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Considering the uncertainty on the network parameters in the optimal planning of measurement systems for Distribution State Estimation

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Abstract – This paper proposes an optimization algorithm based on the techniques of the dynamic programming and suitable to choose the optimal number and position of the measurement devices in Distribution State Estimation procedures used in modern electric distribution network. The goal is to guarantee at the same time the minimum cost and the accuracy required to the measured data needed to operate management and control issues, such as energy dispatching 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. Random changes of the loads are considered to establish adequate reference conditions for the tests. Tests relevant to a real size distribution network are presented to show the validity of the proposed approach. The results emphasize how the influence of the tolerance on the network parameters can be dramatically minimized by suitably choosing the algorithm to be implemented to solve the Distribution State Estimation problem.

Keywords *– Optimal meter placement, Uncertainty, Monte Carlo methods, Distribution State Estimation, network parameters, dynamic programming.*

I. INTRODUCTION

Throughout the last ages, distribution systems have been subjected to changes more and more significant, such as the market liberalization and the increasing diffusion of Distributed Generation (DG). These changes impact on the power system configuration creating new monitoring, management, and reliability issues. Solving such critical issues need the knowledge of the system to be as comprehensive and reliable as possible. A power system with a measurement device on each node can be totally 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 the nodes. Thus, the data necessary to evaluate the status of the system can be obtained by means of a digital processing technique, the State Estimation (SE). SE is based on mathematical relations between system state variables and measurements achieved from the system. Most of the SE techniques are designed for transmission system. They exploit all the available measurements and measurements retrieved from historical and available data, called pseudomeasurements, obtained from a priori knowledge. In distribution systems the lack of enough real time measurements implies the requirement of numerous pseudomeasurements to obtain the observability of the system. Consequently, it is necessary an *ad hoc* estimator able to give a 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 real 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 a SE solution with the placement of a minimum set of real time measurements (see, for instance, [1] and [2]). Anyway, nowadays the problem of the accuracy related to such solutions gets poor attention. The measurement uncertainty caused by the accuracy ranges of the measurement devices and the uncertainty in the knowledge of the line impedances have been generally neglected. Indeed, in the referenced papers, the accuracy has been estimated in terms of standard deviation of the voltages at the unmeasured busbars, 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 DSE. On the other hand, the line impedances were assumed to be totally known and characterized by their nominal values. In this paper the developments of the approach proposed in [3] are presented: in particular, given that a significant deviation from nominal value is possible in line impedances (see, for instance, [4]), 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 sensitivity to the uncertainty of such parameters. The optimization procedure, owing to its flexibility, can therefore be also a support in the choice of the most robust algorithm for each specific application. As an example, in this paper a DSE approach based only on current measurement and aimed at estimating the status of the systems in terms of current flows is used: these characteristics are expected to make the approach quite insensitive to the variations of the line impedances.

The overall procedure is based on three main steps: a heuristic optimization technique, to find the optimal solution to meters placement; a Distribution State Estimation (DSE) algorithm; a Monte Carlo approach to take into account random load variations as well as the tolerance of both the measured quantities and the line impedances. This approach allows evaluating the propagation of the uncertainty from measured to evaluated data, starting from suitable uncertainty models of each system element.

II. PROBLEM DEFINITION

The main goal of a meter placement technique is to establish number, place and type of meters to be placed on a given system in order 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 cost. The constraint on the maximum acceptable uncertainty for the results means that, in each one of the *Nn* selected nodes of the network, the estimated variance (σ_{xi}, for i=1 to Nn) of the quantity of interest x must not overcome the limit λ_{xi} imposed for that quantity in that node [5]. Since these constraints could be met for different measurement sets, having the same minimum number of measurement units, the optimal set is the one that minimizes the function J, which is the weighted mean value of the variances of the quantities of interest:

$$\min J = \sum_{i=1}^{Nn} \left(\frac{\sigma_{xi}}{\lambda_{xi}} \right)^2 \qquad (1)$$

subject to $\sigma_{xi} \le \lambda_{xi} \quad \forall i = 1,..,Nn$

From a mathematical point of view, this is a non-linear combinatorial optimization problem. Given that a complete enumeration of all the possible combinations of measurement devices placement would be unacceptable also for small size networks, a heuristic approach has been presented in [3] to reduce the computational burden. In the proposed approach, recalled in the next section, the quantities to be estimated are the amplitudes of the currents in all the branches of the network and the constrained minimization problem (1) has been adapted to take into account the peculiarities of the procedure implemented.

III. PROPOSED APPROACH

Figure 1 depicts the whole optimization algorithm. The procedure starts with a definition of those network nodes that are candidate to have a meter device (e. g. network reclosers or breakers).

The inputs are the network topology, the nominal line impedances, along with their tolerance, and the annual medium active and reactive powers drawn by each node. Preliminarily, for each load a set of N possible values for active and reactive power is defined by means of a Gaussian distribution centered on the nominal values and having a prefixed standard deviation. Then, for each line, sets of N possible values for the network parameters are defined by means of uniform distributions centered on the nominal values and having the prefixed tolerance. A Monte Carlo

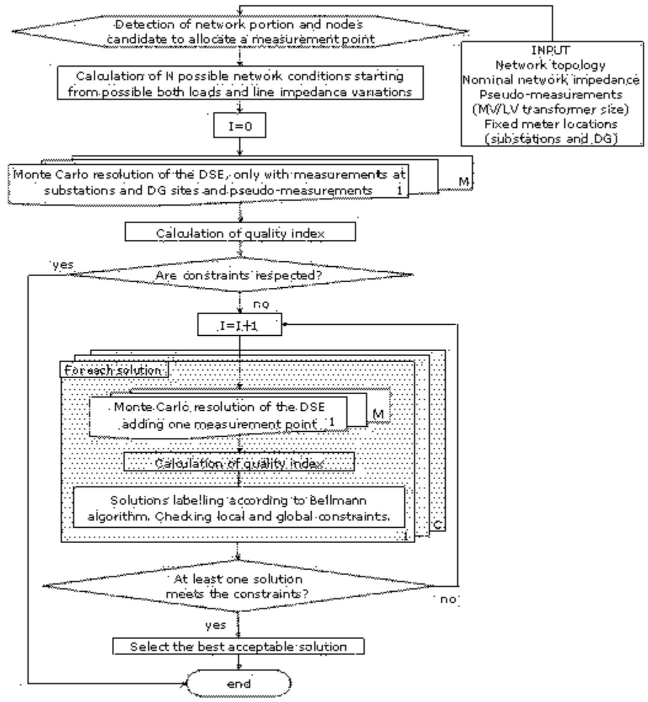

Figure 1 – Flow chart of the optimization algorithm for the optimal placement of measurement devices in distribution networks

approach is used to define, by extracting both powers and network parameters from the relevant set values, a set of N possible network conditions. Finally, a radial load flow is performed on each of these situations, in order to achieve N reference values for all the interesting state variables (essentially currents and voltages). A solution of the optimization problem is represented by a set of measurement devices (all the measurement devices are equal in this application) allocated in a certain set of network nodes.

Preliminarily the DSE (see subsection III.1) is calculated with a Monte Carlo algorithm to take into consideration uncertainties in the inputs, assuming that measurement devices are located only at the substation and DG busbars. The solution is assessed through a suitable quality index and, if the constraints are complied with, such solution represents the optimal one. Otherwise, an optimization algorithm based on the Dynamic Programming (DP) described in III.2 starts. According to the DP, new meter points are added step by step until the accuracy constraints are complied with. The optimal solution is then the one that minimizes the quality index and complies with the constraints.

III.1. Distribution State Estimation

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

$$Y = h(X) + U \qquad (2)$$

where Y is the vector of measurements, h is the function relating state variables to measurement (depending on the system model), X is the vector of 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 SCADA (Supervisory Control And Data Acquisition) and historical data. In these systems the main goal of DSE is the achievement of a 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 able to assess actual feeder loads, voltages at the system buses at any given point in time as well as the status of the protective and switching devices [6].

In usual distribution networks, branches are short, the voltage 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. In fact, these characteristics make the conventional P/Q decoupling used in transmission system analysis 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 by solving algorithms. Another characteristic of distribution system is that the few real time available measurements come from branch current measurement points and not from power measurements. All these characteristics should be taken into account while defining state estimation strategies suitable for distribution systems.

In [3], a practical state calculation algorithm, that uses a modified version of the radial load flow algorithms [7], has been developed. The algorithm is designed to exploit the special characteristics of distribution systems and is suitable also to deal with DG. For the reasons recalled above, 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 branch currents measured at the sending end (primary substations) of the feeders 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 be determined directly by using the constant nodal currents, solving the following equation (3):

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

where Z denotes the network impedance matrix.

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

Once the nodes voltages are known, the branch currents, I_{branch}, are calculated by simply dividing the corresponding branch voltage drop by the branch impedance. The DSE algorithm, evaluating the currents in all the branches of the network, iteratively adjusts the nodal loads by using the difference between the measured data and the calculated ones until the estimated branch currents become sufficiently accurate. More in details, the iterative procedure can be summarized as follows:

1. starting from measurements and pseudomeasurements, solve (3) and evaluate the state variables vector I_{branch};
2. for each *i-th* branch equipped with a measurement device calculate the difference between the calculated current (I_{branch}) and the measured one (I_{meas});
3. sum these differences to assess a quantity Δ that represents a global measure of the discard between the estimated and the real situation, with the following equation (4):

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

   where I_{meas} is the vector of the $N_{\mathbf{meas}}$ measured branch currents;
4. adjust the node pseudomeasured powers on the basis of the quantity Δ;
5. use the new pseudomeasurements to repeat the procedure (return to step 1).

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

The algorithm is extremely simple, robust and reliable. These features make it particularly well suited to be implemented in an optimization procedure to find the minimum number of measurement devices that allow achieving the DSE with a prefixed accuracy.

III.2 Dynamic programming

Dynamic Programming (DP) is an approach developed to solve multi-stage decision problems and is based on the well known Richard 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" [8]. Actually, this approach is equally applicable for decision problems where multi-stage decision making is not in the nature of the problem but is induced only for computational reasons, as it is the optimization problem at hand.

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

DP can be successfully applied when:

- the problem can be divided into stages and a decision is required at each stage;
- a finite number of states is associated with each stage,
- the decision at one stage transforms one state into a state in the next stage,
- there exists a recursive relationship that, provided that the states at stage *j-1* are known, identifies the optimal decisions to reach the states at stage *j,*
- the recursion for determining the optimal decisions at the 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 [3]. The starting point of the procedure is constituted by measurement devices only in substations and DG sites. The following stage could be characterized from one more measurement device with respect to such starting point.

A generic stage represents the total number of devices 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.

Figure 2 depicts the bottom-up approach used here to solve the optimal allocation problem according to the dynamic programming paradigm. At each decisional level D_I, D_{II}, ..., D_n, new metering devices can be added.

The candidates α, β, ..., η, identify the possibility of measuring a given quantity (branch current) in a given location (particular branch in the network).

In order to clarify the process let us suppose that the state β at the D_{II} has to be reached from D_I. Possible states in D_I are α, β, γ, and … η, each one labeled with the optimal value of the objective function, L_I, calculated with a measurement device defined by candidate α, β, γ, and … η 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.

The state β at the level D_{II} is then labeled with the value of the function $L_I(\beta)$ that is the minimum value of the objective function calculated considering the couples formed with β and the remaining available candidates. By so doing, 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 the one 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 so doing, each policy to reach D_{III} from D_{II} will necessarily contain optimal sub-policies and the

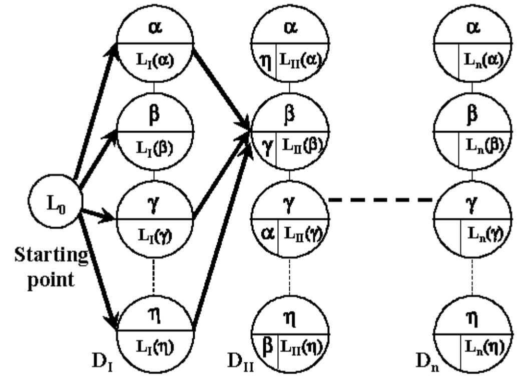

Figure 2– Schematic flow chart of Dynamic Programming

Bellman's Principle will be satisfied. In the proposed application the decision to pass from a stage the successive 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 successive 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 estimates (see subsection III.4).

As for the cost function L, it is the basis on which all decisions to move from one stage to the next one are taken. Here it has been considered a function in which the quantity used for the stopping criterion (i.e. the maximum relative deviation established for the estimates) is averaged on the quantities evaluated in a network condition and, at the same time, on all the *N* reference situations described at the beginning of section III.

III.3. Uncertainty analysis

The uncertainties affecting all the components of the measurement system propagate through the state estimation algorithm and make the final results uncertain too. 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 true above all in case that such decisions could be made on a threshold value.

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

The evaluation of the uncertainty affecting the estimates here is faced by means of Monte Carlo procedures, which have been successfully 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, like the ones used for DSE.

Such procedures, like any other for evaluating the propagation of the uncertainties, are substantially based on two phases: formulation and calculation. In the former a measurement model is derived and the model inputs are quantified, while in the latter the uncertainty affecting the output(s) is evaluated by means of Monte Carlo simulations. Therefore, suitable metrological models of both transducers and instruments should be implemented. Once the above models have been defined, a suitable probability distribution is then assigned to these uncertainty terms, which can be numerically represented by sets of random variables. A large number M of simulated tests is then performed: in each test both the measured data and the network parameters are corrupted by different contributions, whose values are randomly extracted from the above sets, and the DSE algorithm is applied by using this set of input data. The sets of the M obtained output values are finally processed to evaluate the uncertainty of the results.

IV. RESULTS

The proposed optimization procedure has been applied to a small portion of an Italian distribution network which includes DG plants. It is settled in an urban and extra-urban area and it is constituted by one trunk feeder of buried cables and one of overhead lines, with a total length of 41 km. The network is supplied by two 132/20 kV/kV primary substations, which fed 60 MV/LV nodes, 18 trunk nodes and

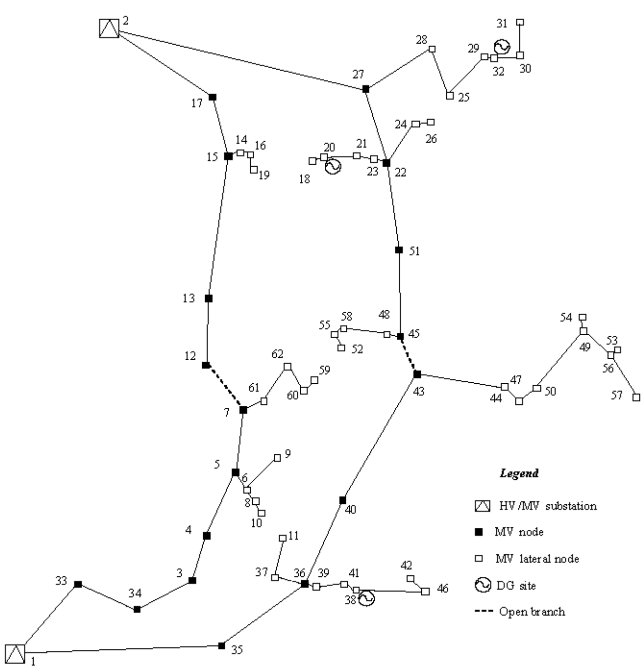

Figure 3 – Scheme of the benchmark network

42 lateral ones, via 62 edges (trunk feeders and laterals), as depicted in Fig. 3. The annual medium active power delivered to MV nodes is about 1.9 MW.

The following values were used in the tests:

- Number of input configurations N = 100;
- Variation of the active and reactive powers, for the definitions of the N conditions: ± 30 % of the nominal value;

The tests have been realized considering the measurement accuracy decreasing from 1 % to 3 % and the tolerance of the line impedances changing from zero to 20 %.

Let us consider two operative conditions, in which the accuracy of the measurement devices is assumed equal to 1% and the tolerance of the network parameters is either equal to 20 % (case A) or neglected (case B). In both cases the solutions present the same number of measurement devices but case A have a slightly worse value of the cost function. Similar results are obtained when the accuracy of the measurement devices decrease until 3%. As a consequence, such results prove the robustness of the proposed DSE algorithm in respect to the tolerance of the network parameters.

Part of the results, is summarized in Tabs. 1 and 2. The values of the cost function are represented normalized, in respect to the solution obtained without presence of DG, considering a measurement device in each branch (with accuracy equal to 1%), and tolerance of the network parameters equal to 20 %.

Tab. 1 refers to the situation where no DG units exist in the network. As it is easy to see, if the measurement accuracy decreases, the values of the metric L consequentially increases.

Finally, three generators have been connected to the network in nodes 20, 32 and 38 (having a rated power of 200 kVA each) to assess the application of the proposed methodology in active distribution networks. The measurement of active and reactive powers supplied by DG can be used by the DSE as well as the other available measurements. Some results are summarized in Tab. 2. Also in these cases the introduction of the uncertainty in the measurement devices and in the network parameters worsens the quality of the solution with respect to the situation without any tolerance in the input.

By comparing Tab. 1 and Tab. 2 it is possible to see that the power measurements due to the presence of DG could lead to either reducing or increasing the number of measurements required by the DSE. This is because the DG sites are considered, as it should be, equipped with instruments suited to measure active and reactive powers. Therefore more measurements are already available in the starting stage of the procedure (see subsection III.2). On the other hand, the imposition of the injected power at some nodes, that modifies the load flow equations, and, consequently, the SE algorithm, may need more information on branch currents, thus requiring the addition of more measurement instruments. The DG effect on a distribution

TABLE 1
TEST RESULTS WITHOUT DG

Measurement device accuracy	Network parameters variation	Number of added measurement devices	Quality of the solution (normalized value)
1%	20%	10	3.12
3%	20%	14	4.58

TABLE 2
TEST RESULTS WITH DG

Measurement device accuracy	Network parameters variation	Number of added measurement devices	Quality of the solution (normalized value)
1%	20%	9	3.11
3%	20%	15	4.25

network, and consequentially 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, on the energy market prices. As a result, the use of optimization procedures is really important to assess different possible alternatives and to make the most acceptable final decision. The problem of finding the minimum set of measurement devices that allows achieving a predetermined level of accuracy falls in the general aforementioned rule and, even in the small example presented in the paper, it is not possible to understand *a priori* the effect of DG on the final optimal solution, thus justifying the resort to optimization tools.

This work is a step toward the understanding of the usability, in practical situations, of SE methodologies; the same authors are working also for the optimal placement of metering points for harmonic state estimation [10], another important issue in the management of electric distribution systems in the near future.

V. CONCLUSIONS

This paper proposes the development of an optimization procedure that optimizes number and position of measurement devices for state estimation in modern electric distribution networks. The optimization procedure is based on the dynamic programming 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 by means of suitable Monte Carlo procedures. The presence of Distributed Generation plants has been considered as well.

The results obtained by applying the proposed procedure to a real size active 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 Distribution State Estimation 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 ones. Owing to its intrinsic nature, this approach results to be quite reliable and robust with respect to the tolerance of network parameters and should be therefore considered well-suited for management purposes in active distribution grids.

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

REFERENCES

[1] Shafiu A., Jenkins N., Strbac G.: “Measurement location for state estimation of distribution networks with generation” Generation, Transmission and Distribution, IEE Proc. Vol. 152, Issue 2, 4 March 2005, pp. 240-246.

[2] Wan J., Miu K. N.: “Meter placement for load estimation in radial power distribution system”, Circuits and Systems, 2004. ISCAS '04, Proc. of the 2004 International Symposium on Vol. 5, 23-26 May 2004, pp. V-916 – V-919.

[3] Muscas C., Pilo F., Pisano G., Sulis S.: “Optimal Placement of Measurement Devices in Electric Distribution Systems” Instrumentation and Measurement Technology Conference, IMTC 2006, 24-7 April 2006, Sorrento (Italy), pp 1873-8.

[4] Martinez J. A., Gustavsen B., and Durbak D.: “Parameter Determination for Modeling System Transients—Part I: Overhead Lines” IEEE Trans. on Power Delivery, Vol. 20, No. 3, July 2005.

[5] Koglin H. J.: “Optimal measuring system for state estimation”. Paper 2.3/12, Proc. PSCC Conf., September 1975.

[6] Baran M. E., Zhu J., Kelley A.W.: “Meter Placement for Real Time Monitoring of Distribution Feeder”, IEEE Trans. on Power System, Vol. 11, No. 1, February 1996, pp. 332-337.

[7] Celik M. K., Liu W.-H. E.: “A practical distribution state calculation algorithm”, Proc. IEEE PES 1999 Winter Meeting, 31 Jan.-4 Feb. 1999, Vol.1, pp. 442 – 447.

[8] Larson R. E., Costi J. L.: “Principles of Dynamic Programming”, M. Decker, New York, 1978-1982.

[9] Ghiani E., Locci N., Muscas C., Sulis S.: “Uncertainty estimation for DSP-based power quality measurements”, COMPEL, Vol. 23 No. 1, 2004, pp. 92-103.

[10] Muscas C., Pilo F., Pisano G., Sulis S.: “Optimal number and location of measurement instruments in distributed systems for harmonic state estimation”, Workshop on Power Definitions and Measurements under Non-Sinusoidal Conditions, Cagliari, July 10-12, 2006, pp. 136-141.