

LOSS ESTIMATION OF MEDIUM VOLTAGE LINES BASED ON REAL AND SYNTHETIC LOAD PROFILES

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ABSTRACT

This paper describes a simple tool for power flow calculations on medium voltage (MV) network lines with the goal to calculate the network losses for every single MV-line in a fast way with sufficient accuracy. The second part describes, how this tool can be combined with a forecast tool. First a bagged regression tree model is used to forecast the overall network load. In a second step, this model is used to forecast the feeder loads in primary substations. By this a day-ahead forecast for line loads and line losses in the MV network is achieved.

INTRODUCTION

In the area of network planning, typically the maximum load flow situations are the critical ones and therefore mainly these calculations are performed. Load flow calculations based on profiles haven't been in focus so far in MV and LV grids.

For the task of a detailed analysis of network losses as well as the calculation of the remaining capacity of lines, the profiles of line loads are needed. Here the actual challenge is not the load flow calculation itself, but rather the data base of the nodal loads which have a high impact on the quality of results.

In the following chapter, the requirements for and the creation of the data basis are described. Further, a profile based load flow calculation is performed to determine the line loads of every single MV line to calculate the network losses.

The last chapters deal with a forecast model, which also is combined with the profile load flow calculation. An approach, how forecast values on the line loads of the network can be calculated by a simple model, is shown.

DATA BASIS

The actual challenge is not the MV-load flow calculation itself, but rather the data base of the nodal loads which have a high impact on quality of results. Typically the load flow calculation is based on yearly or monthly maximum of nodal loads. The purpose is to get information on the capacity of the grid in the most critical situations. Load profiles are not needed for this task.

Results of a load profile based simulation and estimation become important when considering network losses and to optimise network operation. (e.g., to coordinate the work force management with actual and future network loading)

In the SCADA System typically all load values for lines and transformers in primary substations are measured. Therefore all 110 kV lines (connections between primary substations) are measured on both sides. The transformers (in Salzburg 110 kV / 30kV) and the MV feeder-heads are measured in the SCADA system at least in 15 min time resolution. All other nodes in the MV-network are normally not monitored in a SCADA System (Figure 1).

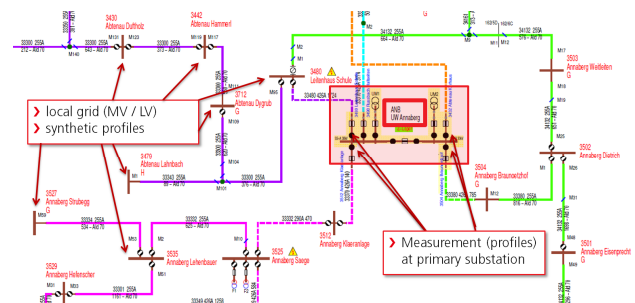


Figure 1: Available measurements and synthetic profiles in the MV-network

Depending on installed power and yearly energy amount, grid customers are measured either with a load profile meter (15 min active power profile) or with a conventional meter (one energy value per year). By using standard load profiles, which are scaled by the yearly energy consumption, also for the second group of customers a synthetic profile based on their assigned standard profile is generated.

One input parameter is the correct assignment of the meters (appr. 450,000 in Salzburg) to the network nodes. Therefore in Salzburg the Geographic Information System (GIS) is used. Hence, synthetic profiles can be assigned to low voltage grid nodes and in further consequence to medium voltage nodes. Since every LV metering point is only connected via one MV network point to the higher voltage levels, an unambiguous assignment is possible. By this, for every secondary substation a load profile in 15 min time resolution (as sum of measured 15 min load profiles and synthetic load profiles) is available.

PROFILE LOADFLOW CALCULATION

To determine the network losses, the line load at every single section is needed. In the case of Salzburg these are about 13,000 line sections with 35,040 values per year (15 min time resolution). For this calculation the loads at the MV-network nodes are needed.

The load profile of the secondary substations are added together and compared with the measured feeder value at the primary substation. The difference between the synthetic profiles and measurement value is calculated for each time point and then allocated equally to the affected network nodes. The majority of the MV-grid is operated as radial network. Therefore a MV-grid node is directly assigned to one single feeder. In case of a ring operation, the sum of the feeders is compared to the connected MV-nodes and then also equally added as an additional consumption / generation to the affected network nodes.

In the next step for the load flow calculation these scaled node loads are used. The load flow calculation itself is performed in MATLAB for every primary substation busbar separately. The simplified DC-load flow calculation assumes a constant magnitude of the voltage. Therefore relation between node power and the node voltage angle can be expressed as shown in equation (1). [6]

$$P_i = -U_n^2 \sum_{j=1}^{n_k} \Im\{Y_{ij}\} \vartheta_j \quad (1)$$

Where P_i is the nodal power of the node i , U_n the rated voltage, Y_{ij} the complex conductance of the nodal point admittance matrix and ϑ_j the nodal angle of the complex voltage pointer.

Equation (1) can be expressed in matrix notation. After the matrix inversion and the elimination of the slack node (the busbar of the primary substation) the angle can be calculated as seen in (2), where \mathbf{B}^{-1} is the inverse of the imaginary part of the nodal point admittance matrix: [6]

$$\boldsymbol{\vartheta}' = -\frac{1}{U_n^2} \mathbf{B}^{-1} \cdot \mathbf{p}' \quad (2)$$

For the load flow the difference of the node voltage angles (3) has to be calculated: [6]

$$P_{ij} = -U_n^2 \cdot \Im\{Y_{ij}\} \cdot (\vartheta_i - \vartheta_j) \quad (3)$$

In combination with the equation (3), this leads to equation (4) which describes the relation between nodal loads (\mathbf{p}) and line loads (\mathbf{p}_1) as matrix equation:

$$\mathbf{p}_1 = \mathbf{B}_1 \cdot \mathbf{A}' \cdot \mathbf{B}'^{-1} \cdot \mathbf{p}' \quad (4)$$

With this line loads, the overall losses can be calculated as sum of the line losses (5), where E_{loss} describes the energy value of losses, $P_k(t)$ the load of line k at the specific time point t , R_k the resistance value of line k and Δt the time interval:

$$E_{loss} = \sum_t \sum_k^{lines} P_k(t)^2 \cdot \frac{R_k}{U_N^2} \cdot \Delta t \quad (5)$$

The DC load flow calculation based determination of line losses takes about 5 to 10 seconds for a primary substation for a whole year in 15 min time resolution.

NETWORK LOSSES IN THE MV-GRID

In the current practise losses of the MV lines are calculated by a comparable easy approach. First the annual energy values for the load flow over the HV/MV Transformers is calculated. To this energy amount the power infeed of generators in network level 5 (MV-grid) is added (see Figure 2 calculation of the network load). From this value, the line losses in the MV network are now calculated by a fixed percentage of 0.8% of the network load in network level 5.

As described in the previous chapter, the results of the DC load flow calculation are the line load values for every line section in 15 min time resolution. In overall these are about 450 million values (13,000 line section times 35,040 time values per year). With these line loads the sum of losses of the MV-network lines is calculated. The resulting value is 0.845% of the network load in network level 5 and therefore very similar to the previous shown experience value. The absolute difference of the two given loss values is about 0.04% of the overall consumption in Salzburg. Therefore the previous used experience values are confirmed.

BAGGED REGRESSION TREE MODEL

In the following chapters the described profile load flow calculation will now be combined with a forecast model. In a first step a model for the overall network load is built. In later chapters the model will be used to forecast the single feeders in the primary substation.

In Figure 2 the definition of the network load of the SCADA system is shown. To the measured power of the grid exchange with the transmission grid, the measured power plants are added to calculate the network load. As shown in Figure 2 this SCADA system network load does not include generation infeed of smaller power plants, which are not connected to the SCADA system.

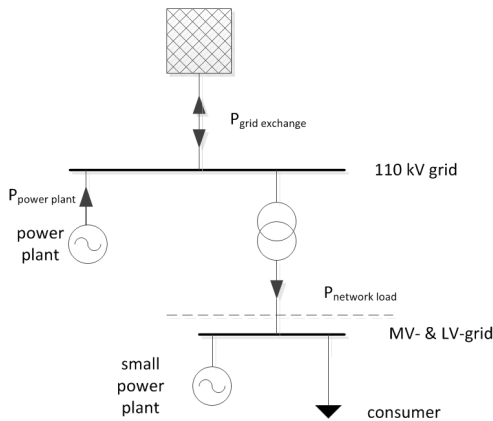


Figure 2: SCADA system network load

On basis of [2], the forecast model for the network load was implemented in MATLAB. Here a bagged regression tree model is used. A regression tree is a special form of a decision tree, where the target variable can take continuous values [3]. The term “bagged” refers to bootstrap-aggregated where the results of many decision trees are combined [5]. Bootstrap aggregating is a machine learning ensemble meta-algorithm designed to improve the stability and accuracy of machine learning algorithms used in statistical classification and regression [4].

In MATLAB the related function is called “treebagger”. The combination of many decision trees reduces the effects of overfitting and improves generalisation. The function `TreeBagger` grows the decision trees in the ensemble using a bootstrap samples of the data. Also the function `TreeBagger` selects a random subset of predictors to use at each decision split [4]. To bag regression trees the method “regression” was used. Also, like in the example [2], the forecast model was built with a number of 20 regression trees.

For the forecast model the network load data over a period of three years was used. The timespan from 2014 to 2015 was used for training the model and then tested with the completely out-of-sample date from the year 2016. The time resolution for all data is 15 min.

Figure 3 shows the input parameters of the forecasting model. The block “seasonality” gives information about the hour of the day, the weekday (Monday to Sunday) and the binary information whether the given date is a working day. The historical load profiles was used for multiple input. So the load values at the same point of time of one day, two days, one week and two weeks before, are given.

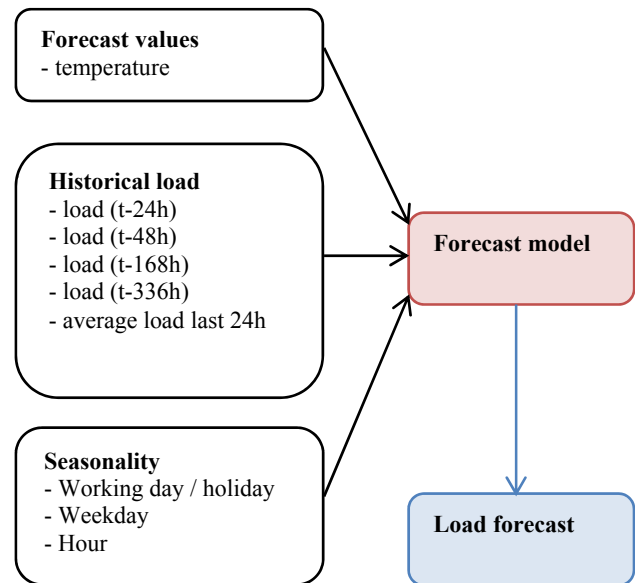


Figure 3: System input and output of load forecast model

Additionally the energy value of the last 24 hours is an input parameter. The temperature is the only forecast input value in this model. The load value of the next 15 minutes is the output value of the forecast model.

Figure 4 shows the importance of the input parameters. The historical load profiles have a similar importance to the output result. The most important parameters are the temperature and the information about the weekday. The given values are a result of the model building function “treebagger”. [5]

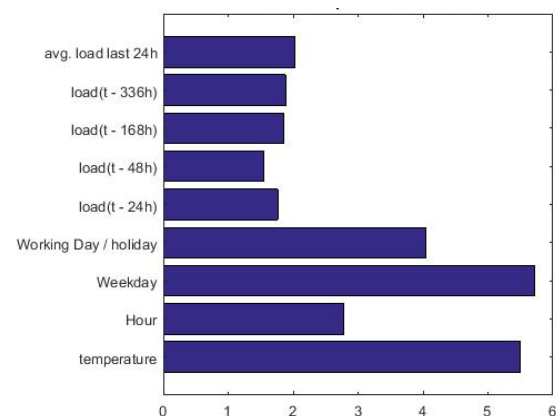


Figure 4: Out-of-bag feature importance results

Figure 5 shows the comparison of forecasting result with the actual network load of the year 2016. As Input for the forecast value “temperature” the actual values of 2016 were used, which results in a “perfect temperature forecast”.

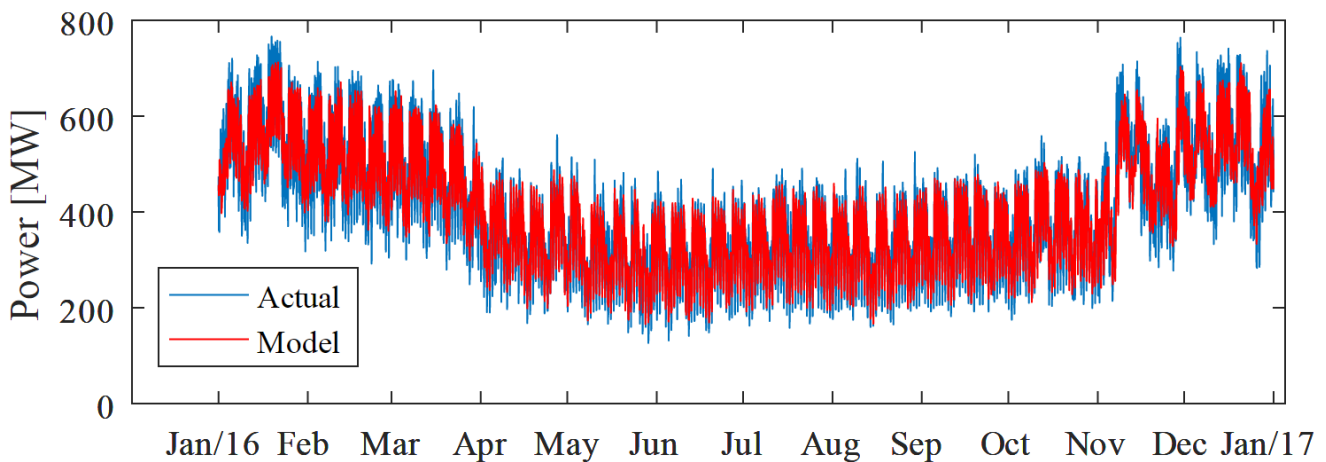


Figure 5: Network load forecast - full year 2016

The load profile shows the typical difference between working days and weekend. Also the higher demand in winter months can be seen. Especially in November, the production of artificial snow in the ski areas is visible. In Salzburg the load of snow cannons has a significant share of the overall network load.

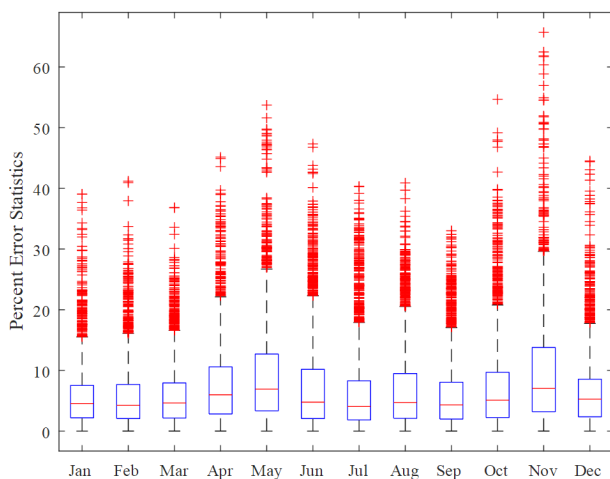


Figure 6: Forecast error by month

The exact point of time, when the snow cannons are in operation, is comparably difficult to predict. Therefore, it can be explained that the relative error in November is higher than in the remaining months (see Figure 6). The mean absolute percent error (MAPE) over the full year is 7.01% with a mean absolute error (MAE) of 25.9 MW.

As described before, the forecast model input parameter “temperatures” are the actual values of 2016. In order to test the influence of temperature forecast errors, a noise signal was added. A random value in the interval $[-5^{\circ}\text{C}, +5^{\circ}\text{C}]$ was added to every 15 min temperature value. Then this input signal was used for the forecast model instead of the actual value.

The resulting forecast of the network load has a MAPE of 7.04%. Therefore an error in the temperature forecast has no extreme effect on the forecast result.

FORECAST MODEL FOR PRIMARY SUBSTATION FEEDERS

The described profile load flow calculation is now combined with the forecast model. Within the project iNIS [1], a forecast model for the primary substation feeder value is generated. The synthetic profiles of the secondary substations are scaled, based on the forecast value of the beginning of the feeder. In combination with the profile load flow calculation in the MV network a forecast of the network losses as well as the remaining line capacities is created.

For every feeder a new model is parameterised. The structure of the model (input values) as well as the method (bagged regression tree with 20 trees) is the same as for the overall network load (see Figure 3).

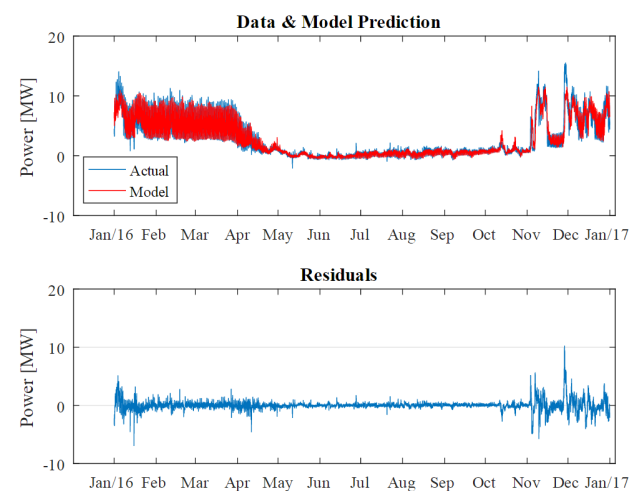


Figure 7: Primary Substation Feeder forecast - full year 2016

Figure 7 shows the forecast model for one feeder over the full year 2016. Additionally the forecast errors are shown in the subfigure.

A major difference between the overall network load and the feeder load is, that the latter is a residual load. At the primary substation, only the difference between load and generation is observable. As shown in Figure 7, this residual load can have values near zero, when generation and loads are balanced within the feeder (here in the summer months). Therefore the MAPE of 54% lacks of significance because of division by values near zero. The MAE of 0.42 MW is about 15% of the mean absolute value of the feeder power. This example shows, that a single feeder is more difficult to predict than the overall network load. But the absolute value seems to be a reasonable level of error.

FORECAST OF NETWORK LOSSES

The forecast model for substation feeders was used for the nine feeders of one particular substation. As described for every feeder a new parameterised model was created.

The DC load flow calculation with the scaling of nodal loads was run twice. One time with the forecast values of the feeder power and one time with the actual values. Then the resulting line loads and line losses over a full year were compared.

Since the line losses are proportional to the square of the line loads, forecast errors have a greater impact. But the annual line losses in the MV-network for this particular primary substation are very similar when comparing the forecasting values (0.50% of the residual load) with the actual feeder values (0.52% of the residual load).

CONCLUSION AND OUTLOOK

The first results with historic data show, that the calculated sum of line losses matches the previous experience values of losses (difference about 1%). These experience values are a simple loss estimation based on the yearly energy demand. A further analysis of the calculation results will be performed.

The bagged regression tree forecast model showed promising results to forecast the overall network load as well as the feeder load in primary substations. In the next steps different forecasting models (like neural networks) will be compared. The goal is to implement a continuous forecast model for line loads in the HV and MV grid.

REFERENCES

- [1] M. Stifter, R. Stütz, K. Diwold: Zuordnung und Topologieerkennung von Sensor und Smart Meter auf Netz- und Strangebene, EnInnov 2016, 14. Symposium Energieinnovation, Graz, 2016
- [2] Mathworks: „Electricity Load and Price Forecasting with MATLAB”; webinar 08. September 2010; <https://de.mathworks.com/videos/electricity-load-and-price-forecasting-with-matlab-81765.html>
- [3] Decision tree learning. (2017, January 10). In *Wikipedia, The Free Encyclopedia*. Retrieved 18:22, January 10, 2017, from https://en.wikipedia.org/w/index.php?title=Decision_tree_learning&oldid=759358443
- [4] Bootstrap aggregating. (2016, November 1). In *Wikipedia, The Free Encyclopedia*. Retrieved 14:17, November 1, 2016, from https://en.wikipedia.org/w/index.php?title=Bootstrap_aggregating&oldid=747282427
- [5] Mathworks R2016b Documentation: „TreeBagger” <https://de.mathworks.com/help/stats/treebagger.html>
- [6] C. Groß, 2013, “Maximizing the renewable generation share of the Austrian electrical energy supply.”, *Dissertation (in German) at TU Vienna University*