Optimal Allocation of Multichannel Measurement Devices for Distribution State Estimation

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***Abstract*—This paper proposes an optimization algorithm that is suitable for choosing the optimal number and position of the measurement devices in distribution state estimation (DSE) procedures used in modern electric distribution networks. The algorithm is based on the techniques of dynamic programming, and its goal is to guarantee both the minimum cost and the accuracy required for the measured data needed to operate management and control issues, such as energy dispatch and protection coordination. Both the uncertainty introduced by the measurement devices and the tolerance in the knowledge of the network parameters (line impedances) are taken into account in the proposed approach. The aggregation of the quantities to be measured in a few measurement points has been favored to reduce the overall cost of the measurement system. Random changes in the loads are considered to establish adequate reference conditions for the tests. Tests relevant to real distribution networks are presented to show the validity of the proposed approach. The results emphasize how both the influence of the tolerance on the network parameters and the cost of the measurement system can dramatically be minimized by suitably choosing the algorithm to be implemented to solve the DSE problem.**

***Index Terms*—Distribution state estimation (DSE), dynamic programming (DP), Monte Carlo methods, network parameters, optimal meter placement, uncertainty.**

I. Introduction

In recent times, distribution systems have been subject to increasingly significant changes, such as market liberalization and increasing integration of distributed generation (DG). In particular, the novel paradigm of distribution implies the active control of loads and DG and real-time network reconfigurations. Reconfigurations aim at increasing the efficiency of power delivery, the integration of DG and renewable energy sources, and the participation of customers in the market. These changes have an impact on the power system configuration, creating new monitoring, management, and reliability issues. Solving such critical issues requires the knowledge of the system to be as comprehensive and reliable as possible. A power system with a measurement device on each node can totally be known, but it is economically unacceptable. In most practical cases, in distribution systems, the number of available measurements is significantly smaller than the number of nodes. Therefore, the data necessary to evaluate the status of the system can be obtained using a digital processing technique: state estimation (SE). SE is based on the mathematical relations between the system state variables and the measurements achieved from the system. Most of the SE techniques are designed for transmission systems. They exploit all the available measurements and information retrieved from historical and available data, which are called pseudomeasurements, obtained from *a priori* knowledge. In distribution systems, the lack of enough real-time measurements implies that numerous pseudomeasurements are required to obtain the observability of the system. Consequently, it is necessary to define an ad hoc estimator that is able to give good state estimation by reducing the number of measurement devices as much as possible. A distribution system state estimator is formulated by selecting the model and the state variables of the system. In particular, it is necessary to detect the real measurements and the pseudomeasurements required to get a certain approximation of the actual system. The knowledge of the system configuration has a great impact on the approximation degree of the solution.

Recently, some techniques have been presented in the scientific literature to obtain an SE solution, with the placement of a minimum set of real-time measurements (see, for instance, [1] and [2]). In those studies, the problem of the accuracy related to such solutions gets little attention. The measurement uncertainty caused by the accuracy of the measurement devices and the uncertainty in the knowledge of the line parameters have generally been neglected. Indeed, in the referenced papers, the accuracy has been estimated in terms of the standard deviation of the voltages at the unmeasured busbars, which is caused only by random load changes.

In a previous work [3], the authors have considered, as a first step for a novel and comprehensive algorithm for the optimal meter placement, the influence of the measurement uncertainty on the results of the distribution SE (DSE). On the other hand, the line parameters were assumed to be totally known and characterized by their nominal values. In [4], the developments of the approach proposed in [3] are presented: In particular, given that a significant deviation from the nominal value is possible in line impedances (see, for instance, [5]), variations in the network parameter values are taken into account. From this point of view, it is expected that different approaches to the DSE problem could feature different sensitivities to the uncertainty of such parameters. The optimization procedure, owing to its flexibility, can therefore also support the choice of the most robust algorithm for each specific application. As an example, in [4], a DSE approach based only on current measurements

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and aimed at estimating the status of the systems in terms of current flows is used: These characteristics make the approach quite insensitive to the variations of the line impedances.

The overall procedure is based on three main steps: 1) a heuristic optimization technique for finding the optimal solution to meter placement; 2) a DSE algorithm; and 3) a Monte Carlo approach for taking into account random load variations and the tolerance of both the measured quantities and the line impedances. This approach allows evaluation of the propagation of the uncertainty from measured to evaluated data, starting from suitable uncertainty models of each system element.

In this paper, further refinements of the procedure are discussed. They mainly consist of the possibility of reducing the costs related to the implementation of SE by measuring more than one quantity (i.e., either more than one type of measurand or more measurands of the same type) in a single measurement point. It should be considered that a solution that features a minimum number of devices does not guarantee the minimum total cost. Indeed, the additional cost of measuring a new quantity in a site where a measurement device is already present is certainly less than the cost needed to install an instrument dedicated to that quantity in a new location, because the predominant cost is in the base unit, whereas the incremental cost for additional channels is relatively small [6]. New results obtained by applying the optimization technique to two portions of the Italian distribution network are also presented.

II. Problem Definition

The main goal of a meter-placement technique is to establish the number, position, and type of measurement instruments to be placed on a given system to achieve an observable system. The aim of a minimal meter placement is to obtain a distribution system that is observable with established accuracy and minimum cost. The constraint on the maximum acceptable uncertainty for the results means that, in each one of the N_n selected nodes of the network, the estimated variance (σ_{xi}, for $i = 1, \ldots, N_n$) of the quantity of interest x must not overcome the limit λ_{xi} imposed for that quantity in that node [7]. Since these constraints could be met for different measurement sets having the same minimum number of measurement units, the optimal set is the set that minimizes function J, which is the weighted mean value of the variances of the quantities of interest, i.e.,

$$\min J = \sum_{i=1}^{Nn} \left(\frac{\sigma_{xi}}{\lambda_{xi}}\right)^2$$
$$\text{subject to } \sigma_{xi} \leq \lambda_{xi} \qquad \forall i = 1, \ldots, N_n. \tag{1}$$

From a mathematical point of view, this is a nonlinear combinatorial optimization problem. Given that a complete enumeration of all the possible combinations of measurement device placement would also be unacceptable for small-sized networks, a heuristic approach has been presented in [3] to reduce the computational burden. The proposed approach will briefly be recalled in the next section.

III. Proposed Approach

The idea behind the methodology proposed in this paper is to find an optimal set of measurement devices that is able to identify the state of a given distribution system with a predefined accuracy, taking into consideration the stochastic behavior of loads and generators and the variability of the line electrical parameters. Furthermore, by observing that the state estimation is affected by the uncertainty of the measurements, the data processed by the state-estimation algorithm are affected by the uncertainties introduced with the measurement and acquisition chain. The Monte Carlo approach is used to solve the problem.

To better explain the process, let us assume that a given measurement system had been placed in the network. Starting from the distribution density functions of loads and generators, N different network conditions may be produced by randomly extracting power demand and generation (loads and generators are treated as stochastic variables having a Gaussian distribution density function centered on the nominal values and a prefixed standard deviation) and the value of the network parameters, which are also subjected to random variations. By solving N load flows, the nodal voltages and the line currents may be calculated; every achieved solution represents a network state that the DSE algorithm should be able to identify with a certain precision.

The input data to the DSE are the pseudomeasurements (estimates of the load demand achieved with historical data) and the measurements from the measurement devices placed in the network. (In the simulation, the measurements are based on the aforementioned load flow calculations.) In this paper, powers in the generation plants (default measurement points) and currents in the feeders are measured. The DSE algorithm uses the exact (nominal) value of the line parameters for the network calculations. Inaccuracies in state estimation are caused by the small number of measured quantities, the use of pseudomeasurements, the uncertainties in network data (real data differ from the nominal data stored in the SE), and the uncertainties introduced by the measurement system. To properly consider such uncertainties, the Monte Carlo algorithm produces, from each reference condition in the set with N elements, other M_c network states that are obtained by applying the instrument uncertainty to the measured data. Thus, the proposed Monte Carlo approach allows assessment of the performance of the DSE, considering all the causes of uncertainties in the state-estimation process.

The described Monte Carlo algorithm is applied to different combinations of measurement devices; each combination represents a possible solution to the problem of finding the minimum set of measurement devices to allow the DSE to give an acceptable performance. In other words, a solution of the optimization problem is represented by the optimal number and position of the instruments used to evaluate the state variables with a predefined accuracy.

Fig. 1 shows the whole optimization algorithm, whose main steps can be summarized here.

Step 1) Define a set of $N \times M_c$ cases. Each one of the N reference network states produces M_c different

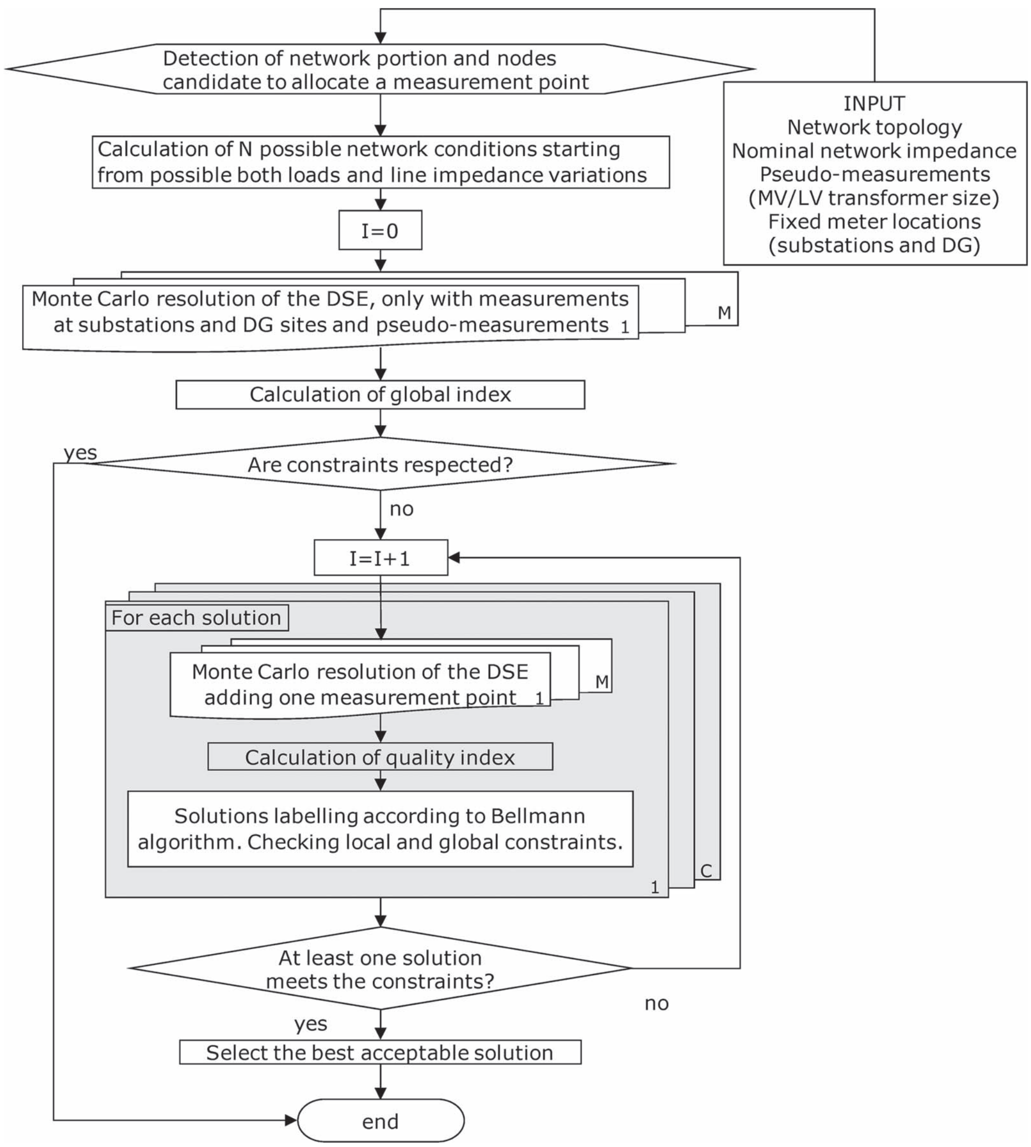

Fig. 1. Flowchart of the optimization algorithm for the optimal placement of measurement devices in distribution networks.

states due to the uncertainties of the measurement devices.

Step 2) Define the candidates for the allocation of the measurement devices. The candidates identify the possibility of measuring a given quantity (the line current in the case at hand) in a given location (a particular line in the network).

Step 3) To explore the space of solutions, the combinations of candidates are considered. An optimization algorithm based on the dynamic programming (DP) described in Section III-B is used to reduce the number of combinations to be examined to find the optimal solution. The first combination used to assess the DSE (see Section III-A) is the combination with measurement devices located at the busbars of the primary substation that supplies the network. According to DP, new meter points are added step by step until compliance with the accuracy constraints is achieved. The Monte Carlo procedure is used to take into consideration uncertainty sources (see Section III-C). The solution is assessed through a suitable quality index, and if compliance with the constraints on the accuracy are achieved, such a solution represents the optimal solution.

A. Distribution State Estimation

In standard SE, to relate measurements and state variables, the following model is used:

$$Y = h(X) + U \tag{2}$$

where Y is the vector of measurements, h is the function relating state variables to measurements (depending on the system model), X is the vector of the state variables, and U is the measurement uncertainty. The state variables that may be used are voltages, branch and nodal currents, active and reactive powers, phase angles, etc.

Focusing on the distribution systems, the SE aims at providing a real-time model of power network based on supervisory control and data acquisition and historical data. In these systems, the main goal of the DSE is the achievement of good state estimation with very few real time data. For this reason, special state estimation techniques have been proposed to produce good real-time network models that are able to assess actual feeder loads, voltages at the system buses at any given point in time, and the status of the protective and switching devices [8].

In normal distribution networks, branches are short, the voltage are quite regulated, and the solution of load flow equations may lead to convergence problems due to the network matrix sparsity and the high r/x ratio. These characteristics make the conventional active power/reactive power (P/Q) decoupling used in transmission system analyses inaccurate and, consequentially, unsuited to be integrated in a DSE algorithm. On the other hand, the radial nature of the majority of distribution networks can be exploited to reduce the computational complexity and memory requirement. Another characteristic of distribution systems is that the few real-time available measurements come from branch current measurement points rather than power measurements. All these characteristics should be taken into account while defining state estimation strategies that are suitable for distribution systems.

In [3], a practical state calculation algorithm that uses a modified version of the radial load flow algorithms [9] has been developed. The algorithm is designed to exploit the special characteristics of distribution systems and is also suitable in dealing with DG. For the reasons previously discussed, the branch currents have been chosen as state variables of the proposed DSE algorithm, whose main goal is to estimate, with a given level of accuracy, the currents flowing in each branch.

In the proposed approach, the input data are the measured branch currents and the powers in each node—pseudomeasured or measured—if related to loads or generators, respectively. Starting from these input data, the nodal currents can be calculated by using the nominal voltage. In this sense, loads and generators are modeled as constant current nodes. Then, the voltage in every node can directly be determined by using the constant nodal currents, solving the following:

$$[V] = [Z] \cdot [I] \tag{3}$$

where Z denotes the network impedance matrix.

It is worth noticing that, with this simple approach, the significant impact of DG on the network voltage profiles has also been properly taken into account. Due to the radial nature of distribution networks, the algorithm does not require the solution of the complete load flow equations.

Once the voltages in the nodes are known, branch currents I_{branch} are calculated by simply dividing the corresponding branch voltage drop by the branch impedance. The DSE algorithm iteratively adjusts the nodal loads by using the difference between the measured data and the calculated data until the estimated branch currents become sufficiently accurate. Moreover, the iterative procedure can be summarized.

1) Starting from measurements and pseudomeasurements, solve (3), and evaluate the state variables vector I_{branch}.
2) For each ith branch equipped with a measurement device, calculate the difference between the calculated current I_{branch} and the measured current I_{meas}.
3) Sum these differences to assess a quantity Δ that represents a global measurement of the difference between the estimated and real situations with the following:

$$\Delta = \sum_{i=1}^{N_{\mathrm{meas}}} \left(I_{\mathrm{branch}}(i) - I_{\mathrm{meas}}(i)\right) \tag{4}$$

where I_{meas} is the vector of the N_{meas} measured branch currents.
4) Adjust the node pseudomeasured powers based on the quantity Δ.
5) Use such new pseudomeasurements to repeat the procedure (return to step 1).

The algorithm stops when the corrective quantity becomes less than a prefixed threshold or when the maximum number of iterations is reached.

B. Dynamic Programming

DP is an approach developed to solve multistage decision problems and is based on the well-known Bellman's Principle of Optimality: "An optimal policy has the property that no matter what the previous decisions have been, the remaining decisions must constitute an optimal policy with regard to the state resulting from these previous decisions" [10]. DP is naturally suited for solving multistage decision-making problems. However, it may also be applied to solve problems where the multistage decision making is induced for computational reasons, and for this reason, it has widely been applied in a large variety of engineering problems.

DP tends to break the original problem into subproblems and finds the best solution of the subproblems, beginning from the smallest in size. When applicable, DP dramatically reduces the runtime of some algorithms from exponential to polynomial.

DP can successfully be applied when five conditions hold.

1) The problem can be divided into stages, and a decision is required at each stage.
2) A finite number of states are associated with each stage.
3) The decision at one stage transforms one state into a state in the next stage.
4) There exists a recursive relationship that, provided the states at stage $j-1$ are known, identifies the optimal decisions to reach the states at stage j.
5) The recursion for determining the optimal decisions at stage j only depends on the states at stage $j-1$ and not on the way these states have been reached.

The problem of the optimal allocation of the measuring devices in a distribution network may be formalized according to the aforementioned points. A generic stage represents the total number of measured variables added in the network with respect to the starting level. The states in a stage define the exact position of the measurement points in the network.

The starting point of the procedure is constituted by measurement devices only in substations. The following stage could be characterized by one more measured current with respect to such a starting point.

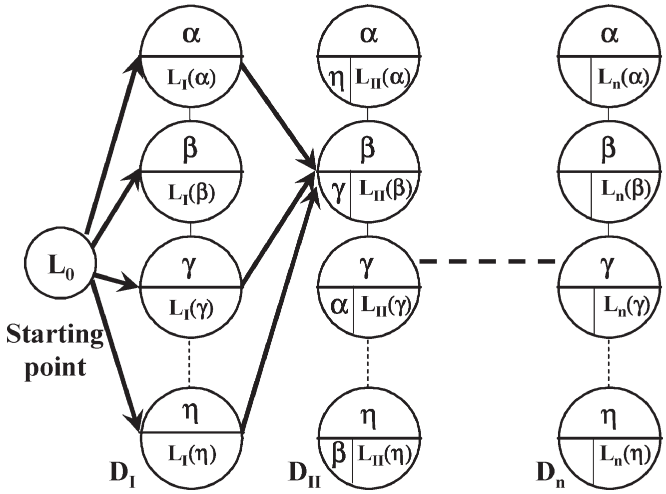

Fig. 2. Schematic flowchart of DP.

Fig. 2 shows the bottom–up approach used here to solve the optimal allocation problem according to the DP paradigm. At each decisional level $D_{\mathrm{I}}, D_{\mathrm{II}}, \ldots, D_n$, new measured variables can be added.

The candidates $\alpha, \beta, \ldots, \eta$ identify the possibility of measuring a given quantity (the branch current in the proposed DSE) in a given location (a particular branch in the network). The candidates could either refer to different branches or to the same location equipped with an instrument that is able to measure more currents in branches leaving from the same node. In this case, the measurements are in the same site. Therefore, they can be measured by a multiple-channel instrument and can be called "aggregated measurements."

To clarify the process, let us suppose that state β at D_{II} has to be reached from D_{I}. Possible states in D_{I} are $\alpha, \beta, \gamma, \ldots, \eta$, each one labeled with the optimal value of the objective function L_{I} calculated with a measurement device defined by the candidates $\alpha, \beta, \gamma, \ldots, \eta$, respectively.

Preliminarily, all the couples formed by adding β to all the possible remaining candidates are examined, and the objective function is assessed for each couple.

State β at level D_{II} is then labeled with the value of the function $L_{\mathrm{I}}(\beta)$ that is the minimum value of the objective function calculated, considering the couples formed with β and the remaining available candidates. By doing so, the optimal policy to reach β at level D_{II} from D_{I} is univocally determined. (In Fig. 2, the optimal path to β has been assumed through γ.)

By repeating this procedure for all the states at the D_{II} stage, the optimal couple of measurement devices that minimizes the cost function is simply that with the smallest label (e.g., if β was the state with the smallest label at level D_{II}, the optimal placement of measurement devices would be in γ and β). The optimal policy corresponds to reach the state in D_{II} with the smallest label, but it is worth noticing that all the states in D_{II} are reached through an optimal policy. By doing so, each policy for reaching D_{III} from D_{II} will necessarily contain optimal subpolicies, and Bellman's Principle will be satisfied. In the proposed application, the decision to pass from one stage to the next is based on the accuracy constraints. For instance, if all the solutions at level D_{II} do not comply with the accuracy constraints, the procedure is iterated by labeling the candidates at the next stage until the goal has been reached.

A critical point of the overall procedure is the definition of both the stopping criterion and the cost function.

In the case at hand, the optimization procedure ends when, at a given stage, at least one solution exists for which the accuracy requirements are met on every estimate (see Section IV).

Cost function L leads the movement from one stage to the next and allows determination of the ranking of each subpolicy at a certain level. The function L used in the proposed application is based on the maximum deviation of the estimates performed by the DSE. The maximum deviation is averaged on the $N \times M_c$ examples passed to the DSE, so that at a given stage of the DP algorithm, the most convenient combination of measurement devices is represented by that having the smallest maximum deviation. Finally, the DP algorithm is forced to use, when technically convenient, multiple-channel measurement devices, because this choice generally leads to economic savings. This result is achieved by giving a premium factor heuristically determined for each state that utilizes aggregated measurements. In the transition from one stage to the next, for those states that adopt multichannel instruments (i.e., states that measure two or more currents from the same node), the incremental benefit achievable with the addition of a new aggregation is exalted by a 30% reduction of the maximum deviation of the estimates in the relevant branch, thus leading to a suitable reduction of the L function.

C. Uncertainty Analysis

The uncertainties affecting all the components of the measurement system propagate through the state estimation algorithm and make the final results uncertain. Such uncertainty can influence the information provided and, consequently, the eventual decisions based on this information. Obviously, the larger the uncertainty on these results, the greater the risk of taking incorrect decisions based on them. This is particularly critical when such decisions are to be made on a threshold value.

Both the metrological characteristics of the measurement devices and their placement significantly affect the accuracy of the estimates. It is therefore necessary to take into account these items to guarantee that the estimated variables comply with a prefixed level of accuracy.

The evaluation of the uncertainty affecting the estimates here is faced using Monte Carlo procedures, which have successfully been used to solve this kind of problems in many circumstances where the analytical law of uncertainty propagation is either difficult or impossible to apply. This is the case, for instance, of complex measurement algorithms, such as those used for DSE.

Such procedures, like any other procedure used for evaluating the propagation of uncertainties, are substantially based on two phases: 1) formulation and 2) calculation. In the former, a measurement model is derived, and the model inputs are quantified, whereas, in the latter phase, the uncertainty affecting the output(s) is evaluated using Monte Carlo simulations. Therefore, suitable metrological models of both transducers and instruments should be implemented [11]. Once the

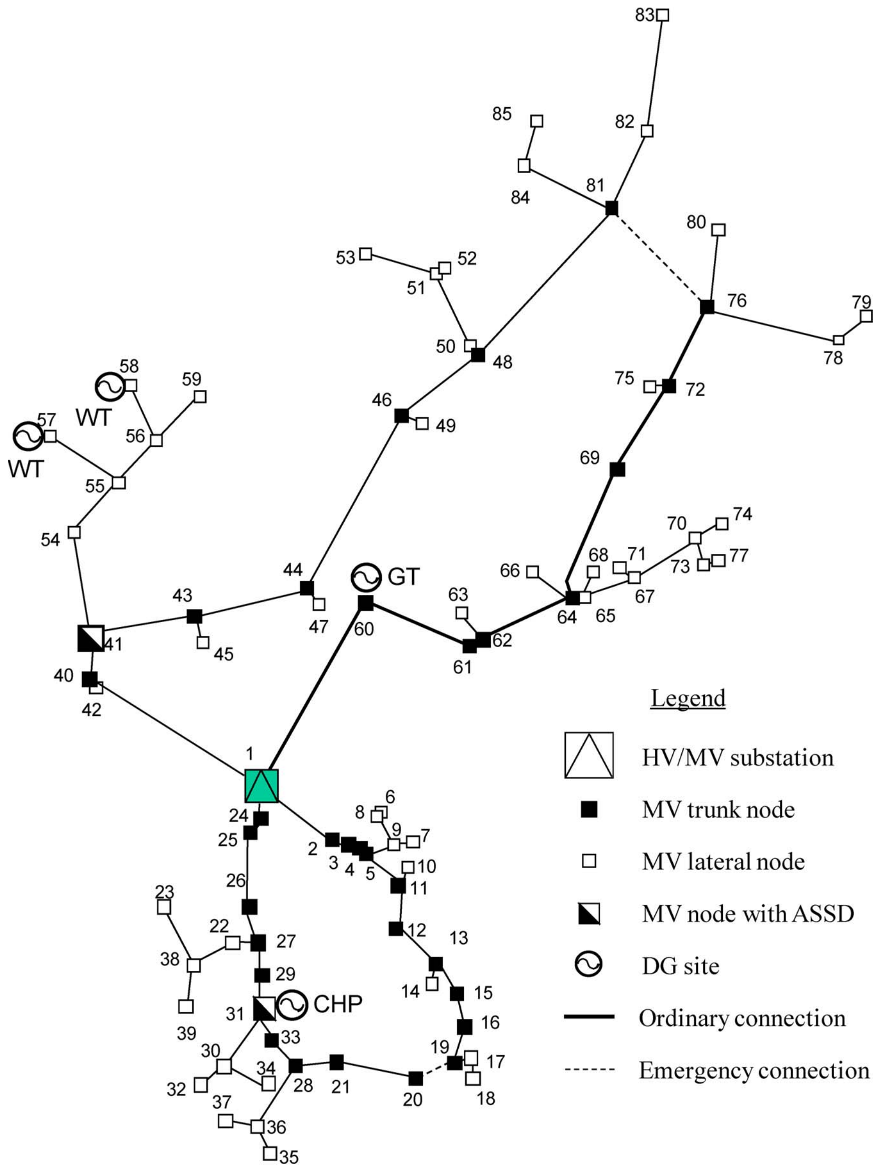

Fig. 3. Scheme of the benchmark network 1.

aforementioned models have been defined, a suitable probability distribution is then assigned to these uncertainty terms, which can numerically be represented by sets of random variables. A large number M_c of simulated tests are then performed: In each test, both the measured data are corrupted by different contributions, whose values are randomly extracted from the aforementioned sets, and the DSE algorithm is applied by using this set of input data. The sets of the M_c obtained output values are finally processed to evaluate the uncertainty of the results.

IV. Result

To show the effectiveness of the optimization procedure, the proposed methodology has been applied to two portions of an Italian distribution network. In the first network (network 1 in Fig. 3), one primary substation supplies 84 MV nodes (33 trunk nodes and 51 lateral nodes) that deliver power to medium voltage (MV) and low voltage (LV) customers. The network is radial with emergency tie connections. Two areas can be identified in the figure. In the upper part of the network, there are long overhead lines feeding small loads. The cross section of the conductors is relatively small because of the low load density. In the lower part of the figure, urban/industrial loads have to be supplied. Here, underground cables with bigger cross section are used due to the high load density. Five types of loads have been considered: 1) residential; 2) industrial; 3) tertiary; 4) agricultural; and 5) public lighting. Three types of generators have been taken into account: 1) wind turbine (WT); 2) cogeneration (CHP); and 3) gas turbine (GT). One 0.5-MVA CHP is installed in the urban area. Two small 1-MVA WTs and one 1.25-MVA biomass gas turbine are installed in the rural area. The annual medium active power delivered to the MV nodes is about 14.2 MW, divided into 10.9 MW for the urban feeder and 3.3 MW for the rural feeder.

The other network (network 2 in Fig. 4) is supplied by two primary substations, which feed 51 MV/LV nodes, 20 trunk nodes, and 31 lateral nodes, and includes DG plants. The active

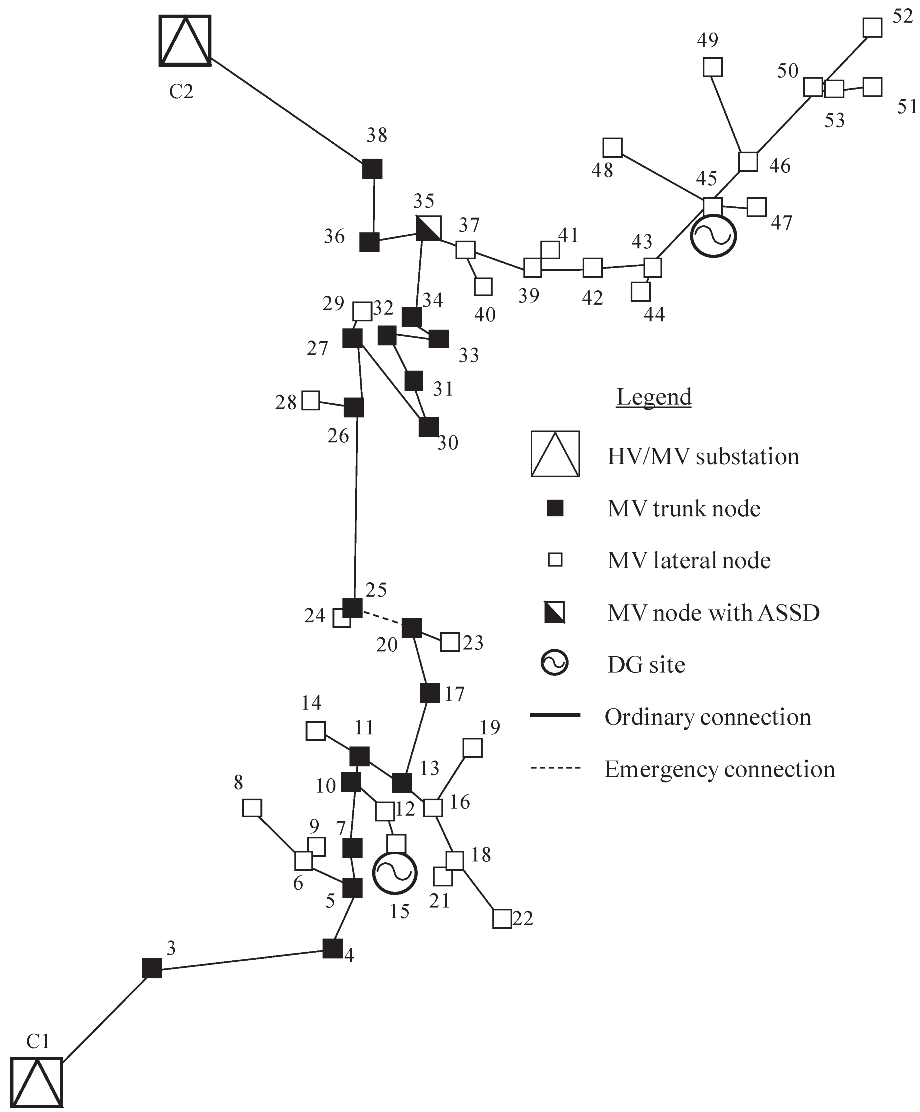

Fig. 4. Scheme of the benchmark network 2.

power delivered to the MV nodes is 4.44 MW. The nodes are mostly rural or suburban, and thus, the network has a majority of overhead lines, although some buried cables are used to feed some particular nodes.

In the tests, we assume the following:

1) number of input configurations $N = 100$;
2) standard deviation of the active and reactive powers for the definitions of the N conditions: $\pm10\%$ of the nominal value;
3) measured variables: branch currents;
4) number of Monte Carlo iterations: $M_c = 100$;
5) measurement accuracy of either 1% or 3% for magnitudes (0.5 or 1.0 crad for phases);
6) tolerance of the line impedances changing from 0% to 20%.

First, it is worth observing that the robustness of the proposed DSE algorithm with respect to possible variations in the values of the network parameters has been proven by the overall results. The solutions obtained on equal accuracy conditions (1% or 3% for magnitudes) present the same number of measurement devices and approximately the same value of the L function both when the tolerance of the network parameters is equal to 20% and when it is neglected (nominal values of the network parameters). In the following, for the sake of brevity, only the results with 20% of tolerance will be shown.

Furthermore, the impact of aggregating several branch current measurements in a single site has been studied. In broad terms, the number of measured variables and the number of corresponding measurement points of the solution may agree. Otherwise, if the optimization is properly driven to prefer more than one current measured in a single site, the number of measurement instruments may be considerably smaller than the currents measured. As a consequence, the overall cost for an accurate DSE may significantly be reduced.

Two kinds of test have been performed. In the first test, the optimization is addressed to prefer aggregated measurements of different quantities; in the second test, the aggregation of the measurements has not been favored.

Let us highlight the algorithm behavior for network 1, considering the accuracy of the devices to be equal to 3% for the magnitudes and 1 crad for the phases. Table I reports the results

TABLE I
NETWORK 1: TEST RESULTS WITH DG

Aggregation favored	Accuracy of measurement devices	Variation of network parameters	Added measured variables	Added measurement instruments
no	3%	20%	33	25
yes	3%	20%	35	23

TABLE II
NETWORK 2: TEST RESULTS WITHOUT DG

Aggregation favored	Accuracy of measurement devices	Variation of network parameters	Added measured variables	Added measurement instruments
no	1%	20%	10	9
yes	1%	20%	11	8
no	3%	20%	13	11
yes	3%	20%	14	10

TABLE III
NETWORK 2: TEST RESULTS WITH DG

Aggregation favored	Accuracy of measurement devices	Variation of network parameters	Added measured variables	Added measurement instruments
no	1%	20%	9	8
yes	1%	20%	10	7

obtained by optimizing the number and position of the currents to be measured to comply with the accuracy constraint. In the general case, without any forcing, 33 branch currents have to be measured, and 25 measurement devices serve the purpose. (Seven aggregations have been realized by the algorithm itself.) In the case of favored aggregation, 35 branch currents are necessary for the SE, and only 23 measurement instruments are used due to ten "forced" aggregations.

Considering network 2, Table II refers to a fully passive distribution network (no DG installed). Two remarks may be done by analyzing the results. The first remark is that the number of line currents that have to be measured for good state estimation increases as the accuracy of the measurement decreases. The value of the measurement aggregation clearly emerges; by adopting multichannel measurement devices, similar or even better performances can be achieved with significant savings.

Finally, to apply the proposed methodology in active distribution networks, two 200-kVA distributed generators, which are connected to nodes 15 and 45 in Fig. 4, have been considered. Some of the obtained results are reported in Table III. By comparing the results in Tables II and III, the test with DG (with accuracy equal to 1% and 20% of the tolerance for the network parameters) leads to a solution with a lower number of quantities to be measured with respect to the case without DG. At the same time, the presence of DG drives the algorithm to an aggregation greater than that in the passive case (i.e., without DG); thus, the solution presents fewer measurement points. In particular, in node 45, the algorithm places three aggregated branch current measurements—one more than in the passive case—clustered in a single multiple-channel device; as a consequence, the solution is less expensive.

It is worth noticing that the imposition of the injected power at some nodes using DG modifies the load flow equations. As a consequence, situations in which the DSE algorithm needs more information on branch currents, requiring the addition of more measurement instruments, may exist. The DG effect on a distribution network and, consequently, on its state estimation strictly depends on various facets, e.g., the allocation of generators, the network configuration, the variability and correlation of loads and generators, and, finally, the energy market prices. As a result, the use of optimization procedures is really important in assessing different possible alternatives and making the most acceptable final decision. The problem of finding the minimum set of measurement devices that allows for the achievement of a predetermined level of accuracy falls in the general aforementioned rule, and even in the small example presented in this paper, it is not possible to understand *a priori* the effect of DG on the final optimal solution, thus justifying resorting to optimization tools.

It should be emphasized that the presented solutions have been found by exploring a number of combinations that are much smaller than those necessary with complete enumeration techniques. For instance, considering the last case in Table II (14 added measured variables), about 29 000 combinations have been explored against about $2 \cdot 10^{13}$, which would be necessary with complete enumeration techniques.

This work is a step toward the understanding of the usability, in practical situations, of DSE methodologies; the authors are also working toward the optimal placement of metering points for harmonic state estimation [12], which will be another important issue in the management of electric distribution systems in the near future.

V. CONCLUSION

This paper has proposed the development of an optimization procedure that optimizes the number and position of measurement devices for state estimation in modern electric distribution networks. The optimization procedure is based on DP and takes into account the changes in the load power demand, the uncertainty of the measurement devices, and the tolerance of the value of the network parameters using suitable Monte Carlo procedures. The impact of favoring the aggregation of the measured quantities has been studied. The presence of DG plants has also been considered.

The results obtained by applying the proposed procedure to two portions of the Italian distribution network show that the influence of the uncertainty affecting the knowledge of the network parameters strongly depends on the algorithm implemented to solve the DSE problem. In the case dealt with in this paper, the DSE is faced by a technique based only on current measurements and on an iterative procedure that adapts the estimated quantities to the measured quantities. Owing to its intrinsic nature, this approach seems to be quite reliable and robust with respect to the tolerance of network parameters and should therefore be considered well suited for management purposes in active distribution grids.

Expected future developments of this research include the possibility of dealing with meshed networks and the introduction of suitable changes to guarantee a prefixed degree of redundancy for the measurement system.

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