Load Allocation in DMS with a Fuzzy State Estimator

Vladimiro Miranda, Jorge Pereira, and João Tomé Saraiva

***Abstract*—This paper describes a Load Allocation model to be used in a DMS environment. A process of rough allocation is initiated, based on information on actual measurements and on data about installed capacity and power and energy consumption at LV substations. This process generates a fuzzy load allocation, which is then corrected by a fuzzy state estimator procedure in order to generate a crisp power flow compatible set of load allocations, coherent with available real time measurements recorded in the SCADA.**

I. Introduction

IN RECENT years, control centers in distribution went through some drastic changes. Evolving from simple SCADA systems, the concept of DMS—Distribution Management Systems gained growing acceptance.

A DMS must provide a set of functions, namely for switching decisions and operation, which rely on the basic tool of power flow calculus. The problem of generating a coherent load set is critical in distribution, because usually, the only real time measurements available at a SCADA system are power or current values at the sending end of a feeder emerging from a MV substation. One must therefore rely on other type of data, recorded in commercial files, to try to infer the values of loads.

The need of an inference mechanism resulted in a large research effort in many places; some models had a more heuristic approach, while others had a probabilistic theoretical background [1]. Some of the primitive approaches to assessing line flows in distribution systems addressed the "peak flow" problem: one was only trying to assess the peak flow that could occur at any time in every section of the network.

But a modern DMS must try to address the problem of evaluating actual synchronized flows and making this compatible with any measurements available at a SCADA system at any time t. This is a must if the DMS is to be used as an effective operation tool—for instance, some switching maneuvers leading to load transfers may be possible under certain conditions and not possible in other cases.

The complexity of the problem increased with the connection at distribution level of dispersed generation from industrial co-generation or independent producers with thermal, diesel, wind or just mini-hydro generators. This had two effects: a) it changed the top-down traditional character of power flows in distribution systems, usually operated under radial configurations, and b) in many cases, this power injection is monitored and more real-time measurements are available at the SCADA, both for power injections and for some line flows.

Under contract for EDP—Electricidade de Portugal, SA, INESC has developed a model [2] to derive characteristic load curves for LV substations from commercial data. This model, based on neural networks, was tested and adopted by the utility and is giving remarkably accurate results.

However, we can not imagine that all utilities will be using such model or have available, for every LV substation, descriptions of its characteristic daily load curves, for distinct week days and seasons of the year. As INESC was contracted by EFACEC—Sistemas de Electrónica, SA, to help developing software models and modules for a DMS, we realized that a) a general load allocation model had to be implemented, and b) we had ready a set of very modern techniques, based on fuzzy set models, that could provide a good operating answer to the Load Allocation problem for DMS.

The core of the technique is the Fuzzy State Estimation model, whose principles were described in [3] and [4]. This new model is presented in the following sections. It refers specifically to three phase (admitted balanced) networks, such as commonly used in Europe, but its extension to systems where an explicit per-phase representation is required will present no difficulties.

II. Data

A. Load Classes

The loads in a MV network will be basically LV distribution substations, either public or private. We have classified them in 4 general types:

- Type POWER - Substations for which one only knows transformer installed capacity or peak load; capacitors are treated as loads by being transformed into reactive power values under nominal voltage
- Type ENERGY - Substations for which there is also knowledge about their load composition in terms of three classes of consumers (domestic, industrial and commercial) and their energy consumption, including at peak, normal and light hours for some of them
- Type CURVE - Substations for which there is also a model, such as described in [2], that allows a prediction of the load at a given hour
- Type MEASURED - Substations where there are real time power consumption measurements

B. Source Classes

The power injection sources are classified as:

- Type ROOT - Main injection point, usually the connecting substation to a higher voltage level grid

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V. Miranda and J. T. Saraiva are with the FEUP—Fac. Engenharia Univ. Porto (e-mail: vmiranda@inescn.pt; jsaraiva@inescn.pt).

J. Pereira is with the FEP—Fac. Economia Univ. Porto, INESC—Instituto de Engenharia de Sistemas e Computadores, P. República 93, 4050 Porto, Portugal (e-mail: jpereira@inescn.pt).

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- Type SOURCE - Any dispersed generation facility for which there are real time measurements at the SCADA
- Type NEGATIVE LOAD - Generators for which there are no real time measurements - they are treated as negative loads; depending on the type of information available, they are assimilated to one of load types.

C. Measurements

The measurements available for the node ROOT, obtained as SCADA information, would ideally be active and reactive power. But it is common that the measurement is just current; then, we fix a direction and a power factor to transform it into power values (the definition of direction and power factor is based on system history - and this is done only for the rough allocation phase, referred to below; in the final adjustment, phase, the current measurement is fully taken in account). All other measurements will be transformed into active or reactive power or voltage. In this model, current measurements will be all transformed into power measurements until the last correction phase. We also consider two types of measurements:

- NODAL - at nodes (root, sources or loads)
- BRANCH - inserted in branches (lines or transformers)

III. General Model

The basic constraints of the model are:

- It must represent flows at a given time, compatible with the Kirchhoff Laws
- It must present coherency between estimated loads and measurements
- The load allocation must be independent of the network topology under operation

This last point is important: it would be unacceptable, from an operator point of view, that the estimated load for a given node would "magically" change if he performed some switching or load transfer simulation. The traditional concept of "loss of diversity," when one moves down in a radial network, has no application - in fact, this concept applies to peak values, but it gave place to misconceptions on several occasions.

Besides, the model we will describe does not really require the network topology to be radial: it may be applied to systems with several injection points and to systems with closed loops, with slight adaptations, making it general.

The model requires the specification of values for balancing parameters $m, \lambda \in [0, 1]$. This is a tuning process to be done taking in account system history and operator experience. For instance, if $\lambda = 0$ the allocation will be done only proportionally to installed capacity or peak values, and if $\lambda = 1$ the allocation will be proportional to average energy consumption values. The uncertainty parameter x may be derived from a linguistic interface about how uncertain does an operator feel about estimating loads from installed capacities.

The model is divided in two main phases: a) a rough load allocation; b) a corrective phase (described in theoretical detail in Section IV). Its general logic is the following, for a load allocation at time t:

ROUGH_ALLOC

Discount all MEASURED loads to the ROOT

Predict load P_{alloc} at every CURVE node and discount it to ROOT. If ROOT power less than a specified threshold (0, by default) CURVE nodes will be treated as ENERGY nodes

For CURVE nodes, fix $[P_{\min}, P_{\max}]$ according to (fuzzy) precision indications associated with the curve models

For nodes in (ENERGY, POWER) calculate, from the installed capacity and peak information, the power P_{power}, using a balancing parameter $m \in [0, 1]$ and $P_{\mathrm{power}} = (1 - m)P_{\mathrm{peak}} + mP_{\mathrm{installed}}$.

For nodes in (ENERGY) calculate, from the energy consumption information, the average power P_{ave} for the period of the day including time t. The ratio $\sum P_{\mathrm{power}} / \sum P_{\mathrm{ave}}$ at the root is applied by default to the nodes in the POWER set to calculate P_{ave} for these latter.

For nodes in (ENERGY, POWER), two load allocations are performed:

P_E, distributing the injected remaining undistributed power at ROOT in proportion to each node estimated P_{ave}

P_P, distributing the injected remaining undistributed power at ROOT in proportion to each node estimated power P_{power}

For nodes in {POWER}, do:

$P_E = P_E - x\%$; $P_P = P_P + x\%$ (*because* $P_E = P_P$; x *is an uncertainty parameter*)

A primary allocation is obtained for (ENERGY, POWER) with $P_{\mathrm{alloc}} = (1 - \lambda)P_P + \lambda P_E$, where $\lambda \in [0, 1]$ is a balancing parameter

Repeat the procedure for reactive power values, using estimated or default power factor values when no measured information is available. This will result in a pair of estimates Q_P and Q_E and a reactive power nodal allocation Q_{alloc}.

{*At the end of this procedure, we get the following:*

an interval for active and reactive load allocated to each node $[P_{\min}, P_{\max}]$ *and* $[Q_{\min}, Q_{\max}]$ *obtained after convenient ordering of* P_P *and* P_E *or* Q_P *and* Q_E

a DC load flow coherent set of nodal active powers P_{alloc}

a set with similar coherency for nodal reactive loads Q_{alloc}}

CORRECT_ALLOC

Define the sets $(P_{\min}, P_{\mathrm{alloc}}, P_{\max})$ and $(Q_{\min}, Q_{\mathrm{alloc}}, Q_{\max})$ as triangular fuzzy numbers at each node.

Input all measurements and fuzzy loads and run an algorithm of Fuzzy State Estimation type and, as a result, calculate

For each load, the final P_{alloc} and Q_{alloc}

For each branch, a credible flow F and an upper bound F^{upper}

Compare branch flow limit F^{limit} with F and F^{upper} and set, if necessary, a level of alarm.

{*At the end of this procedure, the* P_{alloc} *and* Q_{alloc} *values plus the measurements form an AC Power Flow coherent set of values*}

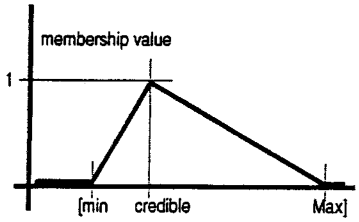

Fig. 1. Triangular fuzzy number, with an uncertainty range interval [min, Max] and a most credible value.

IV. Fuzzy Loads and Fuzzy Allocation with Fuzzy State Estimation

At INESC we have considerable experience in using fuzzy numbers to express unknown or uncertain measure values in power systems:

—fuzzy numbers are able to translate to a numerical form qualitative linguistic declarations, of the uncertain number type ("around 3") or the uncertain interval type ("roughly between 2 and 4"); the most practical fuzzy information is translated by a triangular fuzzy number such as in Fig. 1 and is in terms of a range of uncertainty (an interval) plus an interior "most credible" value.

—a fuzzy number may represent information from billing files, or from clustering exercises on typical load curves, relative to one consumer or a group of consumers, in a part of a network where no measurements are available; this information is not, in general, of the probabilistic type or, even if probabilistic models were conceivable, the cost and effort to develop and validate them would be excessive in most cases.

—the models we have developed are an extension of proven knowledge; they can easily be understood and accepted by those familiar with utility practice; the fuzzy output obtained gives information about sensitivity of the results regarding uncertainty in data.

If some generations or loads are defined as fuzzy, because some uncertainty is associated to them, the resulting uncertain line flows and node voltages may be calculated by a Fuzzy Power Flow (FPF) model, such as in [5]. These results are naturally expressed as fuzzy numbers. In particular, if data were in the form of triangular fuzzy numbers, the FPF model will give the corresponding range of uncertainty and most credible value for all results. However, in the problem of Load Allocation we cannot use a FPF model, both because we have errors in the rough load allocation (and therefore the data set is not coherent with Kirchhoff Laws) and because we have measurements.

Believing that the rough load allocation will give a set of approximate values, what we wish is to adjust the values in that set and comply with the above constraints. Conceptually, this is an exercise of the State Estimation type, where we replace measurements with possibly large errors by more or less qualitative load predictions.

And in the present case, because we have the loads resulting from ROUGH_ALLOC as fuzzy numbers, what we need is a Fuzzy State Estimation (FSE) technique - similar to the one in [3] and [4]. The problem here is somewhat simplified, because

1. We are using triangular fuzzy numbers
2. We are accepting as known the topology of the network

This last point deserves mentioning, because the FSE model in [4] included a procedure to simultaneously evaluate electrical measurements and switch status, which is not needed here.

The Fuzzy State Estimation model is composed of two parts: the application of a classical crisp algorithm, based on the Least Squares principle, and a linearized approach to the computation of fuzzy results, having as departing point the solution of the crisp algorithm.

A. Classical Crisp Algorithm

Consider that m measurements are available and that n state variables were selected. Assume that:

- Z is the measurement vector ($mx1$);
- X is the state vector ($nx1$);
- $h(.)$ is the function vector that relates the state variables and the measurements ($mx1$);
- ε is the measurement noise or error vector ($mx1$).

A general state estimation model is then given by

$$Z = h(X) + e \tag{1}$$

The elements of the measurement vector may be

- bus power injection measurements ($S_i = P_i + jQ_i$);
- branch power flow measurements ($S_{ij} = P_{ij} + jQ_{ij}$);
- bus voltage measurements (V_i);
- branch current measurements (I_{ij}).

As elements of the state vector, one usually chooses bus voltages and phases. The components of vector ε are usually considered to be random variables with zero mean and covariance R. If assumed to be independent, R is a diagonal matrix; its diagonal ii element corresponds to the variance of the i-th measurement σ_i^{-2}. The Least Squares family of algorithms try to solve

$$\min \varepsilon^T R^{-1} \varepsilon \tag{2}$$

The values in R^{-1}, or σ_i^{-2}, are used to apply different weights to the measurements. A larger R may be assigned to measurements of higher quality, while measurements obtained from poor quality equipment will have smaller R values.

Eq. (2) represents a Weighted Least Square problem whose solution is well known and obtained by replacing ε obtained from Eq. (1) in Eq. (2).

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

The solution in terms of the state variables X is obtained from

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

where H represents the Jacobian measurement matrix.

This set of equations can be solved iteratively using the Newton-Raphson's method. At the ($k + 1$)th iteration the refreshed values of the state variables can be obtained from their values in the k-th iteration by

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

where G is the gain matrix given by

$$G^k = (H^K)^T.R^{-1}.(H^K) \tag{6}$$

Several techniques [6] are described in the literature to solve this problem. The most common and well-known are the fully coupled version of the normal equation method and its decoupled formulation.

B. Fuzzy State Estimation

In a Fuzzy State Estimation problem where the fuzzy data are given by triangular fuzzy numbers, the first step is to run a classical crisp State Estimation procedure for the most credible data, i.e., for the vertices of the triangles. The result will be the state vector X_1; it will serve as a basic linearization point for the estimation of the fuzzy state variables.

If a new measurement vector Z' is available, variations $\Delta Z = Z' - h(X_1)$ can be reflected on the results of the state estimation using the gain matrix G obtained in the last iteration of the crisp calculation. Therefore, estimates of the variations and new state variables can be approximated by

$$\Delta X = (G^{-1}H^TR^{-1})\Delta Z \tag{7}$$

$$X = X_1 + \Delta X \tag{8}$$

If instead of deviations we consider now fuzzy numbers Z', Eq. (7) and Eq. (8) must be fuzzified, i.e., in the expressions indicated operations must obey the rules of fuzzy arithmetics [7]. X will be the vector of fuzzy state variables, calculated from a vector of crisp "most credible" state variables and a vector ΔX of fuzzy deviations.

If we take for X node voltages as state variables, we cannot compute directly from them the values of currents and power flows. Instead, the procedure is the following:

- define F_{ij} as generically representing either the branch active, reactive power flows or the currents, all stored in vector FL.
- linearize ΔF_{ij}, taking the first terms of the Taylor series around X_1, using V_i, V_j, θ_i, θ_j as the voltages and angles in buses i and j

$$\Delta F_{ij} \cong \left.\frac{\partial F_{ij}}{\partial \theta_i}\right|_{X1} \Delta\theta_i + \left.\frac{\partial F_{ij}}{\partial \theta_j}\right|_{X1} \Delta\theta_j + \left.\frac{\partial F_{ij}}{\partial V_i}\right|_{X1} \Delta V_i + \left.\frac{\partial F_{ij}}{\partial V_j}\right|_{X1} \Delta V_j \tag{9}$$

The derivatives of P_{ij}, Q_{ij} and I_{ij} can be organized in the matrix $J_{FL}(X)$. Each element of this matrix corresponds to the derivatives of the active and reactive flows and currents regarding the elements of the state vector X_1. Defining ΔFL as the vector of the fuzzy deviations of these variables, we can rewrite Eq. (9) in the form of

$$\Delta FL = J_{FL}(X_1).\Delta X \tag{10}$$

$$J_{FL}(X) = \begin{bmatrix} \left.\frac{\partial P_{ij}}{\partial \theta_k}\right|_X & \left.\frac{\partial P_{ij}}{\partial V_k}\right|_X \\ \left.\frac{\partial Q_{ij}}{\partial \theta_k}\right|_X & \left.\frac{\partial Q_{ij}}{\partial V_k}\right|_X \\ \left.\frac{\partial I_{ij}}{\partial \theta_k}\right|_X & \left.\frac{\partial I_{ij}}{\partial V_k}\right|_X \end{bmatrix}$$

$$\Delta FL = \begin{bmatrix} \Delta P_{ij} \\ \Delta Q_{ij} \\ \Delta I_{ij} \end{bmatrix}$$

Using Eq. (7) in Eq. (10) we obtain

$$\Delta FL = (J_{FL}(X_1)(G^{-1}H^TR^{-1}))\Delta Z \tag{11}$$

This expression is used to evaluate the fuzzy deviations of P_{ij}, Q_{ij} and I_{ij} directly from the fuzzy measurement data. The final membership functions are obtained adding their fuzzy deviations to FL

$$FL = FL(X_1) + \Delta FL \tag{12}$$

C. Currents and Alarm Levels

Similarly to the situation described in [5], due to linearization, errors may occur when building current membership functions, namely for very small current values and the current magnitude may appear with negative values. This happens when triangular fuzzy results are no longer an acceptable approximation for the exact fuzzy membership functions. Corrected values may be obtained if their real and imaginary parts are also calculated. In this case the derivatives of these real and imaginary parts regarding the state variables must be integrated in the $J_{FL}(X)$ matrix and their deviations calculated using Eq. (11).

The real an imaginary parts of a current, at a level α, define a rectangle in the complex plane. This happens namely at the 0 and 1 levels. If one remembers that, for every instantiation of a real and imaginary part, the magnitude of the current must be given by $I_m = \sqrt{I_r^2 + I_i^2}$, we just have to check which pairs of I_r, I_i give the calculated I_m, obtained from Eq. (11), in the feasible region (positive values of I_m).

This gives an indication on the trajectory followed by I_m, within the rectangular region mentioned above; then the calculation of corrected I_m values is straightforward. Of course, if the same magnitude value I_m occurs at different levels α_1 and α_2, we take I_m with a level $\alpha = \text{Max}\,\{\alpha_1, \alpha_2\}$.

Given a calculated possibility distribution $\mu(I)$ for a branch current I and a maximum admissible current (I_{Max} - thermal constraint), one may derive an Alarm Level according to

$$\text{Alarm} = \text{Max}\{\mu(I)\ ,\ \forall I \geq I_{\text{Max}}\}$$

If all the distribution is below the admissible limit, the Alarm Level will be zero (0); if the most credible value for the current exceeds the admissible limit, the Alarm Level is set to one (1). An intermediate case is illustrated in Fig. 2.

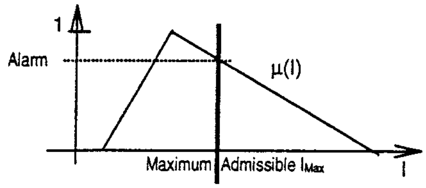

Fig. 2. Deriving an Alarm Level from the uncertainty distribution of branch current and thermal maximum current.

V. Illustrative Example

The Fuzzy State Estimation technique has been illustrated with real size examples in previous papers [3], [4]. We opted therefore to present here a small scale illustrative example of the interesting consequences the Load Allocation procedure.

Figs. 3 and 4 represent variations on a system where at the MV substation we admitted the existence of active and reactive injected power measurements. All the lines have 1 km in length and a series impedance of $0.4 + j0.25\ \Omega$, with capacitance neglected.

We have run a rough load allocation procedure (ROUGH_ALLOC) giving at each of the LV substations, 1 MW and 0.5 MVAr, with an estimated uncertainty range of $\pm 5\%$ (i.e. a 50 kW and 25 kVAr of estimated range) for nodes 2 to 8, 11 and 13, and l.5 MW, 0.75 MVAr, $\pm lO\%$ for nodes 10 and 12.

We defined a <u>*Base*</u> <u>*Case*</u>, with measurements of active and reactive power at the root (node 1 - 12 MW, 6 MVAr), and an <u>*Extra*</u> <u>*Injection*</u> case, with measurements in node 1 (7 MW, 3.5 MVAr), in line 7-9 (-2.8 MW, -1.4 MVAr) and with an independent generation connected to node 9 injecting a measured power (5 MW, 2.5.MVAr).

The most important results for the *Base Case* are in Fig. 3, Tables I and II. In Table I, we have the estimated central active load (MW) and reactive load (MVAr), and the uncertainty ranges around central load values in %; in Table II we have the Sending and Receiving nodes (S-R), the Current in A, the maximum estimated current in A (Max), the thermal line limit in A (Admis.) and the Alarm level.

The Fuzzy State Estimation provided the definition of load uncertainty ranges coherent with the measurements available in this case, at Substation 1. Furthermore, it corrected the rough load allocation by accounting for the line losses.

The ROUGH_ALLOC procedure not only adjusted the estimated uncertainty at each node, but it also provided information about each line flow and its uncertainty range. It is interesting to notice that the relative uncertainty of current in line 1-3 is rather small, although there is a considerable global uncertainty in load allocation dependent of this line (all nodes below 3).

The relative uncertainty grows in lines 3-4, 4-7, 7-9, 9-10, as one moves closer to extreme nodes; the uncertainty at extreme branches (such as 1-2 or 9-12) is similar to the uncertainty in the loads they supply (it should be so). Also, notice that in line (7-9) an alarm level Alarm$=0.8$ has been set.

Fig. 4, Tables III and IV illustrate the results for the *Extra Injection Case*. The ROUGH_ALLOC allocation is strongly corrected in this case, because of the constraints imposed by the known measured values in line 7-9. Also, the uncertainty ranges

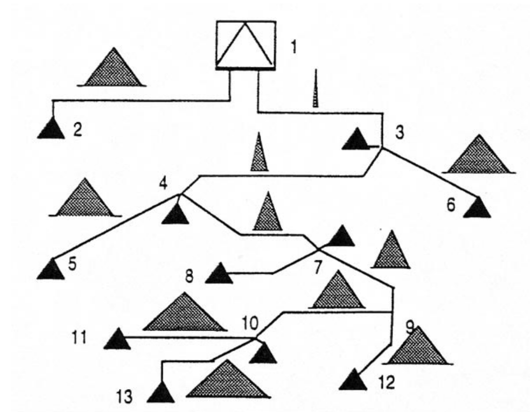

Fig. 3. Base Case—Predicted relative uncertainty range for line currents, in percentage of each line flow.

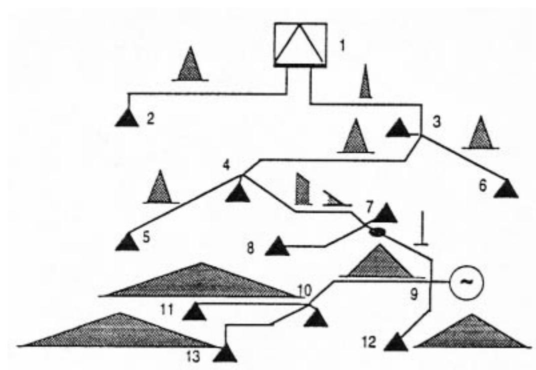

Fig. 4. Extra Injection Case (power measurement in line 7-9).

TABLE I
Base Case—Corrected Load Allocation

node	2	3	4	5	6	7	8	9	10	11	12	13
Active Load	.985	.985	.985	.985	.985	.985	.985	0	1.48	.985	1.48	.985
Uncert range	11.9	12.0	12.0	12.0	12.0	12.1	12.1	0	13.5	16.3	13.5	16.3
React. Load	.491	.491	.491	.491	.491	.491	.491	0	.740	.490	.740	.490
Uncert range	12.1	12.1	12.1	12.1	12.1	12.2	12.2	0	13.6	16.4	13.6	16.4

TABLE II
Base Case—Line Flows

S-R	1-2	1-3	3-4	4-7	7-9	9-10	3-6	4-5	7-8	9-12	10-11	10-13
Current	21	237	194	151	108	76	21	21	22	33	22	22
Max	24	240	201	160	118	84	24	24	24	37	25	25
Admis.	50	250	250	250	110	110	50	50	50	50	50	50
Alarm	0	0	0	0	0.8	0	0	0	0	0	0	0

TABLE III
Extra Injection Case - Corrected Load Allocation

node	2	3	4	5	6	7	8	9	10	11	12	13
Active Load	1.39	1.40	1.40	1.40	1.40	1.40	1.40	-5	.800	.298	.800	.298
Uncert range	6.2	6.1	6.1	6.1	6.1	6.1	6.1	0	25.1	58.7	25.0	58.7
React. Load	.696	.697	.698	.698	.698	.698	.698	-2.5	.399	.149	.399	.149
Uncert range	6.2	6.2	6.2	6.2	6.2	6.2	6.2	0	25.1	58.8	25.1	58.8

TABLE IV
EXTRA INJECTION CASE - LINE FLOWS

S-R	1-2	1-3	3-4	4-7	7-9	9-10	3-6	4-5	7-8	9-12	10-11	10-13
Current	30	121	60	0.11	61	30	30	30	30	17	6	6
Max	32	122	64	3	61	34	32	32	32	22	10	10
Admis.	50	250	250	250	110	110	50	50	50	50	50	50
Alarm	0	0	0	0	0	0	0	0	0	0	0	0

for the sections between the substation and line 7-9 are much narrower than for the sections below this line; this is the consequence of having there more information (measurements at two topologically very separated and distinct points) to be made compatible with load predictions. Fig. 4 also shows that the relative uncertainty range in currents grows in sections away from measurement points.

One should notice the special case of power flow in line 4-7; we obtained for the active power flow the central value of -5 kW and the uncertainty interval of $[-148, +138]$ kW; there is a possible reversal of power flow direction in this branch. The credible value for the current is very small (0.11 A) and so the relative uncertainty range is very large although it is a small interval in A values (maximum 2.9 A). The model also matched correctly the current in line 7-9 and assigned no uncertainty to it, as it was a measured value.

VI. CONCLUSIONS

This paper summarizes an interesting application of fuzzy set techniques to power distribution. It describes how from uncertain data one may produce, in a DMS environment, a consistent load allocation to the system nodes, so that other calculus modules may work, namely load flow routines. DMS modules demand a specific Load Allocation procedure because, contrary to EMS environments for Generation-Transmission systems, there are usually no real time information or measurements of loads in distribution systems.

The results can be no better than the data - this is an elementary truth so many times forgotten. By keeping an explicit interval or fuzzy set representation of uncertainty in load allocation, we wanted to avoid giving to operators a false security impression, which might prove dangerous for equipment or people.

The resulting algorithm gives not only an indication of some range of uncertainty on load allocation, but also allows operators to become aware of levels of risk and possible alarm, if the combination of uncertainties open the possibility to have branch limits to be exceeded by power flows.

The elegant solution reached, making use of Fuzzy State Estimation concepts, is the only one that may guarantee not only a load allocation where total load matches power injections, but also where flows are described by the possible ranges compatible with actual measurements in the distribution network. And, furthermore, the FSE model is *general*, so it can be applied to meshed systems as well as to radial systems.

Finally, it is fair to say that the model described in the paper is currently implemented in a DMS package offered in the market - making it not only a theoretical exercise, but also a case of successful transfer from science to industry.

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Vladimiro Miranda received his Licenciado, Ph.D. and Agregado degrees from the Faculty of Engineering of the University of Porto, Portugal (FEUP) in 1977, 1982 and 1991, all in Electrical Engineering. In 1981 he joined FEUP and currently holds the position of Professor Associado. In 1985 he joined also INESC, a research and development institute, having held for many years the position of Head of Information and Decision in Energy Systems. In 1996 he was appointed President of the Executive Board of INESC-Macau (South China) and Full Professor in the University of Macau. He is a member of several Expert Committees in Power Systems and of EAF—Energy Advisory Foundation. He has had responsibility over several research projects within the European Union programmes and also in cooperation with Latin America and Portuguese speaking African countries. He has authored or co-authored many papers, namely in his areas of interest, related with Power System planning and the application of soft computing techniques to Power Systems.

Jorge Pereira was born in Viseu, Portugal, on April 22, 1969. He received his Licenciado degree from the Faculty of Science of Oporto University, Portugal, in 1991 in Applied Mathematics to Computer Science. In 1995 he got the M.Sc. degree in Electrical Engineering from the Faculty of Eng. of Oporto University. In 1991 he joined INESC as a researcher and is currently a Ph.D. student interested in the application of soft computing techniques to state estimation. In 1995 he joined to the Faculty of Economy of Oporto University where he is Assistant.

João Tomé Saraiva was born in Porto, Portugal, on August 18, 1962. He received his licenciate, M.S. equivalent and Ph.D. degrees from the Faculty of Eng. of Oporto University (FEUP) in 1985, 1988 and 1993, respectively, all in Electrical Engineering. In 1985 he joined FEUP where he is Auxiliar Professor. In 1989 he joined also INESC as a researcher.