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An over-limit risk assessment of PV integrated power system using probabilistic load flow based on multi-time instant uncertainty modeling

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A B S T R A C T

In this paper, the risk assessment of a PV integrated power system is accomplished by computing the over-limit probabilities and the severities of events such as under-voltage, over-voltage, over-load, and thermal over-load. These aspects are computed by performing temperature-augmented probabilistic load flow (TPLF) using Monte Carlo simulation. For TPLF, the historical data for PV generation, ambient temperature, and load power, each collected at twelve specific time instants of a day for the past five years are pre-processed by using three linear regression models for accurate uncertainty modeling. For PV generation data, the developed model is capable of filtering out the annual predictable periodic variation (owing to positioning of the Sun) and decreasing production trend due to ageing effect whereas, for ambient temperature and load power, the corresponding models accurately remove the annual cyclic variations in the data and their growth. The simulations pertaining to the aforesaid risk assessment are performed on a PV integrated New England 39-bus test system. The system over-limit risk indices are calculated for different PV penetrations and input correlations. In addition, the changes in the values of TPLF model parameters on the statistics of the result variables are analyzed. The risk indices so obtained help in executing necessary steps to reduce system risks for reliable operation.

1. Introduction

In recent years, power systems are more often operating under highly unpredictable conditions due to the integration of various renewable energy sources (RESs). Among the RESs, PV generation is greatly favored because of its ability to generate power at varying capacities. This results in uncertainty that sets a higher requirement on system security during planning and operation. Further, geographically nearby PV generations are correlated feed-in. The increase in uncertainty effect due to high PV penetrations and their associated correlations cause system variables to violate the limit and make the system vulnerable. Hence, risk assessment by computing risk indices based on over-limit probability and severity to recognize system weakness more realistically is entailed [1]- [2]. The calculation of risk indices are accomplished with the help of probabilistic load flow (PLF) with respect to input uncertainties and correlations. The accuracy of the computed risk indices depends on the accuracy of the PLF results. The following are the three major requirements to achieve accurate PLF results.

i) Application of an accurate uncertainty handling method,
ii) Establishment of an accurate power system model, and
iii) Accurate modeling of input uncertainties.

The various methods used for PLF are categorized as, numerical methods, analytical methods, approximate methods, and hybrid methods [3]. Monte Carlo simulation (MCS), a typical numerical method is considered as a reference for accuracy comparison of other PLF methods [3–22]. MCS provides numerical estimation of result variables based on random statistical sampling and solves the PLF problem by a series of deterministic routines.

The establishment of an accurate power system model is highly essential in PLF. A majority of the PLF studies except for [6] assume transmission branch resistance as constant. But, branch resistance depends on branch temperature which in turn is a function of a set of factors that are probabilistic in nature; among which ambient temperature is dominant. In order not to overlook the temperature related errors, temperature-augmented load flow (TLF) captures

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electro-thermal coupling effect of transmission branches [23]. The first proposal on sensitivity matrix-based temperature-augmented PLF (TPLF) model is cited in Ref. [22] and the usefulness of probability distributions of TPLF result variables for various power system studies is detailed in Table 1.

In case of TPLF, ambient temperatures of the temperature dependent branches (TDBs) are included in the input vector in addition to the bus power injections. This increases the total number of input random variables (RVs), all of which may not be modeled by any specific parametric distributions. Hence, it is an uphill task to accurately model the probability distributions and to include the associated correlations. Assumption of some parametric probability distributions to quantify the input uncertainties may not always be suitable in all cases. On the other hand, a more realistic probabilistic modeling, incorporating past experiences can be achieved from the historical data. The authors in Refs. [4] [13], [22] [24], have performed uncertainty modeling of input RVs at a particular instant of time. The uncertainty modeling of peak load power (at 7 p.m.) [4], maximum PV generation (at noon) [13] [22], [24], and ambient temperature (at noon) [22] is performed for PLF. In order to remove the trend from load samples, a fitting curve using a set of standard functions is used [4]. In Ref. [13], the periodic effect due to annual positioning of the Sun is removed from PV generation samples by filtering out the daily, seasonal, and annual periodic components whereas; in Ref. [24] the removal of predicable lowest frequency annual periodic component is accomplished with the help of a linear clear sky model. In Ref. [22], ambient temperature data is probabilistically modeled by filtering out the lowest frequency periodic component of one cycle/year. The undertone of removing the trend and the periodic effect from the historical data essentially is not to attribute their variations to a movement in uncertainty.

Although the authors in Ref. [22] successfully have augmented temperature effect in PLF analysis, the influence of variation of TPLF model parameters on the statistics of result variables is overlooked. At a specific time of the day PV generation depends on the geographical and environmental conditions of that location. At different time instants, the production patterns are different and the clear sky model for eliminating the periodic effect as proposed in Ref. [24] may not be suitable as it accounts for only the Sun's height which alone is not adequate. Hence, an accurate clear sky model taking into account the other important factors such as the Sun's direction and the angle of incidence of solar radiation deserves research attention. Similarly, multi-time instant uncertainty modeling of ambient temperature and load power needs to be equally regarded for TPLF. Further, the analysis of the impact of various PV penetrations and different input correlations on TPLF results is imperative in making the over-limit risk assessment more realistic. With this motivation, investigations are performed on the following objectives.

i) An accurate uncertainty modeling of PV generation, ambient temperature and load power at multiple time instants.
ii) An analysis of the effect of various PV penetrations and the variations of TPLF model parameters on the statistics of the result variables.
iii) Over-limit risk assessment considering various PV penetrations and input correlations.

In Section 2, the application of MCS for TPLF is systematically detailed. The input uncertainties are probabilistically modeled and correlation effects are discussed in Section 3. In Section 4, various types of over-limit risk indices are elaborated. In Section 5, modified New England 39-bus power system is used to analyze the effect of PV penetration and the value of model parameters on statistics of result variables. In addition, the system over-limit risk indices are computed for various PV penetrations and input correlations. Finally, the concluding remarks are given in Section 6.

2. PLF in temperature-augmented power system model

The power system model as developed for TLF is the basis for TPLF using MCS. TLF assumes that the power system is both in electrical and thermal steady state. It is a general conception that electrical dynamics is neglected in load flow. Again, the thermal dynamics of the branch conductors is assumed short as compared to the changes in conductor loading over time. TLF model can be developed either by considering branch resistance [25] or branch temperature [23] as state variable. The consideration of the latter simplifies the mathematics required for modeling and is computationally more efficient. The transmission branches having non-zero series resistance are referred to as TDBs. The variation in branch reactance due to temperature variation is assumed negligible as in Ref. [23]. The modeling steps of TLF are explained as under.

The resistance of a transmission branch $\mathrm{i-j}$ (branch connecting $\mathrm{i^{th}}$ bus and $\mathrm{j^{th}}$ bus) is expressed as,

$$R_{\mathrm{i-j}} = R_{\mathrm{Ref,\ i-j}}\left(\frac{T_{\mathrm{i-j}} + T_{\mathrm{F,\ i-j}}}{T_{\mathrm{Ref,\ i-j}} + T_{\mathrm{F,\ i-j}}}\right) \tag{1}$$

where $T_{\mathrm{i-j}}$ is the conductor temperature of the branch $\mathrm{i-j}$, T_{F} is the temperature constant, $R_{\mathrm{Ref,\ i-j}}$ and $T_{\mathrm{Ref,\ i-j}}$ are the reference values of $R_{\mathrm{i-j}}$ and $T_{\mathrm{i-j}}$ respectively. According to thermal resistance model, $T_{\mathrm{i-j}}$ is expressed as,

$$T_{\mathrm{i-j}} = T_{\mathrm{Amb,\ i-j}} + T_{\mathrm{Rise,\ i-j}} = T_{\mathrm{Amb,\ i-j}} + R_{\theta,\ \mathrm{i-j}}P_{\mathrm{Loss,\ i-j}} \tag{2}$$

where, T_{Amb} and T_{Rise} are the ambient temperature and branch temperature rise above T_{Amb} respectively and R_{θ} is the thermal resistance. By using (2) let us define,

$$T'_{\mathrm{i-j}} = T_{\mathrm{i-j}} - R_{\theta,\ \mathrm{i-j}}P_{\mathrm{Loss,\ i-j}} = T_{\mathrm{Amb,\ i-j}} \tag{3}$$

Since the real and reactive bus power injections (P and Q respectively) are specified, the mismatch equations ΔP and ΔQ

Table 1
Usefulness of probability distributions of the TPLF result variables.

Result variable	Adequacy indices
Bus voltage magnitude	Steady state under and over voltage probabilities can be obtained.
Branch temperature	Probability of branch temperature above the allowable maximum limit i.e., thermal over-load probability can be ensured.
Generator bus reactive power	Capability of the system to maintain bus voltage magnitudes at desired level can be evaluated.
Branch power flow	Steady state overload probabilities of the transmission branches can be identified to take decisions regarding reinforcement plans and operations.
Slack bus power	Probability of slack bus power exceeding the limit can be known.