Estimate Power generation of invisible solar site using State estimation

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***Abstract*—**

***Index Terms*—**

I. Introduction

Increasing of solar PV.

State estimation provides the optimum estimate of power system state based on received measurement units and the knowledge of network modeling. The measurement units may include as follows:

- power injection (real/reactive),
- power flow (real/reactive),
- bus voltage magnitude,
- phase angle,
- line current magnitude,
- current injection magnitude.

In this paper we used Bayesian, SVM techniques to detect invisible solar PV generation.

II. Literature reviews

A. Applications of State estimation in power system

State estimation on distribution power system is reviewed in [9].

State Estimation provides various benefits for power system analysis as follows:

1) Real time mornitoring: for power system in transmission and distribution levels [5]. The Advance Meter infrastructure (AMI) data are fed into SE to real-time mornitor distribution power system in [7]. It improved the accuracy comparing to pseudo measurment based on historical load.

2) Load allocation: in distribution power system. SE assigns active and reactive power values to bus downstream [6]. Class curves and individual average demand of clients improved accuracy of load allocation [4]. The data from AMR system, which are used as the pseudo-measurements, was used to estimate load on the distribution transformers. [5].

PEA, AIT, NEU

3) Bad data analysis: in several real application, it happens that some flow measurement has no sign or the sign is wrong. A re-weighting technique was used to reduced the weights association to these measurements [6]. It also could helps to treat of power flow with erroneous sign. Futhurmore, SE was implemented in cyber attack events [10] on power system states. A detection false data injection method is proposed in [8].

4) Topology indentification: the status of branches and switches are indentified in [6].

B. previous solar PV detection techniques

The previous studies has been done on detection of location and estimation of power generation of invisible solar PV sites. Reference [11] proposed a change-point detection algorithm for a time series for residential solar PV detection. These method required smart meter data and historical load profile. The uncertainty of solar PV site and the data generated by a small set of selected representative sites were taken into account to estimates the power gneneration of known solar PV site in [12]. The new hybrid k-means and PCA techniques provided good accuracy of estimating invisible solar PV sites. The big data characterization of smart grids and two-layer dynamuc optimal synchrophasor measurement devices selection algorithm for fault detection, identification, and causal impact analysis was proposed in [13]. The utility data based on random matrix therory (RMT) are used in detection and estimation of invisible solar PV in real case in China in [14].

C. Contributions

This paper proposed method which identify location and estimation solar PV installation capacity at invisible site.

III. Problem Formulation

A. Measurement devices, measured data and accuracy

To generate measurement data for testing prurposes, measurement error was added to tha actual measurements as shown in Equation 1.

$$Z = Z_a \pm +e_z \tag{1}$$

where Z_a is actual data and e_z is error added base on accuarcy of the measurement. In this study, bus measurement has 3% error. line measurement has 5% error.

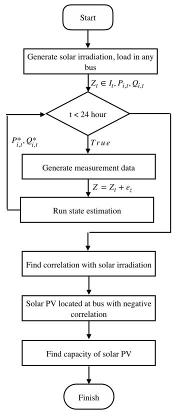

Fig. 1. conceptual methodology

These error are assumed to be modeled independent Gaussian random variable [2]. where where the error value is expected value from gaussian distribution. noise is guassian distribution,as shown in Equation 2

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}((x-\mu)/\sigma)^2} \tag{2}$$

1) State variable description:: voltage, current, power flow from measurements devices

B. Peform SE to find

1) LWS:

2) Branch current, load allocation based state estimation: is based on the weighted least square (WLS) approach [1]. the method solves the following WLS problem to obtain an estimate ofthe system operating point defined by the system state x:

$$\underset{x}{min} J(x) = \sum_{i=1}^{m} w_i (z_i - h_i(x))^2 = \left[z - h(x)\right]^T W \left[z - h(x)\right] \tag{3}$$

where w_i and $h_i(x)$ represent the weight and the measurements function associated with measurement z_i, respectively. For the solution of this problem the conventional iterative method is adape by solving following normal equations at each iteration, to compute the update $x^{k+1} = x^k + \Delta x^k$

$$\left[G(x^k)\right] \Delta x^k = H^T(x^k) W \left[z - h(x^k)\right]$$

Where

$$G(x) = H^T(x) W H(x)$$

is the gain matrix and H is the jacobian of the measurement function $h(x)$.

C. Find correlation with solar irradiation

A correlation is a statistical measure of relationship between two variables. The measure is best used in variables that demenstrate a linear relationship between each other. The correlation coefficient that indicates the straength of the relationship between two variables can be found using following formula:

$$\mathrm{r}_{xy} = \frac{\sum(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum(x_i - \overline{y})^2 (y_i - \overline{y})^2)}} \tag{4}$$

where r_{xy} is the correlation coefficient of the linear relationship between the variables x and y, x_i is the values of the x-variable in a sample, $\overline{x}$ is the mean of the varialbes of the x-variable, y_i is the values of the y-variable in a sample, $\overline{y}$ is the mean of the varialbes of the y-variable.

The negaive correlation shows that the variables tend to move in opposity directions (i.e., when one variable increases, the other variable decreases).

D. Find capacity of solar PV using changing point method

IV. Test cases and Results

The proposed solar PV detection was implemented using python language. Two power system are tested. There two test cases are based on four bus system and CIGRE Task Force C6.04.02 paper [3].

A. Test cases

1) four bus system: The one line diagram of the four bus system is shown in Fig. 2.

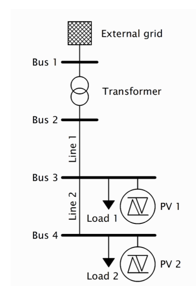

Fig. 2. four bus system

Table I shows the results. From the table, I it can be seen that the proposed method can predict perfectly location of solar PV.

TABLE I
Results of 4 bus system

[random PV location at bus (size of PV kW)]	Solar PV detection
[1(10)]	[1(8)]
[1(10), 2(20)]	[1(9), 2(17)]

2) CIGRE system: Table II shows the results. From the table, II it can be seen that the proposed method can predict perfectly location of solar PV.

B. Results

V. Conclusion

Here is Conclusion.

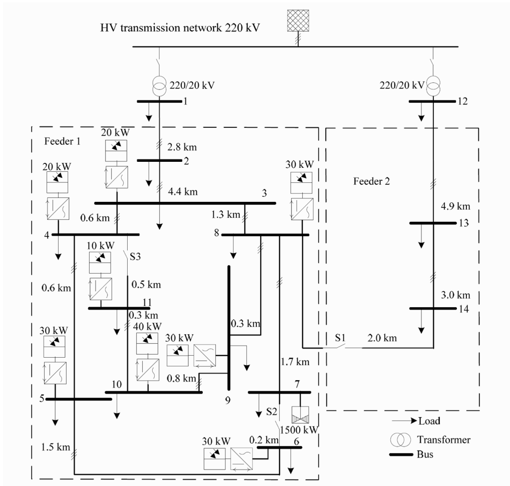

Fig. 3. CIGRE network

TABLE II
RESULTS OF CIGRE

[random PV location at bus (size of PV kW)]	Solar PV detection
[1(10)]	[1(8)]
[1(10), 2(20)]	[1(9), 2(17)]

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