

A Comprehensive State Estimation Approach for EMS/DMS Applications

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Abstract - In the paper we describe a State Estimation model to be used in Energy/Distribution Management Systems – EDMS. This model is an important evolution of the concept first presented in [1] and deals with the increase in complexity that derives from handling different voltage levels in the modern controlled systems. There are some important improvements included in this model. In the first place, the model has the possibility of using qualitative information affected by uncertainty - modeled by fuzzy numbers. Secondly, it can deal with unknown topology and with erroneous topology data using variables to model the status of switching devices. Thirdly, it also can, in a single run, transparently fix and work with more than one angular reference if it is necessary. The model includes in all nodes having power injection a voltage phase pseudo-measurement and the number of voltage and phase state variables are twice the number of nodes. Finally, the results also provide an overloading risk index evaluated for all network equipments, which allows the user to assess the system security level, as well as nodal voltage risk levels. This model is already in use in an EDMS software package available in the market and being installed in some utilities.

Keywords: EMS, DMS, State Estimation, Switching, Splitting, Fuzzy measurements, Overload Risk.

I. INTRODUCTION

For several years from now, state estimation studies are performed in generation/transmission control centers. Running state estimation modules in these centers is explained by the need to have a set of coherent values for voltage magnitudes and phases, power injections, branch power flows and currents reflecting the available measurements in a certain instant. In fact, measurements can be affected by errors, either related to the quality of measurement devices or due to transmission deficiencies. Time skew problems are also an important issue when trying to install state estimation codes. In fact, due to the characteristics of the communication systems used to link the control center with the substations, the set of measurements available in a certain instant will generally correspond to different sampling instants. This is not a serious problem if the system is operating in steady state conditions and the topology of the network is considered to be fixed. However, it contributes to increase the incoherence that usually affects the available measurements. Finally, running state estimation models for

generation/transmission systems is possible given the large investments directed to automation, telemetering devices and communication systems on these subsystems.

The migration of several traditional EMS functions to the distribution networks has always been difficult and became an important question only in recent years. Planners clearly concluded that new improvements in the quality of supply could only be obtained if new investments were directed to the distribution level. A change was also determined by the advent of cogeneration systems linked to the distribution level, by the move to deregulation and by recognizing that electricity is a product that, apart from the price, is characterized by a set of quality parameters. The new way of facing distribution activities imposed a new accent on upgrading existing SCADA systems to turn them real DMS systems.

The migration of state estimation to DMS systems places several challenges:

- firstly, in distribution networks there is a traditional lack of real time measurements that can only be solved by continuously investing during next years. If one wants to run state estimation models now, new approaches will have to be adopted to solve this problem;
- secondly, topology changes are much more frequent in distribution networks than in generation / transmission systems. This means that considering a fixed and constant topology for the network is not a valid assumption any more;
- thirdly, admitting some degree of uncertainty affecting the current status of switching devices means that one should also consider the possibility of system splitting. That is, splitting in several islands can, in some cases, be much more adequate to explain the available measured values;
- finally, distribution networks have a much larger size when compared to generation/transmission systems imposing new challenges on real time applications.

With this paper we aim at presenting an integrated State Estimation model that incorporates solutions and techniques to deal with the previously referred questions. Therefore, in section 2 we characterize the data to be used in such a State Estimation model, namely referring the main characteristics of a Load Allocation procedure designed to give initial values for loads supplied by feeders.

In section 3 we revise the traditional Weighted Least Squares formulation of the State Estimation problem that will certainly have a important role in any code.

In section 4 we present a novel way to treat topology

variables and system splitting. The binary nature of topology variables is incorporated by substituting them by continuous variables associated to a constraint having 0 and 1 as its unique solutions. This maintains the continuous nature of the problem while enforcing the binary behavior of the variables.

Finally and apart from the Load Allocation referred, the observability issue is addressed in section 5 by admitting that measurements are affected by uncertainty represented by Fuzzy Numbers. In this case, the Fuzzy State Estimation model can be interpreted as a tool to reflect data uncertainty in the results. These will no longer be crisp values but, on the contrary, will be represented by fuzzy membership functions translating the possible behavior of the system.

In section 6, and before presenting some conclusions, we will present a case study to illustrate the application of the model.

II. MEASUREMENTS; QUALITATIVE DATA AND LOAD ALLOCATION

Data to be used by the State Estimation algorithm have several origins:

- from measurement devices distributed by the network. This is the typical source of information in generation/ transmission systems. These devices provide values for power injections, voltage magnitudes and branch power flows and currents. In distribution networks the number of measurement devices is not generally very large that may lead to observability problems;
- in distribution networks it is very frequent to have information about power injections on the feeders coming from a HV/MV substation. If one wants to run the state estimation in the whole network a load allocation procedure has to be adopted to get initial values for loads supplied by each feeder. The load allocation procedure uses historical information stored in the system database about past energy consumptions, typical load curves [2] and real time measurements in each feeder if available. This process can be divided in two main steps. The first one attempts at performing a rough load allocation that outputs values that may still display some incoherences. The second phase corresponds to the state estimation procedure itself that is used to identify a global coherent picture of the current system operation point;
- the lack of measurements typical of distribution networks can also be addressed by incorporating data modeled by fuzzy numbers. This possibility turns the problem into Fuzzy State Estimation and contributes to give more flexibility to the formulation and certainly to widen its scope of application.

A fuzzy set \tilde{A} [3] is related to a membership function that expresses the compatibility of the element x to the set. The membership degree takes values in $[0.0;1.0]$ contributing to make it gradual the transition between the extreme situations of complete membership - degree 1.0 - and no membership at all - degree 0.0. Several applications

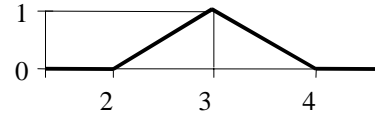


Fig. 1 - Triangular fuzzy number.

use Fuzzy Numbers - a special class of fuzzy sets - to model the uncertainties related to phenomena incompletely defined or inherently related to human language propositions.

Figure 1 depicts a triangular fuzzy number that can be used to model the uncertainty affecting the value 3. According to this representation values in $[2;3]$ and in $[3;4]$ are not discarded. In this sense a decreasing membership degree is assigned to values from 3 to 2 and from 3 to 4. An α -cut of a fuzzy set \tilde{A} corresponds to the crisp set A_α incorporating all values x so that the membership degree $\mu_{\tilde{A}}(x)$ is not inferior than α . Finally, the central value of a fuzzy set is the average value of its 1.0-cut. For the triangular fuzzy number of Figure 1, the central value is 3 and the 0.5-cut, for instance, is the interval $[2.5;3.5]$.

III. TRADITIONAL STATE ESTIMATION REVIEW

State Estimation models use a set of measurements available in the system database in order to get a coherent picture to characterize the current operation point. This is motivated by three main reasons. Firstly, there are not measurements for every variable needed to define the operation point. Secondly, the available measures are generally affected by errors related to the quality of the measurement devices. Thirdly, the set of measurements available at a certain instant can be related to different sampling instants due to time skew problems. This leads to a set of measurements that does not give neither a complete nor a coherent picture of the current operation point.

This problem turned into one of the basic and more frequently addressed ones in generation/transmission control centers. It is generally solved by a State Estimation exercise that aims at computing the values of the state variables that explain more adequately, according to some criterium, the available measurements. These may include bus injections, branch flows, bus voltage magnitudes and branch currents.

Let us consider a power system with n nodes for which m measurements are available. The state variables are usually the voltage magnitudes and phases. Assuming that the phase in one bus is set to zero, as reference, we have to calculate the values of $2 \times n - 1$ state variables using the values of m measurements. The number m of measurements must be at least $2 \times n - 1$, but practical approaches require some degree of redundancy to get a larger immunity to measurement errors.

Let us consider that:

- Z is the measurement vector ($m \times 1$);
- X is the state vector ($(2 \times n - 1) \times 1$);
- $h(\cdot)$ is the function vector expressing each measurement in terms of the state variables ($m \times 1$);
- ε is the measurement noise or error vector ($m \times 1$).

A general state estimation model is then given by (1).

$$Z = h(X) + \varepsilon \quad (1)$$

In this model no assumptions are made on the distributions of the components of vector ε . They are simply considered random variables having zero mean and covariance R . The variances and covariances of the measurements can be organized in matrix R , whose element R_{ij} is the covariance between the errors of measurements i and j and R_{ii} is the variance of the error of measurement i , σ_i^2 .

In most State Estimation approaches the measurement errors are independent random variables, leading to a diagonal R matrix. The Least Square formulation of the State Estimation problem aims at computing the X state vector so that the weighted sum of the squares of the errors is minimized (2).

$$\min \varepsilon^T R^{-1} \varepsilon \quad (2)$$

The elements of R^{-1} can be interpreted as the weights assigned to each measurement. For instance, if a measurement device has poor precision characteristics the corresponding variance is large and so the weight σ_i^{-2} is small. This means that such measurements will very poorly determine the final result of the state estimation exercise. On the contrary, a smaller σ_i^2 may be assigned to measurements of higher quality.

Substituting the expression for ε obtained from (1) in (2) we obtain (3) from which the corresponding stationary conditions (4) can be derived. This corresponds to a set of non linear equations in which H is the Jacobean matrix of the measurement vector h .

$$\min [Z - h(X)]^T R^{-1} [Z - h(X)] \quad (3)$$

$$H(X)^T R^{-1} [Z - h(X)] = 0 \quad (4)$$

This set of equations is usually solved adopting the Newton Raphson iterative method so that at iteration $(k+1)$ the refreshed values of the state vector are computed using (5). In this expression G is the gain matrix given by (6).

$$X^{k+1} = X^k + (G^k)^{-1} [H(X^k)]^T R^{-1} [Z - h(X^k)] = 0 \quad (5)$$

$$G^k = [H(X^k)]^T R^{-1} [H(X^k)] \quad (6)$$

Once the iterative process converges and the state vector X is computed, one can calculate the corresponding values for injections, branch active and reactive flows and losses and branch currents.

Several techniques [4] are described in the literature to solve this problem. The most common and well known are the fully coupled version of the Weighted Least Square method and its decoupled formulation. Some other techniques having a more specialized nature can also be found. For instance, [5] describes an approach specially interesting for distributing networks for which current measurements are very common. In this paper, measurements are converted into equivalent current measurements leading to a state estimation approach in which the gain matrix is constant during the iterative process.

IV. SWITCHING VARIABLES AND SPLITTING

In distribution systems frequent topology changes together with the small number of measurement devices lead to situations in which the topology of the system that is currently in operation is not completely known. This issue can be addressed by incorporating in the state vector topology variables D_{ij} that represent the knowledge about branch ij being or not in operation. This variable has a binary nature in the sense that it takes value 1 if branch ij is in operation and 0 if it is disconnected. The incorporation of binary variables in optimization problems increases its complexity leading to non-convex and non continuous solution sets.

Apart from this, the introduction of such variables originates changes in the functions $h(X)$ regarding branch active and reactive flows, injected powers and currents. As an example, (7) to (10) represent the new expressions for the active and reactive flows and injected powers.

$$P_{ij} = \left[\left(g_{ij} + \frac{g_{shij}}{2} \right) V_i^2 - V_i V_j (g_{ij} \cos(\theta_{ij}) + b_{ij} \sin(\theta_{ij})) \right] D_{ij} \quad (7)$$

$$Q_{ij} = - \left[\left(b_{ij} + \frac{b_{shij}}{2} \right) V_i^2 + V_i V_j (g_{ij} \sin(\theta_{ij}) - b_{ij} \cos(\theta_{ij})) \right] D_{ij} \quad (8)$$

$$P_i = \sum_j P_{ij} \quad (9)$$

$$Q_i = \sum_j Q_{ij} \quad (10)$$

Several formulations treat binary variables by admitting for them a continuous behavior in the interval $[0.0; 1.0]$ and rounding them, at the end, to the closer extreme value while others adopt Branch and Bound type methodologies.

A novel way of addressing this problem corresponds to admit that these variables have a continuous nature imposing, for each of them, a constraint having 0.0 and 1.0 as its solutions. Equation (11) can be used for this purpose.

$$x^2 - x = 0 \quad (11)$$

Using this idea, the knowledge regarding the state of a branch ij is modeled considering two possible situations. In the first one, there is information in the database regarding the state of the branch. However one admits that the available value may be erroneous so that the function to be included in vector $h(X)$ is given by (12). In this expression, ε_k is the element of the vector of errors related to this measurement.

$$D_{ij}^{mes} = D_{ij}^2 + \varepsilon_k \quad (12)$$

In the second one, we consider that there is no information regarding D_{ij} in the database so that (13) is the function to include in vector $h(X)$.

$$0 = D_{ij} - D_{ij}^2 + \varepsilon_k \quad (13)$$

Regarding equations (12) and (13), one should notice that when the error tends to zero the only feasible solutions are 0 or 1. This way we are able to enforce the binary behavior of topology variables while not compromising the continuous nature of the state estimation problem.

The introduction of uncertainty affecting topology variables gives us a way to treat the problem of system splitting. In fact, traditional state estimation approaches

assume that the topology is known and that the whole system corresponds to an unique connected island. Admitting uncertainties regarding the state of branches implies that one should also admit that the current system in operation may integrate a set on non-connected islands. In some situations, this is a very appealing possibility since, from a state estimation point of view, the available measurements for voltage magnitudes, injected power and branch flows can be more adequately explained considering a non-connected system. This means that the sum of the squares of errors can be smaller if one admits splitting when compared to the values for an unique island topology. In other words, this increases the flexibility of the model and definitely contributes to model real systems in a more adequate way.

In traditional formulations splitting was not possible since there was an unique bus selected for reference of the phases. If splitting occurred some matrices would be singular compromising the solution of the state estimation problem.

This difficulty can be solved if one associates to each generation node a phase measurement to which the 0 value is initially assigned (14).

$$\theta_i = 0 + \varepsilon_k \quad (14)$$

Since one does not know if the system is actually splitted or not, a large weight is assigned to the phase measurement in the node where the largest generation is connected. The weights of the remaining phase measurements are smaller. This does not compromise any of the two possible ways of operation:

- if operation in an unique island is the more adequate one, from the state estimation point of view, the estimated phase for the larger generation node will be zero while the initial values of phases in the remaining generation nodes are affected by errors. However, the corresponding residuals will not determine in a significant way the final state vector since their weights are small;
- on the other hand, if splitting is the most convenient situation, one has the possibility of obtaining a zero phase reference in each island if at least one generation node exists in each of them.

V. INCORPORATION OF FUZZY DATA

The migration of State Estimation approaches to distribution networks has traditionally been difficult. Among other reasons, this is due to the small number of real time measurements available in SCADA systems. This is explained by the reduced investments directed to distribution systems when compared to the situation in generation/transmission systems. This situation started to be corrected only in recent years but, given the extension of distribution networks, observability problems will remain in the future if no improvements are introduced in traditional State Estimation approaches.

One possible way of addressing this issue corresponds to the specification of measurements affected by uncertainty and mathematically modelled by fuzzy numbers. Fuzzy concepts were already successfully

integrated in several power system models. For instance, references [6] and [7] present a fuzzy AC power flow and a fuzzy DC OPF model. Reference [7] also describes a Monte Carlo simulation approach that corresponds to an hybrid model in the sense that it combines fuzzy data and probabilistic models that represent the reliability of system components. References [1] and [8] describe in a detailed way the incorporation of fuzzy measurements in the State Estimation problem that will now be summarized.

The fuzzy state estimation approach admits that, at least, one measure is modelled by a triangular fuzzy number. Its first step is a traditional crisp State Estimation exercise for the set of crisp measurements related to the central values of the fuzzy numbers. The result of the crisp study is a crisp state vector X_1 that is used as a linearization point. This means that in the second phase we want to reflect on the state estimation results the fuzzy variation computed by (15). This will be performed using the gain matrix G built in the last iteration of the crisp state estimation study so that the fuzzy state vector \tilde{X} is built using (16) and (17). These expressions use fuzzy arithmetic rules to perform the product of real numbers by fuzzy numbers in (16) and the addition in (17).

$$\Delta \tilde{Z} = \tilde{Z} - h(X_1) \quad (15)$$

$$\Delta \tilde{X} = (G^{-1} H^T R^{-1}) \Delta \tilde{Z} \quad (16)$$

$$\tilde{X} = X_1 + \Delta \tilde{X} \quad (17)$$

Regarding active and reactive flows and currents the following procedure is adopted:

- consider that F_{ij} generically represents branch active, reactive power flows and currents;
- linearize ΔF_{ij} , taking the first terms of the Taylor series around X_1 , (18), using V_i , V_j , θ_i , θ_j as the voltages and angles in buses i and j ;

$$\Delta \tilde{F}_{ij} \cong \sum_{k=i,j} \left[\frac{\partial F_{ij}}{\partial \theta_k} \Big|_{X_1} \Delta \tilde{\theta}_k + \frac{\partial F_{ij}}{\partial V_k} \Big|_{X_1} \Delta \tilde{V}_k \right] \quad (18)$$

- the fuzzy deviations of voltage phases and magnitudes can be calculated using (16) in terms of the fuzzy measurement vector. This means that expression (19) can be directly used in order to reflect the measurement uncertainties in branch flows and currents.

$$\Delta \tilde{F}_{ij} = \left[J_{FL}(X_1) (G^{-1} H^T R^{-1}) \right] \Delta \tilde{Z} \quad (19)$$

In this expression J_{FL} represents the derivatives of F_{ij} regarding voltage magnitudes and phases;

- the final membership functions are obtained adding their fuzzy deviations to the crisp value obtained for the state vector computed with the initial crisp study;

The adopted linearized approach is responsible for errors in building membership functions of the results. This is specially true for membership functions of currents in lightly loaded branches. In these cases, triangular fuzzy results are no longer an acceptable approximation for the exact fuzzy membership functions. In reference [8] we presented a corrective procedure to be used in these cases.

The derivation of fuzzy membership functions for branch currents turns it possible to compute an Overload

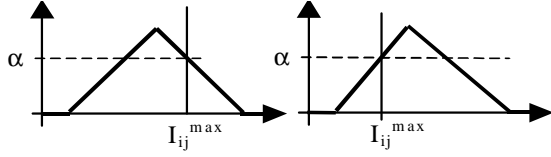


Fig. 2 - Membership functions of the current in branch ij .

Risk Index - ORI - expressing the risk that a component operates in overload conditions given the specified uncertainties. The ORI index can be defined as the maximum membership value of all values that are in overload (20).

$$ORI = \max \{ \mu_{I_{ij}}(I_{ij}) : I_{ij} > I_{ij}^{max} \} \quad (20)$$

Let us consider Figure 2 in which the membership function of the current in branch ij is represented in two situations. For the membership function in the left side, the ORI index is α since the overload may occur for some current values under α uncertainty level but no overload occurs for the 1.0 α -cut. On the contrary, for the right hand side membership function, ORI is 1.0 since all values in the 1.0 α -cut correspond to the violation of the limit of the current.

VI. ILLUSTRATIVE EXAMPLE

In this section we include results obtained for a case study using the IEEE 24-bus test system described in [9] and depicted in Figure 3. In order to fully test the developed algorithm, namely the splitting procedure, we built a system using 4 networks, like the one of Figure 3, connected as indicated in Figure 4. In Figure 4 each square represents the 24 bus test system and each of them has two connections with other IEEE 24 bus system.

For each of the four IEEE 24 buses, we considered 9 voltage magnitude measurements, 4 active and reactive injected power measurements and 20 active and reactive power flow measurements. The location of the measurement devices is shown in Figure 3. The measured values correspond to results of two power flow studies run

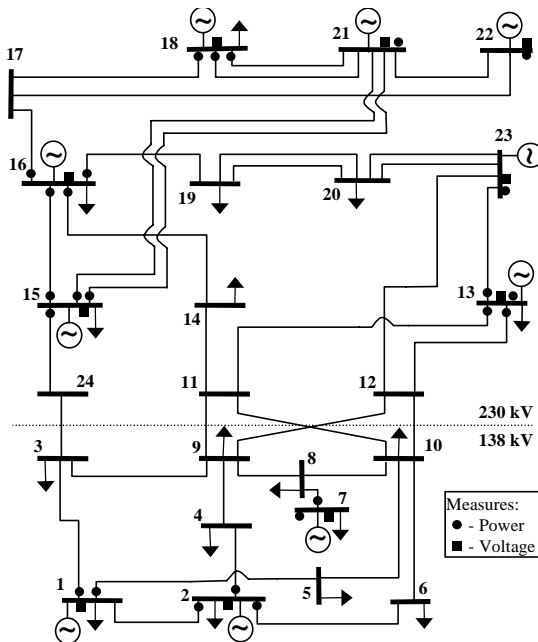


Fig. 3 - IEEE 24 test system.

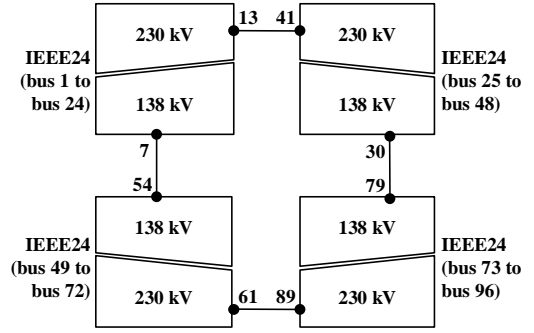


Fig. 4 - test system based in the IEEE 24 test system

for the upper and the lower systems of Figure 4 considering that lines 7-54 and 30-79 are opened. The results to be used as measured values were afterwards randomly affected by errors.

Triangular fuzzy numbers represents loads. The central value corresponds to the IEEE 24 bus specified values multiplied by 1.8. The extreme values of the 0-cut of these numbers correspond to 0.95 and 1.05 of the central value (similar to points 2 and 4 in Figure 1).

Apart from this, we considered that the state of 4 interconnection lines of Figure 4 was not known for sure. This means that we integrated topology variables for these lines. In order to be able to solve the state estimation problem we used phase angle measurements in the 40 generation buses, that is, 10 in each IEEE 24 bus system.

As for results, it is important to refer that the developed algorithm indicates, as expected, that lines 7-54 and 30-79 are opened while lines 13-41 and 61-89 are in operation. This was the correct result since this corresponds to the topology used to obtain the measured values.

In Figure 5 we display the measured and the estimated values for the active and reactive load in bus 3. These membership functions deserve two comments:

- firstly, the uncertainty at level 0.0 estimated for both the active and reactive loads is smaller than the previously specified. This means that the specified triangular numbers, namely at level 0.0, included values that are clearly out of the pattern of the whole set of measurements. Therefore, the state estimation algorithm acts as a filter eliminating values that can not be explained by available measurements;
- secondly, the measured and estimated central values of active and reactive loads do not match. This simply means that the set of central values of all measurements do not match the power flow equations. Therefore, the state estimation algorithm estimates voltage magnitudes and phase angles, and also generations and loads, that better explain the available measurements while matching the power flow equations;

In Figure 6 we display the estimated membership functions obtained for the active, reactive flows and current in line 4-9. These functions reflect the uncertainty affecting the measurements giving an idea of the possible range of values that these variables can assume. The value of the ORI index is also shown. For this line, considering for instance a 700 A thermal limit, this index is 0.42. This gives an useful information regarding the risk of branch

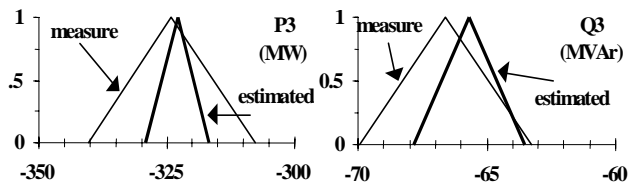


Fig. 5 - Measured and estimated injected powers in bus 3.

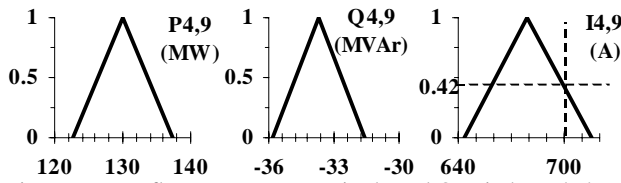


Fig. 6 - Power flows, current magnitude and ORI in branch 4-9

overload for the level of uncertainties affecting measurements.

Finally, the developed procedure is very efficient from a computational point of view. To make some comparisons let us refer to the computational time to perform a deterministic state estimation study assuming that the topology is known, that is lines 7-54 and 30-79 are opened. If the state of the connection lines is unknown the computational time increases 55% mainly due to the increase of the number of iterations from 5 to 7 needed to get convergence. The integration of fuzzy measurements is a final non iterative process that uses already available information - the inverse of the gain matrix. This means that surplus computational time is negligible when compared to the time of the iterative initial procedure.

VII. CONCLUSIONS

In this paper we described a new state estimation methodology including a set of modules and approaches that turn it closer to reality. Among them, it should be pointed out the novel, mathematically sounded and computationally efficient treatment given to uncertainties affecting the current state of switching devices and the new and effective way adopted to address numerical problems due to system splitting.

It should also be referred that this approach is very efficient regarding computational time. For the present case study, the surplus of computational time (55%) seems to be a small price to pay to get a more complete and realistic picture of system operation is obtained.

Finally, the possibility of integrating fuzzy representations appears important in the scope of the move to restructure power systems. This clearly leads to a more uncertain world so that this kind of algorithms can play an important role in control centers of transmission or distribution systems.

This model has already been integrated in a software EDMS package and applied in some utilities in the world.

VIII. ACKNOWLEDGMENTS

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X. BIOGRAPHIES

Jorge Pereira was born in Viseu, Portugal, on April 22, 1969. He received his Licenciado degree from the Fac. of Science of Porto University, Portugal, in 1991 in Applied Mathematics to Computer Science. In 1995 he got the MSc. degree in Electrical Engineering from the Fac. of Eng. of Porto University. In 1991 he joined INESC as a researcher and is currently a PhD. student. In 1995 he joined to the Fac. of Economy of Porto University where he is Assistant.

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