Short-term transmission system losses forecast based on supervised machine learning

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***Abstract*—Although active power losses in transmission networks are not significant in percentage, especially compared to the distribution networks, they constitute a major expense for the system operators. Predicting these losses and procuring them in a most feasible way becomes of out-most importance. The paper discusses the importance of short-term active power losses forecasting of different scales and proposes a model based on supervised machine learning to tackle the issue. Support vector regression method with weather forecasts as input data is validated on Croatian Transmission System Operators (HOPS) data, showing significant improvements as compared to business-as-usual approach. The developed model is integrated into a software tool and deployed at HOPS.**

***Index Terms*—active power losses, short-term forecast, supervised machine learning, transmission system operator**

I. Introduction

Since the liberalization of electrical energy markets, most of electrical energy is bought and sold on the markets. It is a general empirical rule that the earlier one buys electrical energy, the less the average price will be. For various technical and financial reasons the majority of the electrical energy traded through power exchanges is bought and sold one day in advance on the day-ahead markets. Most of these markets still operate on an hourly trading intervals. This implies that the demand for electrical energy needs to be predicted on an hourly resolution at least 12 hours before the actual delivery, which clearly points to the value of accurate forecasts for both production and consumption. The advantage of controllable power plants is that they can easily adjust their production and correct any forecast errors if needed. This reduces the significance of forecasting their generation. It is more important, but also more difficult, to forecast uncontrollable power sources, especially wind and photovoltaic power plants, because of their continued increase in the energy mix. On the consumption side, forecasting the load receives the most focus, especially the low voltage distribution. Higher voltage consumption is usually easier to predict, while the complexities and challenges raise as we move towards the end-users in the low voltage networks. In this sense, weather forecasts, especially the temperature, which is the easiest meteorological parameter to predict, play a role in the forecasting of the load.

The Transmission Systems Operator (TSO) needs to ensure secure and stable operation of the entire system; this means that, in addition to the above mentioned data and predictions, it needs to ensure procurement of non-frequency services and power losses. Accurately predicting quantity and optimizing the source of service provision can result in lower cost for the TSO and higher overall social benefit. It needs to be emphasized that both prediction and optimization is in reality conducted on multiple time steps preceding the actual need for the service and that trade-off of service cost and prediction forecast is the key in minimizing the total TSO cost.

In this paper we address the problem of short-term active power losses forecasting, while the market aspect of procuring them is outside of the scope of the paper. However, we believe that the methodology and the logic presented here can be easily extended to other services and their market procurement.

To systematically address the problem of forecasting the active power losses (in further text: losses) one has to solve a problem of creating a power flow forecast of the entire transmission system. Inputs to the power flow forecast are forecasts of all generation, consumption and cross-border transits. It is clear that the complexity of such a forecast is much greater than any other forecast related to power systems. To the best of authors knowledge there is limited research focusing on transmission system losses, especially those capturing the full complexity behind the problem. As one of rare papers in that area we recognize the work in [1].

The complete solution, as described in [1], is to create a forecast of power flows in all of the power lines. To create a forecast of power flows, one has to start with a separate generation forecast and load forecast. Not only the total generation and load has to be forecasted, but generation and load forecast has to be produced for every node of the transmission system. To complete the input parameters for power flow calculation of a transmission system, one has to create a power transit forecast, for generation and load that is not included in the nodes of the transmission system being observed. The next step is to create a topology forecast. Once

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topology and all the generation and loads are calculated, power flow calculation is done. From the historical measurements, the relation of power flows and active power losses for each of the powerlines is inferred. Finally, using that relation and the forecasted power flow through the powerline, one calculates the active power line loss. Similar procedures can be done to find losses in the nodes from the historical data and power flows calculation.

This complete procedure requires a tremendous amount of input parameters, many of which have to be measured in real time. The infrastructure for such data availability is costly, and that cost is not justified by the savings from a more accurate losses forecast alone. Since this is not the only advantage from digitalization of transmission systems on the required scale, it is likely that in the future the required data will be available which will result in the possibility to implement the described procedure in reality.

In the absence of full data availability, most of the research focuses only on specific aspects of the active power loss forecasting problem. An example of that is recognizing and selecting only influencing variables from the available data and creating forecasts only based on that; a good example of that is using weather condition data. There are two main reasons for this: the weather conditions impact the generation and consumption in general (also their forecasts), but also the same power line flow can create different power losses under different weather conditions. By far, the most important weather condition for losses is the presence of water on the power lines and transformer nodes. Thus, high humidity and rain [2] increase the losses. The effect is even greater if the water is frozen. The frozen water can be in many forms: frost, snow, solid ice [3], hoarfrost [4]. Even without the entire model of the transmission system, the authors of [5] have shown that by tracking what percentage of transmission system is under the relevant humid and icing conditions, one can increase the accuracy of the losses by a considerable amount. Additional meteorological parameters are also important for losses forecast, however, their impact is less pronounced: wind, air temperature [6] and sun irradiance. Besides the meteorological parameters, power flows intensity influence the active power loss. We have already discussed the difficulties in performing power flows forecasting, but [7] and [8] cleverly sidestep the full power flow forecast by looking only at the cross border trade. Because the increased cross border trade increases power flows, the losses increase. They show that they can use the cross border trade contracts to improve the losses forecast.

The paper focuses on the currently available data for creating a tool to predict power losses in the Croatian transmission network based on real data obtained from the Croatian Transmission System Operator (HOPS). Future work will focus on expanding the model and the accuracy of prediction by including newly available data. In this sense, the work presented here can be regarded as the initial step in organizing and processing vast amount of data for the purpose of improving HOPS forecasts and therefore the operation of the Croatian transmission system. We here present the results obtained so far.

The paper is organized as follows: In Section II-A the current standard operating procedure of forecasting losses in TSO is described. Section II-B describes available input data for machine learning algorithm and Section II-C describes the selection of algorithm itself. Criteria for the developed model evaluation are discussed in Section II-D. In Section III the results of the research are presented after which in Section IV the argument is concluded and future work is discussed.

II. Methodology

A. Standard procedures in HOPS and forecast requirements

As stated, many TSOs, including Croatian transmission system operator - HOPS (*from Croatian: "Hrvatski Operator Prijenosnog Sustava"*) have a legal obligation to cover the costs of losses. To cover the cost at the lowest price, the TSO participates in multiple electrical energy markets. The most important market for this paper is the Cropex (Croatian power exchange) day-ahead market [9]. The rules are similar to many European day-ahead energy markets (like Elspot of NordPool). The price setting at Cropex day-ahead market is a two-sided, uniform price auction, where the system price is given as the intersection between the aggregate supply and demand curves. Hourly bids have to be submitted by noon for every hour of tomorrow, i.e. from 12 hour into the future to 36 hours into the future. From the fact that the bids on the market are on hourly timescale, it is concluded that the forecast has to have hourly granularity i.e. the forecast has to predict how much of the losses will occur at each hour. The horizon of the forecast has to be 36 hours at minimum (from noon today to midnight tomorrow). The granularity and time horizon for which the forecast is generated can be different (e.g. for longer periods), however, this depends on the procedures and requirements by the user. The error in the forecast causes the mismatch in bought and used electrical energy, so the TSO has to pay the balancing cost or cover the difference in some other way. On average, this balancing cost or other solutions are more expensive than the day-ahead price, so it is of financial interest to have the smallest error possible.

The current standard procedure in the HOPS system operation department for creating forecasts relies on the similarity of losses in the similar weather conditions. The procedure is done manually by a human expert with the assistance of the software NetVision DAM [10]. The software can combine some historical data with the current (or planned) network topology. However, as the main purpose of the software is not to forecast losses, there are some drawbacks. The software does not take into the account changes in meteorological parameters, unplanned power flows and is blind to some parts of the grid. Additionally, it is not automated, so every morning at 9 AM human experts have to manually configure the software. Although this procedure yields only an 3 $\%$ error aggregated for the whole month, if viewed as an hourly forecast the average error is between 15 $\%$ and 25 $\%$. Since the market bids are hour based, the latter, higher error will be transferred to the market bids errors.

B. Data availability and data preparation

For the reasons mentioned in Section II-A we set out to create a new software tool for automatic forecasting of losses. The schematic of the software tool data flow is shown in Fig. 1. The first step was considerable data analysis and data validation. There are two main sources of input data. The first one is the TSO's historical data warehouse (DWH) accessible through the IBM Cognos Analytic reporting system that contains the measurements from the transmission system. Among other data, the DWH contains historical data on the hourly losses. These hourly losses are not measured directly, but calculated by subtracting all outputs to the TS (consumption, export...) from all inputs to the TS (generation, import...). It is calculated as a single number for the entire transmission system. Given the high quality of the data, no extensive data preparation was needed.

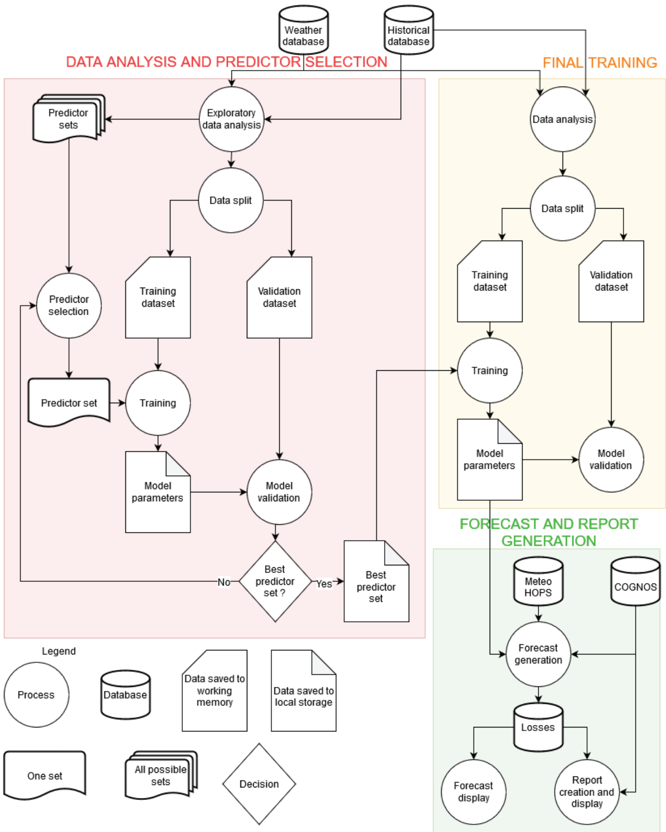

Fig. 1. Schematic of the software tool data flow.

The second source of data is the TSO's local weather database that contains the TSO's weather measurements and NWP (numerical weather prediction) forecasts, specifically the meteorological forecasting model WRF [11]. WRF forecasts are calculated every 6 hours, so the WRF database has new meteorological forecasts every 6 hours starting from midnight UTC each day. The weather measurements are available in real-time. There is a huge number of meteorological parameters which include measurements and forecasts. To select which of these parameters influence the losses, linear correlation analysis was done correlating losses and all of the meteorological parameters. The ones that had significant correlation were selected as predictors - inputs to the machine learning model.

C. Algorithm selection and implementation

Since the exact modeling of the problem required much more data than was available, the problem of losses forecast was tackled with machine learning. Machine learning tools are comparatively old, dating to the 1950s. The methods have gained much more popularity in recent years due to more computing power and more data availability. In creating a machine learning model, the exact instructions are not explicitly programmed into the software. Rather, the algorithm is data-driven and we say that the algorithm learns from the data, hence the term machine learning. There are multiple different types of machine learning, but for forecasting, the type of machine learning most commonly used is supervised learning. In this type of machine learning, we split the data into two parts. One part is used for training and another part is used for testing. In the training phase, we supply the algorithm both the input data and the expected result. In this manner, the algorithm can ”learn” the relation between input data and actual result. Thus we create (or train) our forecasting model and we can use it to make the predictions. In the operation phase, we supply the model with the input data, but not the expected result. The model now generates the result from the relation between input data and expected results it learned in the training phase. In our case input data was weather forecasts for the forecasted hour and historical technical losses. I.e. value of losses in the same hour, but yesterday, or the day before. The expected result, in our case, was the actual value of technical losses for the observed hour. The name supervised learning can be a bit misleading, it comes from the training phase, where the training ”supervisor” is the actual data. When selecting the machine learning algorithm for some specific application one has to pay attention to specifics of the problem. In our case it was the large number of predictors and the importance of interpretability. Interpretability is always important to consider when dealing with transmission systems. Large number of predictors could be avoided in future work as more granular data becomes available. However, in the current model, we forecast losses of the entire TSO in the same model, therefore, all weather predictors have to be in the same model. Because of these reasons we didn't resort to artificial neural networks or deep learning, but remained at classical machine learning. Our problem is suited for supervised learning, and since we try to predict a number it, we need to use the regression subtype. There are different options in this domain, but we chose support vector regression [12] for its interpretability, efficiency and speed of execution. Support vector regression is a modification of a much more common algorithm that is used for classification: Support vector machine. In our case, the support vector regression (SVR) was implemented in *Python* programming language [13] using the machine learning library *Scikit-learn* [14]. As discussed before the model has a large number of predictors. For this reason we were limited to the use of a linear kernel. However, this also means we could not use the full potential of the method. Still, the obtained results were sufficiently better than the baseline to stop our search for a better algorithm. We decided to train 72 models, one for the forecast 1 hour into the future, another for forecasting of losses 2 hours into the future, and so on until we train one model for forecasting 72 hours into the future. The next step after selecting the algorithm was selection of predictors, i.e. the input data we will feed to the algorithm. We used two types of predictors: historical losses data and weather forecasts as described in Section II-B. For the predictors from historical data, we exploited the fact that losses values often follow a daily cycle behavior. Because of this, we chose to have predictors the values from the same hour, but yesterday, i.e. 24 hours into the past. We sometimes denote this as t-24 (from time – 24 hours) or d-1 (from now – 1 day). Similarly, we chose d-2, d-3 and w-1 (from now – 1 week) values of losses for predictors that are values at the same hour but 2 and 3 days ago respectively. Another fact we exploited is the fact that losses typically change slowly. We therefore used the last measured value of losses as a predictor. We show the importance of these 5 predictors as a function of forecasted hour in the figure Fig. 2.

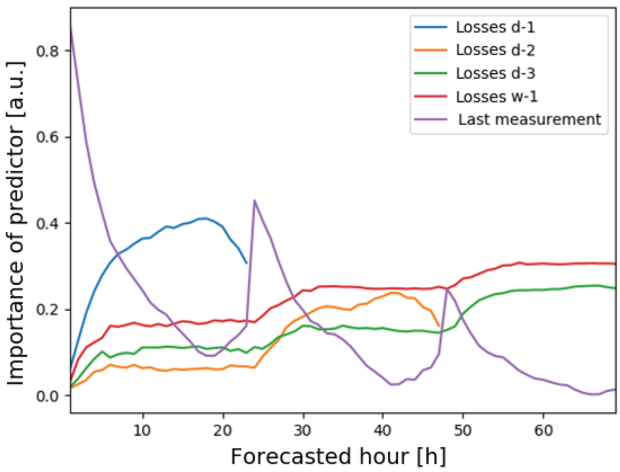

Fig. 2. Importance of historical predictors.

Predictor "last measurement" was more important in the first hours of forecast than in the later ones, because of the slowly changing nature of losses. Note that predictors d-1 and d-2 are not available to us after one and two days respectively. Introducing weather forecast parameters as inputs improves the losses forecast, but increases the complexity of the model. Thus a balance has to be found in improving the results without overwhelming the model. This was done by evaluating model performance with and without certain parameter to test its importance. We used snow, wind speed, air pressure, air temperature, rain, air humidity and dew point temperature. Additionally, most of the parameters forecasts were at multiple locations scattered around Croatia. Thus we accounted for weather changes on the entire Croatian TSO. In the end we selected 33 weather forecast parameters as predictors. Together with 5 predictors from losses history, we thus used 38 predictors.

Duration of the training phase was roughly 20 minutes for each model on an Intel dual-core i7 CPU. Since we trained one model for each of 72 hours, total training time was roughly 24 hours. Testing phase is only a few seconds long in total.

D. Model evaluation

The model accuracy evaluation was performed to test the validity of the model. Because the model is data-driven, care has been taken to train the model on one set of data and then to evaluate the model on a different set of data. The purpose of this split of the data is to evaluate if the model has learned the general patterns of relations between input predictors and losses forecast. It is possible the model has learned only the specific relations of the training dataset. If that were the case the model would perform poorly on the different set of data. We call this type of model over trained. On the other hand if it performs well on a different set of data, we say the model is general.

We used two different method test-train splits of the data. The first split randomly selected 80 % of the data for training and 20 % of the data for validation. Advantage of this test-train split is that it encompasses all months from the available dataset, and with it all available weather conditions. The drawback is that the model is possibly over-trained and would perform worse in system operation. This is because of high correlation between neighboring hours. Thus, this data split gives us an optimistic view of model performance.

The second data split is chronological. Everything before a certain date is a training set of data and everything after that date is the validation set of data. Since not all available months are used, and thus, not all weather conditions are used, the model will perform worse in validation than in system operation. Thus, this data split gives us a pessimistic view of model performance.

We expect the actual results in system operation to fall somewhere between optimistic and pessimistic model evaluation.

In choosing the accuracy metric the main purpose of the forecast has to be taken into account. In our case, the purpose is trading in the electrical energy markets. Therefore, a linear difference between the true and the forecasted value is desired in the metric of accuracy. Among those accuracy metrics, the mean average percentage error (MAPE) was chosen because this is a standard metric in HOPS, so the comparison of results proved easier. MAPE is defined as

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{L_{True} - L_{Forecasted}}{L_{True}} \times 100\%\right|,$$

where at each time point L_{True} and $L_{Forecasted}$ represent the true observed/measured losses and forecasted losses respectively. N is the number of data samples for the time scale.

III. Results and discussion

Comparison of the results between SVR model and current system operation methodology are shown in Fig. 3. In plotting

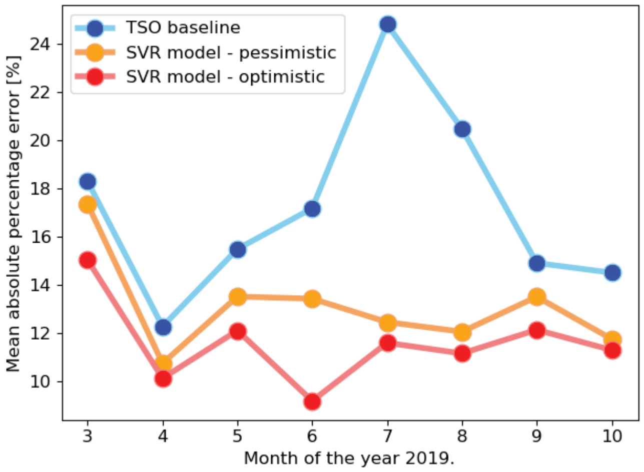

Fig. 3. Comparison between SVR model and current system operation baseline results.

these results and all others, *Python Matplotlib* library [15] was used. We see that both the pessimistic and optimistic split of the data discussed in Section II-D show superior results compared to current system operation methodology. As explained, we expect the results in the testing phase to fall somewhere between optimistic and pessimistic results.

Standard purchasing procedure, described in Section II-A, is to bid for all 24 hours at the same time as is a standard procedure for the day-ahead markets. MAPE shown in Fig. 3 was averaged for all 24 bids. However, electric energy to cover losses need not be purchased in day-ahead markets, but can be purchased earlier or later. To help facilitate that decision, we analyzed the MAPE for different forecasting horizons. From the Fig. 4 it can be seen that forecasting losses one hour in advance, produces MAPE of approximately 6%. On the other hand forecasting losses 36 hours in advance, produces MAPE of approximately 11 %. Thus, using the proposed model, one should consider covering the losses on some markets that are closer to real time than day-ahead markets. This idea is not further explored here, because it is not the central topic of the paper. Additionally, magnitude of improvement from weather forecast data can also be seen from the Fig. 4. Inclusion of weather data reduces the error, but increases dispersion of error, especially after the 60^{th} hour in the future. The reason for this is reduced availability of weather forecasts for such a long time horizons, and consequently less training data available. Losses forecasts are mainly used up to 48 hours, so it is not a large concern.

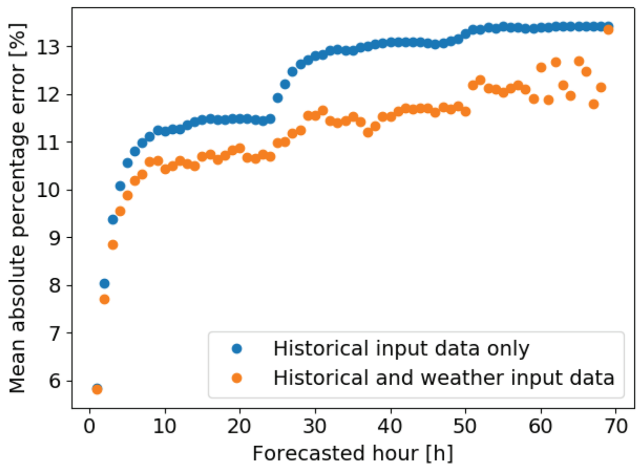

Fig. 4. MAPE accuracy for each forecasted hour with and without weather data.

A. *Losses forecasting tool*

The software tool for losses forecasting was created with the described SRV model at the core. The purpose of the tool is to facilitate the usage of the developed model for standard every day operations at the TSO. The tool automatically generates losses forecasts 4 times a day - every time after a new weather forecast becomes available. Internal structure of the software tool has several layers of back-end and a front-end. The first layer of the back-end is hosted on a dedicated server, implemented using *Play* framework and relies heavily on the *Akka* framework. Internally, it uses *Python* script in which the described SVR algorithm is implemented. Another back-end layer serves front-end static resources and hosts application programming interfaces for the front-end. This part is also implemented in the *Play* framework. All forecasts and integrated error evaluation can be accessed through custom made front-end part that is implemented in *React/Redux* frameworks and host of smaller libraries from *React* ecosystem. Example of the front-end user interface is shown in Fig. 5.

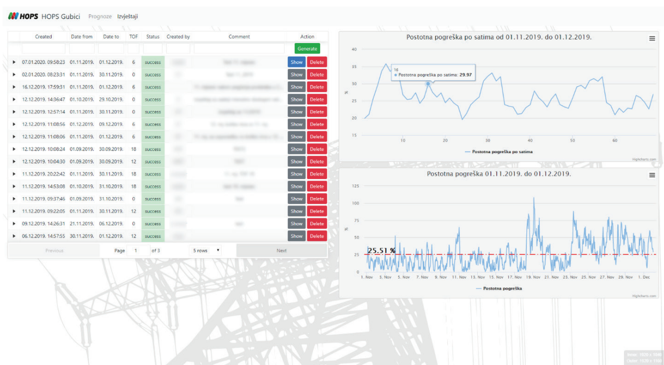

Fig. 5. Appearance of software tool user interface used for viewing and evaluating losses forecast.

IV. Conclusions and Future Work

Model for generation of losses forecasting was created using SVR supervised machine learning algorithm. Input data used are historical losses and weather forecasts. Validation of the model on the data unseen by the model in the training phase suggests that the model will perform significantly better than the current method in operation. The described model was integrated into a software tool for automatic losses forecasting in the entire Croatian transmission system. The tool is currently being tested at the TSO in parallel with their conventional method to see how it performs in operation on real-time data. The testing is in the early phase, so it is too early to present conclusions, but all the indications is that the developed model and the developed tool improved the operations. Analysis of the validation data demonstrate that the losses forecast is much better for the first few hours, so the option of covering the losses on some market closer to real time, rather than day-ahead marked, should be considered. The main drawback of the model presented in this paper is that it calculates losses for the entire Croatian transmission system at once. Because of this, a large number of predictors is used as inputs to the model, which prevents the usage of more advanced machine learning methods. This drawback is to be corrected with additional data available in the future research as the focus is shifted towards smaller geographical regions, even individual lines or nodes of the transmission system. Fig. 6 shows the

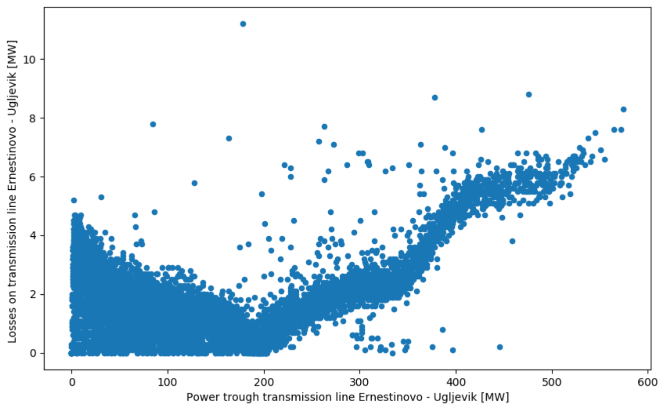

Fig. 6. Example of one power line in Croatian TS: non-linear dependence of power line losses to load.

measured dependence of power line losses to load for one 400 kV power line in the Croatian transmission system. It can be seen that the dependence is highly non-linear. Additionally, the shape of the curve can be very different, even for adjacent power lines. Moreover, the dependence showed in the Fig. 6 is only on one parameter: load. The losses, however, are dependent on multiple parameters, especially on the weather conditions. As in the presented SVR model, the future work will focus on forecasting losses from multiple parameters, including weather parameters. Since it will be geographically limited it will have fewer parameters. Therefore, the usage of some non-linear method will be easier.

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