Estimate Power generation of invisible solar site using State estimation

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***Abstract*—**

***Index Terms*—**

I. Introduction

Sixty years ago, the price of solar panels was astronomical. The price was over 1,000 US dollars per watt in today's money with 1 percent efficiency [1]. As the cost continues to drop, solar panel systems are becoming much more viable for the average household. Today's price is less than 2.8 US dollars per watt for solar panel system including solar module, inverter, wiring hardware, labor cost, and maintenance cost [2]. As result of exponentially acceralate increasing in number of globally solar PV integration, especailly in residential sector.

Many researchers have studied the impacts and risks of PV on distribution systems [3]- [8]. However, the detection and monitoring of residential PV systems has not been the focus of the studies and related research.

Recently, the highest penetration of solar PV, recognized a large number of unauthorized solar PV installation [9]. Unauthorized solar PV installation creates safety risks and lack of visibility may result in incorrect planning, and operation, including over-voltage, back-feeding. Futhermore, in worst case scenario, it may damange system equipment such as transformers, voltage regulators, as well as customer applicants [10], [11]. In previous studies, there are various reasons for unauthorized or incorrectly registered PV system: a) owner decided not to apply for a permit to avoid fees [12], b) regulations were required after the system was installed, c) lack of awareness by the owner of diverse permitting rules, d) difference rules depending on size and type of PV installation can make the owners believe they do not need a permit e) change in property ownership including transfer, f) multiple system installed or future iaddition at the same premise, g) incorrect third party handling of the permit appication, h) data entry and data maintenance errors.

The rest of the paper is structured as follows: Section II reviews related research on state estimation application for power system and previous detection and estimation techniques on invisible solar PV site. Section III formulates the mathenatic model of measurement data as well as the structure of proposed method. Section IV shows the results of proposed method on test cases. Section V conclueds the paper and dicusses future research oppotunities on PV system detection and estimation.

PEA, AIT, NEU

II. Literature reviews

A. *Applications of State estimation in power system*

State estimation on distribution power system is reviewed in [21].

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.

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

1) Real time mornitoring: For power system in transmission and distribution levels [17]. The Advance Meter infrastructure (AMI) data are fed into SE to real-time mornitor distribution power system in [19]. 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 [18]. Class curves and individual average demand of clients improved accuracy of load allocation [16]. The data from AMR system, which are used as the pseudo-measurements, was used to estimate load on the distribution transformers. [17].

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 [18]. It also could helps to treat of power flow with erroneous sign. Futhurmore, SE was implemented in cyber attack events [22] on power system states. A detection false data injection method is proposed in [20].

4) Topology indentification: the status of branches and switches are indentified in [18].

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 [23] 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 [24]. 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 [25]. 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 [26].

C. Contributions

Many researchers have studied the detection and estimation location of invisible solar PV installation [23] [26]. These study depended on smart meter data, data set of solar PV generation, as well as historical demand of customer in each load. This paper proposed method which identify location using state estimation and correlation techniques and estimate the installation capacity using change point method of invisible solar PV site. The require data are measured solar irradiation data, the measurement in distribution system. The proposed method consists of four steps:

- collect solar irradiation, measurement data
- allocate power demend in each buses, nodes.
- indentify invisible solar PV site
- estimate solar PV site's installation capacity

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.

These error are assumed to be modeled independent Gaussian random variable [14]. 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

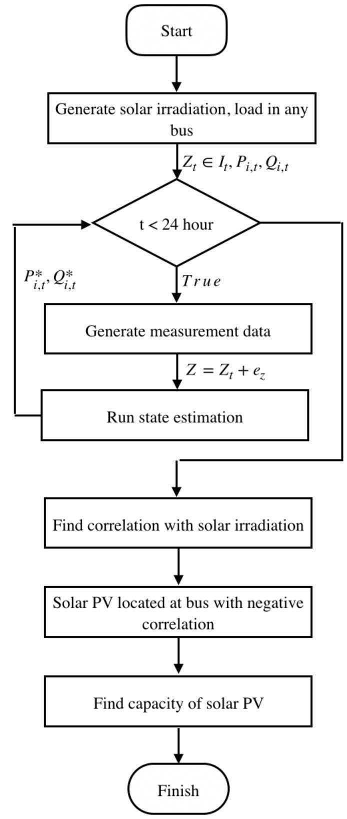

Fig. 1. conceptual methodology

B. Peform SE to find

1) LWS:

2) Branch current, load allocation based state estimation: is based on the weighted least square (WLS) approach [13]. 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 [15].

A. Test cases

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

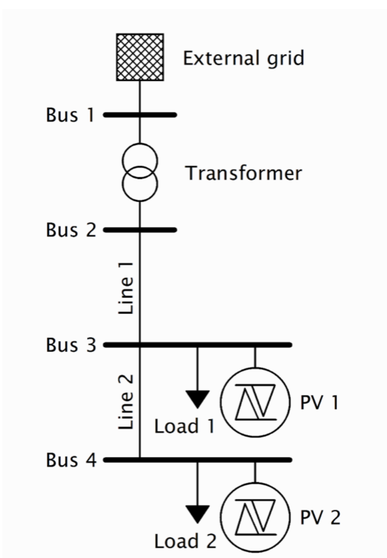

Fig. 2. four bus system

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

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.

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)]

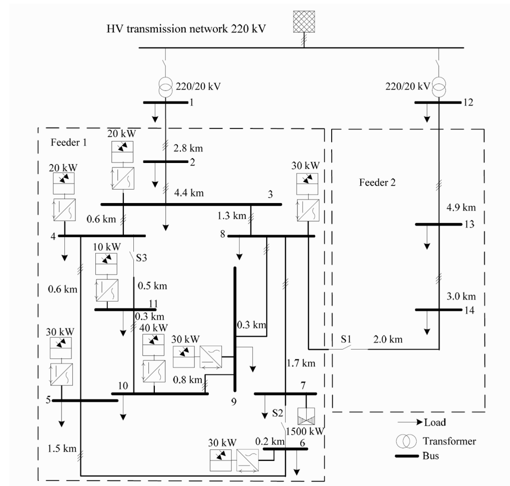

Fig. 3. CIGRE network

B. Results

V. Conclusion

Here is Conclusion.

Acknowledgment

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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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