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SOME PRACTICAL ISSUES IN THE MIGRATION OF STATE ESTIMATION MODULES FROM EMS TO DMS SYSTEMS

Jorge Pereira
Fac. de Economia da Univ. do Porto
jpereira@inescn.pt

J. Tomé Saraiva
Fac. de Engenharia da Univ. do Porto
jsaraiva@inescn.pt

Vladimiro Miranda
Fac. de Engenharia da Univ. do Porto
vmiranda@inescn.pt

Instituto de Engenharia de Sistemas e Computadores – INESC Porto
P. República 93, 4050-497 Porto, PORTUGAL
Fax: +351.22 208 4172

Abstract – In this paper we address some practical issues arising when passing from both theoretical state estimation algorithms and EMS approaches to DMS applications. These issues comprise the absence of real time measurements in large portions of distribution networks, the existence of dispersed generation and the uncertainty regarding the status of switching devices leading to an incomplete knowledge of the topology of the network in operation and eventually related to system splitting. The paper also includes a definition for a risk index translating the ability of the system to accommodate the uncertain results of the state estimation regarding branch limits. At a final section, we illustrate the proposed methodology with a case study based on a IEEE test system.

I. INTRODUCTION

During several years traditional vertically integrated utilities directed large parts of their budgets to the generation/ transmission areas leading to high levels of automation and telecontrol. On the other side, distribution networks remained till recently as the poor part of the systems thus having much lower levels of quality of service, automation and telecontrol capabilities. In recent years, the accent on the overall requirements of service quality, the move to consider electricity as a commodity in the scope of the implementation of market mechanisms as well as new regulatory and tariff schemes pressed companies to direct larger parts of their budgets to the distribution sector. In this scope, the traditional SCADA – System Control and Data Acquisition systems are being upgraded to more powerful systems that, to a certain extent, apply some characteristics present in EMS - Energy Management System to distribution networks. However, this migration of EMS to distribution can not be done directly given the particularities of this sector. This paper reports some results of the research undergone in the Power Systems Unit of INESC Porto leading to new contributions in the area of state estimation algorithms specially conceived to be run in distribution networks. It should be emphasized that our main concern is to turn feasible the application of State Estimation Algorithms in a real time industrial environment. This concern comes from recognizing that theoretical contributions frequently fail in their ability to be implemented in real systems. This lead to an hybridization between traditional probabilistic state estimation approaches and fuzzy set models specially devoted to capture the uncertainty that may affect the knowledge of some injections in distribution networks. The treatment of practical implementation issues was also motivated by the integration of this software module, as well as other application functions, in a DMS - Distribution Management System developed by a Portuguese manufacturer – EFACEC Sistemas de Electrónica SA – under a contract with INESC Porto.

In Section II of this paper we detail the main factors determining the current move to achieve higher levels of automation and telecontrol in distribution networks as well as the main issues that have to be addressed when passing from EMS systems to DMS. In Section III we characterize the sources of data to be used by application functions and particularly by State Estimation algorithms focused in distribution networks. Section IV describes the developed state estimation algorithm including:

- the treatment of uncertain measures modelled by fuzzy concepts;
- the integration of topology variables to address the lack of knowledge regarding the topology in operation;
- the modifications introduced in order to allow the network to split in several islands if that is more adequate to explain the available data;
- the definition of the Overload Risk Index – ORI – that can be useful in order to characterize the ability of the system to accommodate the specified uncertain injections without violating branch limits.

In section V we finally present a case study based on an IEEE test system to illustrate the developed methodology.

II. FROM EMS TO DMS SYSTEMS

In recent years, power systems are experiencing substantial changes from organizational, regulatory and technological points of view. These changes are strongly related in the sense that one of the driving forces of the re-regulation of power systems is the advance in communication, computer science and applications specially directed to power systems. To a certain extent, these advances enabled the introduction of competition and the generalization of market mechanisms in America, Europe and Australia turning feasible and less costly solutions that previously were impossible to consider.

The liberalization trend started in generation but soon spread to large consumers – eligible consumers – distributors and retailers turning more independent the entities responsible for the flow of money and for the flow of electricity. The creation of more business opportunities – and also more risks – was balanced by a larger emphasis on quality of service leading to the need to monitor and control not only transmission networks but, most of all, distribution ones.

The automation of distribution networks was also motivated and determined by the liberalization of the ownership of small generation and the incentives to install cogeneration plants as a way to use endogenous and in many cases renewable resources. This liberalization occurred in many countries prior to the re-regulation and, to a certain extent, it can be seen as a first step in this move that contributed to reduce the role of traditional utilities. The presence of a large number of those plants in traditionally poorly automated distribution networks required to the monitorization of the systems and pressed utilities to invest in automation and in installing the first generation of SCADA systems.

These systems allowed the operators to have a graphic vision of the networks including real time available measurements, to implement in a remote way several control actions on switching devices, transformers, capacitors and other equipment. However, the data base of those systems was very incomplete in the sense that it was not possible to have a mathematical model of the system able to support more complex power system functions as state estimation, power flow and short circuit analysis, contingency, fault identification or service restoration. The inclusion of these modules meant that existing databases had to be enlarged and that several new issues had to be addressed if some applications were to migrate from well developed EMS – Energy Management Systems – existing in generation/ transmission control centres to distribution systems. These issues include the following aspects:

- in generation/transmission systems there is a sufficiently large number of real time measurements leading to an acceptable redundancy level in terms of state estimation algorithms. This is a direct consequence of the investments that for many years were directed to generation/transmission systems leading to high levels of automation, telecontrol capabilities and quality of service;
- on the contrary, in distribution networks the number of real time measurements and the degree of automation is traditionally reduced leading to the impossibility of directly install and run EMS state estimation modules;
- a second major issue is related with the course of dimensionality. In fact, distribution networks are much larger than transmission ones turning it more demanding the use of any algorithms in real time;
- these networks traditionally have poor levels of quality of service leading to the adoption of frequent switching strategies to restore the supply of electricity in several areas. The adoption of these strategies is also imposed by the possibility of changing of supplier in the scope of the move to the market and by the penalties imposed to companies if quality indices are not met. These strategies also mean that distribution networks are not so stable from a topological point of view as transmission ones. The action of switching devices lead to topology changes regarding which there may exist uncertainty on the control centre. This means the operator, depending on the automation and telecontrol levels, may not be sure about the topology of the system in operation;
- tariff schemes adopted to remunerate companies for the use of their distribution networks in the scope of the move to competition are often based on flows of energy or on average powers. This means these values have to be measured or have to be estimated in some way. This opens new fields of application of state estimation algorithms also contributing to turn them more crucial in control centres since their results can directly determine the flow of money between several entities;

These concerns impose new challenges to the industrial and research communities leading to new levels of cooperation and to hybrid models and applications often combining traditional approaches with emerging techniques. This evolution is finally leading to applications more adapted to the characteristics of distribution networks called DMS – Distribution Management Systems – in an analogy to already existing EMS systems.

III. DATA

Traditional state estimation uses static and dynamic data located in the EMS data base or received from remote telemetering stations. Static data corresponds to characteristics of lines, cables, transformers and generators. Dynamic data include both digital and analogue measurements related to the status of switching devices and to branch currents and powers, generations and loads, node voltages, reactive powers injected by reactive devices and active and reactive injections due to connections with other networks. Traditionally, EMS systems perform topology analysis running topology processor applications in order to identify the configuration of the system in operation and to simplify the network data creating a mathematical model of the system. At the end of this process uncertainties regarding the status of switching devices are eliminated eventually by comparing digital measurements with analogue ones related, for instance, with current or power flows in branches converging to the node to which a particular device is connected. Once the topology is fixed, state estimation applications use analogue measurements to identify the state of the system – typically to compute node voltages and phases – that more adequately explain the available measurements.

Topology issues were rapidly recognized as crucial ones since, according to the previous paragraph, state estimation applications run over a pre-identified topology. This means that the state of switching devices have no correspondence to any topology variable and that state variables – voltages and phases – have to adapt along the iterative process to the previously and externally fixed topology even if the identified topology is not the correct one. This motivated the publication of several papers on this issue as [1], [2] and [3]. The use of real time telemetered data creates several other practical problems as the ones related to time-skew issues. The use of a set of measurements received in the control centre at different time slots may not be critical if power, currents or voltages vary in a slow way, but can certainly lead to erroneous conclusions if some disturbances or topology changes occur meanwhile. In this case, the use of measurements referred to different system states will certainly lead to the estimation of voltages and phases – and, in fact, all other variables – far way from their actual values.

Once applying state estimation algorithms to distribution networks, one has to deal with the reduced number of real time

measurements. This may cause observability problems leading to the impossibility of running state estimation algorithms. This can be addressed in several ways as, for instance, running load allocation applications, estimation of load curves according to the characteristics of consumers and using billing data.

Load allocation procedures are based on real time measurements available for power injections in feeders coming from HV/MV substations. A complete algorithm to tackle this problem is described in [4]. It aims at distributing those injections by the MV/LV substations supplied by each of those feeders using information available in the database for past consumptions, typical load curves for supplied consumers as well as any real time measurement in any point of those feeders, if available. This procedure provides a rough allocation of those feeder injections that contribute to eliminate observability problems. It should be emphasized that its results are neither exact nor coherent ones in the sense that, for instance, they will not generally include information for voltage drops or power losses. This is not critical in itself given that these values will be used to run the state estimation algorithm. This will adjust node voltages and phases to the available measurements according to Kirchoff circuit laws thus correcting the powers provided by the load allocation module.

To a certain extent, a general Load Allocation program would correspond to a two step procedure. The first one corresponds to the rough allocation phase while the second is the state estimation itself in the sense it finally produces a coherent picture of the state of the system.

The problem of assessment of load curves was, for instance, addressed in [5] and [6]. In both cases the authors use the concept of "typical load curves" to classify and cluster industrial, domestic or commercial loads. Regarding [6], the Power Systems Unit of INESC Porto developed a novel approach under a contract with a local utility. Data collected in measurement campaigns was analysed and classified using a neural network system.

The previous concept – "typical industrial, domestic or commercial load curve" – makes the connection to the last source of data that can be used in novel state estimation algorithms. The concept of typical, as well as words like approximately, around, about, … are very commonly used in human language reflecting our ability to structure and condense information and our desire to turn our knowledge more stable even though a particular numeric value changes. In any case, system operators have knowledge regarding typical values that may be assumed by power flows, currents, injections, loads or voltages. Often, this knowledge is expressed in a non deterministic nor probabilistic way in sentences like "the load in node 6 is around 7 MW". This knowledge reflects the past experience of the operators and inherently integrates uncertainty in the sense that 7 MW is the most likely value but one would not like to discard values around 7 MW, let us say from 5.5 to 8.5 MW. The incorporation of uncertainty using Fuzzy Set Theory should not be seen as a drawback of recent models in several scientific areas. On the contrary, it contributes to formalize human knowledge, to give it a mathematical framework that will turn models and results more robust and less sensitive to variations in data, provided those variations are incorporated in models.

In terms of state estimation studies, the integration of subjective assessments is not a novelty if one remembers that the incorporation of pseudo-measurements was a way to address observability problems. Often, this approach was criticised because one would be mixing data having different sources and different degrees of credibility. Pseudo-measurements can now be substituted by fuzzy concepts – fuzzy numbers, in particular – with the advantages both of assigning credibility levels to values in different degrees of uncertainty and of adopting a more adequate mathematical and conceptual framework.

A fuzzy set can be interpreted as a generalization of crisp sets since the dichotomous 0-1 behavior is replaced by a gradual transition from the complete lack to the full membership of an element to a set. A fuzzy set $\tilde{A}$ can be viewed as a set of ordered pairs integrating, each of them, an element x of the Universe X and the membership or compatibility degree of x to $\tilde{A}$ (1). In normalized fuzzy sets the membership function maps the elements in X in the interval $[0.0;1.0]$.

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)), x \in X\} \quad (1)$$

Fuzzy Sets have been used in applications in several scientific domains. They are specially adequate to translate subjective human propositions, to deal with very complex or poorly defined phenomena as well as whenever the available information is not enough to adopt other mathematical tools.

For the purposes of this paper the following concepts and definitions are important:

- an α-cut is the crisp set integrating all elements in $\tilde{A}$ that have a membership function not inferior than α (2);

$$A_\alpha = \{x : x \in X \text{ and } \mu_{\tilde{A}}(x) \geq \alpha\} \quad (2)$$

- a fuzzy number [7] is a fuzzy set defined in the real axes and having a convex and step-wise continuous membership function. In Fig. 1 we represent a trapezoidal fuzzy number that can be used to translate the uncertainty around the interval $[a2, a3]$. Values in this interval are the most likely ones but one would not like to discard values in $[a1, a2[$ and in $]a3, a4]$.This means the membership degree is maximum in $[a2, a3]$ and decreases from 1.0 to 0.0 when going from a2 to a1 and from a3 to a4;

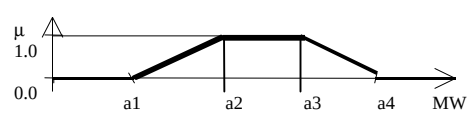

Fig. 1 – Trapezoidal fuzzy number.

- fuzzy numbers, in general, and trapezoidal ones in particular are very appealing since arithmetic operations

are performed on them using computationally efficient rules derived from a max-min convolution principle;

- the Central Value of a fuzzy number is the average value of its 1.0-cut. Regarding the number in Fig. 1, the Central Value is CV(Ã)=(a2+a3)/2.

IV. DMS STATE ESTIMATION ALGORITHM

A. General Issues

State estimation studies play a central role in the control and monitorization of power systems being well established in EMS control centres for many years from now. In general, state estimation aims at computing the values of a set of state variables using a set of available measurements in order to get a coherent picture of the current operation point of the system. These variables, if topology is fixed, usually correspond to node voltages and phases but some versions include transformer taps and some of them consider topology aspects as [1], [2] and [3].

Despite the traditionally higher levels of redundancy, state estimation procedures are well justified even in generation/transmission systems since metering devices have errors that turn the set of measurements not coherent and not in accordance with the Kirchoff circuit laws.

Recently, several reports were published reporting applications directed to distribution networks. Reference [8], for instance, describes a three-phase model using rectangular coordinates and current measurements. The authors convert all measurements in equivalent currents reducing the computational time since some matrices remain constant along the iterative process.

A. WLS Algorithm

The Weighted Least Squares is perhaps the most widely used state estimation algorithm. As stated before state estimation aims at computing the values of node voltages and phases according to a specified criterium so that the calculated values explain as adequately as possible the available measurements. For sake of clarity we will now briefly describe this algorithm on which further developments are based.

Let us consider a power system with n nodes. After selecting one phase for reference, we get 2n-1 state variables (n voltages and n-1 phases) to be computed. Let us assume there are m measurements available (voltages, active and reactive flows, generations or loads, and branch currents). In practical situations redundancy is highly desirable to get a larger immunity to errors in some particular measurements. Let us consider that Z is the vector of available measurements, X is the vector of 2xn-1 state variables, h(X) is the vector of functions relating measurements and state variables and ε is the vector of the measurement errors. These vectors are related by (3).

$$Z = h(X) + \varepsilon \tag{3}$$

State estimation models assume that the errors are random variables having 0 mean and covariance R. Variances and covariances are organized in a matrix R in which R_{ii} is the variance of the ith measurement. For practical purposes, R is usually taken as diagonal. Using the above variables, the state estimation problem can be formalized by:

> Compute the state variables X that better explain the Z available measurements according to (4).
>
> $$\min f = \varepsilon^T R^{-1} \varepsilon \tag{4}$$

The elements of the R^{-1} diagonal matrix are the inverse of the variances of the errors and can be used to express the quality of measurements. For instance, high quality measurements have a small error variance so that its inverse is large. Therefore, such measurements will largely determine the values of state variables since the terms on them in (4) have larger coefficients.

Substituting (3) in (4) gives (5) from which we can derive the optimality conditions. The corresponding set of non-linear equations can be solved by the Newton method leading to (6) in which G^k is the Gain matrix (7) computed in iteration k.

$$\min f = [Z - h(X)]^T R^{-1} [Z - h(X)] \tag{5}$$

$$X^{k+1} = X^k + \left(G^k\right)^{-1} \left[H\left(X^k\right)\right]^T R^{-1} \left[Z - h\left(X^k\right)\right] \tag{6}$$

$$G^k = \left[H\left(X^k\right)\right]^T R^{-1} \left[H\left(X^k\right)\right] \tag{7}$$

These expressions can be simplified by adopting the decoupling principle between active powers and phases, for one side, and reactive power and voltages, for the other, as described for instance in reference [9].

B. Integration of Fuzzy Measures

The incorporation of fuzzy measures in the WLS state estimation algorithm is described in detail in [10] and [11]. In general, the Fuzzy State Estimation is organized in two phases. In the first one, we run a traditional crisp state estimation study using a set of measurements in which fuzzy ones are replaced by the corresponding Central Values. This leads to the identification of an operation point, X_c, that will be used as a linearization point for the second phase.

Once X_c is available we can compute the vector of fuzzy measurement deviations (8) used to calculate the fuzzy state variable deviations (9). In (9) we use the Gain matrix available in the last iteration of the Newton iterative process used to solve the crisp study. The final fuzzy state vector is given by the addition of the crisp X_c vector with the fuzzy deviation $\Delta\tilde{X}$ (10). It must be referred that expressions (8), (9) and (10) use fuzzy arithmetic rules to perform the product of a fuzzy number by a real and the addition or subtraction of fuzzy numbers.

$$\Delta\tilde{Z} = \tilde{Z} - h(X_c) \tag{8}$$

$$\Delta\tilde{X} = \left(G^{-1} H^T R^{-1}\right) \Delta\tilde{Z} \tag{9}$$

$$\tilde{X} = X_c + \Delta\tilde{X} \tag{10}$$

Once fuzzy membership functions for phases and voltages are computed, the algorithm proceeds building membership functions for power flows, injections and currents. Any of these are non-linear functions expressed in terms of voltages and phases so that they can be linearized taking the first terms of their Taylor series around X_c. For instance, the fuzzy deviation of the active flow F_{ij} is given by (11) in terms of the fuzzy deviations of voltages and phases in nodes i and j.

$$\Delta\tilde{F}_{ij} = \frac{\partial F_{ij}}{\partial \theta_i}\Delta\tilde{\theta}_i + \frac{\partial F_{ij}}{\partial \theta_k}\Delta\tilde{\theta}_j + \frac{\partial F_{ij}}{\partial V_i}\Delta\tilde{V}_i + \frac{\partial F_{ij}}{\partial V_j}\Delta\tilde{V}_j \tag{11}$$

The fuzzy deviations $\Delta\theta_i$, $\Delta\theta_j$, ΔV_i and ΔV_j can be obtained from (9) leading to a more compact expression to reflect uncertainties in active flows (12). In this expression $JF(X_c)$ represents the derivatives of F_{ij} regarding the voltages and phases in nodes i and j. The final membership function $\tilde{F}_{ij}$ is given by the fuzzy addition of the value coming from the initial crisp state estimation with the fuzzy deviation given by (12).

$$\Delta\tilde{F}_{ij} = \left\lfloor JF(X_c)\left(G^{-1}H^T R^{-1}\right)\right\rfloor \Delta\tilde{Z} \tag{12}$$

C. Switching Variables

Let us consider that the state of the switching device installed in node i of branch ij is not known for sure. The possible behavior of such devices can be modelled by binary variables that take the value 0 when the device is opened and 1 if it is closed. The integration of such variables change the h(X) functions corresponding to power flows, currents or injections. For instance, (13) is the new expression for the active power flow in which D_{ij} is the topology variable related with the state of line ij and thus with the states of devices in its extreme nodes.

$$P_{ij} = \left[\left(g_{ij} + \frac{gsh_{ij}}{2}\right)V_i^2 - V_i V_j\left(g_{ij}\cos\theta_{ij} + b_{ij}\sin\theta_{ij}\right)\right]D_{ij} \tag{13}$$

The integration of binary variables turns the problem into a non-convex and combinatorial one increasing its complexity. Several algorithms solve these problems by turning variables D_{ij} into continuous ones and approximating them to the closest extreme point, 0 or 1, when the solution of the continuous related problem is identified. Other approaches adopt Branch and Bound strategies that are known for their computational burden. A novel way to address this problem consists of integrating in the h(X) vector one equation as (14) for each topology variable in the model. This enables us to preserve the continuity of variables D_{ij} while constraining their feasible values to 0 and 1 since these are the only solutions of (14).

$$x^2 - x = 0 \tag{14}$$

In the first place let us admit there is information in the database regarding the value of D_{ij} that, however, may be erroneous because it was not updated when a topology change occurred. In this case, the function to include in h(X) is given by (15) in which ε_k is the corresponding error. In other cases, there is no indication in the database so that we use (16). It should be realized that when the error tends to 0.0 the only feasible solutions for these equations are 0 and 1.

$$D_{ij}^{meas} = D_{ij}^2 + \varepsilon_k \tag{15}$$

$$0 = D_{ij}^2 - D_{ij} + \varepsilon_k \tag{16}$$

D. Splitting and Phase References

In practical situations the uncertainties affecting switching devices mean that the operator is not sure whether the system is splitted or not. The incorporation of the possibility of system splitting is complex but it is important in itself since that may correspond to the current state in operation. This means that it should be possible to move from a connected network to an islanded one if the sum of the squares of the errors is smaller in this case. The complexity arises from the need to consider one phase reference for each possible island while in traditional formulations for connected networks we only use one reference for the whole network. This can be addressed by assigning one phase measurement equation given by (17) to all generation nodes and to nodes with connections with other networks.

$$\theta_i = 0 + \varepsilon_k \tag{17}$$

At the beginning of the iterative process we assign a large weight to the phase measurement related with the larger generation while all the others remain smaller. This means that if the system is actually connected – if this is the most adequate situation to explain the available measurements – we have a zero phase for the larger generation node while all other phase measurements have large errors. If, on the contrary, the system is split we are able to identify islands having at least one generation node in which we have a zero reference phase.

E. ORI – Overload Risk Index

The fuzzy state estimation algorithm incorporates fuzzy information in terms of fuzzy numbers. The algorithm described in section C translates the uncertainty in data in the results of the state estimation – voltages, phases, flows and injections. This means that the algorithm provides the fuzzy membership function of the current in branch ij represented by a fuzzy number that reflects and is a consequence of admitting uncertainty in measurements. If one wants to activate an alarm because the current thermal limit was exceeded we will have to compare a crisp limit with a range of values organized in terms of a fuzzy number. This leads to the definition of the Overload Risk Index – ORI – of branch ij given by (18). It corresponds to the higher degree of membership of all possible values of the current in branch ij that exceed the thermal limit.

$$ORI_{ij} = \max\left\{\mu_{\tilde{I}_{ij}}(I_{ij}) \text{ such that } I_{ij} > I_{ij}^{max}\right\} \tag{18}$$

This index measures the ability each branch has in accommodating the specified uncertainty. Such information should be presented to the operators by displaying them on the DMS screens. This can be done by colouring branches with different colours selected according to ranges of the values of the ORI index, that is, ranges defined in $[0.0;1.0]$. This index does not mean that a given branch is overloaded but simply indicates that, underlining the specified uncertainties, such branch may be is an overload situation. This corresponds to a risk index in the sense that the operator can adopt averse risk strategies corresponding to change the operation point to a situation in which the ORI of all branches, that is the ORI of the entire system, is 0. The ORI of the whole system simply corresponds to the maximum of the ORI values of all branches (19).

$$ORI_{system} = \max\left\{\max\left\{\mu_{\tilde{I}ij}(I_{ij}) \text{ such that } I_{ij} > I_{ij}^{max}\right\}\right\} \quad (19)$$

V. CASE STUDY

A. Network and Data

In this section we present the results obtained with a case study based on the IEEE 14 bus test system (Figure 2) that was adapted to illustrate the described State Estimation approach. In this Figure we also indicate the location of measurement devices: black circles for power measurements and black squares for voltage measurements. The white squares and circles correspond to locations in which we have descriptions of power injections or voltages represented by triangular fuzzy numbers.

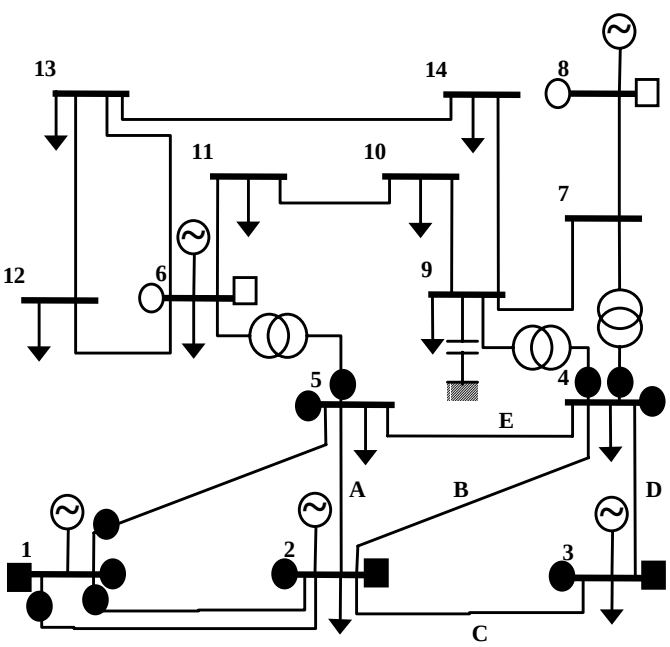

Fig. 2 – IEEE 14 bus test system. Black circles/squares represent traditional measures for power/voltages. White circles/squares indicate fuzzy assessments for power/voltages.

As indicated in the Figure we distributed the measurements in two main areas. For the bottom part of the system we considered there were power and voltage measurements available from metering devices. On the contrary, and in order to simulate a more realistic situation, for the top part we supposed there were no metering devices installed or, if there were some, a communication problem with the control centre had occurred. This situation imposes observability difficulties on top part of the system that can be circumvented by using fuzzy assessments and by running a load allocation algorithm as it will be detailed.

In Tables I and II we indicate the nodal and branch measurements that were used. Table I refers to nodal active and reactive power and voltage measurements while Table II includes measurements for active and reactive power flows. Some of those measurements – namely nodal values for nodes 6 and 8 – were modelled by triangular fuzzy numbers corresponding to fuzzy assessments provided by the operators. The values indicated in Table I for these measurements correspond to the Central Value (CV) of those fuzzy numbers. In this case, since we adopted triangular number, the CV corresponds to the value having degree of membership 1.0. The 0.0 level of uncertainty of those numbers range from 0.9 to 1.1 times the CV.

node	active power (MW)	reactive power (MVAr)	voltage (p.u.)
1	41.552	14.435	1.060
2	18.515	-24.384	1.045
3	-4.2	-40.601	1.010
4	-47.805	3.829	---
5	-7.699	-1.622	---
6	68.8 (CV)	49.85 (CV)	1.070 (CV)
7	0.0	0.0	---
8	10.0 (CV)	23.25 (CV)	1.090 (CV)

Table 1 – Nodal power and voltage measurements.

line	active power (MW)	reactive power (MVAr)
5- 6	-27.790	-36.604
4 - 7	1.951	-18.113
4 - 9	24.284	1.324
1 - 2	25.397	18.683
1 - 5	16.154	-4.236

Table 2 – Line measurements.

In order to avoid the referred observability problems we conducted a load allocation procedure considering that all injection values in the top part of the system were known. In fact, we know line flow measurements for branches 5-6, 4-9 and 4-7 as well as fuzzy injection descriptions for nodes 6 and 8 that is, we know the global injection in the top part of the circuit. The global active and reactive injections were then distributed by the loads in nodes 9 to 14 in a proportional way regarding their nominal powers. This procedure supposes this information is available in the database of this system. The values obtained correspond to rough approximations of the real ones since the network is meshed and it is not included information about transmission losses.

B. Estimated Membership Functions

In the first place we performed a state estimation study using the above referred data. It should be emphazised that the methodology described in Section IV is able to use both deterministic traditional measurements – although affected by

metering errors – as well as fuzzy descriptions as the ones referred before. In any case and as a result of the specified uncertainties, the state estimation results are also affected by uncertainty. This means we obtain a description of the possible state of the system as a result of the referred uncertainties. This means that the fuzzy state estimation procedure can be interpreted as a way to reflect uncertainties on data on the usual state estimation results.

In order to illustrate this procedure, we present the membership functions of several variables in Figures 3 to 7. In Figure 3, 4 and 5 we present the results (thick line) obtained for active and reactive injections and voltages for buses 6 and 8. In order to compared with data, we also represent the fuzzy numbers specified for these variables (thin line).

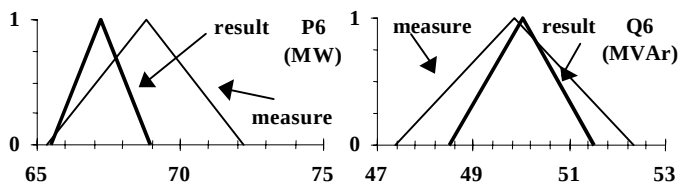

Fig. 3 - Membership functions for specified (thin) and calculated (thick) active and reactive injection in the bus 6.

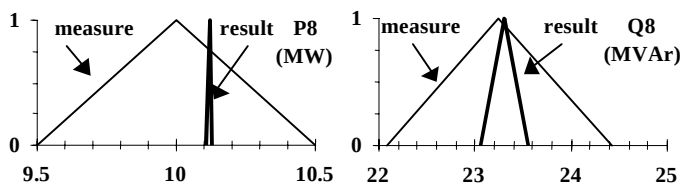

Fig. 4 - Membership functions for specified (thin) and calculated (thick) active and reactive generated in the bus 8.

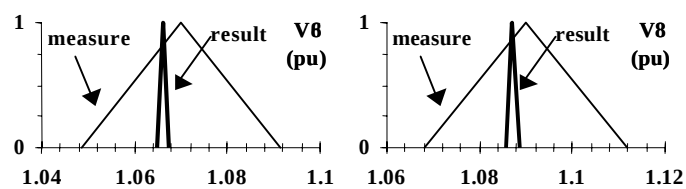

Fig. 5 - Membership functions for specified (thin) and calculated (thick) voltage in the buses 6 and 8.

On analysing these results it is important to notice two points:

- in the first place, the central value of the specified and computed membership function has slightly changes. This is understandable considering that this set of values is used to perform the initial crisp state estimation study aiming at obtaining a coherent operating point of the system. This means that, due to metering errors and to fuzzy assessments, this set of values does not correspond to a coherent picture possibly not being in accordance with Kirchoff laws of circuits;
- secondly, the range of the 0.0 level of uncertainty is in all these cases much reduced when passing from specified data to the computed membership functions. The explanation for this is similar to the above one. The specified data naturally has several incoherent scenarios in the sense they correspond to sets of measurements that do not match the Kirchoff circuit laws. In a certain way, the fuzzy state estimation procedure acts as a filter eliminating all these incoherent values;

In Figures 6 and 7 we present the input data (as provided by the load allocation module) and the results obtained for the active and reactive loads in buses 9 and 10.

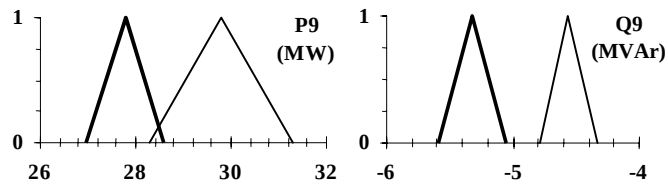

Fig. 6 - Membership functions for input (thin) and computed (thick) active and reactive loads in bus 9.

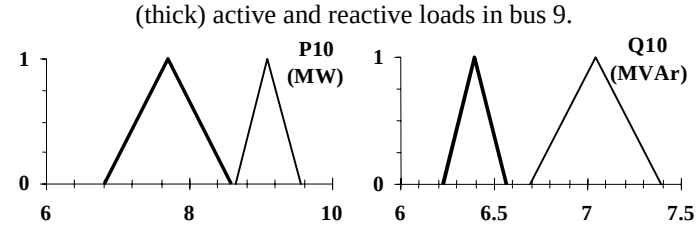

Fig. 7 - Membership functions for input (thin) and computed (thick) active and reactive loads in bus 10.

Regarding these results it becomes more evident that the data provided by the load allocation module has a rough nature and that it does not take into account the operation features of power systems. These membership functions clearly indicate that the values having membership degree 1.0 do not lead to a coherent operation point in the sense they are not in accordance with Kirchoff laws of circuits. The state estimation algorithm corrects these incoherencies. This occurs not only for the initial crisp study – clearly illustrated in these figures by the deviation of the Central Value of the input and computed functions – but also for the 0.0 level of uncertainty – apart from its width, its relative position is changed.

C. Illustration of Topology Identification

In order to illustrate the topology identification algorithm detailed in Section IV.D and E we considered there were switching devices installed in branches denoted by A, B, C, D and E in Figure 2. We adopted a reference topology in which branches A and B are disconnected and branches C, D and E are in service. For this reference topology we ran a power flow study in order to obtain a coherent set of values for injections, voltages and branch flows. Some of those variables were adopted as measured ones and the metered values corresponded to the value provided by the power flow study affected by a random error. This way, we were able to simulate the metering errors affecting measurements leading to a non coherent set of values.

Afterwards, we conducted a set of tests in which we changed the information regarding the status of the branches existing in the database according to the indications in Table 3. As examples:

- CASE 0 – in this situation the topology data in the database regarding branches A, B, C, D and E is correct. The algorithm converges in 3 iterations;
- CASE I - we supposed that all branches were connected but that the information on the database could be erroneous. This lead to the inclusion of 5 equations as (15) in vector h(X). In this case, the algorithm successfully identified the correct topology and took 8 iterations to converge;
- CASE II – we supposed that branches A and B were disconnected and that there were no information regarding the status of C, D and E. This lead to the integration of three equations like (16) in vector h(X). In this case, the algorithm successfully identified the correct topology and it took 7 iterations to converge;
- CASE IV – in this case we considered that the information in the database was the contrary regarding the correct one for all branches. In this situation, the number of iterations to get convergence is increased to 15 meaning that the algorithm had greater difficulty in identifying the correct topology. This is clearly due to a large set of incorrect topologic information concentrated in the same area.

	0	**I**	**II**	**III**	**IV**	**V**
A	open	close	open	close	close	?
B	open	close	open	close	close	?
C	close	close	?	?	open	?
D	close	close	?	?	open	?
E	close	close	?	?	open	?
Success	YES	YES	YES	YES	YES	YES

Table 3 – Illustration of topology identification.

D. Risk Indices

In Figure 7 we present the membership functions computed for the current flowing in branches 1-6 and 2-6. The figure also indicates the thermal limit adopted on those branches. These limits indicate that the ORI index is 0.49 for branch 1-6 and 0.84 for branch 2-6 meaning that, underlining the specified uncertainties, the system is not robust in sense that risky operating situations can occur. Having this information, the operation can adopt a risk averse strategy changing the operating point so that the system is able to accommodate the specified uncertainties without violating any limits.

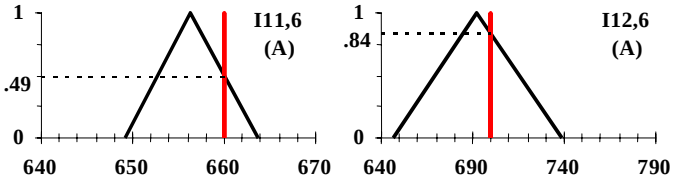

Fig. 7 - Membership functions for current in lines 11 – 6 and 12 – 6, and with ORI index evaluated for each line.

VI. CONCLUSION

In this paper we described a complete State Estimation methodology aiming at identifying the state of distribution networks. The software is highly flexible in terms of the data it can incorporate – traditional real time measurements, fuzzy evaluations and results from load allocation procedures – as well as its ability to address topology issues. These are related with the uncertainty that may affect the knowledge of switching devices and thus it is important to give the system the ability to split in several islands if that is more adequate to explain the available measurements. This means that we enlarged the traditional nature of WLS state estimation algorithms explicitly dealing with topology aspects. This also implies that the state of the system is not only characterized by voltages and phases but also by topology variables that are computed by the algorithm.

This kind of applications have a large potential of use in the future given that they are more adapted to represent reality in a closer way and that they provide a more complete knowledge about the system in operation. Apart from that, the treatment of topology issues will certainly contribute to increase the ability of the software to correctly identify the state of the system. It should be referred that despite the use of topology variables, the algorithm is computationally very efficient since, in average, the surplus of execution time when compared with traditional WLS approaches is only 55%. This seems a well reduced price to pay when considering the more complete knowledge about system behavior that is provided.

Finally, it should be stressed that in this approach we combine traditional WLS probabilistic algorithms with fuzzy concepts. This reflects our desire to use the most adequate mathematical tools for each particular situation, our purpose to use emergent techniques and our belief that fuzzy concepts, despite very appealing, will not replace probabilistic concepts.

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