SMARTCITYVILLACH: FINAL RESULTS OF FIELD TEST VALIDATION OF A VOLTAGE ESTIMATION APPLICATION THAT SUPPORTS DISTRIBUTED VOLTAGE CONTROL IN TIMES OF COMMUNICATION LOSS

Roman SCHWALBE, Mark STEFAN, Friederich KUPZOG
AIT Austrian Institute of Technology GmbH – Austria
roman.schwalbe@ait.ac.at, mark.stefan@ait.ac.at, friederich.kupzog@ait.ac.at

Christian SCHNEIDER
Kärnten Netz GmbH – Austria
christian.schneider@kaerntennetz.at

Alfred EINFALT, Albin FRISCHENSCHLAGER, Wolfgang RITTSTEIGER
Siemens AG Österreich – Austria
alfed.einfalt@siemens.com, albin.frischenschlager@siemens.com, wolfgang.rittsteiger@siemens.com

ABSTRACT

This paper presents estimation strategies for voltage measurements developed to enhance the robustness of distributed voltage control in secondary substations in case of communication delays and failures. Different estimation concepts are described and benchmarked. The most promising concepts were implemented and validated in field tests in two low voltage grids for several months. Results from these field experiments and underlying simulations are shown and the impact of the estimation concepts on the voltage control process is discussed.

I. INTRODUCTION

Voltage rise has turned out to be the most critical system boundary for the integration of distributed generation in rural low voltage grids. Distributed voltage control can effectively solve upcoming voltage problems with the requirement of a reliable communication infrastructure. Within the project "SmartCityVillach – Vision Step I" [1] a novel voltage estimation concept was developed to support distributed voltage control in case of communication loss or delays. The voltage estimator was implemented as additional component for the voltage control environment which was developed within the "DGDemoNet SmartLVGrid" [2][3] project, where different voltage control strategies were tested in three Austrian LV grids. In this predecessor project the MV/LV-transformer's tap position was controlled under consideration of actual voltage measurements from the grid provided by smart meters over power line communication.

Based on findings and experiences within the predecessor project a goal within "SmartCity Villach – Vision Step I" was it to improve the robustness of developed control approaches against communication failures. The new voltage estimator component supplies the low voltage grid controller with substitute values in case of a medium and long-term communication failure. Therefore, different methods for voltage estimation were investigated and benchmarked against each other. An overview of the investigated voltage estimation methods is given in chapter II.

The most promising of the investigated concepts were tested in a field test over several months in Austrian LV grids described in chapter III. The field test setup and the system architecture are described in chapter IV. The recorded data from the field test grid was used for simulations to compare the performance of the most promising estimation methods that were investigated (chapter V).

State of the art

State estimation is state of the art for monitoring and control on HV level and it is nowadays also common to be used on MV level [4]. However, for LV systems the existing solutions do not scale well and also suffer from high engineering effort for configuration. Therefore, more tailored solutions for LV circumstances are required. Several research projects investigate in state estimation and voltage control especially for LV grids [3][5][6].

When communication failures occur, pseudo-measurements can be used for state estimation, leading to a decrease in estimation quality especially when multiple meters fail at the same time [4].

Distributed voltage control concepts for LV grids as developed in [2][3] have less system requirements on the grid, so a complete state estimation or providing topology information is not necessary. Consequently, new estimation methods have to be developed that have low requirements on configuration and maintenance.

II. INVESTIGATED VOLTAGE ESTIMATION ALGORITHMS

Within the project, five different voltage estimation algorithms were analysed which can be categorized as 'topology based' or 'history based':

Topology based algorithms

The first category is based on topology information from the grid and is stateless which means that no learning phase for the algorithm is necessary, because all information for the estimation process is given. Within the project, two topology based algorithms were investigated:

Distance-matrix algorithm

The voltage estimator has as rough topology information a matrix with the distance from each node to each other.

When a communication loss to a meter occurs, the estimator takes the value from the meter with the least

distance as a replacement value.

Kriging algorithm

This method is initially used in geostatistics for interpolation of missing values (coordinates) [7]. The model was adapted to be used it in low voltage network, namely by using line impedance instead of geographic coordinates. A weight-function is used to estimate missing values.

History based algorithms

The second category has no dependency on any grid information like topology or load profiles because the algorithms learn the grid characteristics by building up a history database. Within the project, three history based algorithms were investigated:

Root-mean-square-deviation minimization ("Base")

Each time every communication link is available, the whole set of measurements are stored in a database by adding a line to a matrix. Every line of the matrix represents a vector of voltage values of each measurement point at one timestamp, and each column represents a series of measurements of one smart meter. In times a communication link is broken, the existing measurement vector is compared against each vector stored in the database matrix. In the vectors with the least square error to the existing measurements, the values that correspond to the inexistent measurements are taken for the estimation of the missing values.

Weighted K-nearest Neighbour regression ("Mean10")

The quality of the estimation of the "Base" algorithm can be improved by averaging over more than one vector with the smallest square errors. Simulations showed, that an optimum of maximal 10 vectors should be considered, when considering more, results get worse again.

Optimized regression algorithm ("Opt10")

This algorithm is an extension of the "Mean10" algorithm, where the weighting factors for the linear combination of the chosen vectors are the solution of a constrained quadratic optimization problem.

Benchmark of voltage estimation algorithms

The advantage of topology based algorithms is that the algorithm is immediately available for operation, but the grid information has to be provided and maintained manually. The history based algorithms do not need any grid data update in case of topology changes, but the algorithm requires some operation uptime before meaningful estimation results can be achieved. Simulations that assume a sufficient operational uptime of the history based algorithms nevertheless showed that estimations results of history based algorithms have a slightly higher *mean* estimation error than topology based algorithms. On the other hand, the *maximal* estimation error was significantly lower for the history based algorithms. Considering the requirements of voltage control, it is more

important to have a smaller maximal estimation error than having a lower mean estimation error. Therefore history based algorithms were used in field tests and are further analysed.

III. FIELD TEST GRID

Field tests were operated in two Austrian LV grids over several months. This paper focusses on the discussion of the results obtained in the bigger grid. In this grid around 100 customers are supplied by a 250kVA 20kV/0.4kV transformer that is equipped with an OLTC with +/-4 taps with 1.5% voltage change each tap. A part from rather short feeders there is one long feeder with around 590m in the grid with a 50kWp PV inverter connected at the end of this feeder (Figure 1). Within this grid, 19 smart meters on selected critical nodes regularly transmit actual voltage values to the centrally operated voltage controller over PLC. The most critical nodes are meter 1 and 9 being the points in the grid with the lowest voltages and meter 14 and 17 being the points with the highest and sometimes also the lowest voltages in the grid (see Figure 1).
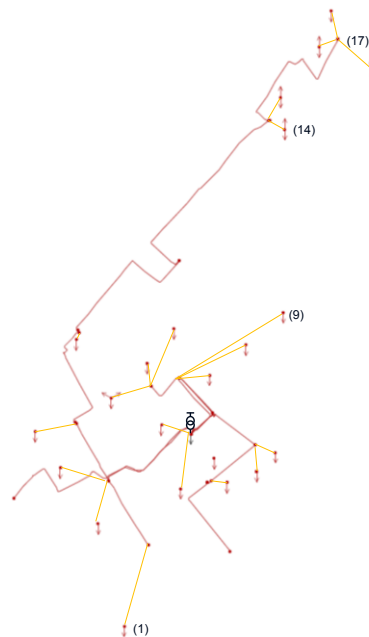

Figure 1: Austrian field test low voltage grid with the for four most critical points in the grid (1) (9) (14) (17)

IV. SYSTEM ARCHITECTURE AND FIELD TEST SETUP

For field tests, the system architecture that was developed within the "DGDemoNet SmartLVGrid" [2][3] project was used and extended by the voltage estimation application. The estimation application receives all voltage measurements from the grid and in case of a communication loss to one or more meters the estimator calculates replacement values and sends them to the voltage controller (Figure 2).
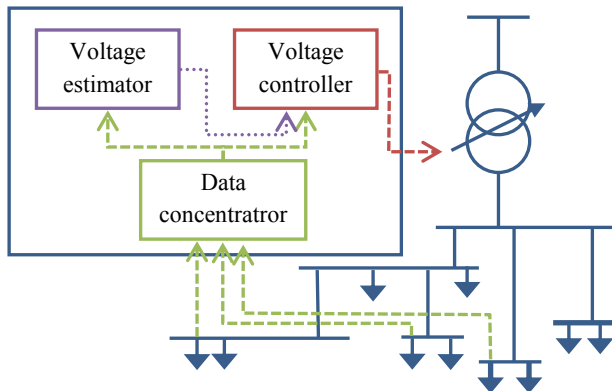
Figure 2: Schematic representation of relevant system components for voltage-estimation and -control

During the field test period, voltage measurements from the grid were intentionally suppressed on a daily basis to activate the estimator on these days. This process was automatized so that days with and without communication losses were switched in a daily cycle. When suppressing only one meter at once, voltage estimation will be a very easy task because adjacent voltage measurements are still available. To test the estimator comprehensively, both meters at the end of the longest feeder (meter 14 and 17) in the grid were suppressed simultaneously, so that no adjacent measurement is available. Additionally it was decided to suppress meter 1 and 9, which both show low voltages at the same time. While this suppression was performed, the suppressed values were logged to be able to benchmark the estimation values.
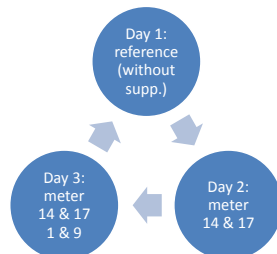

Figure 3: Filter cycle for suppression of voltage measurements in the field test grid (failure scenarios)

V. FIELD TEST RESULTS

A direct benchmark of the voltage estimation algorithms can be achieved by comparing the estimated voltages against the suppressed measurements voltages from the grid. This is shown in Figure 4 for the investigated algorithms 'Base', 'Mean10' and 'Opt10' (see chap. II for description). For the 'Base' algorithm, the estimation error is below 1.4V for 50% of the time, and it is below 3.7V for 95% of the time, but the highest errors go up to 10.4V when considering communication loss to meter 14 and 17. While 'Mean10' leads to significantly better results than 'Base', 'Opt10' performs best, even if the results are not significantly better than the ones from 'Mean10'. When considering the additional communication loss to meter 1

and 9, maximal estimation error is lower, which can be considered as a numerical contingency, but all other percentiles behave as expected. In general, the estimation error decreases with higher algorithm complexity.
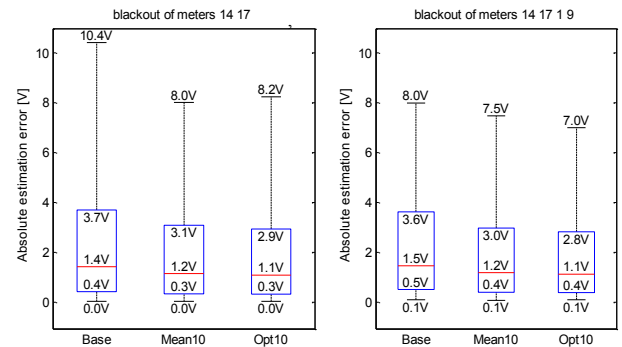

Figure 4: Absolute estimation error of three algorithms in cases of the investigated failure scenarios (boxplots show the 0, 5, 50, 95 and 100% percentiles)

Figure 4 does not give any information about the impact on the voltage control process. A high estimation error is only severe in cases were the highest grid voltage is estimated too low, or the lowest grid voltage is estimated too high. In these cases the voltage controller gets an incomplete view on the grid situation and thus violations of voltage limits can occur. In cases were the highest grid voltage is estimated too high or the lowest too low, the voltage limits will be maintained even with safety margins (as long as the estimation error is not too high).

The impact of the different estimation methods on the power quality in the grid is shown in Figure 5. All boxplots show the 0, 5, 50, 95, and 100% percentiles of the 10min-average-values of grid voltages. The grey dotted lines indicate the voltage limits that were configured in the voltage controller. The first boxplots in both diagrams show that grid voltage limits can be maintained when no communication failure occurs. The second boxplots show that grid voltages will be violated on the upper and on the lower limit when communication failure occurs and no estimation is performed. The 'Base' method leads to slight violations in voltage limits, but 'Mean10' and 'Opt10' were nearly able to fully avoid voltage limit violations.

In both failure-scenarios, remaining estimation errors lead to an increase of the used voltage band from 8.8% without communication failure to 9.3% in the best case 'Opt10'.

Summing up, the results show that voltage limit violations can be significant if no replacement values are available for voltage control in times of communication loss to critical nodes, and history-based estimation algorithms with medium complexity were effectively able to avoid voltage limit violations. According to these results, the estimation algorithm 'Opt10' with the highest complexity brings best results, but the improvement compared to 'Mean10' is not significant.
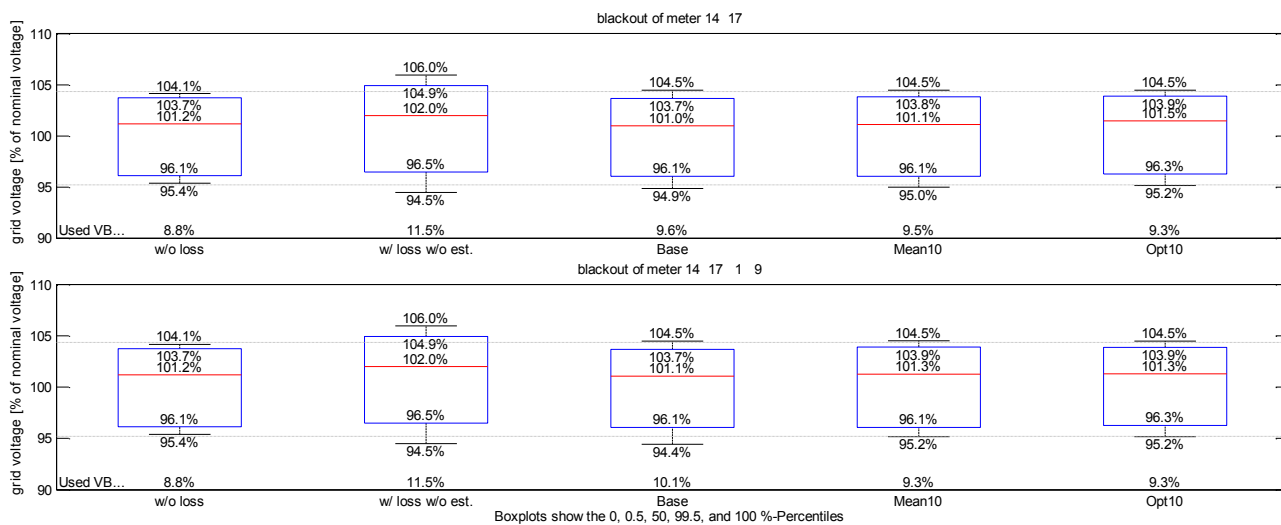
Figure 5: Impact of the different estimation methods on the power quality through different information bases of the voltage controller (boxplots show the 0, 5, 50, 95 and 100% percentiles of the voltages) for two failure scenarios

VI. OUTLOOK

Although the performance of the history-based algorithms (in the 95%-Percentile and below) look very promising, there are many possibilities to further improve the algorithms. The current implementation of the history-based algorithms only considers voltages resulting from the grid's power flow for finding the best match in the database. In future it can be analysed whether information about daytime or day of week can increase the voltage estimation quality (assuming recurring customer behaviour). Furthermore the transformer power flow can be also a criterion for comparison. In grids with significant PV infeed, a PV reference measurement can also help to improve estimation quality. And finally the combination of history-based and topology-based algorithms might bring very robust results.

Nevertheless the focus must be kept on solutions that are easy to install and easy to configure with low maintenance effort. Otherwise solutions will get close to LV grid state estimation, which will may be necessary in case of urban grids due to taking also current measurements into consideration.

VII. CONCLUSION

Simulations as well as field tests showed the general feasibility of the developed solutions. The field test component showed in real operation the expected behaviour according the preceding simulations. Concerning the estimation error, 95% of the estimations were calculated successful with small estimation errors. Higher estimation errors that could have negative influence on the voltage control process occur only rarely. This critical point can be refuted by the fact that bad estimations will not necessarily lead to negative effects in the voltage control process because not every lost communication package is a critical one. Simulations showed that despite the rare occurrence of high estimation errors the voltage estimator supports the voltage controller in maintaining voltage limits effectively. The modular design of the estimation component and the fact that no configuration is needed for history-based methods enables a comfortable integration of the component into the existing framework.

ACKNOWLEDGEMENT

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