Evaluation of Different Development Possibilities of Distribution Grid State Forecasts

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Abstract: The number of renewable energy systems is still increasing. To reduce the worldwide CO₂ emissions, there will be even more challenges in the distribution grids like currently upcoming charging stations or heat pumps. All these new electric systems in the low voltage (LV) and medium voltage (MV) levels are characterized by an unsteady behavior. To monitor and predict the behavior of these new flexible systems, a grid state forecast is needed. This software tool calculates wind, photovoltaic, and load forecasts. These power forecasts are already in the focus of research, but there are some specific use cases, which require a more specific solution. To get a variously applicable software tool, different new functions to improve an already existing grid state forecast tool were developed and evaluated. For example, it will be proofed if a grid state forecast tool can be improved by calculating the number or the base load of the loads in grid areas by just one available measurement. Another big subject exists in the exchange of forecast information between different voltage levels. How this can be realized and how big the effect on the forecast quality is, will be analyzed. The results of these evaluations will be shown in this paper.

Keywords: grid state forecast; smart grids; distribution grids; congestion management

1. Introduction

To achieve the aim of energy supply without pollutant emissions, what could be reached until 2050 according to [1], a further expansion of renewable energy systems is needed. Due to that, there will be more and more non time-discrete loads and generators in the distribution grids, which stress the grids in various ways. In a few times, there could occur different improbable load and generation situations at the same time, which could cause grid congestions. One example of these unfavorable overlaps could be a situation of less load and much generation. To prevent these rare situations, a grid state forecast is favorable as information source for the distribution system operator (DSO).

Thereby the grid congestion is predicted soon enough to react by a local flexibility market presented in [2,3] or by a preventive controlling smart grid system. In these concepts, the predicted voltage and current values of all nodes and branches are evaluated for a voltage boundary violation or a cable overload. Then, the according algorithm calculates how the grid congestion could be prevented. This could be done by load shifting or throttling down a generation system for example. That these preventive concepts of using flexibility can be more effective and less expensive than conventional grid enhancement is shown [4].

In the literature, there are some approaches for grid state forecasts shown in [5–7], but none of them seem usable for this specific use case. The biggest common disadvantage is the dependence of...
available measurements. For a local flexibility market or a preventive controlling smart grid system, a high temporal resolution of the forecasts is mandatory, so that the runtime is not in real-time, but in the minute range. The forecast has to be applicable for small loads like households or greater aggregated consumptions like medium voltage (MV)/low voltage (LV) transformers. The forecast should be capable to process topology changes and changes of the supply task. The grid state forecast should also be robust against communication failures and restarts, which means that the forecast should calculate values also without actual or previous measurements by means of a replacement value creation.

The bottom-up approach, which will be presented in this paper, can handle different situations, which can occur in a real-time use of a grid state forecast. The bottom-up approach is constructed by different levels of available information. The already existing grid state forecasts from the literature, like they are presented in [5–7], are all constructed to handle many measurements from the grid and there is no solution to handle grids without measurements. Many load forecasts, like [8–10], need every load node to be measured to predict it. This is not realistic and will not happen next time in the low and medium voltage grids. The developed bottom-up approach can handle situations with no measurements or with just one time step measured, for example, after a restart of the system. The load forecast differs if there are schedules, smart meter data, load types, previous voltage drops, or current measurements. The bottom-up approach allows it to exchange forecasts between different voltage levels, which is important to improve the forecast quality.

To predict voltage and current values of high quality, the grid state forecast has to take into account every load and generation in the grid, so that a modular bottom-up approach is used, which is shown in Figure 1.

![Figure 1. Procedure of a grid state forecast by a bottom-up approach.](image)

Assuming the bottom-up approach, the grid is separated into different grid areas. These are defined by the positions of the sensors in the grid. One example is shown in Figure 2. By the difference between incoming and outgoing currents out of the grid area, the obtained currents in the grid area can be calculated. The calculated grid area power can then be separated into load and generation by some reference generation systems, which are measured. By this procedure, for example, the generation of all photovoltaic systems in the grid can be calculated by one measured photovoltaic system. This method is inspired by the estimation of feed-in in smart grid systems as in [11].

The generation systems are all predicted on their own by several models for each type. For photovoltaic systems, the characteristics of the module, the geographical position, and the date are needed to calculate the theoretically possible feed-in of the considered day. This photovoltaic power can then be calculated with external weather forecasts. Other feeder models, as for example the wind forecast, are similarly structured. For storage systems, biogas systems, and other generation systems with plannable generation, the availability of schedules is assumed to be integrated in a modular manner into the forecast concept.
These forecasts can be improved by some single measurements at the reference systems. How the measurements can improve the forecasts is shown in [12]. How it is realized in the presented grid state forecast shows Equation (1). The factor for considering the measurements \( f_T \) is the result of the difference between the real apparent power \( \mathbf{s} := (\mathbf{s}_1, \ldots, \mathbf{s}_n)^T \) and the predicted apparent power \( \mathbf{s}^p := (\mathbf{s}^p_1, \ldots, \mathbf{s}^p_n)^T \) of \( n \) time steps. The factor of the previous forecast \( f_{T-1} \) is included with the weighting factor \( w \), which can be values between zero and one. Which value for the weighting factor gets the smallest forecast error has to be analyzed with more data. By this approach, the forecast can react on actual weather changes for example.

\[
f_T = w \cdot f_{T-1} + (1 - w) \cdot \frac{1}{n} \sum_{t=1}^{n} \frac{\mathbf{s}_t - \mathbf{s}_t^p}{\mathbf{s}_t^p}
\]  

(1)

Due to the modular bottom-up approach, these mathematical models could easily be replaced by other models. In the literature, neural networks as presented in [13,14] are very often used for grid state forecasts. Nevertheless, neural networks cannot calculate forecasts without measurements. To assure, that also in the case of absence of measurements, forecasts can be generated, the mathematical models should be kept as a backup solution, so that the plug-and-play functionality remains.

For the loads, this nodal treatment is not practicable, because single households cannot be simulated by a periodic mathematical model as well as renewable energy systems. The load behavior does not follow a single pattern, but rather shows some random effects with recurring patterns.

To get a first estimation, standard load profiles from [15] can be used for the load forecast, but if there are measuring sensors in the grid, these measurements should be used instead.

If every node in the grid is measured, an approach like for example the one shown in [16] can predict the loads all by their own. Especially in low voltage grids, this complete database will properly never be reached. Due to the fact that normally not every load is measured separately, the load is predicted for aggregated loads in grid areas as shown in Figure 2.

The load forecasts of these grid areas are based on the measurements of the past weeks, out of which an average load profile is built. If there are fewer measurements, the average of just one week or at least the last day is taken into account. By exponential smoothing, the power peaks, which are not every week at exactly the same time, are smoothed. In every time step, the load forecast is corrected by the actual measurements also by Equation (1).

Every section of this paper shows a new functionality of grid state forecasts to handle some specific new use cases. Other existing methods for grid state forecast do not handle specific use cases like these. A possible improvement of this load forecast will be presented in Section 2. In the end, the load has to be distributed to all nodes in the grid areas to get voltage and current values by a power flow calculation. For this distribution, several methods are possible, which will be shown and evaluated in Section 3. These distribution methods and the power flow calculation itself require lots of runtime. To examine if this effort is necessary, a second method without load distribution and power flow calculations has been implemented, which will also be evaluated in Section 4. In Section 5, it will be evaluated how an exchange of forecast information between different voltage levels can improve.
the grid state forecast quality. In Section 6, there is a short discussion of this concept, and in Section 7, a conclusion is made.

2. Improvement of the Load Forecast

The advantage of this modular-bottom-up approach consists in the possibility to react on different situations, which can occur during a longer time of cyclic executions of a grid state forecast software tool. One example can be the first start or a restart of the software tool. Grid state forecasts, which consist of neural networks or autoregressive models, cannot calculate valid forecasts in such a situation. They need a lot of training time, in which they collect measurements, before they are executable. By which new functionality the modular bottom-up approach can handle this situation, will be explained in the following.

At the beginning of recording measurements, there are not enough measurements to get a forecast out of them, for which at least a whole day is needed. To estimate the load base anyway, standard load profiles can be combined with the first measurements. For this method, the standard load profiles named H0 for households (written in the vector \( h := (h_1, \ldots, h_n)^T \)), G0 for industry (written in the vector \( g := (g_1, \ldots, g_n)^T \)), and L0 for agriculture (written in the vector \( l := (l_1, \ldots, l_n)^T \)) are used [15]. These profiles are not suitable for single households, but for a few hundred in aggregation.

Due to this fact, this method will be working better in medium voltage grids than in low voltage grids, because there are more households in the grid areas, which are at large more similar to a standard load profile. Nevertheless, this method should be used also in low voltage levels, because this database is better than one single measured value, which does not identify the behavior over the whole day with sufficient accuracy. In the following, multiple possible cases with different available information of the loads are explained based on Figure 3.

![Figure 3. One example of a medium voltage grid area with different load types.](image)

The most simple case consists in grid areas, where all loads and the number of load types \((N_h, N_g, N_l)\) are known. This case exists if the considered grid is a LV grid and the loads in the grid area are known or in the case of a MV grid, where only MV/LV transformers with known load types can be estimated. According to Figure 3, this would be the case if the two MV/LV transformers would be the only loads in the highlighted grid area and the subordinate load types would be known. The calculation of the predicted grid area load \( s^p_{Load} \) in these cases is based on the Equation (3):

\[
s^p_{Load} = N_h \cdot h + N_g \cdot g + N_l \cdot l \quad \text{with} \quad s^p_{Load} := (s^p_{Load,1}, \ldots, s^p_{Load,n})^T
\]

At the system start or when the topology has switched and the old measurements cannot be used anymore, there is initially only one measurement. This data can be converted to the grid area power, which is not sufficient for calculating the grid area load forecast by an average day, but should still be used to calculate the number of loads in the grid area. For LV and MV grids, different cases can occur:

The first case is a medium voltage grid where all loads in the grid area are MV/LV transformers and the number of load types in the LV grids is not known or a LV grid, where the number of loads in the considered grid area is not known. In Figure 3, this would be the case if the two MV/LV transformers are
the only loads in the highlighted grid area and the subordinate load types are not known. In this case, the assumption is made that all loads in the grid area are of the load type “household”. The prediction of the grid area load by the calculation of the number of households with one measurement $s_t$ of the time step $t$ is based on Equation (3).

$$s^p_{Load} = \frac{s_t}{h_t} \cdot h$$

(3)

According to Figure 3, the opposite would occur if the two MV/LV transformers would not exist and all loads in one MV grid area would be industrial loads without available slave pointer values. However, if there are slave pointer values of the stations, these are assumed as constant loads. The first approximation in this case is using the G0 standard load profile to calculate the base load. This approximation is calculated using Equation (4).

$$s^p_{Load} = \frac{s_t}{g_t} \cdot g$$

(4)

If there are $N_{MV/LV}$ MV/LV transformers and industrial loads in a MV grid area (as it is shown in Figure 3) and the number of load types in the LV grids is known, the grid area load is calculated using Equation (5).

$$s^p_{Load} = x + \frac{s_t - x_t}{g_t} \cdot g \text{ with } x := (x_1, ..., x_n)^T = N_h \cdot h + N_g \cdot g + N_l \cdot l$$

(5)

If there are mixed loads and the number of load types in the subordinate grids is unknown, Equation (6) can be used.

$$s^p_{Load} = \frac{s_t}{h_t \cdot (N_g + N_{MV/LV})} \cdot h \cdot N_{MV/LV} + \frac{s_t}{g_t \cdot (N_g + N_{MV/LV})} \cdot g \cdot N_g$$

(6)

An evaluation of this new method is unnecessary, because the alternative method would be to use the standard load profiles with an assumed specific number of households, which does not change. In this case, the forecast error depends on this assumption, so it can randomly match the real number of households but in most cases, it will not fit at all. Due to this, the results of a case study would just depend on the assumptions and would not be significant at all.

Other developed methods for short-term load forecasts, like [9,17], also depend on measurements and do not work at all in such cases. These methods would distribute no valid forecasts at all.

3. Improvement of the Grid Area Load Distribution

To calculate the voltage and current values at all nodes respectively branches, power flow calculations are used, but a power flow calculation cannot handle with grid area loads, because it needs a power value for every node in the grid. Therefore, the grid area loads have to be distributed to the nodes within the grid areas. To estimate the relation of the loads more realistically, some data like smart meter data, load types, or voltage and current measurements can be used. Different methods, how state estimation approaches can be adapted to a grid state forecast, will be presented in the following.

The use case for the methods, which will be shown in this chapter, is the following: At first, the grid area load is predicted by measurements of the past weeks. Second, the predicted load has to be distributed to the nodes within the grid area. For this distribution, different methods will be shown. For every grid area, it has to be decided which method is practicable for the load distribution. After the load distribution of every grid area, a power flow calculation can be done to calculate the voltage and current values for the considered grid.
3.1. Distribution by Load Types or Smart Meter Data

For distributing the predicted grid area loads to the nodes within the corresponding grid areas in low voltage grids, smart meter data are useful to calculate the household’s percentage of the total grid area load for the considered time of the day, based on previous measurements. That previous smart meter measurements can improve the grid state estimation was already shown in [18]. This relation can be used for the distribution of the grid area load forecast.

At first, these calculated percentages of the total grid area load are assigned to the according smart meter nodes. After this, the remaining load is distributed to the other nodes depending on their load types and their relations to each other. One example of a load distribution is shown in Figure 4. In this case, the predicted grid area load is 20 kVA. The smart meter households get the calculated percentages depending on their previous smart meter data. The rest of the predicted power is distributed by the relations of the load types to the standard load profile of households. Due to this, the factor F for households is one. In this time step, the factor F of industry loads amounts 2. These factors are calculated with the predicted grid area power and are divided by the sum of all factors.

![Figure 4](image)

These load types are the same as already presented in the section before. To use them for the load distribution, the relation of the standard load profiles must be established for each season, every weekday and every time. For example, on Sundays at noon, a household receives more energy than an industrial load—on weekdays it is the other way around.

If there is no information about the loads and no smart meter data, only a linear distribution is usable, so that the same load is applied to each load node.

3.2. Improved Distribution by Measurements

To distribute the grid area load to the nodes within, previous measurements are helpful to detect load centers, which obtain more load than the other nodes. The two corresponding methods, which will be explained in the following, are usable at every voltage level.

3.2.1. Load Distribution by Voltage Measurements

If more than one voltage measurement exists in the grid area, which is the case especially in meshed grids, the voltage drop across the grid area can be examined, which can provide information about the load relation between the nodes in the grid area. This can be done by using the method to
estimate the relation between the individual loads in the grid area presented in [19,20]. The novelty presented in the following is the usage of this method for a load distribution of a grid area load in the context of grid state forecasts by using previous measurements for the forecast of the load distribution in the future.

To detect the relation of the loads in one grid area by means of the voltage drop, the sensitivities in the grid area have to be investigated. The sensitivity describes the influence of a power change of one considered node on the voltage of the other nodes in the grid. How the sensitivity matrix can be calculated was already shown in [21]. The node with the highest sensitivity on the first sensor of the grid area is now detected as the best-case node, the node with the lowest sensitivity as the worst-case node. These designations result from the fact that the voltage drop would be small if the whole grid area load would be obtained by the best-case node and large if it would be obtained by the worst-case node. In addition, there is the linear case, where the whole load is shared equally among all load nodes in the grid area.

Which of these three cases is the most probable in the considered grid area at the considered time, can be calculated by evaluating the measurements of the weeks before, of which the measurements of the same time of the same weekday are considered. To proof, which case existed in the weeks before, a power flow calculation has to be done for every case. The measured load of the grid area is first linearly distributed, then placed completely on the worst-case node and finally on the best-case node. In all three variants, the remaining nodes in the grid are treated equally in all cases. The case whereby the calculated voltage values most closely match the measured values is chosen for this time step. Out of this calculation a factor $a$ for every week $k$ results, which can take values between one and three, whereby one stands for the worst-case, two stands for the linear distribution, and three represents the best-case. The weeks are weighted using Equation (7), so that the newest measurements are weighted the most to get the predicted factor $a^p$ of the load distribution of the considered time step.

$$a^p = \sum_{k=1}^{n} \frac{2 \cdot (n + 1 - k) \cdot a_k}{n \cdot (n + 1)}$$

If there are more than two sensors in the grid area, then the two sensors are used for this procedure, which are separated by the most load nodes.

Figure 5 shows the used grid to simulate this use case of a grid state forecast. It is a real rural LV grid with 51 load nodes and 18 photovoltaic systems. It shows two highlighted grid areas, which are usable for the load distribution with the help of voltage measurements. The rest of the grid areas, which are not highlighted, are not usable for this method for the load distribution, because in each case there is just one single voltage sensor, which defines the grid area. In these areas, other methods like the linear load distribution or the distribution by smart meter data are usable.

To evaluate this method in the shown grid, a load flow simulation tool [22], which simulates the behavior of the load nodes by standard load profiles, is used instead of real grid measurements. For the generation of the photovoltaic systems, real measurements are used and converted to the installed powers, so that pseudo weather forecasts can be calculated by them. It runs a power flow calculation and creates pseudo measurements for the measured nodes, which are delivered to the grid state forecast. By using this simulation tool, the grid state forecast can be evaluated at all nodes in the grid and not just at the measured nodes. The process can be described as follows: At first, the load flow simulation tool delivers the pseudo measurements to the grid state forecast tool. After collecting enough measurements, a grid area load forecast can be done by calculating an average load profile out of the measurements of the previous days. This grid area load forecast is once distributed linearly, so that every load node gets the same load forecast, and once distributed by the measured voltage drops of the previous days. The nodal powers, which result by these two different approaches, are calculated to voltage and current values by a power flow calculation. By this method, the predicted
voltages at the nodes between the measurements can be compared to the calculated values of the load flow simulation as reference.

Figure 5. A low voltage grid with sensors at the transformer and the wiring closet at node 9.

To analyze the method to distribute the load within the grid areas, in every highlighted grid area is randomly placed one centered load, which obtains multiple power than the other nodes. These two load centers are set to a constant power demand through all time steps. Due to this, at all time steps the voltage-based load distribution should place the most of the predicted area load to the detected load center. Power losses are neglected.

Figure 6 shows the node voltages at one time step of the simulation. Through this method, the exact load center cannot be detected, but the voltage course over the nodes in general can be estimated much better with the help of older voltage measurements.

The analysis of the forecast errors are done by using the mean average percentage error (MAPE), because this measure is state of the literature and also used in like [8] or [10] for example. Equation (8) shows how the MAPE is calculated. \( F_t \) stands for the predicted value (depends on the analysis, if it is voltage, current, or power) and \( A_t \) stands for the real value of time step \( t \). The MAPE is then the average of \( n \) time steps of this calculation.

\[
\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \frac{|A_t - F_t|}{A_t}
\]  

(8)

The MAPE over all nodes could be reduced from 0.69% to 0.62%, so this load distribution method is very advisable to generate more information out of the measurement database.
All voltage forecast errors of this grid areas over all simulated time steps are shown in Table 1. In general, it can be concluded, that the voltage-based load distribution can improve the grid state forecast a lot. To evaluate the applicability of this approach in the context of grid state forecasts in general, more simulations have to be done. Especially other topologies have to be analyzed, because the most LV grids are not meshed, like this example grid. Anyway, for this approach, meshed grids are nevertheless representative, because especially in meshed grids, the grid areas are defined by more than one sensor. Due to this fact, this approach will be used more often in meshed grids, than in grids with single strands.

### Figure 6. Improvement of the forecasts by using the voltage-based load distribution (one time step)

### Table 1. Voltage forecast errors at the highlighted nodes.

| Node | MAPE in % linear load distribution | MAPE in % voltage-based distribution |
|------|-----------------------------------|-------------------------------------|
|      | 0.59 0.49 0.60 0.87 0.79 0.87 0.88 0.84 0.81 0.71 0.41 0.46 | 0.60 0.48 0.55 0.74 0.68 0.74 0.78 0.75 0.72 0.63 0.38 0.37 |
|      | Average: 0.69                      | Average: 0.62                       |

3.2.2. Load Distribution by Current Measurements

In equivalent to the already shown method, current measurements can also be useful to estimate the load relation within one grid area. As a new expansion to the voltage depended procedure, a current-based method was developed, which is a new possibility to distribute the loads within one grid area. This method could be assumed for state estimations, too, if the following evaluation shows that it estimates the load distribution better than the linear distribution.

This method is useful, if there are not two voltage measurements limiting the grid area or if there are two measurements, but they are not at the edges of the grid area, so that they cannot give an useful information about the relation between all nodes in the grid area.

Mostly this concept is usable for ring structures, if there is just one voltage measurement, but two current measurements that define the considered grid area. In this case, the same procedure as in the case with two voltage measurements can be used. The past current measurements can give the information, if there exists mostly a best-case, a worst-case, or a linear case of the load relation in the grid area at the considered time step.

To proof the impact on the forecast quality, the already mentioned simulation tool can be used, too. The same grid is usable, but with another load scenario and another number of measurements. Power losses are neglected in this case, too. In this case, there are just the measurements at the
transformer and not the measurements at the wiring closet, so that just one big grid area results, which is shown in Figure 7.

In the simulation, node twelve obtains much more load than the other nodes, to prove if the forecast detects this load center. All other time series are the same as in the example before. At node one, where was a load center too in the example before, a time series is set, which is more similar to the other nodes.

Due to that, the voltage-based method cannot be chosen and the load distribution by previous current measurement is executed by the grid state forecast.

Table 2 shows the mean average percentage errors of the highlighted nodes over all simulated time steps. The mean error of all node voltages is reduced from 0.55% to 0.44%, which is a big impact and underlines that this new method to distribute the grid area load is very useful.

One time step is shown in Figure 8. It is obvious that the load center is well detected and that the voltage forecasts at all nodes in this grid area can be improved by using the current measurements for the load distribution.
Table 2. Voltage forecast errors at the highlighted nodes.

| Node | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   | Average |
|------|------|------|------|------|------|------|------|------|------|------|------|------|---------|
| MAPE in linear load distribution | 0.39 | 0.39 | 0.47 | 0.69 | 0.63 | 0.69 | 0.7  | 0.67 | 0.64 | 0.54 | 0.30 | 0.47 | 0.55    |
| MAPE in current-based distribution | 0.25 | 0.25 | 0.31 | 0.50 | 0.43 | 0.50 | 0.59 | 0.59 | 0.59 | 0.53 | 0.38 | 0.38 | 0.44    |

Figure 8. Improvement of the forecasts by using the current-based load distribution (one time step).

Figure 9 shows, that also the branch current forecasts can be improved by the presented method. In general, the mean current forecast error could be reduced by 5%. This load center detection can thereby help to predict cable overloads. Particularly in regards to the increasing number of electric vehicles in the LV grids, this load center detection can be helpful to predict recurring charging patterns.

Figure 9. Simulated branch currents in comparison to the forecasts at one time step.
Finally, this approach is useful in the context of grid state forecasts, so it is conjecturable that it is also useful for state estimation in real-time smart grids solutions. This application should be investigated in further research in the context of smart grids.

4. Simplification of the Grid State Estimation

The recently shown load distribution is needed for the power flow calculation, which is used to calculate the nodal voltages and the branch currents. Now it will be analyzed, if this big effort and the thereby resulting longer runtime can be reduced by using another method to calculate the voltage and current values without a power flow algorithm. For this scope, sensitivities could be helpful. This approach only calculates voltage and current forecasts for the measured nodes and branches. If the positions of the sensors are chosen appropriate and cover the important hotspots of the grid, these forecasts could suffice to classify the whole grid state. One advantage of the chosen sensitivity approach shown in [21] is that it is a deterministic method and always calculates a result. The power flow calculation instead does sometimes not converge. That the sensitivity approach can be useful in similar cases was already shown in [20].

The sensitivity matrix $X$ of the grid consists of the impact of apparent power changes on the changes of the voltages at all nodes.

Equation (9) shows the predicted voltage change at node $i$ $\Delta U^p_i$ caused by a predicted change of the apparent power at node $k$ $\Delta S^p_k$ based on the predicted voltage at node $k$ $U^p_k$ (based on previous measurements as first estimation). The predicted apparent power change is the difference of the measured apparent power and the predicted value for the considered time step. This calculation can be done for every of the $N$ measured nodes.

$$\Delta U^p_i = \sum_{k=1}^{N} \left( \frac{\Delta S^p_k}{3} \right) \cdot \frac{X_{ik}}{U^p_k}$$

The power changes at the $N$ measured nodes cause also current changes at the sensors in the grid. The number of the current sensors must not be the same as the number of voltage sensors. The predicted changes of the branch currents (for example $\Delta I^p_{i,j}$ for the branch between the nodes $i$ and $j$) can be calculated equivalently considering Equation (10) and by using the impedance matrix $Z$.

$$\Delta I^p_{i,j} = \sum_{k=1}^{N} \left( \frac{\Delta S^p_k}{3} \right) \cdot \frac{X_{ik} - X_{jk}}{U^p_k \cdot Z_{i,j}}$$

Due to the fact that the nodal voltage $U^p_k$ is needed for these Equations, this is just practicable for measured nodes and not for the nodes included in the grid areas. To consider also the power of $M$ grid areas, another sensitivity matrix $W$ is built, which describes the relation between the grid areas and all nodes in the grid. In this case, the variable $\Delta S^p_k$ describes the predicted power difference of grid area $k$ and $W_{k,i}$ describes the sensitivity of grid area $k$ on node $i$. The needed voltage value $U^p_k$ is estimated by means of the sensor measurements, which limits the considered grid area. Thereby the Equations (11) and (12) result to consider all grid areas.

$$\Delta U^p_i = \sum_{k=1}^{M} \left( \frac{\Delta S^p_k}{3} \right) \cdot \frac{W_{k,i}}{U^p_k}$$

$$\Delta I^p_{i,j} = \sum_{k=1}^{M} \left( \frac{\Delta S^p_k}{3} \right) \cdot \frac{W_{k,i} - W_{k,j}}{U^p_k \cdot Z_{i,j}}$$
Finally, all of these voltage and current changes were calculated and added to the present measured values \((U_i, j, I_i, j)\). Thereby the forecasts for all sensors in the grid result according to the Equations (13) and (14).

\[
U_{p,i} = U_i + \Delta U_{p,i} + \Delta U_{p,Slack} \quad (13)
\]

\[
I_{p,i,j} = I_{i,j} + \Delta I_{p,i,j} \quad (14)
\]

In Equation (13) \(\Delta U_{p,Slack}\) is the difference between the actual slack voltage at the transformer and the predicted slack voltage for the considered time step. This offset is important, because in the meantime of the forecast the situation in the higher voltage level could change and cause a non-negligible voltage change, which has an impact on all nodes in the considered grid. If the measured values of less than one day exists, the nominal voltage is assumed. Otherwise, the voltage value of the last day is used. If there are more than seven days, the voltage curve of the last same weekday is assumed. Finally, the difference between this forecast and the last measured values is taken into account in order to bring the forecasts closer to the current curve. This difference is considered with linearly decreasing weighting, so that it just has an effect on the next few time steps, because later time steps do not depend on actual short changes.

Figure 10 shows the results of executing the grid state forecast once with the sensitivity approach and once with the load distribution and power flow calculations for one grid. The used data are real measurements at 40% of the load nodes in the grid, for example at the transformer and at some wiring closets. These real measurements of one week for every season were evaluated.

![Figure 10](image)

**Figure 10.** Evaluation of the error increase in one LV grid by using the sensitivity approach

The sensitivity approach is 8% faster (from 7.0 seconds to 6.6 seconds per time step with an Intel i7 quad-core processor and a RAM of 16 GB), but shows voltage errors (MAPE), which are 0.17% higher. In the context that the mean voltage error (MAPE) is 0.87% with the power flow calculation, this difference can be critical. In some situations, the sensitivity approach though can be better than the load distribution with the power flow, because the sensitivity approach uses the currently measured voltages to calculate the forecasts. For the power flow, only the slack voltage is taken into account and the other voltages (at unmeasured nodes and at measured nodes, too) are calculated by the power forecasts. If there are very small power changes predicted, the voltages do not change a lot. The sensitivity approach detects this behavior better, because it predicts an almost equal value to the current value. This could be the cause for the small difference between the two methods in winter. In winter, there are smaller power changes than in summer, because this grid is characterized by a high
photovoltaic penetration. Due to this fact, more evaluations with more other grids have to be done to estimate the effect of the sensitivity approach on the forecast quality.

5. Exchanging Forecasts between Voltage Levels

As already mentioned, voltage changes at the slack node of the grid have a great impact on all nodal voltages. Due to this fact, the quality of the power forecasts is not the only important key factor in this use case. A good forecast of the temporal development of the slack voltage is even more decisive. Out of the considered grid, the forecast of the grid state of the higher voltage level is not feasible without knowing the grid parameters. Therefore, the only information, which is usable, are the previous measurements. It should be an aim to install a grid state forecast also in the higher voltage level, so that both forecasts can profit from each other, as is shown in Figure 11.

![Figure 11. Procedure of exchanging information between the forecasts of two voltage levels.](image)

At first, the LV forecast calculates voltage and power values for all nodes as well as current values for all branches. The MV forecast gets the predicted total power of the LV grid through a defined interface and handles it like a schedule for the according node. Then the MV forecast is executed. The predicted node voltages as output of this forecast can be used by the LV forecast as predicted slack voltage. This information can improve the forecast a lot, because without the predicted slack voltage as input, it has to be predicted without information from the higher voltage level and is very prone to error, which extends to all other nodes in the grid.

Figure 12 shows the measurements for one voltage sensor in one grid. The green line demonstrates the forecasts with known slack voltage. In reality, there would be also a forecast error out of the higher voltage level, but this is neglected in this case. Drawn in blue is the forecast without knowing the slack voltage. The shown forecasts were made at the simulation time step at 11:00 PM for the next 24 h. The figure shows the big effect of knowing the slack voltage for predicting the whole grid state. Through the exchange of forecasts between the different voltage levels, for example the planned step range at the transformer at 12:00 AM can be taken into account for the forecasts, which improves the forecasts very much.

The figure shows a node that is much meshed, so this effect does not just show up at transformer nearer nodes, but also at nodes, which are influenced also by the power changes at many other nodes.

Several of these analyses were made for this LV grid. The evaluations are based on one week for every season (summer, winter, and mid-season). Every half an hour, a forecast in a 5-min resolution for the next 24 h is made. Overall, the voltage forecast errors (MAPE) at the measured nodes improve generally by 0.19%, whereby the general voltage error (MAPE) amounts to 1.3% without known slack voltage. This demonstrates that the knowledge of the predicted slack voltage is decisive for a good forecast.
6. Discussion

In comparison to other approaches of grid state forecasts, the presented software application includes a few more use cases, as for example the missing of previous measurements. Other approaches, like they are shown in [6,7,23], obligatorily need measurements to calculate future grid states. This approach allows it to handle new situations in the grid without the necessity to restart the whole system. For example, this would be the case with a neural network, because it would have to train the system once again when a new generation system is integrated or the topology is changed. In addition, neural networks rely on a big database and a long executing time, which was already analyzed in [14].

The presented bottom-up approach instead needs less data (as shown in Section 2) and does not have to be trained at first. Due to these facts, a substitution of the shown grid state forecast with all its functionalities by a neural network is not possible, but some single forecast modules could be supplemented by other forecast models, like neural networks for example. Therefore, the possibility is given to combine this framework with other forecast methods.

The modular bottom-up approach allows changing single parts like the photovoltaic power forecast for example. The innovation consists therefore of the framework around all these single modules, which decides which module has to be used depending on the actual database.

The presented grid state forecast is realized in a standalone application and is very robust against external effects. In addition, it allows the exchange of forecast information between different voltage levels.

7. Conclusions

Different new functions for a grid state forecast were presented in this contribution. Some additional functionalities can improve the runtime of the software, some functionalities can improve the forecast quality:

- A new approach to calculate load forecasts completely without or with just a few measurements was shown. Thereby the base load can be calculated by the relation of standard load profiles and the measured value. This is a big advantage in comparison to other methods for load forecasts in the literature, because these need many measurements to calculate values for future time steps.
- It was shown that the load distribution by voltage or by current measurements, which is a new method to detect load centers in the grid, are better than a linear distribution. The current based
distribution can be useful for predicting the loads of electric vehicles, if the owner shows recurring charging patterns.

- It was shown that sensitivity approaches could be used for the state estimation instead of a load distribution and a power flow, but just if all critical nodes are measured. This is a condition, because the developed formulas are just usable for the forecast of measured nodes. At these nodes, the forecast quality is almost as good as the approach with the load distribution and the power flow.

- The most important presented functionality is the use of forecasts in coordination with other voltage levels. By the information exchange between the low voltage grids and the medium voltage grids, the slack voltages in the low voltage grids can be predicted much more precisely. It was shown that the knowledge of the slack voltage has a significant impact on all nodes in the analyzed grid and could improve the forecast quality in all cases.

In the future, the grid state forecast can be improved by even more functionalities. According to the modular bottom-up approach, new models can be integrated easily.

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**References**

1. Ram, M.; Bogdanov, D.; Aghahosseini, A.; Gulagi, A.; Oyewo, A.S.; Child, M.; Caldera, U.; Sadowskaia, K.; Farfan, J.; Barbosa, L.; et al. *Global Energy System based on 100% Renewable Energy – Energy Transition in Europe Across Power, Heat, Transport and Desalination Sectors*; LUT University: Lappeenranta, Finland; Energy Watch Group: Berlin, Germany, 2018.

2. Kotthaus, K.; Herrmanns, J.; Paulat, F.; Pack, S.; Meese, J.; Zdrallek, M.; Neusel-Lange, N.; Schweiger, F.; Schweiger, R. Concrete design of local flexibility markets using the traffic light approach. In Proceedings of the CIRED Workshop 2018 on Microgrids and Local Energy Communities, CIRED Workshop, Ljubljana, Slovenia, 7–8 June 2018.

3. Herrmanns, J.; Pack, S.; Kotthaus, K.; Zdrallek, M.; Schweiger, F.; Schweiger, R.; Raczka, S.; Baumeister, C. Preparation of a field test to evaluate a local flexibility market as a smart grid add-on. In Proceedings of the 2019 Conference on Sustainable Energy Supply and Energy Storage Systems, IEEE PES NEIS Conference, Hamburg, Germany, 19–20 September 2019.

4. Biegel, B.; Andersen, P.; Stoustrup, J.; Rasmussen, K.S.; Hansen, L.H.; Ostberg, S.; Cajar, P.; Knudsen, H. The value of flexibility in the distribution grid. In Proceedings of the 2014 IEEE PES Innovative Smart Grid Technologies Europe, IEEE PES ISGT-Europe, Istanbul, Turkey, 12–15 October 2014.

5. Hayes, B.P.; Prodanovic, M. State Forecasting and Operational Planning for Distribution Network Energy Management Systems. *IEEE Trans. Smart Grid* **2016**, *7*, 1002–1011. [CrossRef]

6. Antonicic, M.; Ilkovski, M.; Blazic, B. State forecasting in distribution networks. In Proceedings of the 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), Bucharest, Romania, 29 September–2 October 2019.

7. Zhao, J.; Zhang, G.; Dong, Z.Y.; La Scala, M. Robust Forecasting Aided Power System State Estimation Considering State Correlations. *IEEE Trans. Smart Grid* **2018**, *9*, 2658–2666. [CrossRef]

8. Dehalwar, V.; Kalam, A.; Kolhe, M.L.; Zayegh, A. Electricity load forecasting for Urban area using weather forecast information. In Proceedings of the 2016 IEEE International Conference on Power and Renewable Energy (ICPRE), Shanghai, China, 21–23 October 2016; pp. 355–359.

9. Bennett, C.; Stewart, R.; Lu, J. Autoregressive with Exogenous Variables and Neural Network Short-Term Load Forecast Models for Residential Low Voltage Distribution Networks. *Energies* **2014**, *77*, 2938–2960. [CrossRef]
10. Rejc, M.; Einfalt, A.; Gawron-Deutsch, T. Short-term aggregated load and distributed generation forecast using fuzzy grouping approach. In Proceedings of the 2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST), Vienna, Austria, 8–11 September 2015; pp. 212–217.

11. Neusel-Lange, N.; Oerter, C.; Zdrallek, M. State identification and automatic control of smart low voltage grids. In Proceedings of the 2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), Berlin, Germany, 14–17 October 2012.

12. Kolev, V.; Sulakov, S. Short-term power output forecasting of the photovoltaics in Bulgaria. In Proceedings of the 2018 10th Electrical Engineering Faculty Conference (BuLEF), Sozopol, Bulgaria, 11–14 September 2018; pp. 1–4.

13. Khana, I.; Zhua, H.; Yaya, J.; Khana, D. Photovoltaic Power Forecasting based on Elman Neural Network Software Engineering Method. In Proceedings of the 2017 8th IEEE International Conference on Software Engineering and Service Science, ICSESS, Beijing, China, 20–22 November 2017.

14. Hamid Oudjana, S.; Hellal, A.; Hadj Mahamed, I. Short-term photovoltaic power generation forecasting using neural network. In Proceedings of the 2012 11th International Conference on Environment and Electrical Engineering, Venice, Italy, 18–25 May 2012; pp. 706–711.

15. Schieferdecker, B.; Fünfgeld, C.; Meier, H.; Adam, T. Repräsentative VDEW-Lastprofile. In VDEW-Materialien; VDEW: Frankfurt, Germany, 1999.

16. Yuce, B.; Moursesh, M.; Rezgui, Y. A Smart Forecasting Approach to District Energy Management. Energies 2017, 10, 1073. [CrossRef]

17. Li, Y.; Guo, P.; Li, X. Short-Term Load Forecasting Based on the Analysis of User Electricity Behavior. Algorithms 2016, 9, 80. [CrossRef]

18. Samarakoon, K.; Wu, J.; Ekanayake, J.; Jenkins, N. Use of delayed smart meter measurements for distribution state estimation. In Proceedings of the 2011 IEEE Power and Energy Society General Meeting, 2011 IEEE Power & Energy Society General Meeting, San Diego, CA, USA, 24–29 July 2011.

19. Ludwig, M.; Korotkiewicz, K.; Dahlmann, B.; Zdrallek, M.; Derksen, C.; Loose, N.; Törsleff, S.; Wassermann, E. Agent-based grid automation in distribution grids: Experiences under real field conditions. In Proceedings of the CIRED Workshop 2018 on microgrids and local energy communities, CIRED Workshop, Ljubljana, Slovenia, 7–8 June 2018.

20. Steinbusch, P.; Modemann, M.; Wazifehdust, M.; Zdrallek, M. Fast Distribution Grid State Estimation Using Improved Sensitivity Analysis. In Proceedings of the 8th IEEE PES Innovative Smart Grid Technologies Conference Europe, IEEE PES ISGT-Europe, Sarajevo, Bosnia and Herzegovina, 21–25 October 2018.

21. Wolter, M. Grid State Identification of Distribution Grids; Shaker: Aachen, Germany, 2008.

22. Dorsemagen, F. Zustandsidentifikation von Mittelspannungsnetzen für eine übergreifende Automatisierung der Mittel- und Niederspannungs Ebene, 1st ed.; epubli: Berlin, Germany, 2018.

23. Hayes, B.P.; Gruber, J.K.; Prodanovic, M. A Closed-Loop State Estimation Tool for MV Network Monitoring and Operation. IEEE Trans. Smart Grid 2015, 6, 2116–2125. [CrossRef]

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