A Probabilistic Farmework for Power System Operation Studies in Presence of Dispersed PV Generation

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Abstract—**Variability and uncertainty of solar photovoltaic (PV) generations greatly influence the operation of high PV-penetrated power systems. This paper examines the potential impacts of distributed PV generations on power system operation and congestion costs. PV and loads are stochastically modeled using the real data taken from a balancing authority. Probabilistic optimal power flow (POPF) based on the two point estimate method (2-PEM) is employed to determine the operation and congestion costs incurred by the variable PV power output. Different scenarios are studied on the IEEE 24-bus system to evaluate the dispersed PV generation impacts on the aforementioned objectives. Correlations between the power outputs of different PV plants and various penetration levels are evaluated as the determining factors when choosing PV sites for distributed generation. The obtained results well confirms the proposed method accuracy and efficacy.**

Keywords-** **Distributed PV generation; operation cost; stochastic modeling; transmission congestion; two point estimate method (PEM).

NOMENCLATURE

Variables

CC	Random variable of total congestion cost.
CC_t	Congestion cost at hour *t*.
i	The hourly power measurement.
OC	Random variable of total operation cost.
$OC_{1,t}$	Operation cost at hour *t* with no consideration to transmission line flow limitation.
$OC_{2,t}$	Operation cost at hour *t* considering transmission line flow limitation.
$\mathbf{P_D}$	The vector of demand at each bus.
$p_{d_{i,t}}$	Demand of bus *i* at hour *t*.
$p_{g_{i,t}}$	The generation power of unit *i* at hour *t*.
$\mathbf{PV_{GEN}}$	The vector of PV generation.
$\overline{PV_k}$	The average power output of the k^{th} PV plant.
$PV_{k,i}$	The power output of the k^{th} PV plant.
TOC	The total operation cost provided by all generating units over a 24-hour period.
$\mathbf{X}$	Vector of random input variables.
$\mathbf{Y}$	Vector of random output variables.
μ_{CC_t}	The expected value of congestion cost at hour *t*.
μ_{OC_t}	The expected value of operation cost at hour *t*.
$\mu_{X,k}$	The expected value of **X**.
μ_{TCC}	The expected value of total congestion cost over time interval *T*.
μ_{TOC}	The expected value of total operation cost over time interval *T*.
σ_{CC_t}	The standard deviation of congestion cost at hour *t*.
σ_{OC_t}	The standard deviation of operation cost at hour *t*.
σ_{TCC}	The standard deviation of total congestion cost over time interval *T*.
σ_{TOC}	The standard deviation of total operation cost over time interval *T*.
σ_{PV_k}	The standard deviation of the k^{th} PV plant output.
$\sigma_{X,k}$	Standard deviation of **X**.

Parameters

a_i, b_i	Bid function constants of generator *i*.
$A_{l,k}$	Generalized distribution factor of line *l* with respect to bus *i*.
$\bar{f}$	The maximum flow of line *l*.
n_g	The number of generating units.
$P_{k,i}$	Probability of the i^{th} concentration of random variable *k*.
$\lambda_{k,3}$	Skewness of random variable *k*.
$\xi_{k,i}$	Location of the i^{th} concentration associated with the random variable *k*.

Sets

L	Set of transmission lines.
N_B	Set of power system buses.

I. Introduction

Photo-Voltaic (PV) penetration rates, as a green means of power generation in electric power systems, are growing fast [1]. It is being increasingly recognized as a cost-effective generation source in remote areas. Though PVs are still far from being economic compare to the conventional fossil fuels, they are utilized in remote areas where it is uneconomical to expand the grid [2]. However, the trend toward the reduced manufacturing cost of PVs has been experienced during the last decade [2, 3]. Besides, due to the applied supportive schemes, e.g., federal Production Tax Credit (PTC), state Renewable Portfolio Standards (RPS), and the economic and environmental advantages of solar energy in comparison with other forms of energies, installed solar capacity is expected to have a continuous growth in coming years [4].

As a consequence, PVs are deemed to have considerable impacts on power system operation and planning studies and hence call for their careful investigations. Amongst can be accounted the concerns on voltage and current profiles, power quality, protection, electric losses, power factor, power balancing, reliability, and operability of the system. These impacts can be of different severities as a function of the penetration level and PVs locations as well. In clarifying this, when facing with the large solar PV penetration levels in the traditional feeders, which are commonly designed for radial unidirectional power flows, the feeders would become active circuits and consequently might inject power back to the transmission system [5]. Under such circumstances, voltage profiles, overcurrent protection, capacitor bank and voltage regulator operation are obviously influenced [6].

On the other hand, variability and uncertainty of solar cells power output is the main concern. Accordingly, an appropriate reserve margin provided by the scheduling services may significantly affect the system operating cost [7]. This required reserve margin in response to the PV cells power output variability has to be provided by the conventional fast-response units. Understanding PV variability will allow power system planners and operators to develop operative measures on how to manage the imposed variability at different levels of PV penetration [7]. As a result, this will help to prevent the grid instability due to the high penetration of PVs.

Recently, the solutions toward harnessing uncertain PV solar cells in an efficient manner have been broadly attempted [8]-[12]. Employing different forecasting approaches for the sake of renewable energy output power prediction has been extensively investigated in literature [10]-[14]. Once an efficient short-term forecasting is established, a robust probabilistic process should be pursued to accomplish power system operation studies in presence of dispersed renewable energies. Reference [10] conducted some analyses on the photovoltaic performance evaluation and investigated their impacts on electric utility's load shape under supply side peak load management conditions. An application of a hybrid wind/SPV power generating system as a stand-alone or a connected system is proposed in [11]. An application of artificial neural network for the maximum output estimation of the SPV module considering environmental factors was developed in [12]. In [13], some issues on the optimization of the isolated small PV power generations in remote areas are discussed. It also provides the procedure which helps in evaluating different PV schemes considering the stochastic nature of the insolation and the load requirement.

This paper is motivated by the shortcomings of the past works done in this area. The computationally demanding natures of the past works together with their lower accuracy are among the main concerns this paper tries to deal with. This paper evaluates dispersed PV generation roles on the power system operating reserve requirements. PVs and loads are probabilistically modeled based on the actual data collected from a balancing authority. A robust stochastic approach is employed in this paper, namely point estimate method (PEM), which is capable of effectively handling the existent uncertain nature of PV cells output power.

The paper is organized as follows. Section II elaborates the proposed probabilistic methodology on the basis of optimal power flow and two point estimate method. IEEE 24-bus test system is taken into consideration as the paper case study in Section III on which different scenarios are studied and the associated simulation results are discussed in detail. Finally, Section IV is devoted to the paper conclusion.

II. Paper Contribution

This Section discusses the key issues associated with effects of PV plants in operation of power systems, going to be placed under vast focuses. These issues incorporate the process of uncertainties modeling and the probabilistic optimal power flow based on the 2-PEM analysis. These are placed at the point of great consideration when aiming to the cost evaluation of congestion and operation in power systems.

A. Probabilistic Modeling of PV and Load

The stochastic nature of PV and the load characteristics imposes some degree of uncertainty on power systems with high level of PV power generation. Variability of PV power output [16] and random variations in load **Error! Reference source not found.-Error! Reference source not found.** need to be modeled probabilistically in order to reflect their random characteristics. Using the curve fitting approach, a Normal probability distribution function (PDF) is assigned to the historical hourly PV data gathered from the BPA balancing authority [16]. The same procedure is applied to the historical load data and a Normal PDF is also acquired using the curve fitting approach.

B. Probabilistic Optimal Power Flow Based on the PEM

Considering the probabilistic nature of PV power output accompanied by load variation, deterministic tools for optimal power flow cannot represent the affects of the stochastic factors on the dispatch results [17]. Uncertain factors such as PV power output and variable loads can be taken into account in power flow computations by using a probabilistic optimal power flow (POPF). Several methods have been proposed to perform the probabilistic analysis in POPF problems. These methods are classified as analytical and simulation methods [18]. Monte-Carlo simulation (MCS) is a simple and accurate simulation method that uses historical data of probabilistic quantities to find their probability distribution functions (PDFs). The random values from these PDFs are selected and used to quantify the uncertainties. The large computation effort is the main obstacle usually experienced in such methods. Several approximate methods, e.g., Taylor series expansion method [19], the first-order second-moment method (FOSMM) [20], the Cumulant method [21], and the PEM [22] have been proposed to reduce the computational burden of the probabilistic analysis. PEM has been regarded as an appropriate analytical method because of its accuracy, simplicity, and speed. This method was developed by Rosenblueth in the 1970s for calculating the moments of a random multi variable quantity [22]. Two point estimate method (2-PEM) which is a variation of the original PEM is applied in this paper to model the existent uncertainties. Vectors of input and output random variables, faced in the at hand problem, are given by equations (1) and (2), respectively.

$$\mathbf{X} = [\mathbf{PV_{GEN}}, \mathbf{P_D}] \tag{1}$$

$$\mathbf{Y} = [OC, CC] \tag{2}$$

The moments of random variables are derived based on the distributions of the PV generations and loads. Two estimate points are chosen from each distribution, and the corresponding weighting coefficient together with the probability concentration at each point are then calculated. The deterministic optimal power flow model is used afterward to dispatch the generation for every estimated point. As all the points are calculated, the results calculated by each point and the corresponding probability concentrations are used to derive the expected value and standard deviation of the dispatch results. The POPF algorithm based on 2-PEM is outlined as follows:

- Assign appropriate PDF to each probabilistic variable including loads and PV generations.
- $E(Y) = E(Y^2) = 0$
- Determine the necessary parameters of the 2-PEM:

$$\xi_{k,1} = +\sqrt{n} \tag{3.a}$$

$$\xi_{k,2} = -\sqrt{n} \tag{3.b}$$

$$P_{k,1} = P_{K,2} = \frac{1}{2n} \tag{3.c}$$

- Set k =1.
- Set the concentrations ($x_{k,1}$ and $x_{k,2}$) and run the deterministic OPF using the input vector **X**.

$$x_{k,1} = \mu_{X,k} + \xi_{k,1} \cdot \sigma_{X,k} \tag{4.a}$$

$$x_{k,2} = \mu_{X,k} + \xi_{k,2} \cdot \sigma_{X,k} \tag{4.b}$$

$$X = [\mu_{X_1}, \mu_{X_2}, ..., x_{k,i}, ..., \mu_{X_n}] \quad i = 1,2 \tag{4.c}$$

- Update $E(Y)$ and $E(Y^2)$.

$$E(Y)^{(k+1)} \cong E(Y)^{(k)} + \sum_{i=1}^{2} P_{k,i} \cdot h(Z) \tag{5.a}$$

$$E(Y^2)^{(k+1)} \cong E(Y^2)^{(k)} + \sum_{i=1}^{2} P_{k,i} \cdot h^2(Z) \tag{5.b}$$

- Set k=k+1and repeat two recent steps for all random input variables.
- Calculate the expected value and standard deviation of Y using (6.a) and (6.b).

$$\mu_Y = E(Y) \tag{6.a}$$

$$\sigma_Y = \sqrt{E(Y^2) - \mu_Y{}^2} \tag{6.b}$$

C. Transmission Congestion Cost

Transmission congestion occurs when power flows across the transmission lines is more than the physical rating of the lines. Congestion in the transmission network has become a critical problem during recent years due to the growing installed renewable energies and the transmission expansion barriers [23]. Transmission congestion cost is defined as the difference between the optimal operating cost of power system in two states: with and without transmission line flow limitations. Accordingly, congestion cost is a quantity that measures the optimal operating cost increase due to transmission line flow limitation. Considering the transmission congestion during the peak load hours may lead to an over-estimated cost and conservative designation, for the peak load usually occurs in short periods of time. Rather, total congestion cost is an appropriate measure of the cost imposed by the transmission line flow limitation. Total congestion cost can be formulated as follows:

$$CC_t = OC_{2,t} - OC_{1,t} \tag{7}$$

$$TCC = \sum_{t=1}^{T} CC_t \tag{8}$$

Consequently, Operation cost at hour t is calculated as follows:

$$OC_t = Min\{\sum_{i=1}^{n_g} (a_i p_{g_{i,t}}^2 + b_i p_{g_{i,t}} + c_i)\} \tag{9}$$

As a constraint, the power balance equation at hour t is given by:

$$\sum_{i=1}^{N} p_{g_{i,t}} = \sum_{i=1}^{N} p_{d_{i,t}} \tag{10}$$

The governing equation of the line flow limitation is as follows:

$$\sum_{k=1}^{N_B} A_{l-k} \times (p_{g_k} - p_{d_k}) \le \overline{f_l} \quad l \in L \tag{11}$$

D. Proposed Method

The proposed method uses the POPF based on 2-PEM to calculate the operation and total congestion costs. Operation cost is defined as the cost of required conventional generation to compensate for the PV power output variability. The dispatch results derived from POPF are used to calculate the operation cost. To this end, the expected value and standard deviation associated with the generating unit costs are calculated using POPF based on 2-PEM. Total operation cost provided by the entire generating units over 24 hour period is given by the following equation:

$$TOC = \sum_{t=1}^{T} OC_t \tag{12}$$

Operation cost provided by the i^{th} conventional unit at each hour is a function of the probabilistic load and PV output at that hour. Therefore, operation costs provided by all conventional units at different hours over a time interval T are independent variables. Thus the total operation cost provided by all generating units over a time interval T is a probabilistic variable with the expected value and standard deviation given below:

$$\mu_{TOC} = \sum_{t=1}^{T} \mu_{OC_t} \tag{13}$$

$$\sigma_{TOC} = \sqrt{\sum_{t=1}^{T} \sigma_{OC_t}^2} \tag{14}$$

Congestion cost at hour t, given by equation (7), is a function of probabilistic load, PV output, and the deterministic transmission line limitation at hour t; accordingly, congestion costs at different hours over a time interval T are independent variables. Thus, the total congestion cost over a time interval T given by equation (8) is a probabilistic variable with the expected value and standard deviation as given in below:

$$\mu_{TCC} = \sum_{t=1}^{T} \mu_{CC_t} \tag{15}$$

$$\sigma_{TCC} = \sqrt{\sum_{t=1}^{T} \sigma_{CC_t}^2} \tag{16}$$

Fig. 1 demonstrates flowchart of the proposed method. PV and load data are considered as the inputs to the process. Using the curve fitting approach, a PDF is assigned to each of these variables. A POPF based on 2-PEM is utilized to derive the expected value and standard deviation of the generating units. Both the operation and congestion costs for 24 hours ahead are then calculated based on OPF results.

III. Case Studies

Two scenarios are placed under focuses in this section and the associated results are thoroughly investigated. IEEE 24-bus test system is considered as the paper case study which is illustrated in Fig. 2.

A. Scenario I: Dispersed PV Generation and Total Operation Cost

Scenario I corresponds to the impacts of dispersed PV generation on the total operation cost for the IEEE 24-bus system. PV diversity over a wide geographical area provides an opportunity to compensate for its variability. If solar irradiation is low or changing in one area, then elsewhere it may be high enough to compensate for it.

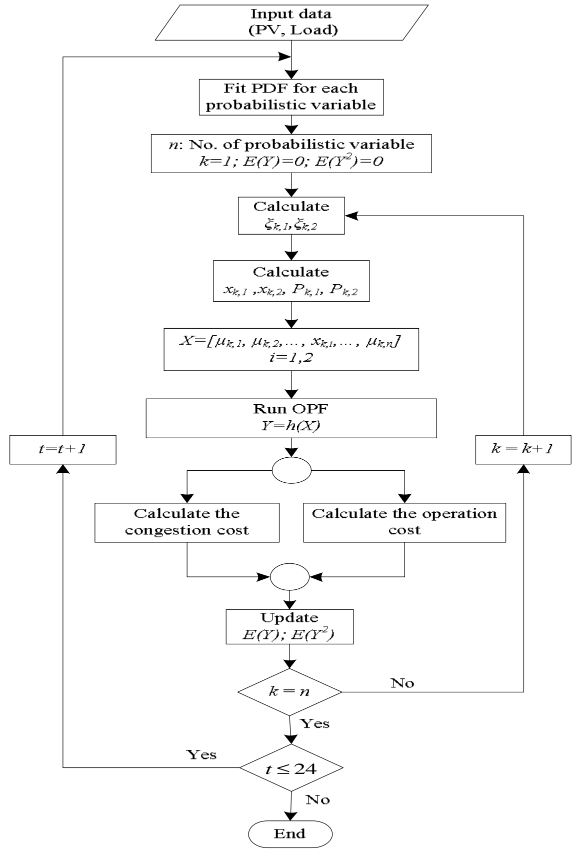

Figure 1. Flowchart of the proposed method

The correlation between the power outputs of different PV plants is an appropriate measure to realize the PV diversity. The correlation coefficients can be calculated as follows:

$$C = \frac{\frac{1}{N}\sum_i (PV_{1,i} - \overline{PV_1})(PV_{2,i} - \overline{PV_2})}{\sigma_{PV_1}\sigma_{PV_2}} \tag{17}$$

Three different cases are investigated in this scenario. For each PV plant, historical hourly data from the Nexant PV plants is used to model it [16]. Case I corresponds to a concentrated PV generating unit located at bus 14. Dispersed PV generating units located at buses 14 and 10 are evaluated in Case II. Dispersed PV generating units located at buses 14, 10 and 20 are evaluated in case III. Table I addresses the information regarding the correlation coefficients for different PV plants.

TABLE I. PV Plants and Their Correlation Coefficients for Cases I-III (Scenarios I & II)

Case	Correlation Coefficient
PV_1 and PV_2	0.7698
PV_1 and PV_3	0.2229
PV_2 and PV_3	0.6028

The total power generations provided by each conventional generator over a 24-hour period in these cases are presented in Table II for different PV penetration levels. Considering 20% PV penetration with respect to the peak load, total power generations provided by the conventional generators decrease from case I (cconcentrated PV plant) to case II (two dispersed PV plants). The same trend is observed for the conventional generators from case II (two dispersed PV plants) to case III (three dispersed PV plants) except for generating units number 7 and 8 in which the expected values of total power generations increase from 307 MWh to 316 MWh. Distributed PV generation has the same impact on total power generation for larger PV penetration levels (30% and 40%) and has decreased the reserve power required to compensate for PV power output variability. This is due to the PV diversity over the given geographical areas which mitigates the variability of output power for dispersed PV plants compared to the concentrated ones.

To have a better understanding, the cumulative distribution of the total generation is calculated for each case and compared with each other. Fig. 3.a illustrates the cumulative distribution function of the total generation requirements for each of the cases at 20% PV penetration. For a given generation level in fig. 3.a, the probability of occurring the cases where the total generation requirement is lower than that level is highest for case III, followed by case II and case I. Fig. 3.b. addresses the cumulative distribution of total operation cost for the cases I to III at 20% PV penetration. For a given cost level, the probability of occurring the case where the total operation cost is lower than that level is higher for case III, then cases II and I. The cumulative distribution function of total generation requirements for cases I to III at 30% PV penetration is illustrated in fig. 4. Increasing the PV penetration level from 20% to 30% decreases the generation level. This is due to the increased level of PV generations.

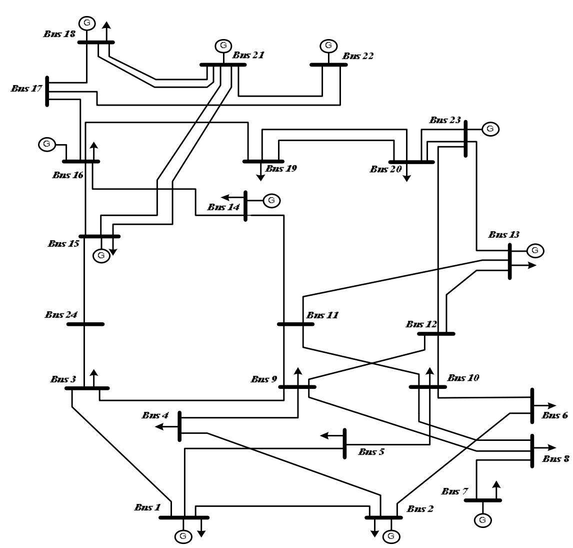

Figure 2. IEEE 24-Bus Test System as the paper case study.

Similarly, for a given generation level at 30% PV penetration, the probability that the total generation requirement is lower than that level is highest for case III followed by cases II and I, respectively. Fig. 5 depicts the cumulative distribution function of total generation requirements for cases I to III at 40% PV penetration.

Increasing the PV penetration level to 40% decreases the total generation level with respect to 20% and 30% PV penetration. If a fixed value for the required generation level at 40% PV penetration is considered, the probability that the total generation requirement is lower than this level is highest for case III respectively followed by cases II and I. Fig. 3 to Fig. 5 clearly indicate that distributing the PV generating units over a wide geographical area with different PV profiles decreases the generation required to compensate for PV power output and load variations. Moreover, The results observed from this scenario indicate that the correlation between power outputs of different PV plants is a key factor in determining the reserve required to compensate for PV variability. When considering distributed PV generation, if low or uncorrelated PV plants are added, the deviation of the average total output is lower than that of the individual outputs. This will lead to a smoother output compared to a concentrated one.

Fig. 6 illustrates the total operation cost for the cases I to III as a function of PV penetration level. Considering 20% PV penetration, the total operation cost for case I is M$1.1435 over a 24 hour interval. Distributing the PV plants in cases II and III decreases the total operation cost to M$1.1327 and M$1.1227 over a 24 hours interval, respectively. These values for 30% penetration level are M$1.10985, M$1.0895 and M$1.0730, respectively. According to this figure, distributing the PV plants can significantly decrease the operation cost.

B. Scenario II: Dispersed PV Generation and Congestion Cost

Scenario II evaluates the impacts of distributed PV generation on total congestion cost in the IEEE 24-bus system. Three different cases are studied in this scenario which are similar to cases I to III in scenario I. Transmission congestion cost is defined as the difference between the optimal operating cost of power system with and without line flow limitations. Fig. 7 demonstrates the total congestion cost of system understudy for the cases I to III as a function of PV penetration level. As it can be seen in fig. 7, total congestion cost of the system using concentrated PV generation in case I is $155.8 for 20% PV penetration level. Distributing the PV resources among two and three generating units decreases the congestion cost to $1.9 and $0.64 in cases II and III, respectively. If the PV penetration is increased to 30% and 40%, congestion cost of the system would be decreased to $2038, $274.2, $2.016 and $4478.1, $1433.9, $34.21 for cases I to III, respectively.

It is worth mentioning that, in general, several factors including PV placement, topological configuration, and transmission line flow limitations can lead to transmission

TABLE II. TOTAL POWER GENERATION FOR DIFFERENT PENETRATION LEVELS (SCENARIO I)

Pen. Level		20%			30%			40%		
Case		I	II	III	I	II	III	I	II	III
TG_1* (MWh)	μ_1	8468	8408	8327	8244	8131	8023	8015	7866	7710
	σ_1	52.7	54.3	46.5	57.0	85.5	67.8	60.7	98.6	92.6
TG_2 (MWh)	μ_2	8469	8409	8328	8248	8132	8024	8026	7870	7711
	σ_2	53.5	54.4	46.53	60.5	85.9	67.9	76.6	98.6	92.7
TG_3 (MWh)	μ_3	9970	9910	9832	9768	9655	9552	9557	9401	9263
	σ_3	58.7	52.3	43.8	70.8	84.4	64.08	78.8	108.1	88.1
TG_4 (MWh)	μ_4	9864	9807	9735	9686	9569	9472	9549	9329	9201
	σ_4	54.6	48.9	41.1	85.4	78.3	60.05	204.9	102.4	82.3
TG_5 (MWh)	μ_5	7277	7202	7105	7020	6896	6751	6744	6586	6392
	σ_5	73.2	65.4	55.07	86.6	87.4	80.51	82.3	114.6	103.6
TG_6 (MWh)	μ_6	7277	7202	7105	7020	6897	6751	6744	6588	6393
	σ_6	73.6	65.5	55.1	86.3	87.04	80.56	77.1	114.6	103.4
TG_7 (MWh)	μ_7	374	354	393	318	321	341	284	307	316
	σ_7	50.1	38.55	30.29	57.2	41.2	29.94	39.9	44.3	30.43
TG_8 (MWh)	μ_8	374	354	393	318	321	341	285	307	316
	σ_8	50.0	38.53	30.28	57.3	41.1	29.92	40.9	44.2	30.39
TG_9 (MWh)	μ_9	11056	10990	10905	10830	10721	10593	10586	10449	10279
	σ_9	64.5	57.6	48.4	76.01	76.7	70.8	70.3	100.4	91.0
TG_{10} (MWh)	μ_{10}	9669	9617	9549	9447	9399	9303	9338	9179	9052
	σ_{10}	51.1	46.5	38.3	69.9	65.6	56.03	122.7	85.2	74.1

*: Total Power Generation

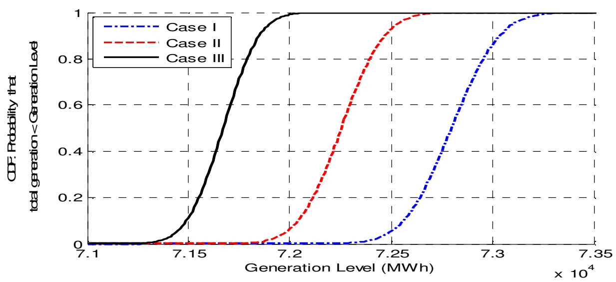

Figure 3.a CDF of total generation for 20% PV penetration (scenario I)

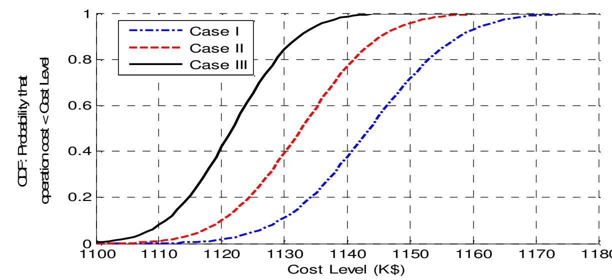

Figure 3.b. CDF of total operation cost for 20% PV penetration (scenario I)

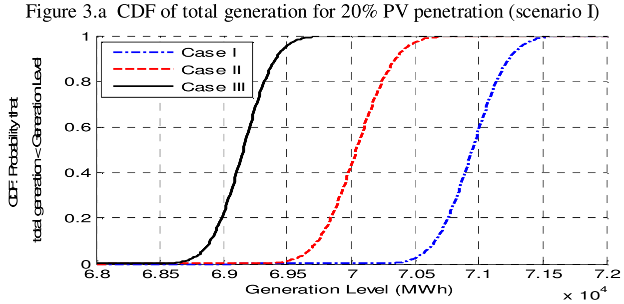

Figure 4. CDF of total generation for 30% PV penetration (scenario I)

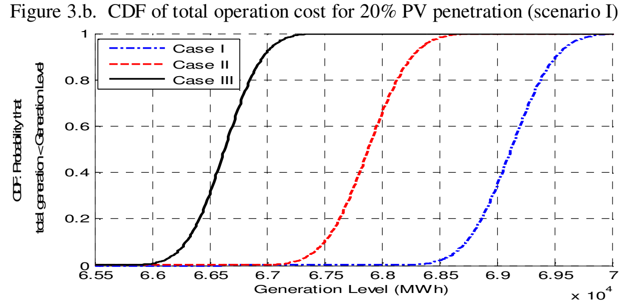

Figure 5. CDF of total geenration for 40% PV penetration (scenario I)

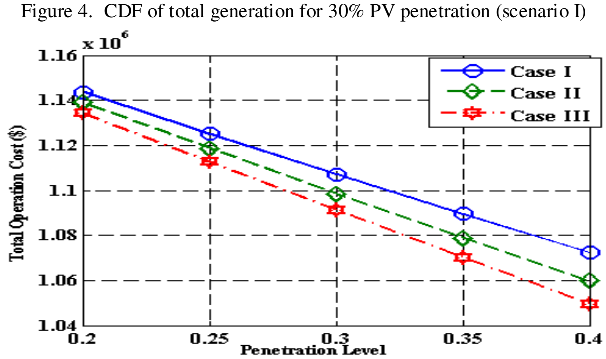

Figure 6. Total operation cost for cases I-III (scenario I)

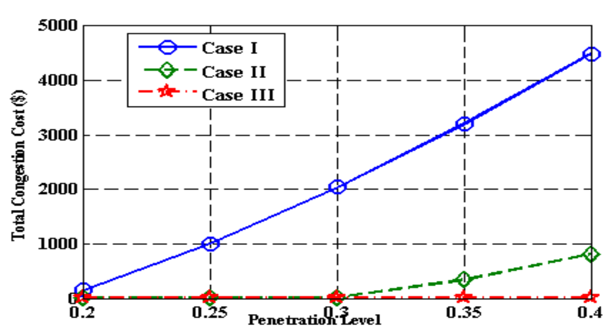

Figure 7. Total congestion cost (scenario II)

congestion occurrence. The level of congestion highly depends on the size of uncontrollable generations. Dispersing PV plants with uncontrollable power generation over a wider area would surely reduce transmission capacity utilizations. As a result, fewer transmission lines may be congested.

IV. CONCLUSION

This paper was concentrated on distributed PV generation and its potential impacts on the operation and congestion costs in power systems. Effectively employing curve fitting approaches, PV and loads were stochastically modeled. POPF based on 2-PEM was proposed to be the cure to the existent concerns on the problem of operation costs modeling in presence of renewable energies. This method was then experienced on the IEEE 24-bus system and different cases were carried out to investigate the factors affecting both the operation and congestion costs. Based on the simulation results, distributing the PV generating units throughout the IEEE 24-bus system decreases the cost of conventional energy required to compensate for PV output variability. Also, low or uncorrelated PV plants were concluded to have higher potentials to reduce the operation cost in a dispersed generation scenario. This reveals the importance of PV generation correlation as a determining factor when choosing PV sites as distributed generation locations. Transmission congestion cost analysis also demonstrated a reduction in cost due to the diversity of PV plants over a wide geographical area.

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