ENERGY LOSS FORECASTING IN ACTIVE DISTRIBUTION NETWORKS

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ABSTRACT

In this paper, energy losses in active distribution networks are estimated by a straightforward technique. This technique, after its first adjustment to a network, does not require any extensive computations such as scenario-based load flow calculations. Active distribution networks are characterized by accommodating more stochastic energy flows due to the proliferation of electric vehicles as well as renewable resources. Accordingly, the proposed algorithm is built on recording typical daily load profiles (TLP) and analyzing them together with typical stochastic energy profiles (TSP) so it can be fitted with a copula model to achieve an updated typical energy flowing profile (TEP). The copula model allows us to capture the strong dependence structure between load, generation and storage variable behaviors involving non-Normal marginal distributions. Furthermore, TLPs and TSPs correlations are in a multivariate context that joining them requires the concept of copula.

INTRODUCTION

Considering the rapid movement of passive power systems towards highly active topologies it seems that the need for modeling of uncertainties will dramatically increase. To take successful steps toward planning and configuring active distribution networks, utilities need to take a predictive look at how the new active system's components would affect the traditional efficiency indexes such as the energy loss. In fact, there will be huge stochastic energy flows stemmed from proliferation of both distributed generation and distributed storage. So, knowing how to calculate and reduce energy loss in such systems is a challenging topic in some way.

As it is well-known, accurate energy loss computation in passive distribution systems require a large amount of reliable data and the computational burden increase dramatically as the size of the network increases. As a result, there have been proposed different straightforward techniques such as using total heavy load loss or loss factors for calculating energy loss. However, the accuracy of these techniques is limited but up to passive networks may be absolutely acceptable [1].

On the other hand, when trying to estimate energy loss in active distribution systems, it is practically necessary using probabilistic methods and/or extensive simulations. There exists some recently published research in this field (e.g. [2-3]) that intends to make an estimation of energy loss by extensive scenario-based simulations. The proposed methods so far, as it may correspond to accurate loss calculation in passive networks, need massive computations or they will suffer significant approximations. From this point of view, it seems that there is a need for a more straightforward method to forecast energy loss in active networks.

In this paper, we try to make an estimation of energy loss in the active distribution systems as accurate as possible. Moreover, the developed algorithm could be used as a generalized subroutine embedded in other system analyses and optimal planning procedures. It allows energy losses to be forecasted without computing load flows for each time interval of the daily load flows and various scenarios of active energy flows.

The proposed algorithm is built on recording typical daily load profiles (TLP) and analyzing them together with typical stochastic energy profiles (TSP) so it can be fitted with a copula model to achieve an updated typical energy flowing profile (TEP). The copula model allows us to capture the strong dependence structure between load, generation and storage variable behaviors involving non-Normal marginal distributions. Such an analysis is to epitomize the aggregate uncertainty corresponding to spatially spread stochastic variables [4].

Here, we consider wind and photovoltaic distributed generations along with a number of plug-in electric vehicles to construct TSPs. The main formula for calculating energy loss is based on a method which only needs mean, variance and correlation information of the net TLPs [5]. Coming along this formula, fitting the copula model allows us to take the TSPs into account; subsequently, the energy loss of the active grid would be forecasted. A main advantage of using this method is its computational efficiency; hence, the use of a multivariate Monte Carlo method would be easy to carry out. On the other hand, the statistical rank moments and the copula model should be obtained only once for all TLPs and TSPs present in the network. It should be mentioned that the whole algorithm is tested using real data.

BASIC CONCEPTS

To make clear the idea proposed in introduction, three concepts should be considered; first, the typical stochastic energy profiles, second, the statistical loss calculation method, and third, the copula theory. These are discussed in satisfactory detail in the following sections. Loss calculation in passive systems and the TLPs are mature concepts; so, they are not presented.

Typical stochastic energy profiles in active distribution networks

Renewable distributed generation (DG) devices interact with the operation, protection and control of the distribution feeder at which they are installed. The produced electrical power via a variety of these generation units is stochastic by a non-dispatchable primary energy source. Therefore, DG systems inherently provide some benefits and produce some potentially unwanted effects. They may improve the load curve and the voltage profile across the feeder, may reduce the loading level of branches and substation transformers, and provide loss reduction benefits from the utility point of view.

Although the practical capacity of these systems is much smaller than the conventional generation units, their integration may significantly alter the behavior of the system across which they are installed. Deterministic modeling of such a system with stochastic non-dispatchable DG units (e.g. wind or photovoltaics) is not trivial [4].

Therefore, the use of stochastic methods (e.g. statistical data analysis such as scenario-based or sample-based modeling) is unavoidable in addition to the basic deterministic methods. This is also correct when considering the plug-in electric vehicle (PEV) loads as deterministic analyses can not account for variations associated with them. Quantification of the system response considering the spatial and temporal variations in PEV loads should be addressed through the probabilistic analyses. The main contribution of the probabilistic analyses are providing empirical data towards likely system behavior in response to likely PEVs and distributed generation loading scenarios.

These scenarios, all together, representing the behavior of the DG/PEV load time series in view of uncertainty, could be used for planning purposes. This provides a scenario-based forecasting of DG/PEV load. It should be noted that the application of point forecasting methods for such data behaviors (even the methods that consider uncertainty) is inappropriate. Indeed, the statistical volatility of DG and PEV load time series makes the point forecasts unreliable in long-term. On the other hand, scenario-based forecasts (or to say "scenario-based modeling" more appropriately) is an attempt to reduce the inaccuracy of representing the reality with a limited number of scenarios. It is supposed that the weighted scenarios by probability produce an aggregate closer to the ideal forecast. An example of such a modeling is illustrated in Fig. 1 by a topological probability sorting graph.

Furthermore, there are two additional considerations for PEVs. First, it is assumed that there is no smart metering system available for PEVs at the moment, so the vehicles will be charged without coordination. In an uncoordinated charging scenario the charging start time depends on incentives that encourage the vehicle owner to optimize the grid utilization or to start charging using off-peak electricity tariffs. Second, loss calculation and minimization is relevant from distribution system operator viewpoint where aggregated PEV load behaviors could be clustered and assumed typical based on the pinpointed scenarios.

Unlike TSPs of renewable DG, but according to TLPs, TSPs of PEVs should be treated differently for different kinds of consumers. Here, on the report of the test system (Fig. 2), three categories are assumed for TLPs and TSPs of PEVs: residential, industrial, and commercial. In case of constructing PEV-TSPs, it is assumed three uncontrolled tendencies for the three consumer/owner groups:

- Uncontrolled tariff-based residential charging mainly occurs between hours 22 and 5 by a Gaussian curve.
- Uncontrolled public industrial charging mainly occurs between hours 7 and 15 by a Gaussian curve
- Uncontrolled public commercail charging mainly occurs between hours 9 and 16 by a Gaussian curve

The resulting scenarios by considering uncertainties as well as confidence interval (CI) probabilities would be used to forecast a typical behavior.

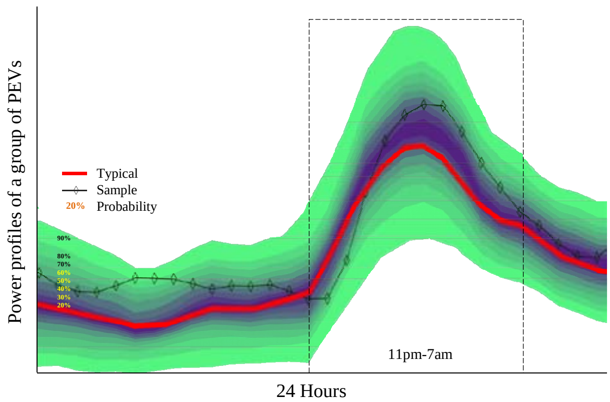
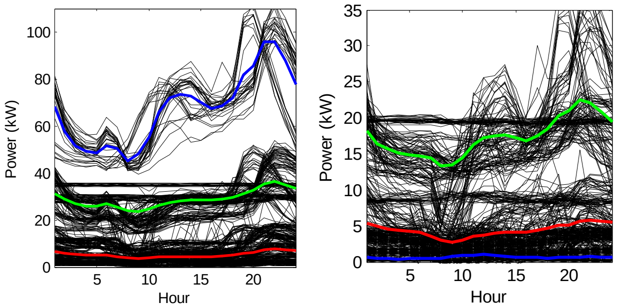


Fig. 1. An illustration of scenario-based approximation of typical PEV load uncontrolled behavior. The color map is to indicate different probability areas over which are located various scenarios (this form of graph has been proposed by [6]).

Based on this approach, it is possible to calculate a typical behavior or daily curve for DG according to [4] and advise a typical behavior or daily curve for PEVs based on the statistical moments (e.g. mean) of PEVs' temporal and spatial diversity scenarios.

The test system and data are chosen from [4]. The typical stochastic energy profiles (TSP) of wind and solar power generation are related to Davarzan area along with the base case distribution system as presented in [4]. The network data is according to Table 1 and distribution of typical wind and solar power behaviors along with three TLPs are shown in Figs. 2 and 3.



(a) (b)

Fig. 2. (a) Active power profiles and (b) reactive power profiles along with three sample cluster centres as TLPs.

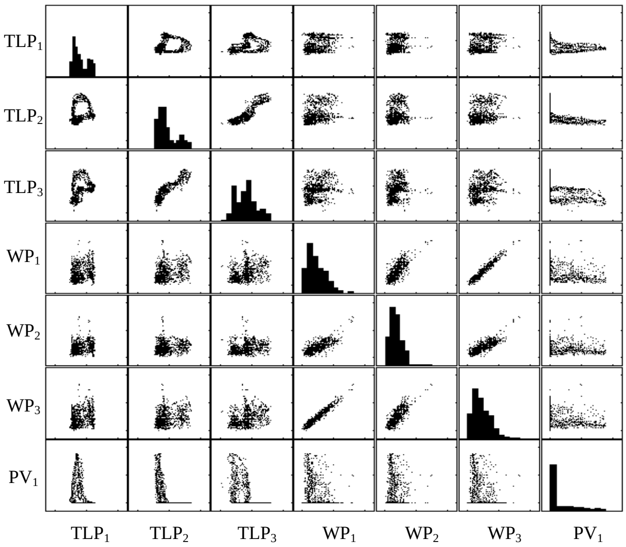


Fig. 3. Modeled typical load, wind, and solar power profile datasets; wind power sets (WP) and solar power set (PV) are a part of TSP.

Table 1. Network data.

Branch No.	Sending Node	Receiving Node	Branch Parameters		Receiving Node Avg. Load	
			r (Ω)	x (Ω)	P (kW)	Q (kVAr)
1	0	1	1.303	0.408	410	350
2	1	2	0.358	0.124	560	420
3	2	3	1.904	0.808	580	360
4	3	4	0.987	0.456	320	280
5	4	5	0.300	0.110	380	210
6	5	6	0.150	0.055	610	430
7	0	7	1.113	0.501	330	260
8	7	8	0.902	0.414	380	200
9	8	9	0.493	0.228	390	270
10	9	10	0.512	0.232	460	230
11	10	11	0.512	0.232	320	240

Substation Voltage: 20 kV
Total: P = 4740 kW, Q = 3250 kVAr

Statistical loss calculation method

Calculation of energy loss in full-size distribution networks is a computationally demanding task even using today's superfast computers. This seems much more challenging considering the fact that new solutions for active distribution networks or smart grids necessitate use of probabilistic/iterative Monte Carlo-based simulations. Such simulations are a source of high computational burden itself. Therefore, in case of active distribution networks, the need for an efficient loss calculation method is much more noticeable than in case of passive systems.

A vast number of research papers have been reported less-demanding loss calculation methods in passive systems. Among them, there are several methods based on some statistical properties of daily load profiles. Such methods are more suitable than deterministic methods when employed in active networks [7]. This is clear considering stochastic behaviors highly penetrated in such networks. Among statistical techniques, Shenkman [5] proposed a technique in which the correlations between different typical load patterns/profiles (TLP) are also considered. This potentially provides a suitable context allowing typical stochastic energy profiles (TSPs) to be joined with TLPs.

Indeed, not taking the dependence structures (correlations) properly into account when joining TLPs and TSPs would contribute to inaccurate results [4].

The main formula for relating energy flows in the network to energy loss are as follows as repeated from [5]:

$$\Delta W = \frac{R}{V^2}\left(P_{rms}^2 + Q_{rms}^2\right)T \qquad (1)$$

where,

$$P_{rms}^2 = \sum_{k=1}^{n} \rho_{2k}^P \bar{P}_k^2 + \sum_{l \neq k}^{n} \rho_{l,k}^P \bar{P}_l \bar{P}_k, \qquad (2)$$

$$Q_{rms}^2 = \sum_{k=1}^{n} \rho_{2k}^Q \bar{Q}_k^2 + \sum_{l \neq k}^{n} \rho_{l,k}^Q \bar{Q}_l \bar{Q}_k, \qquad (3)$$

in which, P_{rms} and Q_{rms} are rms values of active and reactive powers respectively, ΔW is the energy loss in the time period T, $\bar{P}_l$ and $\bar{Q}_l$ are the average value of l-th active and reactive TLP, and $\rho_{l,k}^P$ and $\rho_{l,k}^Q$ are the correlation between l-th and k-th active and reactive TLPs, respectively. In the proposed algorithm TLPs are replaced with TEPs in which the impacts of TSPs are taken into account. The only remaining problem is how to join TLPs and TSPs. This could be perfectly performed by copula theory.

Copula theory

The TLPs and TSPs are both multivariate; so, jointing them needs one of the following approaches:

1. using a multivariate probability distribution function (pdf), or
2. using a linking multivariable function to join one-dimensional marginal distribution functions.

The second approach is called copula theory and the linking function is referred to as copula function. Dealing with the application of this paper, the first approach is inapplicable; because, it requires all marginal pdf's to be identical as well as the number of the variates to be limited (less than three for a reliable application [8]).

The copula theory is considered as a general way of formulating a multivariate distribution in such a way that various general types of dependence can be represented [8]. The approach to formulating a multivariate distribution using a copula is based on the idea that a simple transformation can be made of each marginal variable in such a way that each transformed marginal variable has a uniform distribution. Once this is done, the dependence structure can be expressed as a multivariate distribution on the obtained uniforms, and a copula is precisely a multivariate distribution on marginally uniform random variables. When applied in a practical context, the above transformations might be fitted as an initial step for each marginal distribution, or the parameters of the transformations might be fitted jointly with those of the copula. Fig. 4 illustrates all this by a simple diagram.

There are many families of copulas which differ in the detail of the dependence they represent. A family will typically have several parameters which relate to the strength and form of the dependence. The Frank copula is used in this paper because it allows both negative as well as positive dependence.

A satisfactory presentation of the copula theory is out of the scope of this paper; however, one may refer to [4], [8] for a practical as well as theoretical presentation.

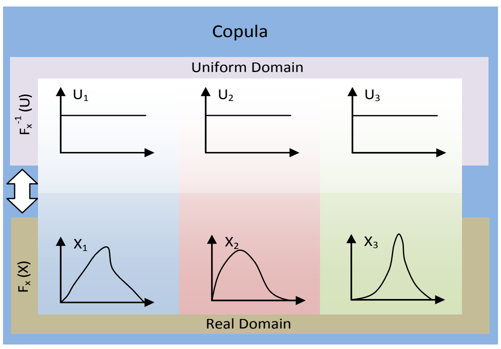


Fig. 4. Copula modeling structure

RESULTS AND CONCLUSIONS

The forecasted power losses are represented in Table 2 for three cases: the base case passive network (without TSPs), without PEVs, and PEV uncontrolled charging.

It is shown by considering Table 2 that uncoordinated/ uncontrolled charging of the PEVs has a non negligible impact on the power losses in active distribution systems.

Table 2. Power losses for the test grid.

Quantities (aggregate of all typical groups)	Base case	TSP penetration level (wind,PV), 15%, without PEVs	TSP penetration level, 15%, PEV uncontrolled, 20%
Peak load (MVA)	4.85	4.22	5.40
Power losses (%)	1.60	1.15	2.10

On the other hand, the other part of the TSPs that is the renewable distributed generation, generally, reduces loss levels. The correlation between different TSPs and TLPs in addition to the internal correlation among various TSPs and TLPs determines how theses stochastic energy profiles affect distribution system performance and losss. It is interesting to note that the proposed method provides a measure to estimate an amount and location (as typical profiles include locational information as well) of renewable distributed generation to compensate impacts of PEVs or even to control PEVs in order to minimize losses.

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