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Inference of the Operative Configuration of Medium Voltage Distribution Networks

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***Abstract*—This paper presents the first part of an approach aimed to infer the operative configuration of medium voltage distribution networks. Here the operative configuration is defined as the state (open or closed) of the protective devices installed in the MV feeders. The methodology is based on the calculation of fault currents using fuzzy arithmetic and the estimation of loads using power flow analysis. Preliminary results are obtained using limited data supplied by SCADA and statistical data processed from CIS. An analysis of the relations between operative configuration, distribution state estimation and quality of service is also presented. The research is oriented toward radial distribution feeders with solid connection to ground and a low degree of real time monitoring and control.**

***Index Terms*—Fuzzy sets, power distribution, power flow analysis, short circuit currents, state estimation, substation measurement.**

I. NOMENCLATURE

AM/FM: Automated Mapping/Facilities Management.
AMR: Automated Meter Reading.
CIS: Customer Information System.
DA: Distribution Automation.
DMS: Distribution Management System.
EMS: Energy Management Systems.
ENS: Energy Not Supplied.
GIS: Geographic Information System.
HV: High Voltage.
OMS: Outage Management System.
MV: Medium Voltage.
SCADA: Supervisory Control And Data Acquisition.
TCC: Trouble Call Center.
ULTC: Under Load Tap Changer.

II. INTRODUCTION

As a consequence of the deregulation of electricity markets, the Latin American distribution utilities are facing an increasingly competitive environment. In this context one of their main objectives is the compliance of the quality of service regulations, specifically those referred to the continuity of supply. The violation of the permitted limits is penalized using values related to the ENS costs. Because of the characteristics of the distribution system, its associated costs and the existence of uncontrollable variables (e.g. weather), it is not possible to guarantee a supply without penalties. However, the quality of service regulations are augmenting their exigencies about the frequency and duration of outages. To comply with these demands and restrictions, the utilities are moving towards the implementation and integration of:

1. Information systems designed for the administration of facilities, commercial data processing and customers services: AM/FM GIS, CIS, TCC.
2. Information systems designed for the analysis, supervision and control of the network: DMS, OMS, SCADA, AMR.
3. DA functions: automatic fault location and restoration, Volt-VAR control, etc.

The starting point for the implementation of DA functions is the distribution state estimation.

III. DESCRIPTION OF THE PROBLEM

The state estimation problem includes two types of results, the operative configuration and the electrical parameters of the network (nodal voltages, currents, power flows, etc). The majority of distribution state estimation approaches are based on the adaptation of the traditional methodologies developed for transmission systems and implemented in the EMS environments. This is not the most adequate solution, at least for Latin American distribution systems, which is due to the structural differences existing between both systems.

In transmission systems, a redundant set of measurements supervised by SCADA is available. This characteristic ensures the observability of the system and the knowledge of its operative configuration. In distribution systems, supervising in real time all the nodes of the network, is not economically feasible, making the system not observable. In order to overcome this problem, pseudo measurements obtained from statistical data, are used. The disadvantage of this approach is the introduction of uncertainties in the process.

In Latin American distribution systems, the majority of measurements available are installed in HV/MV substations. These measurements and the state of circuit breakers are

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supervised by SCADA. In contrast, in the MV feeders, a large amount of measurements, switchgear and protective devices (reclosers, sectionalizers, cutouts) are not supervised in real time. Because of this constraint, the operative configuration is mostly unknown. Additional difficulties arise from the dynamic nature of distribution systems. This is consequence of the large number of devices and switching operations, the large proportion of aerial feeders (especially in rural areas) and the susceptibility of these feeders to the influence of frequent natural phenomena. These conditions, united to the uncertainties associated to nodal demands and pseudo measurements, restrict the validity of the results obtained by classical distribution state estimation approaches. In this sense it is feasible to affirm that for distribution systems with these characteristics, it is not viable to obtain simultaneously both types of results, operative configuration and electrical parameters. A similar conclusion has previously been presented in [1], where the authors indicate that traditional block-organized state estimation procedures are very frequently of limited use, particularly in situations where the state of some switching devices is unknown (e.g. distribution systems).

To solve the configuration problem, in [2] the authors suggest using the state estimator to identify the changes of state of the switching devices (i.e. changes in the operative configuration), however this is only possible if the initial state estimation has been sufficiently precise, but for this requisite is necessary to start from a correct operative configuration, and this aspect is not guaranteed. In [3], a topology processor is developed inside the state estimation scheme. The results of the initial state estimation are used to correct the inputs of the topology processor by means of a feedback loop. In [4], binary variables are used to model the state of switching devices for a state estimator based on the weighted least squares procedure, also fuzzy theory is used to model the nodal loads of the network.

To solve the identified problem, this work proposes to initially obtain the operative configuration of the MV feeders and afterwards its electrical parameters (nodal voltages, power flows, etc). In this order it is also possible to have the chronological data of operation of the feeders, independently of having enough information to execute the state estimation. The chronological data is of vital importance for the applications related to the supervision of the continuity of energy supply and the calculation of quality of service penalties. Using this information, outages could quickly be detected and located, facilitating the displacement of crews and the restoration of service, with the correspondent improvement of the global quality of service of the system.

Because of the logistical limitations previously explained in the majority of cases it is not possible to infer the operative configuration in real time, however the costs associated to the quality of service penalties pressure the utilities to reduce the time of inference to the minimum feasible. To overcome the logistical problem it is necessary to continuously follow all the variables involved in the process, not only those available in real time (seconds), but also those activated in the extended real time (minutes), in this way a minimum time of inference could be achieved. It Is important to highlight that this requisite implies monitoring a through a dynamic time window

To attain this objective, a methodology capable of handling and reduce the uncertainties involved in the process must be developed. This can be achieved by means of integration of the data supplied by:

1. SCADA: magnitudes of fault currents and active and reactive power supplied to the MV feeders.
2. AMR reports: available (in Latin America) only for large or vital customers (factories, hospitals, government buildings, etc.)
3. Customers reports: received and processed by TCC and CIS.
4. Crew reports: line inspections, reports of activated fault current indicators, etc.
5. Indexes of quality of service of the customers.
6. Other sources of qualitative information: type and topology of the feeder, weather, maintenance program, etc.

This point has also been identified in [5], where a fuzzy information filter is developed for the integration and consolidation of the data received by SCADA, TCC and AMR systems, with the purpose of implementing an OMS.

In conclusion, it is necessary to develop an inference engine able to obtain the operative configuration of the distribution feeders, in order to meet the double objective of:

1. To serve as the starting point for the state estimation procedure.
2. To improve the quality of service of the system, reducing the total time of outage location.

The solution of this problem is directed to unsupervised protective devices (reclosers, sectionalizers, cutouts), the state of supervised protective devices is assumed to be known.

This paper deals with the first part of this methodology, the analysis and utilization of the data supplied by SCADA, with the purpose of obtaining an estimation of the operative configuration of the MV feeders. The data used consist in the magnitudes of fault currents, obtained from digital protective relays and the active and reactive power flows measured at the beginning of MV feeders.

IV. STATE OF THE ART

Whenever a permanent fault occurs in a feeder, it causes the operation of a protective device and the disconnection of load. Almost immediately, after this event, three types of data are received in the control center by means of SCADA: the type of fault, the magnitudes of fault currents and the variation of the active power flow delivered to the feeder (ΔP). Given that the data supplied by SCADA is available in real time, its use guaranties obtaining results quickly. If these results are conclusive, the inference is finished and a new operative configuration is obtained. In this case it is not necessary to receive more information (e.g. reports of affected customers) or to send crews to inspect the line. The crews can be immediately dispatched to the faulted zone, reducing the restoration time and avoiding a larger deterioration of the indexes of quality of service. Also, the obtained operative configuration can be used to execute a state estimation procedure based on power flow analysis.

Processing the magnitudes of fault currents and the variation of the power supplied to the feeder, implies the consideration of the uncertainties associated with these variables. In the case of the fault currents, the largest uncertainty is introduced by the fault impedance, but also the equivalent impedance of the HV network, the position of the ULTC and the load currents introduce uncertainties that should be considered. On the power flow side, the behavior of nodal demands is the main source of uncertainties. Given the non-stochastic nature of the variables involved, an approach based on fuzzy sets theory is suggested for their analysis. Fuzzy sets theory permits handling uncertainties and inexact information and provides a scientific and mathematical frame for the utilization of vague information, approximate knowledge and subjective judgments based on experience.

Previous approaches have been presented to model the uncertainties related with the analysis of fault currents using fuzzy techniques. In [6] a fault distance membership function is presented, this function was built using fault data obtained from 50 permanent faults registered in the network of a Finnish utility. The authors use this membership function to consider the uncertainty introduced by fault resistance. In [7], a similar approach is used. The difference is, that the membership function presented is built as a function of the calculated fault current. This function possesses parameters that can be adjusted according to the criteria of the users.

For the power flow analysis, uncertainties associated to nodal loads have been managed using fuzzy and probabilistic techniques. In [8] a probabilistic algorithm is presented to model the nodal loads using the average energy consumptions of customers and typical load curves. The results obtained are used by the probabilistic state estimator presented in [3]. In [9], a method based on fuzzy sets is developed to estimate the currents flowing through the branches of the distribution network, the data used consists of the currents measured in the HV/MV substation and load patterns obtained from the knowledge of operators. In [10] a method based on fuzzy arithmetic and probabilistic analysis is presented; the load profiles of customers are converted from probability density functions to fuzzy membership functions, afterwards these functions are combined with the real time measurements in order to obtain an estimation of the nodal loads for every hour. In [11] a fuzzy load allocation model is presented, which uses real time measurements, installed capacity as well as power and energy consumptions to obtain a rough load allocation, then the initial results are corrected using a fuzzy state estimator.

V. METHODOLOGY

In this section, a novel procedure based on fuzzy arithmetic and Fuzzy Inference Systems (FIS) is used to calculate the fuzzy fault currents on every node of the feeder under analysis. The crisp fault currents obtained from the digital relays are compared with every fuzzy fault current (calculated for the correspondent type of fault determined by the relays) and a first operation index ($\boldsymbol{I_k^I}$) is obtained for every protective device $\boldsymbol{k}$.

Another procedure based on power flow analysis is used to estimate the power flow at every protective device $\boldsymbol{k}$. The power flow values are fuzzified and afterwards compared to the value of ΔP obtained from SCADA. From these comparisons, a second operation index ($\boldsymbol{I_k^P}$) is obtained for every protective device $\boldsymbol{k}$.

Both operation indexes are consolidated using a second FIS, and a final index ($\boldsymbol{I_k^F}$) is obtained for every protective device $\boldsymbol{k}$. The devices with highest $\boldsymbol{I_k^F}$ are selected as candidates for operation. In this way, a first estimation of the operative configuration is obtained.

A. Calculation of fault currents using fuzzy arithmetic

Any crisp theory can be fuzzified by generalizing sets within that theory of fuzzy sets. In particular, it is possible to introduce the concept of fuzzy numbers as the numerical representation of an imprecise knowledge about numerical quantities. Next, traditional arithmetic can be extended in order to deal with computation of fuzzy numbers [12]. Complete and thorough definitions of general fuzzy numbers and descriptions of their properties and applications can be encountered in [14].

The main problem computing fuzzy functions arises calculating algebraic expressions containing multiple occurrence of the same fuzzy variable. In this case, different occurrences of the same variable will be considered as different variables, and the resulting fuzzy number will be less sharp than it should be [12], i.e. the results will have “excessive uncertainty”. To solve this problem there are several approaches, the easiest is to simplify formulas, with the objective that the independent variables appear only once, then fuzzy arithmetic can be applied without problems. In case this is not possible, the correct calculation can be done using directly the extension principle or the fuzzy weighted averages algorithm and its variations [12]-[13].

The calculation of fault currents is a well known procedure, complete studies can be found in [15]. Generally, for distribution systems it is assumed that the positive and negative sequence impedances are equal, these impedances are calculated using the symmetrical components method. This assumption simplifies the classical equations used for the calculation of fault currents. For the description of the procedure developed, the equation of the fault current for a single phase to ground fault is used (1).

$$\overrightarrow{I_f^{\phi-G}} = \frac{3\overrightarrow{U_{pf}}}{2\overrightarrow{Z_T^{(+)}} + \overrightarrow{Z_T^{(0)}} + 3\overrightarrow{Z_f}} \tag{1}$$

In this equation U_{pf} is the pre-fault voltage at the fault point and $Z_T^{(0)}$ and $Z_T^{(+)}$, are the total (zero and positive) sequence impedances viewed from the fault point. In distribution systems, Z_T takes into account the combined effect of the equivalent impedance of the system viewed from the MV bus (Z_{eqMV}) and the impedance of the MV feeder (Z_d).

It is well known that of all the variables involved in the fault current calculations, the most uncertain and influential is the fault impedance (Z_f). However, the uncertainties associated to the remaining variables also affect (to a lesser extent) the final value of the fault current, this influence increases for faults located closer to the HV/MV substation. One of these uncertainties is the position of the ULTC, which affects the value of Z_{eqMV}.

To obtain a closer representation of the majority of possible fault conditions, it is necessary to consider the uncertainties associated to these variables and especially to Z_f. One way to achieve this objective is modeling the variables in the fault current equations as fuzzy numbers and evaluating these equations using the fuzzy arithmetic operations defined in the literature [14]. The fuzzy fault currents obtained consider a greater spectrum of possibilities for the values of the fault currents, in comparison to those derived from deterministic calculations.

For the computation of the fuzzy fault current in node $\boldsymbol{i}$ ($\underline{\boldsymbol{I_i}}$), the variables Z_{eqMV}, U_{pf} and Z_f are treated as triangular fuzzy numbers and Z_d is considered a crisp number. In this point it is important to highlight that for the ease of computation the resistive component of Z_{eqMV} is neglected, also Z_f is treated as a pure resistance and only the magnitude of U_{pf} is used in the calculation. The fuzzy variable $\underline{\boldsymbol{Z_{eqMV}}}$ is modeled considering the effect of the equivalent impedance of the HV network and ULTC position (n_s), for this are used the minimum and maximum values of short circuit power available at the HV bus and the expected variations of n_s (e.g. ±10% of the nominal value n_{s0}).

In the calculation of $\underline{\boldsymbol{Z_f}}$ a Fuzzy Inference System (**FIS$_1$**) is used to obtain an approximate idea of the possible values of $\underline{\boldsymbol{Z_f}}$ as a function of the weather and type of soil. The base of rules in **FIS$_1$** is defined using intuitive criteria, for example it is acceptable to suppose that the possible value of Z_f for a ground fault occurred during a sunny day in an urban zone is larger than the one corresponding to a ground fault occurred during a rainy day in a rural zone. In **FIS$_1$** nine rules are evaluated using conventional max-min composition and triangular membership functions for the antecedent and consequent. The output of **FIS$_1$** is a crisp number, this number is used as the central value of the triangular fuzzy number $\underline{\boldsymbol{Z_f}}$, its interval of confidence is defined around this central value. The objective of **FIS$_1$** is reducing the uncertainty associated to $\boldsymbol{Z_f}$ to an interval narrower than the original.

As has previously been explained, when a fault occurs, the magnitude of the fault currents and the type of fault observed is obtained from the digital relays and reported to the control center by SCADA. To obtain a crisp fault current (I_F) that can be compared with $\underline{\boldsymbol{I_i}}$, it is necessary to subtract the last load currents (reported by SCADA before the fault happened) from the fault currents reported by the relays.

Afterwards, the value of I_F is compared with $\underline{\boldsymbol{I_i}}$, the results are the grade of membership of I_F for every fuzzy set $\underline{\boldsymbol{I_i}}$, this grade of membership is represented as $\boldsymbol{I_i^I}$. Here it is important to remember that the fuzzy numbers are a subset of the general fuzzy sets. The described procedure is showed graphically in Fig. 1.

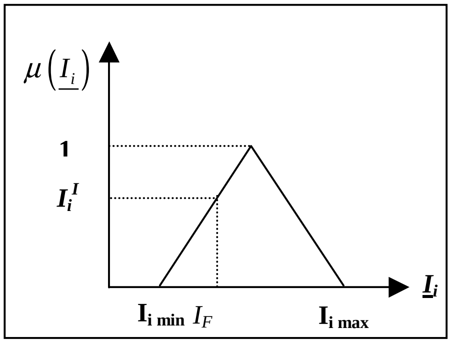

Figure 1

Before continuing it is essential to define two terms, the protective zone $\boldsymbol{m}$ and the protective device $\boldsymbol{k}$. The protective zone $\boldsymbol{m}$ is the group of nodes $\boldsymbol{i}$ located between consecutive protective devices. The protective device $\boldsymbol{k}$ is the responsible one for the protection (disconnection) of the zone $\boldsymbol{m}$. In this point possible coordination errors or malfunctioning of protective devices are not considered.

Once every $\boldsymbol{I_i^I}$ is calculated, its maximum value for every protective zone ***m*** is selected. This value is the operation index of the protective device ***k*** based on the fuzzy fault current criterion and is represented by $\boldsymbol{I_k^I}$ (2).

$$I_k^I = \max_m \left(I_i^I \right) \tag{2}$$

B. Estimation of the power flow at every protective device k.

As was pointed out in section IV, when a fault occurs, the load disconnection caused by the operation of protective devices is a datum that should be used to obtain further information about the operative configuration of the MV feeder.

In many practical situations, knowing the value of ΔP is insufficient to infer with certainty which protective device has operated. However, if ΔP is compared with the active power flow expected at every protective device ***k***, a second operation index $\boldsymbol{I_k^P}$ can be found. The expected power flow must be calculated using the load condition previous to the occurrence of ΔP. Here, the problem is to calculate the power flow at every protective device, because the nodal loads are mostly unknown.

To solve this problem, the iterative method implemented in [16] for demand estimation at MV/LV level is used.

1. Initially, a first estimation of the hourly nodal loads is made, the results are called "power reference vector". The "power reference vector" is obtained from the typical load curves and power factors of customers and the monthly (or bimonthly) energy consumptions of the customers connected to every MV/LV substation. The "power reference vector" is calculated off-line for different load conditions and stored in a data base. Using the "power reference vector", the active and reactive power measured at the beginning of the feeder (P_m, Q_m) are allocated between every MV/LV substations (P_i, Q_i).

2. Using the first load allocation, the active and reactive losses of the feeder (P_L, Q_L) are calculated by means of a power flow software. The nodal voltages (U_i) obtained from the power flow software are used to correct P_i and Q_i . In this way the dependency of the load with respect to the voltage is considered, this correction can be made using any of the demand models proposed in the literature (e.g. the universal demand model). As a result of this procedure, a "corrected power reference vector" (P_{icorr}, Q_{icorr}) is obtained. This correction is important especially in extensive feeders like those existent in Latin American distribution systems. Also the losses in the copper and iron (P_{Fei0}, P_{Cui0}) computed in every MV/LV substation (for nominal capacity S_N and nominal voltage U_N) are adjusted in each iteration, by means of (3) and (4).

$$P_{Fe_i}^{(j)} = P_{Fe_{i0}} \frac{U_i^{(j)}}{U_N} \tag{3}$$

$$P_{Cu_i}^{(j)} = P_{Cu_{i0}} \frac{\left(S_{icorr}^{(j)} \right)^2}{S_N{}^2} \tag{4}$$

3. The "corrected power reference vector", representing the total power viewed from the MV side is calculated using (5).

$$S_{MTi}^{(j)} = P_i^{(j)} + jQ_i^{(j)} = \left\{ P_{Fe_i}^{(j)} + P_{Cu_i}^{(j)} + P_{icorr}^{(j)} \right\} + jQ_{icorr}^{(j)} \tag{5}$$

4. To begin the next iteration P_L and Q_L are subtracted from P_m and Q_m respectively, the resulting value is allocated again to every MV/LV substation using the "corrected power reference vector". This procedure is repeated iteratively (6)-(7) until the active and reactive power flows at the beginning of the feeder are equal to P_m and Q_m. The convergence is quickly reached after a few iterations, satisfying the time requisite necessary for applications designed for continuous monitoring of the MV feeders.

$$P_i^{(j+1)} = \frac{P_i^{(j)}}{\sum_{i=1}^{n} P_i^{(j)}} \left(P_m - P_L^{(j)} \right) \tag{6}$$

$$Q_i^{(j+1)} = \frac{Q_i^{(j)}}{\sum_{i=1}^{n} Q_i^{(j)}} \left(Q_m - Q_L^{(j)} \right) \tag{7}$$

The final results of this procedure are the estimated power flows at every protective device ***k***. These results are highly accurate. However, in order to consider the uncertainties associated to the initial "power reference vector", a fuzzy model is used. The final results are used as the central values of triangular fuzzy numbers that model the power flow in every protective device ***k*** ($\underline{\boldsymbol{PD_k}}$). The support of every fuzzy number is chosen according to the criteria of users and reliability of the data used for the calculation of the initial "power reference vector".

When ΔP is detected, $\underline{\boldsymbol{PD_k}}$ is calculated for the load condition previous to the occurrence of ΔP. Afterwards, ΔP is compared to the calculated $\underline{\boldsymbol{PD_k}}$, This is demonstrated in Fig 2. The result of this comparison is the degree of membership of ΔP for every $\underline{PD}_k$. This value is the operation index of every protective device k based on the ΔP criterion and is represented by (I_k^P).

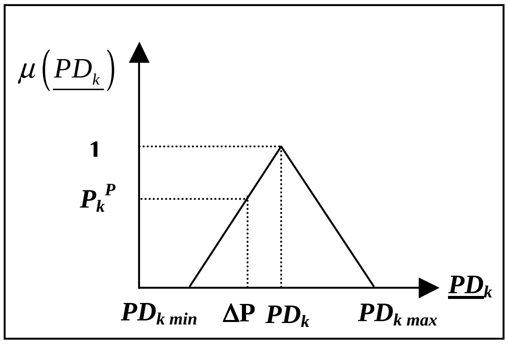

Figure 2

Here it is important to mention that in a practical situation it is necessary to define a minimum value of ΔP to start the inference process, this in order to consider the difference between operation of protective devices and normal load variations, switching of large loads, etc. Given that this method is intended to supervise the MV feeders in real time, the objective is to continuously execute the power flow based procedure previously described, to obtain an approximate idea of the nodal loads for any time. In case that ΔP is larger than ΔP_{MIN} the inference process must be started. A criterion to define ΔP_{MIN} is provided in [17], where a value of 150 KVA per phase is selected and used for any load condition. However this value should depend on the load level of the feeder, its topology and location of protective devices. A possible option could be the nominal power of the smallest MV/LV substation.

C. *Identification of the operated protective device k*

Using the values of I_k^I and I_k^P, a final operation index is obtained for every protective device k. The protective devices with the highest operation indexes are selected as the candidates of having changed their state. For the computation of the final operation index a second Fuzzy Inference System (**FIS**$_2$) is used, their inputs are the individual operation indexes.

The FIS is built using conventional max-min composition, gaussian membership functions for the antecedent (fuzzification) and triangular membership functions for the consequent. The defuzzification is performed using the centroid method. The flexibility of the FIS theory permits modifying this operations according to the criteria of the users. The rule base is developed using intuitive deductions about the possibility of operation of every protective device, e.g.:

"**If** I_k^I is high **and** I_k^P is high **then** the I_k^F is high." (8)
"**If** I_k^I is high **and** I_k^P is cero **then** the I_k^F is low." (9)
"**If** I_k^I is low **and** I_k^P is high **then** the I_k^F is low-medium." (10)

The remaining rules are constructed using similar reasoning, a total of nine rules are defined using two linguistic terms for the antecedent (low and high) and four for the consequent (low, low-medium, medium-high and high), Fig. 3 shows a diagram of the implemented FIS.

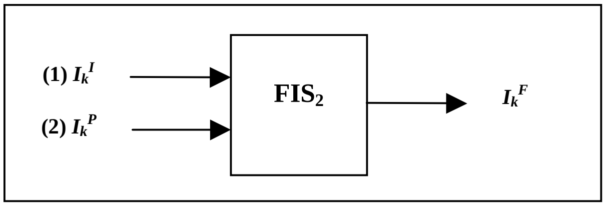

Figure 3

The outputs of the FIS are arranged according to their values, those protective devices with the highest final possibility of operations are selected as candidates of having changed their state. For this selection a minimum of operation index of 0.50 is defined, but it can be adjusted according to the system under analysis. Another advantage of the FIS theory is that the membership functions can be tuned using a neuro-fuzzy model, this is important in order to adjust the inference procedure using the results obtained. Also the weights of the rules of inference can be tuned.

Here it is also important to highlight that the inference presented in this work is intended to be realized a few seconds after the devices have operated, this means that as time increases more information is available, e.g. outage reports from customers, inspections made by the crews, etc. This information should also be dynamically integrated to consolidate the final possibility of operation. Further research is intended in this direction.

VI. RESULTS

The methodology was implemented in Visual Fortran, Visual Basic 6.0 and Matlab 5.3, and tested on a real distribution feeder from the city of San Juan, Argentina. Three different results are presented here for faults simulated in the feeder NAC-NOR from HV/MV substation ANGACO. This feeder has 178 nodes and 53 protective devices, its load characteristic is manly residential. The faults were simulated for a peak load condition (21:00 hours), with P_m=1222.1 kW and Q_m=515.94 kVAR. The feeder analyzed is shown in Fig.4.

Case1:

A single phase to ground fault was simulated in a point closer to the HV/MV substation, specifically in node 556235520562, the protective device associated is F1326, and the input data are I_{FM}=600A and ΔP=710 kW.

In this case the methodology identifies accurately the protective device operated, this can be deduced observing the large differences between the operation indexes shown in Table I. The reason of these differences is that the ΔP detected is unique, no other protective device has a similar power flow, consequently, their I_k^P is cero and (10) is applied. However, the value of I_k^I for F1312 and R021 is high, this is a result of their location with respect to F1326 and the HV/MV substation.

TABLE I
RESULTS OF INFERENCE FOR CASE 1

Prot. device k	I_k^I	I_k^P	I_k^F
F1326	0.7995	0.6627	0.8079
F1312	0.8358	0	0.5018
R021	0.7879	0	0.5018

Case 2.

In this case a single phase to ground fault is simulated in a point far from the HV/MV substation, specifically in node 563813526629, the protective device associated is F1862, and the input data are I_{FM}=160A and ΔP=8kW. This low value of ΔP was selected to show the promising results obtained by this approach.

In this case the methodology identifies two protective devices as candidates, F1320 is the device with the highest operation index and F1862 is the second. However, as can be observed in Fig. 4, both devices are located in the same zone, this is a good signal for the operator, because the possibly affected zone of the feeder has been identified, a phone call from a customer or a report from the crews could help to identify the operated device. The reason for the selection of two candidates is that the value of ΔP is common to various devices. However, as their correspondent I_k^I are low, this information helps to discriminate those devices located closer to the HV/MV substation, that have similar I_k^P but lower I_k^I (11). The results for this case are shown in Table II.

TABLE II
RESULTS OF INFERENCE FOR CASE 2

Prot. device k	I_k^I	I_k^P	I_k^F
F1320	0.9605	0.6507	0.7987
F1862	0.5342	0.5833	0.5933

Case 3:

In this case a single phase to ground fault is simulated in a point located in the middle of the feeder, specifically in the node 557205525911, the protective device associated is F1677 and the input data is I_{FM}=280A and ΔP=170kW.

The methodology identifies two protective devices as candidates, F1677 is the device with highest operation index according to (9) and F2403 is the second. The results are presented in Table III.

TABLE III
RESULTS OF INFERENCE FOR CASE 3

Prot. device k	I_k^I	I_k^P	I_k^F
F1677	0.789579	0.810597	0.8923
F2403	0.87943	0.27239	0.6672

From the cases studied it can be concluded that the performance of the methodology depends widely on the value of P_k^P. However, the nodal load estimation implemented in this work obtains excellent approximations of the power flows in the protective devices, ensuring a precise computation of P_k^P.

VII. CONCLUSIONS

The fuzzy short circuit calculation implemented in this work is a suitable methodological frame for the analysis of the uncertainties associated to the fault currents in MV distribution feeders, especially in those with low monitoring capabilities. Another possible application for this methodology could be the coordination of protections in distribution systems.

The power flow based estimation of the nodal loads is a powerful tool suitable for real time applications. The operation indexes obtained from this analysis have a decisive influence on the final results. The reason is that the interval of confidence of the power flows obtained at the protective devices is narrow, given the high precision of the computations, whose uncertainties mainly depend on the initial “power reference vector”.

The integration of both criteria (I_k^I and I_k^P) gives excellent results, considering that this application runs a few seconds after the detection of the fault currents and ΔP. The obtained results are promising, because in the worst case, the operator obtains an idea of the possibly affected zone of the feeder.

The results obtained can be improved in the extended real time by means of a dynamic integration of the trouble calls received from the customers and the AMR devices and repair crew reports. Furthermore, the qualitative and statistical information of the MV feeders should be considered. Subsequent models should analyze the presence of distributed generation and its influence on the results. Further research in this direction is intended.

VIII. ACKNOWLEDGMENT

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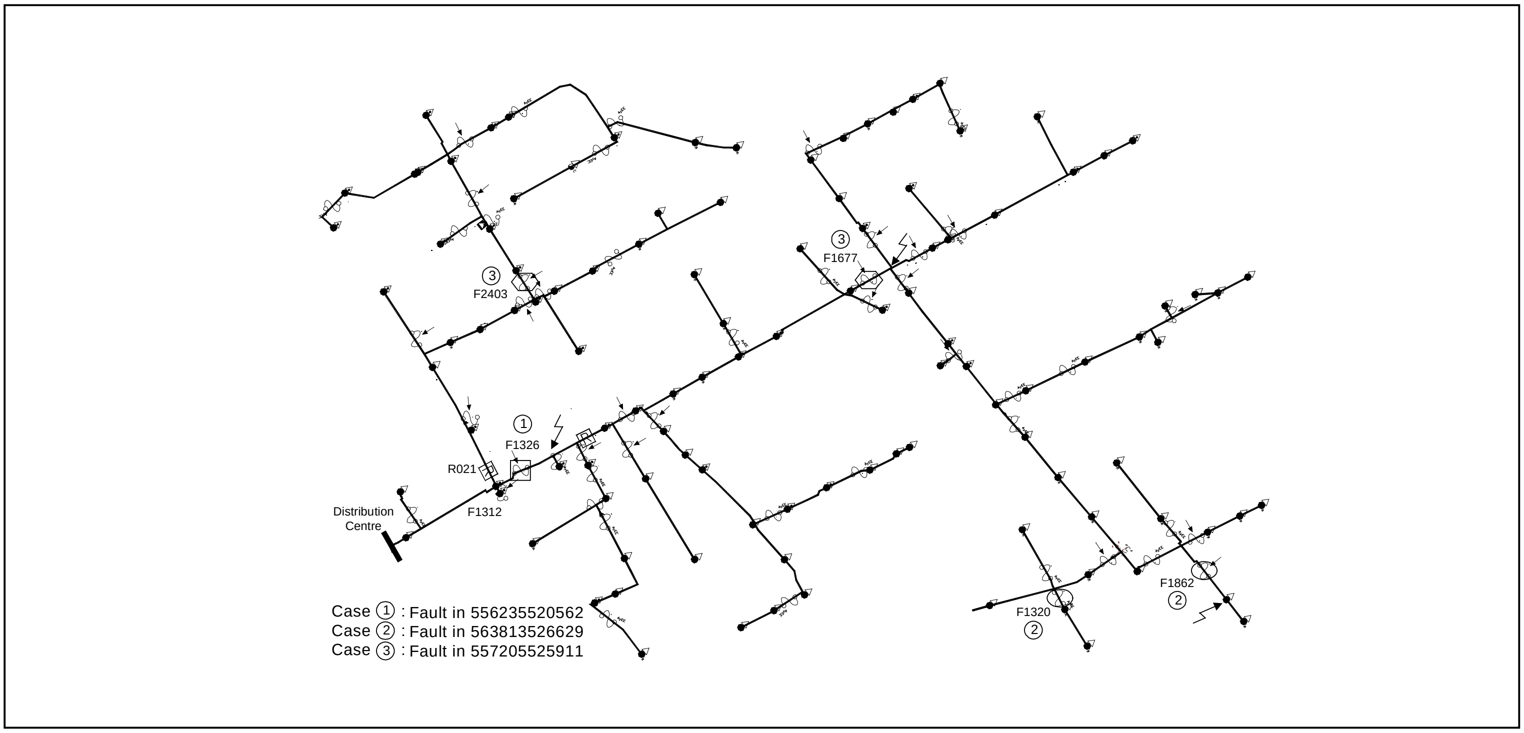

Figure 4

IX. REFERENCES

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