper are described below.

1) Strategy DA: This is idealized baseline strategy assuming the perfect losses forecast is available and all electricity is procured on Day-ahead market. Since the forecast is perfect, no error correction is needed on ID or imbalance market.

2) Strategy ID: This is idealized baseline strategy assuming the perfect losses forecast is available and all electricity is procured on Intraday market for volume weighted price. The variation of prices in each hour is large for ID market, with minimum and maximum prices often double or half the volume weighted price. However, one cannot rely on this prices as it could be only a small fraction of needed volume. For this reason, the min and max ID prices are ignored in this work. Since the forecast is perfect, no error correction is needed on imbalance market.

3) Strategy Imbalance: This is baseline strategy that assumes no forecasts of the power losses or the markets prices. It is the strategy in which no electricity is purchased on the DA or ID markets and acquiring all of the electricity on imbalance market. This strategy is discouraged by the legislators, but as it will be shown, not discouraged financially by the market rules.

4) Best of multiple markets strategies: This set of baseline strategies assumes perfect forecast of power losses as well as perfect forecasts of individual market prices. For example, if prices on the Day-ahead and Intraday markets are known, the strategy is to acquire energy for each hour in the market with lower price. This will result in better performance than any of the single markets. The more markets we include, the better performance can be expected. The best performance is expected when combining all three considered markets: Day-ahead (DA), Intraday (ID) and Imbalance (BA).

5) Worst of multiple markets strategies: To contrast best of markets strategies, we included also worst of markets strategies as a worst case possible. These strategies serve not as a goal, but as a crude measurement of risk. Without perfect market forecasts, if one attempts to profit from choosing the optimal market, some errors will inevitably arise, and the price paid will be higher than any other market individually. It is important to be aware how much worse off one can maximally be by combining different markets.

6) Persistence strategies: Two realistic baseline strategies based on persistence are included in the analysis. Each strategy corresponds to baseline forecast described in chapter III-A. Average baseline strategy consists of buying on DA market the amount predicted by average baseline forecast. The error is corrected on the BA market. Similarly, week persistence strategy consists of buying on the DA market the amount predicted by the week persistence forecast. The error is also corrected on the BA market.

7) Strategy HOPS SVR: This is a realistic strategy that consists of buying on the DA market the amount predicted by our forecasting tool based on machine learning algorithm Support Vector Regression (SVR). The error is corrected on the BA market in the same way as realistic baseline strategies.

The described strategies are tested on an hourly base and the results are grouped by month. Figure 2 shows some expected

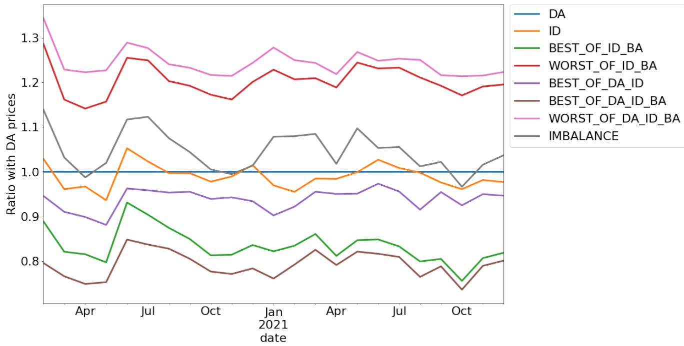

Fig. 2: Financial cost per month of power losses different procurement strategies, relative to DA cost.

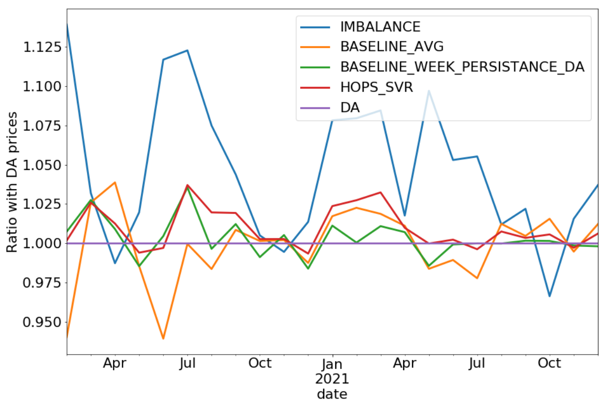

Fig. 3: Financial cost per month of power losses different procurement strategies, relative to DA cost.

and some unexpected results for time period 1.2.2020. - 31.12.2021. It is expected that choosing always the lowest of the available prices leads to best financial outcome - strategy: best of DA, ID and BA. If we remove the balancing option, the financial outcome worsens, but still remains better than single market (DA). The unexpected result is that imbalance (BA) strategy is in some months better than Day-ahead (DA) strategy. This creates the wrong incentive for all suppliers to not buy anything on the DA markets and to wait for the imbalance. This result indicates that in some months there is financial incentive to deliberately increase imbalance volume. This general effect can be seen on power losses example in figure 3, where there are 5 strategies that use progressively sophisticated power losses forecasts. Imbalance strategy does not use any forecast, baseline strategies use simple forecasts, SVR uses sophisticated machine learning forecast and DA uses idealized perfect forecast. One would expect that financial gains improve with each improvement in forecast accuracy, but this result is absent. In some months, the least accurate forecast (imbalance) is better than the perfect forecast (DA). Additionally, imperfect SVR forecast outperforms the perfect DA forecast in some months. In essence then, better power

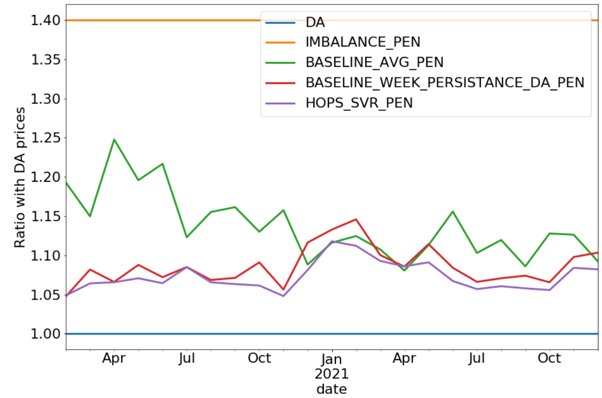

Fig. 4: Financial cost per month of power losses different procurement strategies in simulated penalization imbalance system, relative to DA cost.

losses forecast do not provide direct financial value to HOPS. However, HOPS is obligated by law to try to reduce imbalance. Better forecast, therefore, provide value of following the law, but it is hard to quantify that value.

In order to attempt to quantify that value we now create a simulated two price system for Croatian market. The inspiration comes from observing how some other countries solve this particular problem. There are multiple solutions and some countries, i.e. Nordic countries, create two price balancing system. In contrast to Croatian regulation, this two price system ensures that market participants are never rewarded for inaccurate purchase on DA markets.

The simulated system is constructed with the goal of penalization of every error in the forecasts. It is constructed so that all energy on balancing market is 40 % more expensive than on DA market, regardless of the situation of the system, i.e. regardless of is there a surplus or deficit in the system, the price is 40 % higher than on DA market.

Figure 4 shows the prices in a simulated system. All strategies that have "PEN" suffix are obtained in this simulated system. First example of this strategy is "IMBALANCE_PEN" strategy. In this strategy no energy is bought on DA or ID, and all energy is covered in penalization balancing market. As expected, since the price is always 40 % higher than DA, in the figure normalized to DA, the result is a horizontal line at 1.4 the DA price. Note that DA and DA_PEN strategies are equivalent since idealized perfect forecast is used and no error exists to be corrected on imbalance.

This result on figure 4 display much more desirable characteristics. The perfect forecast DA now always has the best financial outcome. We also see that other forecasts improve with their increase in complexity. The most simple average forecast is the worst. The more sophisticated forecast that repeats last weeks measurements is better, with our machine learning model showing the best overall results. In February, April and July of 2020. it can be seen that week persistence

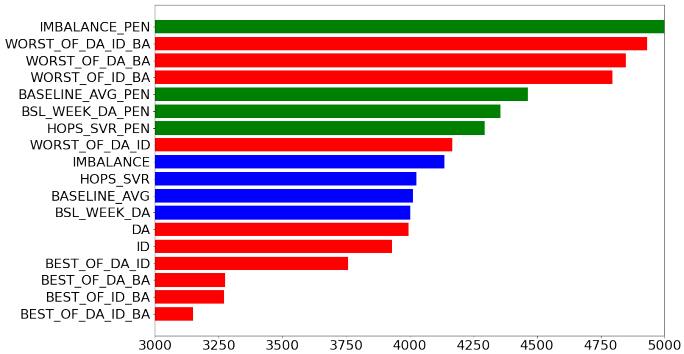

Fig. 5: Average hourly cost of losses procurement for all different realistic baseline strategies (blue), idealized strategies (red) and strategies in simulated framework (green).

forecast and our method have the same error. One of the reasons for this is because in those months we filled our missing data with week persistence (more details in chapter II-E).

Figure 5 shows average hourly cost of power losses procurement for all strategies described in this work. Strategies that are realistic are shown in blue color, strategies that require perfect forecast are shown in red color and strategies that are in the simulated penalization framework. The axes have been deliberately reduced to omit strategy "IMBALANCE_PEN", because its high value of 5592 € obscures the nuances of other strategies. Absolute best strategy requires perfect forecasts of all markets (DA, ID, BA) and of power losses. This strategy on average generates value of 844 € (21 % of total cost) per hour when compared to DA strategy. It is clear that the most value is generated by having perfect imbalance forecast. If we exclude this best BA forecast, the next best strategy requires perfect forecast from DA market, ID market and power losses market. This strategy on average generates value of 236 € (6 % of total cost) per hour when compared to the DA strategy.

In the framework of this penalization system the estimation of the value of power losses forecasts is conducted. The final result is that in the framework of simulated penalization system: strategy based on our SVR forecast on average generates 60 € (1.5 % of total cost) of value per hour when compared with best realistic baseline of week persistence. When the strategy based on our forecast is compared to strategy with perfect forecast (DA), the conclusion is that additional value of 300 € (7.5 % of total cost) per hour is possible with perfect forecast power losses forecast. From the average MAPE of SVR forecast (17.5 %) it can be calculated that each percentage of error reduction in the forecasting is on average worth 17 € per hour. This information is important for future work, because it quantifies the value from improved power losses forecast.

IV. Conclusion and Future Work

In this work the analysis was conducted of the performance of the machine learning based tool for forecasting power losses that operates in real world conditions. The tool performance is on acceptable levels for all months except winter months of high transit in Croatian TS. Additionally, to explore direct and indirect value of forecasts, multiple procurement strategies were created and their value calculated.

The simulation of two-price system was conducted to quantify indirect value that the power losses forecast generate. The value is indirect because there is no direct financial gain, but there is value in following the legislature.

In the future the research is planned to be expanded on several different paths. The first path is improving the machine learning algorithm so that the errors are lower in the winter months. This will require forecasting of high transits in the Croatian power system that are available for intraday trading and not for day-ahead as the current tool is setup.

The second path is creating a machine learning system that tries to lower the cost of electricity procurement by utilising the best strategies explored in this work. This path of research will surely have to include intraday trading in more depth than just volume weighted average.

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