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ACQUISITION OF GRID LOSSES USING INTELLIGENT FORECAST METHODS

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ABSTRACT

Within the framework of this article a method used for the forecast of grid losses in a transmission grid is presented. In addition to the grid load, the amount of grid losses depends on a number of exogenous factors. In the modeling process the identification of the exogenous factors is of vital importance. The actual application necessitates specific requirements in forecast strategy and the concept of the forecast method. Artificial Neural Networks (ANN) are used as model approach for the forecast method. In this context various special network architectures were investigated. The developed grid losses forecast method as the result of the work represents an extension of ANN at an auto-adaptive method for continuous evaluation of the input data and internal parameters. The method was implemented in software engineering and embedded in a certain energy management system.

Index Terms - forecast, Artificial Neural Networks, grid losses

1 MOTIVATION

A part of electric power gets lost at transmission due to transport, transformation and consumption in the transmission facilities. The energy used for compensation of these physical caused grid losses is known as grid losses energy. Under § 10 of the German Electricity Grid Access Regulation (StromNZV) operators of electricity grids are obliged to obtain losses energy at a market-based, transparent and non-discriminatory procedure. Furthermore, operators are obliged to administer a separate balance group which contains only the compensation of grid losses energy [1]. The costs caused by acquisition of grid losses are included in the calculation of grid usage charge. The grid usage charge is subject to approval of the Federal Network Agency (BNetzA).

Transmission system operators (TSO) themselves occur in the market for electricity to acquire such energy services in their own procurement processes as a result of the unbundling required by law and regulations of the Federal Network Agency. For a lowest-cost acquisition of the energy, which is necessary to compensate the grid losses in a control area, intelligent and efficient methods for the forecast of grid losses are needed. This paper presents a method that is used for the forecast of grid losses in the transmission grid of the control area of the transpower Stromübertragungs GmbH.

2 GRID LOSSES AND THEIR EXOGENOUS FACTORS

Grid losses are differences between the injected and the extracted amount of electrical energy in a grid system, caused by the ohmic resistances of conductions, discharge through isolators, coronary discharge or other physical processes [6]. The amount of grid losses at the transmission of electrical energy in the grid depends on e.g. conduction resistances, capacitive and inductive operating resources, the switching state of the grid and power flows in each grid segment. The challenge in forecasting the grid losses in a transmission grid is, inter alia, the fact that grid losses energy depends on a variety of system engineering and energy economic variables. The requirement for a practical application of the grid losses forecast is that exogenous factors have to be identified, which have to be measurable or predictable in a moderate effort. Previously an extensive data analysis was executed to demonstrate the dependence of the grid losses of potential influencing factors.

The grid losses in distribution grids largely depend on the system load. The data analysis has demonstrated that in opposition to distribution grids the systematically related influence of the system load to the grid losses is significantly lower in transmission grids. Nevertheless, the system load is a not negligible factor for the forecast of grid losses.

The wind energy feeding was identified as one of the main influencing factors in the transmission grid of the control area of the transpower Stromübetragungs GmbH. Because of geographic advantages a large part of feeding wind energy occurs in the north of the control area. Regions with high energy demand are placed predominantly in western and southern Germany. So high power flows in the north-south direction are generated in case of heavy wind energy feeding. Due to the large dimensions of the control area and the associated long transport distance the high power flows in the north-

south direction cause significant proportion of the grid losses.

The feedings laid down by the Renewable Energies Act (EEG) in the individual control areas in Germany are highly different. To prevent an excessive cost of transmission system operators with high EEG power feedings, a horizontal load balancing (HoBa) takes place between the control areas. The intention of this horizontal load balancing is the consistent and initiator based allocation of the EEG amount of electricity and the financial charging [2]. The portion of physical Hoba (balancing of electricity), which occurs due to the compensation of wind energy, was also investigated and considered as a potential factor influencing the forecast of grid losses. However the contained wind power feedings are the dominant factors in the calculation of the value that arises from the HoBa. Studies demonstrated that the inclusion of this calculated value is not able to supply a positive contribution to the forecast of grid losses.

Furthermore a strong dependency between the grid losses and transits are detected. Transits occur in the transfer of energy from one control area to a non-adjacent control area. Transits are thus energy channeling through the transmission grid of the intermediate control area.

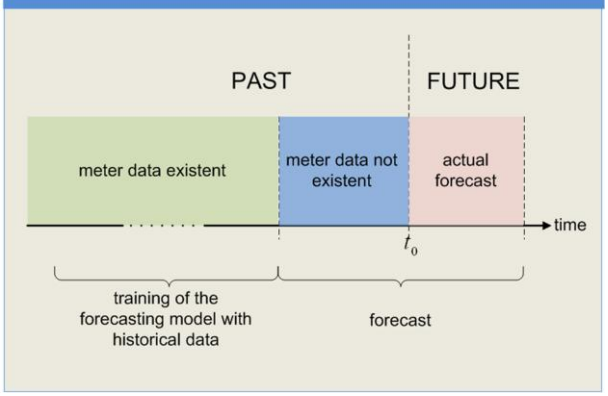
To forecast the grid losses forecasts of exogenous variables may also be required. Therefore a strong dependency of the quality of the grid losses forecast on the quality of forecasts of exogenous variables exists.

3 BOUNDARY CONDITIONS

In Addition to the north-south power flows and the expansion of transition grid in the control area further boundary conditions are taken into account. Situational changes of power flows in the grid, which may be caused e.g. by failure of production facilities or channeling of energy to the interconnections to other control areas, time-varying correlations of the grid losses with all other exogenous variables could be demonstrated. In addition the correlation of the feeding wind energy with the occurring grid losses varies during periods of high and low wind power feeding.

The real grid losses are provided by an automated meter reading (AMR) system as the difference between the sum of all injections and the sum of all extractions at metering points in the control area. The data are collected using remotely readable meters and transmitted to the AMR system. This process of providing the meter data takes a specific amount of time. Thus, a certain time offset between the forecast and the last known meter data of the real grid losses originates. This time offset is a huge challenge. If the time offset is so large, such that beyond this time offset no correlation between current grid losses and historical values of grid losses exists, the result is that neither autoregressive fraction nor historical values of the grid losses are able to be used as input values for the forecast. The forecast of grid losses can thus only be made on the basis of exogenous factors. The data analysis demonstrates that the time offset is small enough to use the data as forecasting input, and also beyond this time offset significant correlations to the historic values are detected. It is recommendable also to forecast the time window, in which meter data are missing (cf. Fig. 1).

Figure 1: forecast with time offset to meter data



4 SPECIAL STRUCTURES OF ARTIFICIAL NEURONAL NETWORKS

Artificial Neuronal Networks are information processing systems, which are based on natural neural networks such as the brain or spinal cord. The technical reproducing of biological neural networks is less the intention. Rather the primary aim is the abstraction of information. Like their biological ideals, Artificial Neural Networks consist of a variety of neurons (nodes) that have a simple structure compared to the total system and the nodes are networked with each other through a certain structure. The high performance of the total system is only achieved by networking the multitude of neurons. The numerous nodes in Artificial Neural Networks are usually arranged in different layers and interconnected through a given structure. The layers of an Artificial Neural Network differ in input layer, hidden layer and output layer. The input data are applied to the nodes of the input layer. The input layer serves as an input interface of the Artificial Neural Network. The applied signals of the input data are passed on directly connected nodes. The task of the nodes of the output layer is to generate the output of the network. Normally the actual information processing occurs in the hidden layers. It is possible to arrange any number of layers between the input and output layer. The number of hidden layers and the number of contained nodes are free parameters of the network.

The structure of an Artificial Neural Network depends on the arrangement and the interconnections of the nodes. There are different types of connections. Forward directed connections link nodes in a layer with nodes in the next layer. Direct connections link nodes to themselves. So-called lateral connections link nodes within the same layer. Furthermore connections to

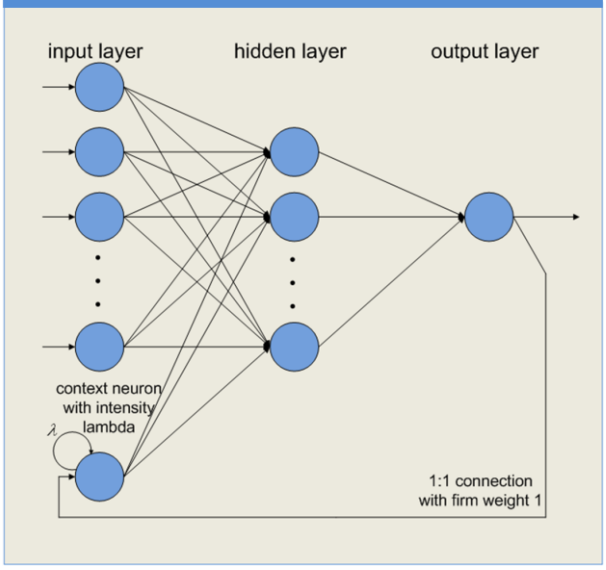
nodes at upstream layers may exist (recurrent connections). Because it is possible to combine the different possibilities to connect nodes in an Artificial Neural Network with each other, a variety of different network structures are imaginable.

For the forecast of grid losses, a number of network structures have been studied for a practicable use. In particular, so-called feed-forward networks and networks with recurrent connections are taken into consideration.

Feed-forward networks are generally noted as the default network structure. The connection structure is exclusively forward focused, so the network can only have access to the current data applied to the input node. Time past records can only be considered through the additional feed at the entrance, but not stored.

So-called recurrent networks differ from feed-forward networks in the connections to upstream layers (networks with feedback). By such recurrent connections cycles are formed. By the existing feedbacks the network not only process information but also store information beyond. While the information processing of the current input values the network access to previous results. A recurrent network structure makes it possible, that the time sequence of the input data influences the output [3]. One of the investigated network structures is shown in Fig. 2 as a schematic presentation (exemplary with one output node). This is a recurrent network with the feedback of the output. The illustrated network structure is also known as Jordan network.

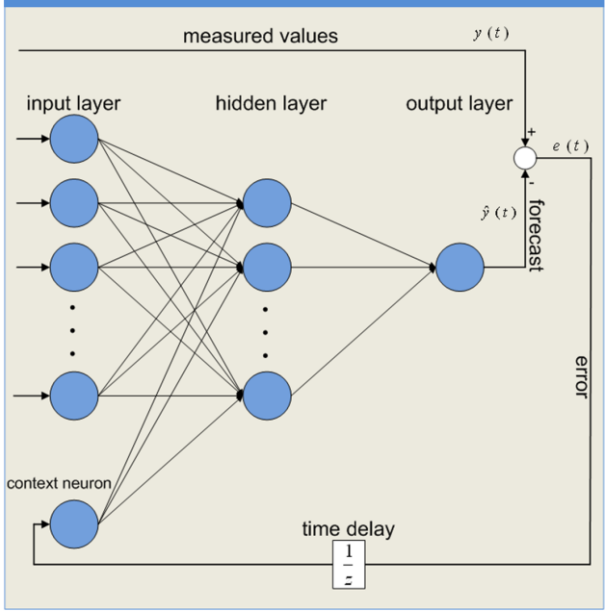
Figure 2: Rekurrent Neuronal Network (Jordan Network)



Jordan networks are feed-forward networks that are extended by so-called context nodes to store the outputs. The number of context nodes is determined by the number of nodes in the output layer of the network. The output values of the network will feed the context nodes via a 1:1 feedback connection. The context nodes have a direct connection of the intensity of λ. The parameter λ although controls the memory performance of the network [4].

A network architecture, in which the model error is fed back, was chosen as a further approach for a structure of Artificial Neural Networks to forecast the grid losses. This special network structure is shows in Fig. 3 (exemplary with one output node).

Figure 3: ANN with feedback of the model error



The shown network structure is a feed-forward networks that is extended by context nodes. The number of context nodes is determined by the number of nodes in the output layer of the network. The model error is caused by the measured values and the model generated output values and is used as input for the context node. Thus, the output values generated by the network do not only depend on the currently applied input data, but also from the past model errors.

With all investigated structures of Artificial Neural Networks extensive test forecasts were conducted in realistic and practical scenarios. Thereby the two presented structures (Jordan networks and ANN with feedback of the model error) have shown itself to be particularly suitable. Compared with feed-forward networks significant improvements in forecast quality have been achieved for the problem of forecasting grid losses for the transmission grid of the transpowerpower Stromübertragungs GmbH.

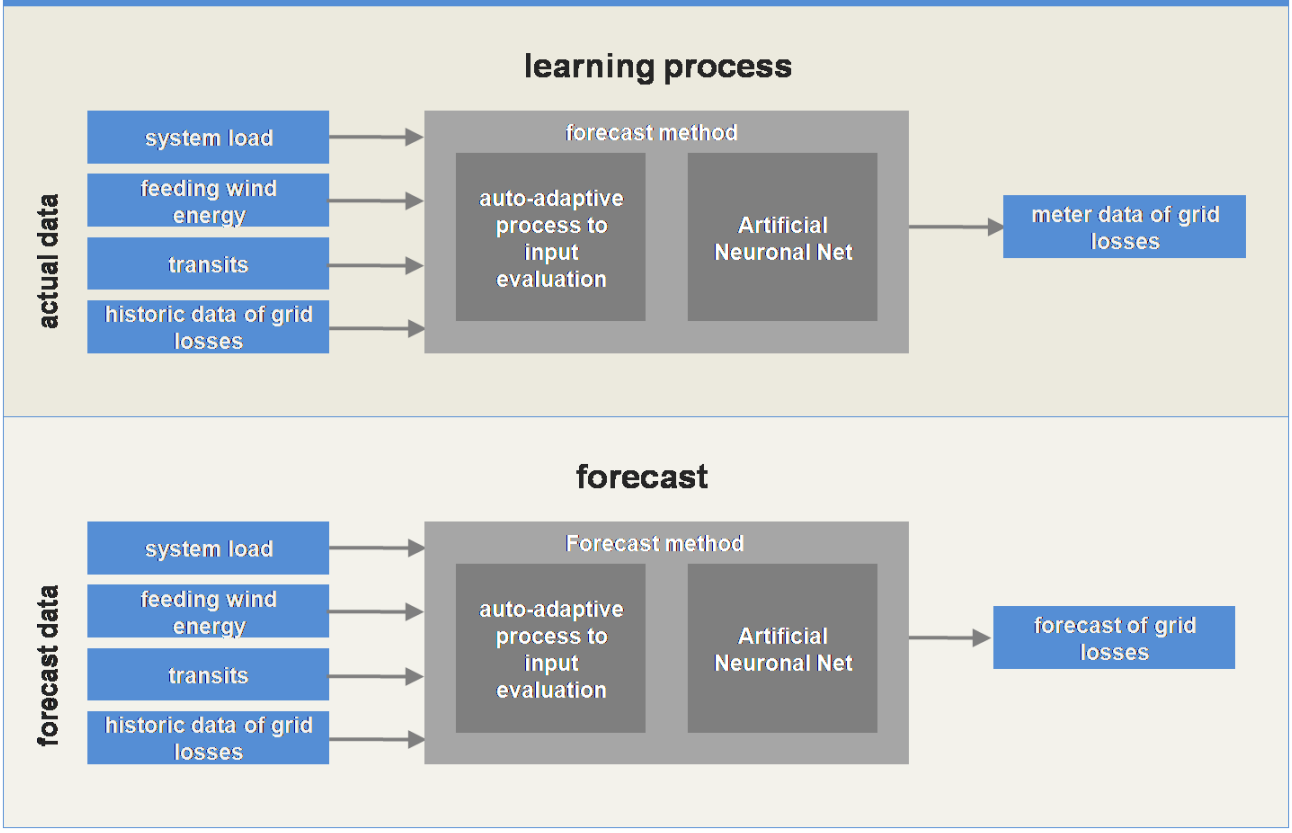
5 FORECAST OF GRID LOSSES BY ARTIFICIAL NEURONAL NETWORKS

With the help of Artificial Neural Networks, it is possible to map nonlinear relationships on an incomplete describable process in a model. The selection of input variables should be reduced to the essential measurable and predictable influencing factors. The forecast with Artificial Neural Networks occurs in two phases (cf. Fig. 4).

In the first phase (adaptation of model parameters) the neural network trained in a process of apprenticeship. Thereby historic values of the input data (actual values) are given at the entrance of the network. And the meter values of the grid losses are given at the output. Therefore the learning process is exclusively based on known data, which are given to the network. In a fixed pattern (learning algorithm) the network reacts to the samples contained in the data by adjusting the model parameters. So the network learns the functional relationships between the input and the output data.

auto-adaptive approach is used, related to the importance of the input variables and the internal parameters of the forecasting model. This auto-adaptive process assesses the relationship of the input data to the target (strong, medium and low correlation) continually and is able to adjust internal settings of the forecast model conformable. Varying correlations of the variables to the grid losses and seasonal influences can be better processed by the auto-adaptive approach. The auto-adaptive process has been developed by the Fraunhofer Application Center System Technology Ilmenau (AST) for better applicability of forecast methods for specific problems.

Figure 4: event forecast of grid losses



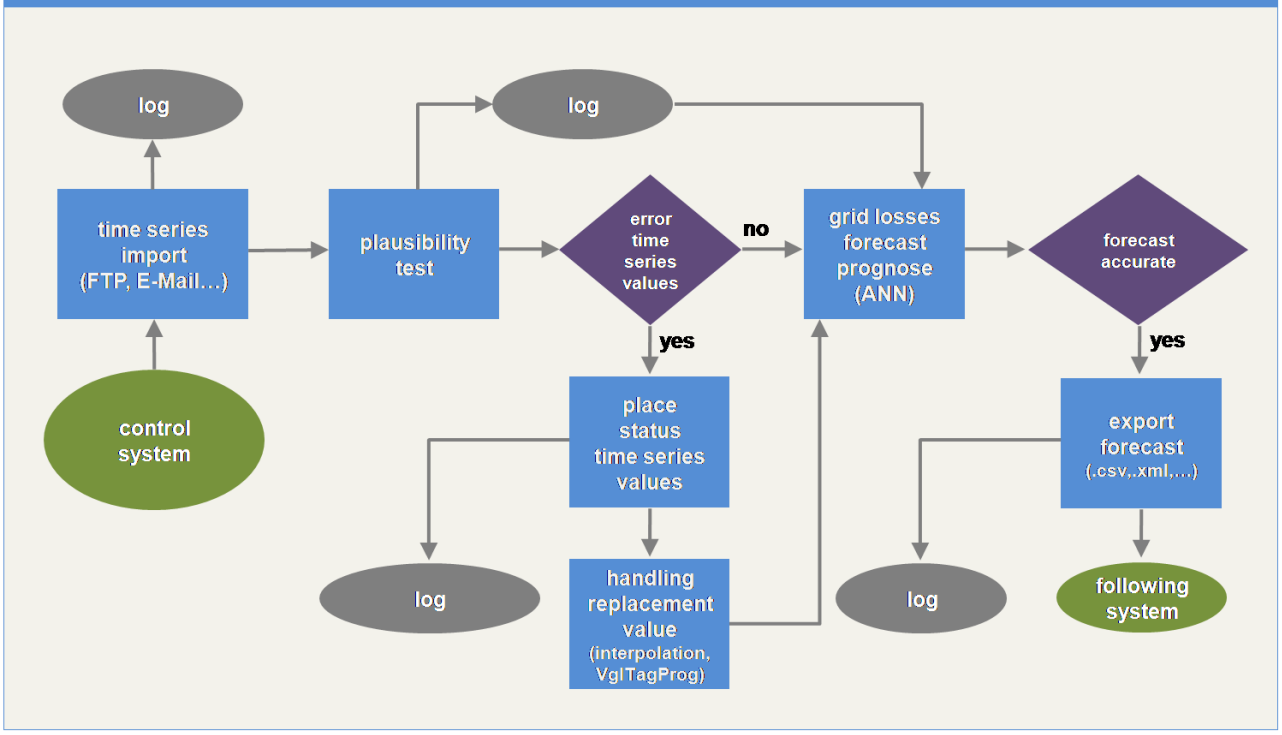
In the second phase, the trained Artificial Neural Network will be applied for forecasting the grid losses. Forecasts of the exogenous variables and historical values of the grid losses are used at the input of the forecast method. At the output of the method the forecast of the grid losses are generated. The principle of the rolling forecast applies. In that case the learning time period for training the neural network has always the same length and it is displaced to follow the forecast period. This ensures that the most current data will always be used for training.

For the forecast only input variables with a significant correlation to the grid losses should to be used. If input variables, which have no correlation to the grid losses, are taken into account, negative impacts on the forecast results are possible. Because of the varying correlations of the input variables to the grid losses an

6 SOFTWARE IMPLEMANTATION OF THE GRID LOSSES FORECAST

The energy management system developed by the Fraunhofer Application Center System Technology Ilmenau (AST) is versatile and sophisticated IT-tool for problems of energy forecasting and optimization, based on a powerful time series management system. Forecasts can be executed manually and automatically. It can create custom workflows with automatic activity. The workflows can be triggered by time and event. Fig. 5 shows a schematic representation of the workflow for the preparation of the grid losses forecast.

Figure 5: automation of grid losses forecast workflow



In the automatic processing, at first time series are imported from upstream systems via FTP or e-mail in a variety of file formats. After importing the time series a set of individually configurable validation checks for time series values is available. Implausible identified values are marked with an appropriate status. For the replacement of implausible values or data gaps different strategies are implemented. Such strategies for the replacement of values contain e.g. linear interpolation for few or single incorrect values. In addition the automatic replacement of whole incorrect days is also possible by using an adequate reference day from the past. Following the verifying of the plausibility of the input data, the actual forecast starts.

The procedure for the forecast of grid losses has been implemented and embedded in the energy management system developed by the Fraunhofer AST. The developed forecasting method is flexible to use in principle. By adjustments of the forecast method a highly specialized and robust forecasting method is occurred. The adjustments are related to the boundary conditions and special circumstances of the set of problems linked with grid losses. Certain settings of the forecasting method, such as inter alia the forecast horizon, the selection of input variables, the time period for the training, the number of hidden nodes of the Artificial Neural Network or the calendar settings are freely programmable. Furthermore, the auto-adaptive method for continuous evaluation of the input data is implemented in the forecasting method. This auto-adaptive method can be switched on and off and the evaluation results are immediately visible. Also three different structures of Artificial Neural Networks are implemented. Alternatively, feed-forward networks, recurrent networks with feedback of the output (Jordan networks) or networks with feedback of the error are usable.

The developed method of grid losses forecasting is part of an extensive library that also includes forecasting methods for electricity, gas and district heating. There are deposited forecast methods with different approaches such as reference day search, ARMAX, fuzzy, pattern-based forecasts or Artificial Neural Networks. Forecast methods can draw on a central calendar function. Following the forecast, data can be sent or exported in different file formats required by the following systems.

For the manipulation of time series extensive mathematical functions are inter alia available. This makes it possible, that any error measures are calculated automatically to evaluate the quality of the forecast. All the processes in the workflow are automatically documented in a logbook. Furthermore, all relevant time series are historicized, and older versions of time series can be recovered. Therefore the individual process steps and the total process keep traceable.

7 CONCLUSION

For the compensation and the acquisition of grid losses energy in a grid, forecasts are needed. With the forecast of grid losses energy for the transmission grid of the control area of the transpower Stromübertragungs

GmbH a set of boundary conditions has been taken into account. Not only the identification of significant Influencing factors is of crucial importance, also the availability and quality of input data is an essential factor for the forecast of grid losses energy.

This was done by developing a powerful method that was integrated in a flexible, scalable and extensible energy management system with a powerful time series management. The implemented forecasting method is based on Artificial Neural Networks, for which different network structures are selectable. Furthermore, within the concept of this forecasting method a powerful auto-adaptive method is integrated with which the input data and internal parameters can be evaluated continuously. This method has proven its worth in extensive tests, because this function can handle the time-varying correlations of the grid losses to their influencing values. The specific issue of grid losses forecast given by boundary conditions could be taken into consideration with the resulting forecast method.

The acquisition of the grid losses energy at the transpower Stromübertragungs GmbH is executed successfully in a fully automated process with the energy management system developed by the Fraunhofer AST including the implemented forecasting method.

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