Self-detection of new photovoltaic power plants using a low voltage smart grid system

Philippe Steinbusch[1], Sebastian Fischer[1], Marcus Stötzel[1], Markus Zdrallek[1], Nils Neusel-Lange[2]

[1]Institute of Power System Engineering, University of Wuppertal, Rainer-Gruenter-Str. 21, Wuppertal, Germany
[2]SAG GmbH, Stockholmer Allee 30b, Dortmund, Germany

philippe.steinbusch@uni-wuppertal.de;
sebastian.fischer@uni-wuppertal.de;
marcus.stoetzel@uni-wuppertal.de;
zdrallek@uni-wuppertal.de;
nils.neusel-lange@sag.eu

Abstract. A rising amount of today's distribution grids are equipped with smart grid systems to face the problems arising from the increasing use of decentralized and renewable energy sources. In comparison to conventional reinforced grids smart grid systems need to be maintained to stay up to date. Especially the installed photovoltaic (PV) power is a very important parameter for the system. Self-learning smart grid systems would reduce the maintenance efforts. A huge step towards this is a self-detection of new PV power plants in the grid. In this paper three methods to detect unknown PV plants in distribution grids are introduced. They are tested and validated in a use case. Additionally the influence of undetected PV power plants to the accuracy of the grid state identification is considered. Because of the huge impact of different factors only rudimentary results are presented and further investigations are focused.

Keywords: Smart Grid System, Self-detection, PV, iNES, Green Access, Cloud Passage Method, Low Mark Method, Power Deviation Method

1 Overview

The German energy supply is going through an enormous changing process. To achieve the political and social objectives the use of decentralized and renewable energy systems is increasing. This change causes new supply scenarios, which stress the public energy grid. One solution for new load flow situations is conventional grid enhancement. Another solution is the use of smart grid systems (SGS). By using these systems, it is possible to monitor (grid state identification) and to control (intelligent grid control) the power supply in the distribution grids. In cooperation with industrial partners, the University of Wuppertal developed the smart grid solution "iNES – smart distribution grid management" [1]. The improvement of the system and the

adfa, p. 1, 2011.

integration in a combined system for medium and low voltage grids are the key assignments in the project[1] “Green Access”. The Project is executed in cooperation with EWE AG, EWE Netz GmbH, Bilfinger Mauell GmbH, BTC AG, Fraunhofer ISE, NEXT ENERGY, OFFIS e.V., SAG GmbH, SMA AG and University of Wuppertal [2][3].

Especially the plug & automate function of the low voltage automation system will simplify the operation of a SGS. The following adaptive functions are part of the project:

- Detection of new distributed energy resources,
- Detection of power-intensive loads,
- Autonomous adaption of topology adjustment,
- Network model validation,
- Assessment of sensor or actor demand.

In this paper the detection of photovoltaic power plants is focused which means the ability of the deployed SGS to identify and integrate new installed systems without a manual recon-figuration by the distribution system operator. That will lower the workload of the operator without an impact for the accuracy of the state estimation. It would improve the robustness of the system. In addition, the expected influence of PV power plants are shown in the following paper.

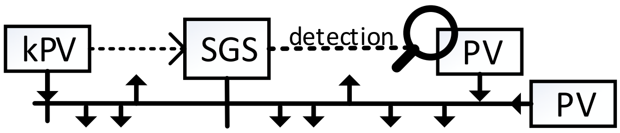

Fig. 1. Detection of new unknown PV power plants

2 Methods

In the deployed SGS, the grid state estimation is realized by measurements of only a few nodes in a grid. These nodes form the limits of several grid districts. Within a grid district the measured load is spread linearly among the not measured nodes. [4] Additionally at least one known PV (kPV) power plant within the grid is measured as a reference. No other nodes are observed. The PV system detection methods need to get along with these measurements. To calculate a proper grid state the information about existing PV power plants is important. (Fig. 1)

Three different methods to detect new or unknown PV power plants will be introduced in the next section:
- The “Cloud Passage Method”,
- The “Power Deviation Method”
- The “Low Mark Method”.

[1] Project sponsored by the German Federal Ministry for Economic Affairs and Energy (BMWI)

2.1 Cloud Passage Method

If a cloud passes the grids area, the PV feed-in of every PV power plant drops in a certain scale. If the cloud is big enough to cover the whole grid district and if it passes fast enough, all the feed-in of the PV systems will drop within a short time in the same scale. This drop of feed-in can be measured at the sensor nodes, which form the district limits. This measured decrease of feed-in respectively increase of load can be compared to a calculated decrease of feed-in. This value is calculated via the measurement of the reference PV system and the known installed PV power in every grid district.

If the measured decrease within a district is bigger than the calculated, a suspicion raises that there is an unknown PV power plant in this district. The installed power of the new system can be calculated from the found difference in power.

Because of variation in load within the same time, the calculated installed power will be defective. After many cloud passages the falsifying load differences shall show a Gaussian distribution and its expectancy value should be the installed power of the unknown PV system.

2.2 Power Deviation Method

The measured power values of the single districts are saved in a database. The known PV power is eliminated via reference PV systems. With this data average days are created for weekdays, Saturdays and holidays. For every new day the known PV power is eliminated in the district's power measurements as well. Afterwards the difference is calculated and compared to the course of the reference PV power. If there is a significant correlation between these two values there is probably an unknown PV system in the corresponding district.

If no new PV power plant is found, the day will be used for the database. If a new system is found, the day will be excluded for further database use.

After an unknown PV system has been detected several days in a row, the average of the calculated installed power values are adopted to the SGS. After that, the new PV plant can be added with hindsight via reference PV system and its power to the excluded days. Then they can be involved in the average days subsequent.

2.3 Low Mark Method

If the feed-in within a district exceeds its consumption the load flow reverses and gets negative. The Low Mark Method (LMM) records the least measured load value of every district. This low marks consist of load and feed-in. To identify the share of unknown PV feed-in the basic load and the known PV feed-in are subtracted. The basic load is determined as the mean load between 00:00 o'clock and 01:00 o'clock. The known PV power is subtracted with its installed power value, not to underestimate its influence. The calculated unknown PV power is also assumed as installed power value. Because of the conservative calculation the found PV power will tend towards underestimation but all of it can be assumed as existent to 100 %.

The single methods are limited in their accuracy and reliability. Therefore, they need to be combined to validate each other. If a certain number of methods detect the same new installed PV system, it can be assumed that it exists with a certain probability. The introduced methods are only able to detect new PV power plants within the grid districts associated with the deployed SGS. For locating new PV systems precisely at grid nodes further consideration is needed.

3 Use Case

The methods are applied to a rural network. The network consists of 149 nodes and 160 lines. It is divided into 6 districts with unequal size and PV feed-in:

Table 1. Use Case network data

District	**1**	**2**	**3**	**4**	**5**	**6**
Number Nodes*	22	5	6	38	31	51
PV systems	3	1	1	2	2	8
PV inst. Power (kW)	93	9	29	91	57	225

*measured nodes at district borders belong to several districts

The used data is measured between August 3rd and September 13th in 2015.

3.1 Use Case Adaption

Since there are no new PV systems to be installed in the use case network there is no real data for a test run. Therefore the data has to be adapted.

After 21 days, when the average days for the Power Deviation Method are build, the known PV power is reduced by the share that is to be detected. So the next days measured power values are not reduced by the whole amount of existing PV. Thus the deleted PV power remains in the following measurements, whereas the values of the average days have been reduced by the actual PV power.

4 Results

The three explained methods are applied to the above use case. Their results are very heterogeneous:

4.1 Results Cloud Passage Method

The Cloud Passage Method (CPM) has evaluated between 58 and 112 cloud passages depending on the district during the examined period. The computed differences between measured and calculated variation of load are shown in the box-plot-chart in figure two. It shows the calculated discrepancy between measured and expected load variation, converted into installed PV power, for every cloud passage. The median of every district builds the assumed unknown PV power.

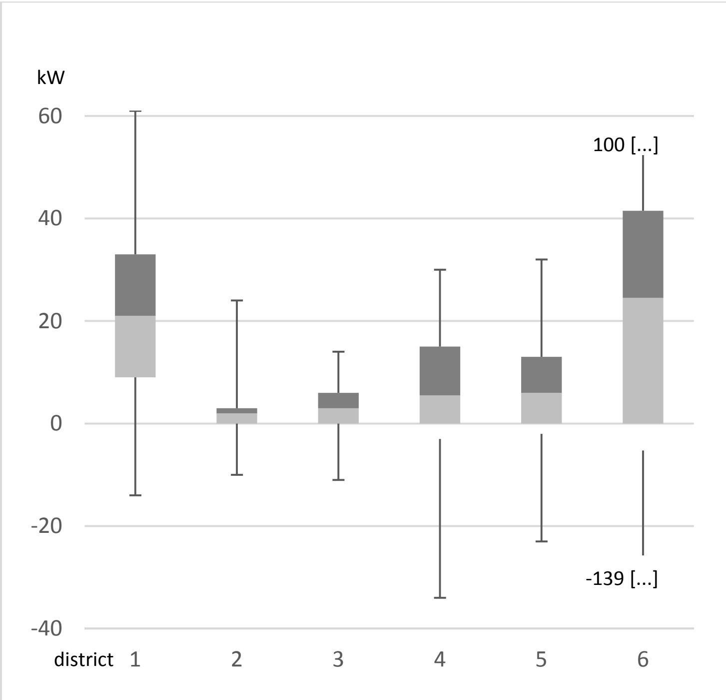

Fig. 2. Computed gain of PV in districts 1-6 (CPM)

The resulting new PV power for every district is shown in table two. CPM detects only 12 % to 42 % of the expansion in PV feed-in. Reasons for this are the different efficiency factors, azimuth and elevation angles of the PV systems. If these aren't the same as the ones of the reference PV power plants, the elimination of known PV feed-in from the load data is not accurate. This is a cause of defects. Additionally the variation of loads during the cloud passage causes defects that can only be enhanced by a larger sample size.

4.2 Results Power Deviation Method

The results of the Power Deviation Method (PDM) are shown in figure three. It shows the calculated differences in PV power for every day where the significant correlation between the deviation to the load of the corresponding average day and reference PV is reached. In district two and four the method does not detect any new PV power. In the other districts there is some PV power detected, but only 30 % to 67 % of the gain.

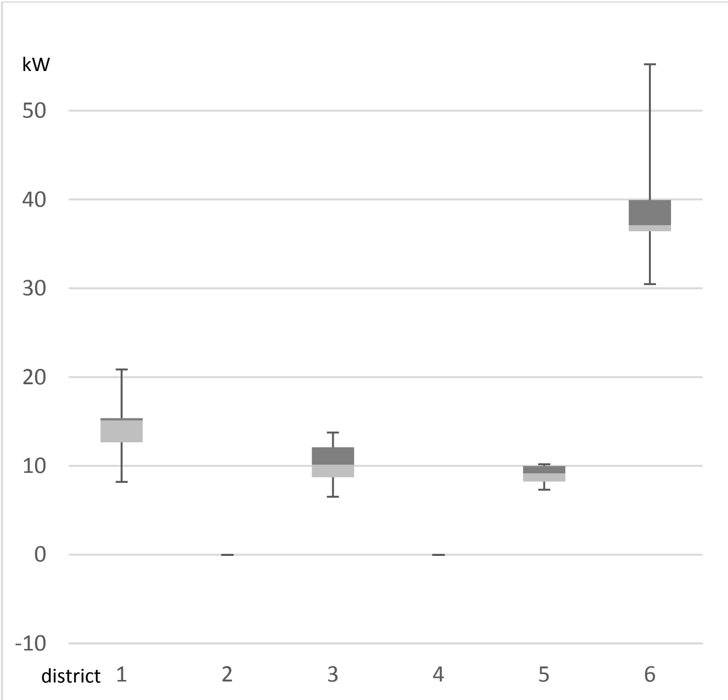

Fig. 3. Computed gain of PV in districts 1-6 (PDM)

4.3 Results Low Mark Method

LMM springs into action if there is a new low mark measured. Because of this the values for new PV systems do not change often. In table two the new PV power calculated by LMM is given. LMM does not detect the whole amount of new PV but with a very high certainty.

Only in district two LMM finds too much PV power. This can be explained by measurement errors, an unusual low load during the day or an unusual cos-phi.

4.4 Overall Results

To determine the conclusion of all detection methods ($new\ PV_{inst}$) the following formula is used:

$$new\ PV_{inst} = \max(res_{LMM}, mean(res_{CPM}, res_{PDM})) \quad (1)$$

res_{LMM}, res_{CPM} and res_{PDM} are the results of LMM, CPM and PDM.

Table 2. Use case results: detected unknown PV systems

District	1	2	3	4	5	6
Known PV Power (kW)	43	4	14	41	27	125
Unknown PV Power (kW)	50	5	15	50	30	100
Gain of PV Power (%)	116	125	107	121	111	80
Detected by CPM (kW)	21	2	3	6	6	25
Detected by PDM (kW)	15	0	10	0	9	37
Detected by LMM (kW)	44	6	6	22	17	38
Conclusion detection (kW)	44	6	6.5	22	17	38

Almost all detected PV power plants can be added to the smart grid's set of parameters as additional installed PV power. Only in district two this would lead to an overestimation of the installed PV power.

5 Validation

For the validation of the developed methods, the whole system is implemented in a simulation environment. This tool considers following actuators:

- Behavior of renewable energy systems,
- The load characteristic of the consumer,
- The limitation of the distribution grid,
- SGS with a minimum of sensors.

With this simulation, it is possible to analyze the impact of new PV systems.

To check the impact, the described use case is implemented in the simulation tool. For this approach following scenarios are simulated with the tool:

1. Installation of one 30 kW PV power plant at a:
   (a) Node near a sensor
   (b) Node without special properties
   (c) Node with a bad sensitivity (worst case)
2. Installation of one 50 kW PV power plant at a:
   (a) Node near a sensor
   (b) Node without special properties
   (c) Node with a bad sensitivity (worst case)
3. Installation of one 100 kW PV power plant at a:
   (a) Node near a sensor
   (b) Node without special properties
   (c) Node with a bad sensitivity (worst case)

With the results of these expansion scenarios the influence of new not implemented PV systems can be derived.

5.1 Results of the simulation

The simulation shows the sensitivity of a distribution grid with increasing PV generation. The accuracy of the grid state identification has the lowest deviation, when all PV systems are known. By implementing a new single generation system without reconfiguration of the system the accuracy decreases. This decrease is depending on the installed PV power and on the properties of the grid. Also important is the electrical distance to the next measurement sensor. If the new PV power plant is near to a sensor the algorithm observes the new system without knowing it. In contrast if the PV system is far away from a sensor the algorithm can't take the generation into account. Otherwise if an enormous increase of the PV power is based on a lot of spread systems the grid state analysis doesn't lose much accuracy. This is based on the fact, that the algorithm performs a linear reject of the measured load. Therefore following characteristics are decisive for the influence of new installed PV systems.

- Properties and topology of the grid
- Current load situation
- Implementation of the SGS (number and position of the sensors)
- Power and number of the existing PV systems
- Power and number of the new PV systems

All these dependencies influence the accuracy of the SGS. The first rudimentary results are presented but more scenarios and simulations are needed for a final validation. On this account further investigations are focused for a final analysis.

6 Conclusion

This paper shows the ability of including new PV systems without a manual reconfiguration of the SGS. Additionally it points out, that the data of a smart grid system like "iNES" has to be up to date. With the actual information about the grid configuration and the connected customers, the system is able to perform reliable and accurate. This is one major requirement from the distribution system operator's point of view. The presented detection methods help to meet this requirement without an increasing workload for the grid operator. The influence of new PV systems on the grid state identification is presented. The impact of different factors on the accuracy is presented. It is incidental that more simulation scenarios are needed for a final analysis.

7 References

1. C. Oerter and N. Neusel-Lange, “LV-Grid Automation System - A Technology Review,” in *IEEE Power&Energy Socity General Meeting (PES)*, Washington, 2014.
2. “Green Access - Intelligente Verteilnetzautomatisierung für einen erhöhten Zugang regenerativer Energien,” Bergische Universität Wuppertal, 2015. [Online]. Available: http://www.evt.uni-wuppertal.de/forschung/forschungsgruppe-intelligente-netze-und-systeme/green-access.html.
3. “Stromnetze Forschungsinitiative der Bundesregierung,” 10 2015. [Online]. Available: http://forschung-stromnetze.info/projekte/intelligente-netze-fuer-die-integration-regenerativer-energien/.
4. N. Neusel-Lange, C. Oerter and M. Zdrallek, “Sichere Betriebsführung von Niederspannungsnetzen durch dezentrale Netzautomatiserung,” in *ETG-Kongress*, Würzburg, 2011.

Supported by:

Federal Ministry
for Economic Affairs
and Energy

on the basis of a decision
by the German Bundestag

STROMNETZE
Forschungsinitiative der Bundesregierung