EFFICIENT FORECAST SYSTEM FOR DISTRIBUTED GENERATORS WITH UNCERTAINTIES IN THE PRIMARY ENERGY SOURCE

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ABSTRACT

A high degree of variability reduces the available capability of Distributed Generators (DGs) based on renewable energy sources because their power output is uncertain. To determine the true available capability of this kind of DG, this uncertainty must be reduced so that these DGs can be regarded as a reliable alternative. In this work, an efficient forecast system for DGs with uncertainties in the primary energy source is proposed. The power generation uncertainty of these DGs is reduced by running a multi-objective optimization algorithm in multiple probabilistic scenarios combining the Monte Carlo method and the Markov models.

INTRODUCTION

The need for more flexible electrical systems, technological advances, rising global fuel prices, and a renewed interest in environmental issues are playing a key role in the development of distributed generation, considering the benefits that they can bring to electrical systems and to the environment [1]-[4].

Generally, the power generated by Distributed Generators (DGs) based on Renewable Energy Sources (RES) varies considerably over time. A high degree of variability reduces the available capability of these DGs because their power output is uncertain. To determine the true available capability of this kind of DG, this uncertainty must be reduced so that these DGs can be regarded as a reliable alternative.

In this work, an efficient forecast system for DGs with uncertainties in the primary energy source is proposed. The power generation uncertainty of these DGs is reduced by running a Multi-objective Optimization Algorithm (MOA) in multiple probabilistic scenarios through the Monte Carlo Method (MCM), and defining the time series associated with the active power generated by such DGs through the Markov Models (MkvM).

The formulated problem is of a mixed integer non-linear programming nature. The objectives to be minimized are active power generation of the DGs and losses in branches of the distribution network.

For each DG, a set of discretized Generation States (GSs) is defined, and the MkvM are described in terms of the transition probabilities which determine the probability of moving from an initial GS *i* to a final GS *j*. These probabilities depend on collected statistical data (e.g., wind or solar radiation) and they form a matrix of transition probabilities. A very small number of GSs does not adequately represent the operation of the DGs, while a very large number of GSs could introduce large forecast errors. The best number of GSs, i.e., the best size of the matrix of transition probabilities, is defined through a method proposed in this work.

The main contributions of this work are listed below:

- The uncertainty of DGs based on RES is reduced by a proposed efficient forecast system.
- It calls for more active participation of DGs due to their potential benefits and increasing penetration into the system.
- To bring simulations to the real operation of a distribution system, the expansion of the time horizon of the method (several states of customers demand and DGs generation) is considered.

MATHEMATICAL FORMULATION

The proposed mathematical formulation of the multi-objective optimization problem (for each time t in the study time for evaluation of the system Γ), is shown below.

$$\text{Min } TP_{\text{DG}}^{(t)} = \sum_{i \in \mathcal{DG}} P_{\text{DG},i}^{(t)} \quad (1)$$

$$\text{Min } TP_{L}^{(t)} = \sum_{km \in \mathcal{L}} P_{L,km} \quad (2)$$

subject to:

$$P_{\text{ca},i}^{(t)} - P_{\text{sp},i}^{(t)} = 0 \qquad \forall i \in \mathcal{N} \quad (3)$$

$$Q_{\text{ca},i}^{(t)} - Q_{\text{sp},i}^{(t)} = 0 \qquad \forall i \in \mathcal{N} \quad (4)$$

$$P_{\text{DG},i}^{\min,(t)} \le P_{\text{DG},i}^{(t)} \le P_{\text{DG},i}^{\max,(t)} \qquad \forall i \in \mathcal{DG} \quad (5)$$

$$Q_{\text{DG},i}^{\min,(t)} \le Q_{\text{DG},i}^{(t)} \le Q_{\text{DG},i}^{\max,(t)} \qquad \forall i \in \mathcal{DG} \quad (6)$$

$$V_{i}^{\min} \le V_{i}^{(t)} \le V_{i}^{\max} \qquad \forall i \in \mathcal{N} \quad (7)$$

$$0 \le I_{km}^{(t)} \le I_{km}^{\max} \qquad \forall km \in \mathcal{L} \quad (8)$$

where $TP_{\text{DG}}^{(t)}$ is the total active power generated by all DGs; $P_{\text{DG},i}^{(t)}$ is the active power generated by the DG *i* of the set of DGs $\mathcal{DG}$; $TP_{L}^{(t)}$ is the total active power losses in branches of the network; $P_{L,km}$ is the active power loss in branch *km* of the set of branches $\mathcal{L}$; $P_{\text{ca},i}^{(t)}$, $Q_{\text{ca},i}^{(t)}$, $P_{\text{sp},i}^{(t)}$ and $Q_{\text{sp},i}^{(t)}$ are, respectively, active and reactive power calculated and specified at bus *i* of the set of buses $\mathcal{N}$; $P_{\text{DG},i}^{\min,(t)}$, $Q_{\text{DG},i}^{\min,(t)}$, $P_{\text{DG},i}^{\max,(t)}$ and $Q_{\text{DG},i}^{\max,(t)}$ are, respectively, active and reactive power generation minimum and maximum limits of the DG *i*; $V_{i}^{(t)}$, $V_{i}^{\min}$ and $V_{i}^{\max}$ are, respectively, voltage and minimum and maximum voltage limits at bus *i*; and, finally, $I_{km}^{(t)}$ and $I_{km}^{\max}$ are, respectively, current and maximum current limit in branch *km*.

Expressions (1) and (2) represent, respectively, the minimization of the active power generated by the DGs and the active power losses in branches of the network. Buses active and reactive power balance constraints are guaranteed in (3) and (4), respectively; active and reactive power outputs of the DGs must be within operational limits according to (5) and (6), respectively; bus-voltages must be within regulated limits (7); and branch-currents must be within their limits (8).

SOLUTION METHODOLOGY

To reduce the uncertainty of DGs based on RES, an algorithm combining the MCM and the MkvM is implemented in this work.

To have an overall view of the solution methodology, the main parts that compose it are presented in Fig. 1.

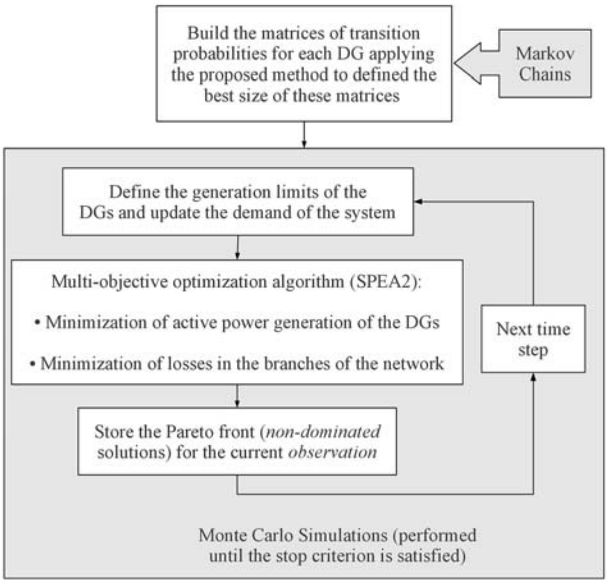

Fig. 1. Overall scheme of the solution methodology

Markov Models

The MkvM represent a stochastic process that moves through discrete time steps. A stochastic process with a random variable which takes a value from the initial state S_i in the period τ, is said to satisfy the hypothesis of first-order MkvM if, to move from S_i to the final state S_j ($i, j \in \{1, \ldots, m\}$; where m is the total number of states), the process depends only on the state in the period $\tau - 1$ [5]. According to this theory, it is possible to formulate the matrix of transition probabilities Pr (9).

$$Pr = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \quad (9)$$

According to this representation, each row of this matrix corresponds to the current state of the process, whereas each column corresponds to the next possible state. The element p_{ij} of Pr can be calculated as the number of transitions from the state S_i to the state S_j divided into the number of *occurrences* of the state S_i (where an *occurrence* is defined as the number of times in which the random variable is in a state).

In this study, the random variable of the time series represented by the first-order MkvM is the active power generated by each, and each state S_i is renamed as GS_i. An example of the discretization in five states of the maximum active power generation of a DG, say P^{max}, is shown in Fig. 2. For clarity, only the probabilities from state three, i.e., the third row of Pr, are presented in this figure.

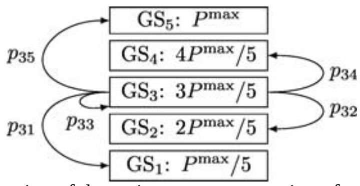

Fig. 2. Discretization of the active power generation of a DG

Best Size of the Matrix of Transition Probabilities

As presented above, the transition probabilities depend on collected statistical data (e.g., wind or solar radiation) and they form a matrix of transition probabilities. However, choosing the appropriate number of discretizations, that is, the size of the matrix of transition probabilities, is very important for the efficiency of the forecast system. A very small number of GSs does not adequately represent the operation of the DGs, while a very large number of GSs could introduce large forecast errors. The best size of the matrix of transition probabilities is defined through a method proposed in this work, which flowchart is presented in Fig. 3.

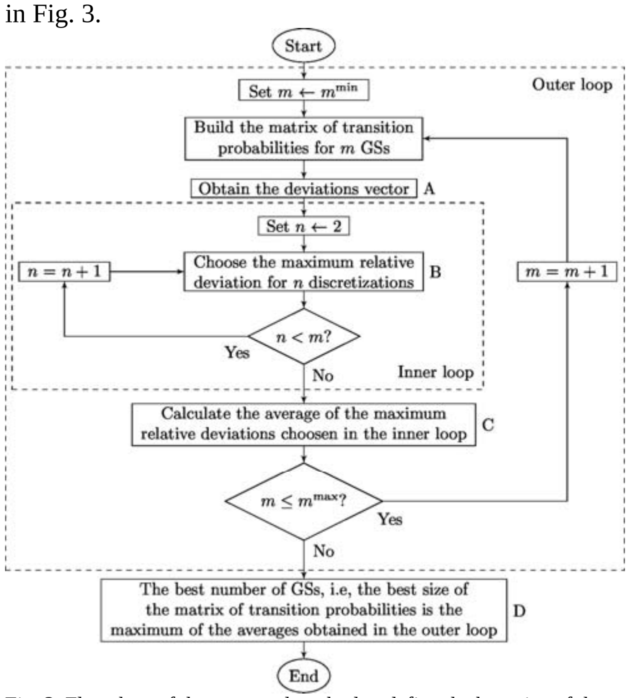

Fig. 3. Flowchart of the proposed method to define the best size of the matrix of transition probabilities

In Block A of the flowchart of Fig. 3, the deviations vector, say *dev*, is obtained by simulating the random variable (active power generation of a DG) using the matrix of transition probabilities built for *m* GSs, and registering the number of times in which a deviation between GSs occurs. Deviations between GSs are defined as the absolute value of the difference between predicted and true GSs. Thus, for example, for a case with $m = 5$ and assuming that the predicted value of current simulation is GS_3, a deviation of value 2 occurs if the corresponding true value is GS_1 or GS_5. Note that, for $m = 5$, the maximum deviation occurs when the predicted value is GS_1 and the true value is GS_5 (or vice versa).

To choose the maximum relative deviation for *n* discretizations and *m* GSs in Block B of Fig. 3, say $MRD^{m,n}$, the relative deviations $RD_i^{m,n}$ ($\forall\ i = 1, 2, \ldots, n$) in expression (10) must be calculated. The relative deviation *i*, $RD_i^{m,n}$, is the number of equivalent deviations, from the vector *dev*, when the active power generation of the DG is redefined to *n* discretizations. As an example, consider a case with $m = 5$ and vector dev = [843 397 96 6 1], and suppose that the relative deviations for $n = 2$ are being calculated. In this case, $RD_1^{5,2} = 843 + 397 + 0.5 \times 96$ and $RD_2^{5,2} = 0.5 \times 96 + 6 + 1$. The aim of using relative deviations is to consider all possible discretizations (from $n = 2$ to $n = m$) for choosing the best size of the matrix of transition probabilities.

$$MRD^{m,n} = \max\left\{RD_1^{m,n}, RD_2^{m,n}, \ldots, RD_n^{m,n}\right\} \qquad (10)$$

The average of the maximum relative deviations for *m* GSs, say $AMRD^m$, is calculated in Block C of Fig. 3 using the values obtained in the inner loop, as presented in (11).

$$AMRD^m = \frac{\sum_{n=2}^{m-1} MRD^{m,n}}{n-1} \qquad (11)$$

Finally, the best size of the matrix of transition probabilities, say m^*, is calculated in Block D of Fig. 3 using the values obtained in the outer loop, as presented in (12).

$$m^* = \max\left\{AMRD^{m^{min}}, AMRD^{m^{min}+1}, \ldots, AMRD^{m^{max}}\right\} \quad (12)$$

Power Flow and Multi-Objective Optimization Algorithm

Bearing in mind factors such as speed of convergence, accuracy and robustness, a power flow based on the backward-forward method [6] is used in this work.

The multi-objective optimization is based on the concept of *Pareto optimality*. A solution is said to be Pareto-optimal if not one of its objective functions can be improved without degrading all others, that is, a solution is Pareto-optimal if it is not "dominated" by others. The MOA implemented in this work is based on an evolutionary optimization technique known as Strength Pareto Evolutionary Algorithm 2 (SPEA2) [7].

Monte Carlo Method

The MCM is based on random simulation of scenarios to mimic the operation of a real system and determine the future behavior of a random variable.

In this work, the historical variations of the random variable (active power generation of the DGs) will be characterized by transition probabilities between discrete states, obtained from the MkvM. Each simulated scenario is defined as an *observation*. The algorithm to perform the MCM is presented below [8].

- *Step 1*. Choose Γ. Choose the total number of *observations* $\aleph$. Set the *observations* counter $k \leftarrow 1$.
- *Step 2*. Set $t \leftarrow 0$. For each DG, define an initial GS_i, i.e, an initial upper limit of active power generation.
- *Step 3*. For each DG, generate an uniform random number between 0 and 1. Link these numbers to p_{ij}, from the Pr matrix associated to the corresponding DG, to move from the current GS_i to the next GS_j, i.e., to define the upper limit of active power generation at the next time instant t.
- *Step 4*. The simulation will increase from the current reference to the time corresponding to $t+1$.
- *Step 5*. Perform the MOA considering that, for each DG, the upper limit of active power generation is determined by the corresponding GS_j. Store the results (set of *non-dominated* solutions).
- *Step 6*. If $t > \Gamma$, then set $k \leftarrow k+1$ and go to the next step. Otherwise, set $GS_i \leftarrow GS_j$ and return to *Step 3*.
- *Step 7*. If $k < \aleph$, then set $t \leftarrow 0$ and $GS_i \leftarrow GS_j$, and return to *Step 3*. Otherwise, stop.

Note that, as a result of the MCM implementation, $\Gamma \times \aleph$ sets of *non-dominated* solutions will be obtained. In a pessimistic scenario, the proposal is to select the set of *non-dominated* solutions with the worst solutions when compared to the corresponding sets of *non-dominated* solutions for each time t.

Another important issue is the criterion used for selecting the solution of the set of *non-dominated* solutions for each time t. This depends on the interests of the system operator; however, in this work, the proposal is to select an *intermediate solution*, which represents a trade-off between the total active power generated by all DGs and the total active power losses in branches of the network.

TESTS AND RESULTS

To show the efficiency of the proposed forecast system, several tests were performed considering five DGs (wind turbines) in a modified IEEE 37 bus distribution test system, which is shown in Fig. 4.

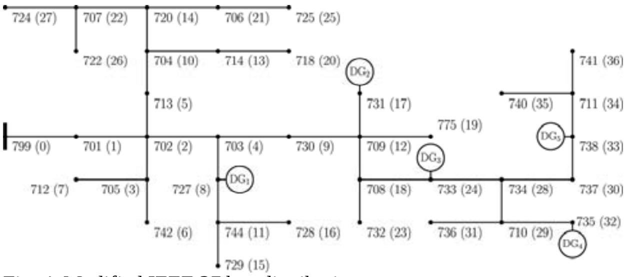

Fig. 4. Modified IEEE 37 bus distribution test system

The best sizes of the matrices of transition probabilities for DG_1 to DG_5 , obtained with the proposed method, are 6, 5, 7, 6 and 6, respectively.
The average absolute deviations of predicted values with respect to true values for DG_1 to DG_5 are 1.47, 1.55, 1.78, 1.24 and 1.87, respectively. True and predicted values for transitions between GSs and *occurrences* for DG_5 (which is the DG with the worst average absolute deviation) are presented in tables I, II and III. Low errors show the high accuracy of the proposed forecast system.

Table I. True and predicted values for transitions between GSs for DG_5

GS_j / GS_i	1		2		3	
	True	**Pred.**	**True**	**Pred.**	**True**	**Pred.**
1	34346	34624	388	375	10	8
2	475	487	1697	1553	223	218
3	3	4	175	170	232	207
4	0	0	11	8	98	85
5	0	0	0	0	35	38
6	0	0	0	0	0	0

Table II. True and predicted values for transitions between GSs for DG_5 (continuation)

GS_j / GS_i	4		5		6	
	True	**Pred.**	**True**	**Pred.**	**True**	**Pred.**
1	0	0	0	0	0	0
2	15	15	2	1	0	0
3	117	105	25	20	8	5
4	241	207	87	74	35	27
5	80	65	547	609	207	197
6	89	91	145	139	709	668

Table III. *Occurrences* for DG_5

GS_i	***Occurrences*** DG_5	
	True	**Pred.**
1	34744	35007
2	2412	2274
3	560	511
4	472	401
5	869	909
6	943	898

Results regarding active power losses in branches of the network and active power generation of the DGs are presented in Figs. 5 and 6, respectively. The results show the improvement of the losses when compared to the base case (without DGs).

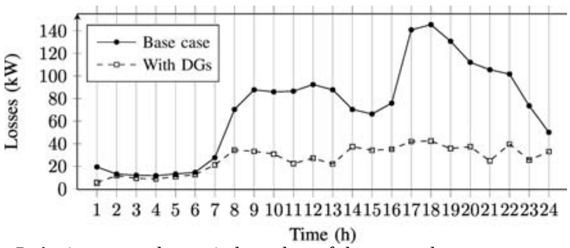

Fig. 5. Active power losses in branches of the network

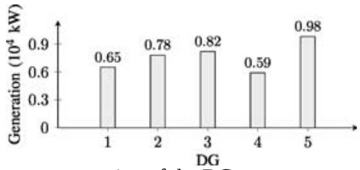

Fig. 6. Active power generation of the DGs

CONCLUSIONS

An efficient forecast system for DGs with uncertainties in the primary energy source is proposed in this work. In this forecast system, the generation uncertainty of these DGs is reduced using a method which combines the MCM and the MkvM.
The best size of the matrices of transition probabilities between GSs of the DGs is defined through a proposed method. The aim of this method is to represent adequately the operation of the DGs by finding the best number of discretizations of their active power generation outputs and, at the same time, by reducing forecast errors.
The efficiency of this method was proved by the results of tests performed in a 37 bus distribution test system considering 5 DGs. Low differences between predicted and true values show the high accuracy of the proposed forecast system.

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