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A novel non-intrusive method using design of experiments and smooth approximation to speed up multi-period load-flows in distribution network planning

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ABSTRACT

Alternative solutions to network reinforcement are now being investigated in distribution network planning studies to reduce the costs and periods for integrating renewable energy sources. However, a thorough techno-economic analysis of these solutions requires a large number of multi-period load-flow calculations, which makes it hard to implement in planning tools. A non-intrusive approximation method is therefore proposed to obtain fast and accurate multi-period load-flows. This method builds a surrogate model of the load-flow solver using polynomial regression and kriging, combined with Latin hypercube sampling. Case studies based on real distribution networks show that the proposed method is more efficient for distribution network planning in presence of renewable energy sources than time subsampling, line model simplification, and voltage linearization. In particular, accurate 10-min profiles of voltages, currents, and network power losses are obtained in a satisfactory computation time.

1. Introduction

To enable the expected intensive development of Renewable Energy Sources (RES) and new electrical usages (active demand, electric vehicles, etc.), distribution network planning needs to evolve quickly [1,2]. Today, most of the voltage/current constraints due to RES are removed by reinforcing the network, i.e., by replacing existing network infrastructures or adding new ones. As these network adaptations may be expensive and take time, several alternative solutions, such as Volt–VAR control and load/generation curtailment, are now being investigated to reduce the costs and periods for integrating RES while ensuring an acceptable level of risk and quality in the network. Unlike network reinforcement, alternative solutions may have operating limits in energy or duration and important operational costs depending on the voltage/current constraints which have been avoided. Therefore, to assess the techno-economic impacts of these solutions and find the best ones, network planning methods should allow, not only to detect any risk of constraint as it is done today, but also to characterize the constraints in terms of depth, duration and frequency. This implies studying multi-year profiles of load and generation, and thus performing multi-period load-flow calculations [2].

The time uncertainty and power variability of intermittent RES must be taken into account in order to accurately assess the temporary constraints, and thus the techno-economic performance of the solutions. It is thus essential to study a large number of load/generation profiles, with a time step ΔT which is as small as possible (no more than 10 min, see Section 3.2). This nevertheless leads to an intensive use of a time-consuming "load-flow solver" method for solving the nonlinear load-flow equations. For instance, if $p = 100$ yearly load/generation profiles with a time step of $\Delta T = 10$ min are considered over a period of $A = 10$ years ($\approx 5.3 \times 10^6$ min), then $n = pA/\Delta T \approx 5.3 \times 10^7$ load-flow calculations are required to assess the performance of alternative solutions for a given network. This means around seven hours of computation[1] when using a Forward–Backward load-flow solver [20] under MATLAB for one of the radial 400-bus networks studied in Section 3.2. Such a computation time is not acceptable for Distribution System

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[1] All the computation times presented in this paper are obtained with a laptop with a 2.50-GHz processor (Intel Core i7 4710MQ) and a 16-GB RAM.

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Operators (DSO), who are often responsible for the medium/long-term development of several hundred or even thousand primary substations.

The possible options to reduce the computation time needed for multi-period load-flow calculations can be classified into three categories: (1) time subsampling of the load/generation profiles, (2) intrusive approximation of the load-flow solver, and (3) non-intrusive approximation of the load-flow solver.

Time subsampling consists in using only a part of the available input data, by either increasing the time step ΔT of the yearly load/generation profiles or, in rarer cases, selecting only a few daily profiles for each year. Yearly profiles averaged over a time step of $\Delta T = 30$ min or $\Delta T = 1$ h are commonly used to study alternatives to reinforcement [3–6]. Time subsampling is easy to implement, which accounts for its popularity, but the results are not very accurate compared to the time savings (see Section 3.2.3).

Intrusive approximation consists in simplifying the load-flow equations using physical assumptions and/or intrusive approximation techniques. This option is often used to study network stability [7] or the statistical impacts of load and generation power variations [8]. The most popular approaches are to linearize the load-flow equations at one or several operating points, to simplify the voltage equations by assuming voltage angles equal to zero, or to model the electrical lines by series resistances and reactances only. The effectiveness of this option strongly depends on the assumptions and intrusive approximation techniques used.

Non-intrusive approximation consists in building a surrogate model for the load-flow solver using approximation techniques that treat the load-flow solver as a "black box". The effectiveness of this option depends on the sampling methods used to select the operating points where the exact model (the load-flow solver here) is evaluated, and on the approximation methods used to build a surrogate model based on the evaluation results. To our knowledge, non-intrusive approximation has rarely been used in network studies and, if so, only in a simple form like nearest-neighbor interpolation [9,10]. Smooth approximation techniques, such as polynomial regression or kriging, seem not to have been investigated in network planning studies so far.

This paper investigates the latter option, i.e., non-intrusive approximation, to obtain fast and accurate multi-period load-flows. The proposed method builds a surrogate model of the load-flow solver using polynomial regression and kriging combined with Latin hypercube sampling. The paper is organized as follows. Section 2 describes a generic approximation procedure to estimate any function, then presents the proposed method for multi-period load-flows. Section 3 illustrates the performance of the proposed method, in terms of computation time and approximation errors, through several case studies based on real distribution networks and 10-min profiles of load/generation. The effectiveness of the proposed method is compared with four other methods commonly used in network planning: the use of 30-min averaged load/generation profiles, the computation of a single load-flow iteration, the modeling of electric lines by series resistances and reactances only, and the linearization of the voltage load-flow equations. Finally, Section 4 discusses the validity area of the proposed method.

2. Proposed method for the approximation of the load-flow solver

2.1. A generic non-intrusive approximation procedure

Let us consider a real s-dimensional variable $y = [y_1 \ldots y_s]$, which is the result of a function f when applied to the real m-dimensional variable $x = [x_1 \ldots x_m]$: $y = f(x)$. The purpose is to calculate the n values of y, gathered in the matrix Y:

$$Y = \begin{bmatrix} y^{(1)} \\ \vdots \\ y^{(n)} \end{bmatrix} = \begin{bmatrix} y_1^{(1)} & \cdots & y_s^{(1)} \\ \vdots & \ddots & \vdots \\ y_1^{(n)} & \cdots & y_s^{(n)} \end{bmatrix},$$

that are associated with n given values of x, gathered in the matrix X:

$$X = \begin{bmatrix} x^{(1)} \\ \vdots \\ x^{(n)} \end{bmatrix} = \begin{bmatrix} x_1^{(1)} & \cdots & x_m^{(1)} \\ \vdots & \ddots & \vdots \\ x_1^{(n)} & \cdots & x_m^{(n)} \end{bmatrix}.$$

Let us assume that: (1) the number of points n and the output dimension s are very large, and (2) the evaluation of f is time-consuming, which makes it difficult or even impossible to compute Y using f and X directly. An approximation procedure is therefore required to estimate Y precisely in an acceptable computation time.

Table 1 details a generic non-intrusive approximation procedure to estimate the output-value matrix Y. Different variants of this procedure have already been used in several application fields [11–13]. This procedure is based on a sampling method, a dimension reduction method, and an approximation method.

The sampling method selects a small set of input points, called design of experiments, so as to guarantee a high-quality approximation (step 2 in Table 1).

The dimension reduction method decreases the dimension of the output variable y, and thus reduces the number of times the approximation method is used in the procedure (step 4 in Table 1). We detail here the Principal Component Analysis (PCA), which is

Table 1
Generic non-intrusive approximation procedure to estimate any s-dimensional variable $y = f(x)$.

(1) Select a sampling method and an approximation method.
(2) Apply the sampling method to build a design of experiments: $X^* = \begin{bmatrix} x^{(1*)} \\ \vdots \\ x^{(n*)} \end{bmatrix}$ where n^* is substantially smaller than n.
(3) Compute the output Y^* associated with X^* using the exact model f:
$\forall i \in [1* ; n*] \quad y^{(i)} = f\left(x^{(i)}\right)$.
(4) Perform the Principal Component Analysis (PCA) to convert Y^* into a reduced set of the q first principal components: $Z^* = [Z_1{}^* \cdots Z_q{}^*] = \begin{bmatrix} z_1^{(1*)} & \cdots & z_q^{(1*)} \\ \vdots & \ddots & \vdots \\ z_1^{(n*)} & \cdots & z_q^{(n*)} \end{bmatrix}$, as follows:
$Z^* = \left(Y^* - \mathbf{1}.\bar{Y}\right) W$,
where $\bar{Y} = [\bar{y}_1 \cdots \bar{y}_s]$ is the empirical mean vector of Y^*, $\mathbf{1}$ is the $n^* \times 1$ vector of ones and W is the $s \times q$ matrix composed of the weighting coefficients from the PCA (i.e., the columns of W are the orthonormal eigenvectors of the empirical covariance matrix corresponding to the q largest eigenvalues).
(5) Create a surrgate model for each principal component: $f_1{}^*, \ldots, f_q{}^*$. For each principal component k, estimate the parameters of the surrogate model $f_k{}^*$ based on the pair $(X^*, Z_k{}^*)$.
(6) Compute the matrix $\tilde{Z}$ of approximate principal components associated with X using the surrogate models $f_1{}^*, \ldots, f_q{}^*$:
$\forall k \in [1 ; q] \quad \forall i \in [1 ; n] \quad \tilde{z}_k^{(i)} = f_k{}^*\left(x^{(i)}\right)$.
(7) Perform the inverse PCA, i.e., compute the matrix $\tilde{Y} = \mathbf{1}.\bar{Y} + \tilde{Z}.W^T$ of approximate output values, where $\mathbf{1}$ is the $n \times 1$ vector of ones.