# Inference of Operative Configuration of Distribution Networks Using Fuzzy Logic Techniques-Part II: Extended Real-Time Model

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***Abstract*— In Part I of this two-paper set, the inference of the operative configuration (OC) in real-time, has been analyzed. This Part II presents an approach to infer the OC in extended real-time, by proposing a mathematical model based on fuzzy relation equations and fuzzy abductive inference. This model sets a methodological framework to integrate the real-time data from SCADA, the qualitative data supplied by expert operators and the extended real-time data (customer trouble calls) from CIS. In this way, all the knowledge available is used, and the results are dynamically improved as more data are received. At every stage, all the plausible alternatives of solution are calculated and a complete outlook of possible options is obtained. The results from testing the methodology on a real distribution feeder are presented and discussed.**

***Index Terms*—Fuzzy sets, fuzzy logic, fuzzy systems, distribution networks, diagnostic reasoning, fault diagnosis.**

## I. NOMENCLATURE

CIS: Customer Information System.
CTC: Customer Trouble Call.
ERT: Extended real-time (minutes).
HV/MV SE: High Voltage/Medium Voltage Substation.
QS: Quality of Service.
RT: Real-time (seconds).
SCADA: Supervisory Control And Data Acquisition.

## II. INTRODUCTION

THE increasing levels of QS demanded by regulatory agencies and customers, have encouraged Latin American distribution utilities to improve their outage management and operation strategies as a means to reduce economic penalties. In this context, the identification of the OC plays an important role. The OC is defined as the state (closed/open) of the protective and switching devices installed on the medium voltage distribution network. In [1], the first part of a methodology aimed at solving the OC problem using RT data and qualitative expert knowledge was introduced. In this paper, the second part of that approach is proposed.

Traditionally, the solution of the OC problem has depended mostly on CTCs (trouble call analysis) and feeder inspections, because scarce RT data have been available at the distribution level [2]-[10]. However, CTCs may not be received immediately after the outages have occurred [11]. Furthermore, various CTCs or feeder inspections may be necessary to locate the operated devices. Other difficulties arise from the susceptibility of distribution networks to natural phenomena (e.g., multiple outages caused by storms), which may imply additional requirements of personnel and resources. These characteristics tend to augment the duration of outages up to unacceptable levels, with the corresponding deterioration of QS and economic penalties upon the utilities. In recent years, distribution SCADA has become accessible, at least at the HV/MV SE level, providing important RT data for several applications. However, the coverage of distribution SCADA is generally insufficient to obtain an accurate assessment of the OC using only RT data [11]. In this sense, it has been noted that a convenient strategy to infer the OC is to integrate the data supplied by CIS and distribution SCADA [11]-[17]. In this way, their individual deficiencies are overcome and their potentialities are fully exploited. To achieve this goal, this work proposes a diagnostic model based on fuzzy relation equations and fuzzy abductive inference. This model is intended to refine the initial solution obtained in Part I [1].

Diagnosis is a problem in which, given a set of effects (manifestations, symptoms), the diagnostician must explain why those findings are present. Problems of this kind are very common: they include diagnosing the symptoms of a patient in medicine, localizing a fault in a circuit, and other occurrences [18]. The identification of the OC in ERT is a fault diagnosis problem in which, given the CTCs, the objective is to identify the operated protective devices. To solve this problem, it is also necessary to consider the additional information available (RT results, cause-effect relationship among protective devices and customers groups, etc).

The fault diagnosis problem has been addressed by various kinds of techniques, depending on the type of failure to be detected or isolated and on the available knowledge. Among these techniques, fuzzy relation-based models are particularly interesting for this work because they are suitable to handle uncertainty in a non-probabilistic way, i.e., they do not presuppose the ability to quantify conditional probabilities nor does it assume that prior probabilities of fault modes are available [24]. This is an important feature because in many

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distribution networks there are not enough data to calculate accurately the prior probabilities of fault occurrences used in other diagnostic models [26].

Fuzzy relation-based models are an approach to abductive reasoning, which is defined as the process of reasoning from principles to facts under uncertainty by using quantitative measures. Abductive reasoning is conducted as follows: "M is true if D is true, and if M is observed, then there are some reasons to think that D may be true". This view contrasts with deductive reasoning, which is the process of inferring a conclusion from observables such that, if the premises are known with certainty, then the conclusion is certain. Besides, it contrasts with inductive reasoning, which is the process of reasoning from specific examples to general principles. It is thus noted that abduction preserves explanation, deduction preserves truth and induction preserves consistency [27].

Fuzzy relation-based models describe the association of causes (disorders, diseases, etc) and effects (manifestations, symptoms, etc) by means of a fuzzy relation. Then, possible causes from a set of observed effects are identified after solving a fuzzy relation equation. A fuzzy relation allows the modeler to weigh the association between a disorder (or a set of simultaneous disorders) and a manifestation (or a set of manifestations). In addition, a fuzzy set represents the levels of presence (intensity, or certainty of presence according to each case) of manifestations [23].

Among the fuzzy relation-based models to solve diagnostic problem proposed in the literature, fuzzy abductive inference models are particularly attractive because they use an efficient method to obtain the combinations of candidate disorders for the given manifestations [28]-[31]. This method is based on the parsimonious set covering theory (PSCT) [18]-[22]. However, these models deal with diagnostic problems in which the fuzzy relation and the fuzzy set of manifestations represent the levels of intensity of gradual manifestations. Therefore, they are more suitable for applications related -for instance- to medical diagnosis, chemical process, etc.

The identification of the OC in ERT is a diagnostic problem in which the fuzzy relation and the fuzzy set of manifestations must represent the certainty of presence of binary manifestations. In this sense, the model proposed in [23]-[25], is the most appropriate one, and is used here as mathematical framework to infer the OC in ERT. A detailed description and the solution methodology are presented next.

## III. MATHEMATICAL MODEL

An example of a typical radial MV distribution feeder with a low degree of monitoring and control in RT is shown in Fig.1 [9]. The protective devices ($d_1$-$d_7$) and the protected zones or groups of customers ($m_1$-$m_7$) are associated by means of a cause-effect relationship. This means that the operation of a protective device causes outages on the zones downstream from its location. Therefore, it also causes the CTCs received from these zones. This relationship can be represented by a fuzzy relation-based model, where the disorders are the state of the $n$ protective devices, and the manifestations are the state of the $n$ protected zones (groups of customers) of the feeder.

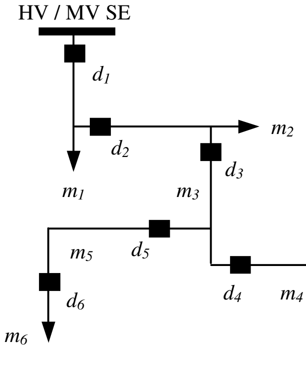

Fig.1. Example of a radial MV distribution feeder with low level of supervision and control in RT.

### A. Disorders and manifestations

The disorders are modeled by means of the crisp set **D** (1), where the element $d_i$ represents the state of the $i$-th protective device. The manifestations are modeled by means of the crisp set **M** (2), where the element $m_j$ represents the state of the $j$-th zone or group of customers of the feeder.

$$\mathbf{D} = \{d_1 \quad d_2 \quad \dots \quad d_n\} \tag{1}$$

$$\mathbf{M} = \{m_1 \quad m_2 \quad \dots \quad m_n\} \tag{2}$$

The *"more-or-less" certainly present* and *"more-or-less" certainly absent* manifestations are modeled by the type-1 fuzzy sets $\boldsymbol{M}^{+}$ (3) and $\boldsymbol{M}^{-}$ (4), respectively. The grades of membership of the fuzzy sets $\boldsymbol{M}^{+}$ and $\boldsymbol{M}^{-}$ model the certainty of presence and absence of a binary manifestation, respectively [23]. These sets satisfy the requirement $\boldsymbol{M}^{+} \cap \boldsymbol{M}^{-} = \varnothing$, which means that it is not possible to be somewhat certain both on the presence and on the absence of the same manifestation, simultaneously. The complement of fuzzy set $\boldsymbol{M}^{-}$ ($\bar{\boldsymbol{M}}^{-}$) models the *"more or less" possibly present* manifestations.

$$\boldsymbol{M}^{+} = \frac{\mu_{m_1}^{+}}{m_1} + \frac{\mu_{m_2}^{+}}{m_2} + \cdots + \frac{\mu_{m_n}^{+}}{m_n} \tag{3}$$

$$\boldsymbol{M}^{-} = \frac{\mu_{m_1}^{-}}{m_1} + \frac{\mu_{m_2}^{-}}{m_2} + \cdots + \frac{\mu_{m_n}^{-}}{m_n} \tag{4}$$

$$\bar{\boldsymbol{M}}^{-} = \frac{1-\mu_{m_1}^{-}}{m_1} + \frac{1-\mu_{m_2}^{-}}{m_2} + \cdots + \frac{1-\mu_{m_n}^{-}}{m_n} \tag{5}$$

The pair $\boldsymbol{M}^{+}$ and $\bar{\boldsymbol{M}}^{-}$ satisfies the usual duality between what is *"more-or-less" certain*, i.e., *necessarily true*, and what is *"more-or-less" possibly true*. The certainty levels and their meanings are:

- $\mu_{m_j}^{+} = 1$ and $\mu_{m_j}^{-} = 0$ indicate that manifestation $m_j$ is certainly present. This means that, on the basis of the CTCs received, it is certain that an outage is affecting all the customers of zone $m_j$.

- $0 < \mu^+_{m_j} \leq 1$ and $\mu^-_{m_j} = 0$ indicate that manifestation $m_j$ is present but with some uncertainty. This means that, on the basis of the CTCs received, it is uncertain whether an outage is affecting all the customers of zone $m_j$ or not.
- $\mu^+_{m_j} = 0$ and $\mu^-_{m_j} = 0$ indicate complete ignorance on $m_j$. This means that no CTCs has been received from zone $m_j$. Therefore, it is absolutely unknown whether an outage is affecting zone $m_j$ or not.

The meaning of presence or absence of a manifestation is related to the presence or absence of CTCs, which confirm that an outage is affecting all the customers of zone $m_j$. In this way, the uncertainty associated to CTCs is taken into account, and this is a necessary condition because the received CTCs may be related to a LV problem instead of to a MV outage. In this work, only outages caused by the operation of MV protective devices (reclosers, sectionalizers, branch fuses) are analyzed. This decision is based on an evaluation of priorities, i.e., the number of customers affected and the energy not supplied is greater in MV outages than in LV problems. Hence, in a multiple faults situation where independent MV and LV outages are present, the operators firstly take care of MV outages, leaving LV problems for a subsequent stage.

The operators, reasoning on their own criteria, choose the certainty levels of (3) and (4). These levels depend mostly on the type (residential, business, industrial, etc) and number of customers who made calls, and on the description of the suspected problem (if available). It may be convenient to assign linguistic qualifiers to these certainty levels in order to facilitate the communication among operators, crews and customers. In this work, the qualifiers suggested in [24] are used. These qualifiers are presented on Table I.

TABLE I

| Linguistic Qualifier | $\mu^+_{m_j}$ | $\mu^-_{m_j}$ |
|---|---|---|
| Certain | 1.00 | 0.00 |
| Almost certain | 0.70 | 0.00 |
| Likely | 0.30 | 0.00 |
| Unknown | 0.00 | 0.00 |

### *B. Cause-effect relationship*

The cause-effect relationship between disorders and manifestations is modeled by matrices $\mathbf{\mu C^+}$ (5) and $\mathbf{\mu C^-}$ (6). The elements of $\mathbf{\mu C^+}$ model the relationship among all the disorders and their *"more-or-less" certainly caused* manifestations. The elements of $\mathbf{\mu C^-}$ model the relationship among all the disorders and their *"more-or-less" impossibly caused* manifestations. Here, $\mu c_{ij}^+$ and $\mu c_{ij}^-$ express the certainty levels of presence and absence of manifestation $m_j$ when only disorder $d_i$ is present, respectively. A matrix arrangement has been selected conveniently to facilitate the explanation of the solution procedure. Formally, as explained in [23]-[25], the $i$-th row of $\mathbf{\mu C^+}$ is the fuzzy set of manifestations that are *"more-or-less" certainly present* when only disorder $d_i$ is present ($\mathbf{M}(\boldsymbol{d_i})^+$). The $i$-th row of $\mathbf{\mu C^-}$ is the fuzzy set of manifestations which are *"more-or-less" certainly absent* when only disorder $d_i$ is present ($\mathbf{M}(\boldsymbol{d_i})^-$).

$$\mathbf{\mu C^+} = \begin{bmatrix} \mu c_{11}^+ & \mu c_{12}^+ & \cdots & \mu c_{1n}^+ \\ \mu c_{21}^+ & \mu c_{22}^+ & \cdots & \mu c_{2n}^+ \\ \vdots & \vdots & \ddots & \vdots \\ \mu c_{n1}^+ & \mu c_{n2}^+ & \cdots & \mu c_{nn}^+ \end{bmatrix} \tag{5}$$

$$\mathbf{\mu C^-} = \begin{bmatrix} \mu c_{11}^- & \mu c_{12}^- & \cdots & \mu c_{1n}^- \\ \mu c_{21}^- & \mu c_{22}^- & \cdots & \mu c_{2n}^- \\ \vdots & \vdots & \ddots & \vdots \\ \mu c_{n1}^- & \mu c_{n2}^- & \cdots & \mu c_{nn}^- \end{bmatrix} \tag{6}$$

The certainty levels and their meanings are:

- $\mu c_{ij}^+ = 1$ and $\mu c_{ij}^- = 0$ altogether mean that manifestation $m_j$ is always present when only disorder $d_i$ is present.
- $0 < \mu c_{ij}^+ \leq 1$ and $\mu c_{ij}^- = 0$ express the uncertainty level on the presence of manifestation $m_j$ when only disorder $d_i$ is present, i.e., it is a grading of the uncertainty of causation.
- $\mu c_{ij}^+ = 0$ and $\mu c_{ij}^- = 1$ indicate that $m_j$ is never present when only disorder $d_i$ is present. This does not mean that $d_i$ prevents $m_j$ from occurring (when other disorders are also present), but only that $d_i$ cannot cause $m_j$.

The elements of $\mathbf{\mu C^+}$ are computed with the T2-FLS proposed in [1]. Here, it is necessary to recall that, in order to select the candidate devices, a decision condition has been chosen for the RT model ($\mu c_{iC}^+ > 0.5$). However, other decision conditions may be selected as well, e.g., $\mu c_{iL}^+ > 0.5$ or $\mu c_{iU}^+ > 0.5$. Therefore, a general decision condition can be defined by (7), where, $\mu c_{iL}^+ \leq \mu c_{iD}^+ \leq \mu c_{iU}^+$ and $0 \leq \mu c_{imin}^+ \leq 1$. In this work, $\mu c_{iD}^+ = \mu c_{iC}^+$ and $\mu c_{imin}^+ = 0.5$.

$$\mu c_{iD}^+ \geq \mu c_{imin}^+ \tag{7}$$

$\mu c_{iD}^+$ plays a double role. From the RT viewpoint, $\mu c_{iD}^+$ represents the certainty of operation of the $i$-th protective device [1]. However, from the ERT perspective $\mu c_{iD}^+$ represents a causality relation between the operation of the $i$-th protective device and the reception of CTCs from its protected zones. The ERT interpretation is based on the following approximate reasoning: the more certain the operation of a protective device, the more certain the reception of CTCs from its protected zones. Besides, the value of $\mu c_{ij}^+$ is the same for all the $m$ zones downstream the $i$-th protective device (8). This simplification is founded on the following analysis: as the outage duration increases, CTCs will be received from all the affected zones (but with an unknown order). Therefore, a relation of certainty exists among the operation of the $i$-th protective device and the reception of CTCs from the zones located downstream. This relationship also justifies the adoption of the model proposed in [23]-[25].

$$\mu c_{i1}^+ = \mu c_{i2}^+ = \ldots = \mu c_{im}^+ = \mu c_{iD}^+ \quad i = 1,\ldots,n \tag{8}$$

The values of $\mu c_{ij}^+$ are dynamic and they depend on the data available [1]. The elements of $\mathbf{\mu C^-}$, on the contrary, are defined according to the initial configuration of the feeder, which is assumed as known. The initial values of $\mu c_{ij}^{-}$ are zero or one and they change only if reconfiguration is executed. $\mu c_{ij}^{-} = 1$ if $m_j$ is never present when only disorder $d_i$ is present and $\mu c_{ij}^{-} = 0$ for any other case.

## IV. METHODOLOGY OF SOLUTION

The ERT model is solved with a procedure based on the PSCT, which is used here only as a computation algorithm to generate the solution hypotheses. The notion of causality proposed by the PSCT is not used in this work. The more general proposal of [23]-[25] is used instead. The procedure begins with the formulation of a crisp diagnosis problem, where the uncertainties are not taken into account. The PSCT is then used to calculate the disorders (or combination of disorders) that can explain the observed manifestations. Then, the selected disorders are ranked according to a plausibility criterion, which takes into account the certainty of presence and absence of manifestations and the fuzzy causality relations. Finally, the results are presented to the operator.

### *A. Solution of the crisp model*

The first step for the solution of the fuzzy model is to solve its crisp version. In order to do this, $\boldsymbol{\mu}\mathbf{C}^{+}$ and $\boldsymbol{M}^{+}$ are substituted for their crisp equivalents **C** (9) and $\mathbf{M}^{+}$ (10) [28].

$$\mathbf{C} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nn} \end{bmatrix} \tag{9}$$

$$\mathbf{M}^{+} = \{ m_1 \quad m_2 \quad \ldots \quad m_k \} \tag{10}$$

These equivalents are obtained by substituting the elements of $\boldsymbol{\mu}\mathbf{C}^{+}$ and $\boldsymbol{M}^{+}$ that are greater than zero for ones. The elements of $\boldsymbol{M}^{+}$ that are equal to zero are disregarded. Hence, $\mathbf{M}^{+}$ will have only $r$ elements, where $r \leq n$. The crisp problem is defined as the quad-tuple $\mathbf{P}=<\mathbf{D}, \mathbf{M}, \mathbf{C}, \mathbf{M}^{+}>$, where **D** and **M** are (1) and (2), respectively. To address this problem, the concepts of effects, causes and covers [28] are introduced. Then, for any $d_i \in \mathbf{D}$ and $m_j \in \mathbf{M}$ in a diagnostic problem **P**:

- effects($d_i$) = $\{m_j \mid c_{ij} > 0\}$
- causes($m_j$) = $\{d_i \mid c_{ij} > 0\}$
- For any $D_I \subseteq \mathbf{D}$, effects($D_I$) = $\bigcup$effects($d_i$), $d_i \in D_I$
- For any $M_J \subseteq \mathbf{M}$, causes($M_J$) = $\bigcup$causes($m_j$), $m_j \in M_J$
- The set $D_I$ is a cover of $M_J$ if $M_J \subseteq$ effects ($D_I$)

The premise of the PSCT is that a plausible diagnosis hypothesis of **P** must be a parsimonious cover of $\mathbf{M}^{+}$. The parsimonious covers are known as explanations. The most plausible explanation is the solution of **P**. A cover is parsimonious if it satisfies the parsimony principle (or simplicity principle), typically known as Ocam's razor, which states that simple solutions are preferred over complex ones. This is intuitively satisfactory, because it is well known that simple faults are more likely to occur than multiple faults. Up to date, several criteria have been proposed in the literature to evaluate the parsimony of a cover. Some of the most commonly used ones are [28]:

- Single disorder restriction: a cover $D_I$ of $\mathbf{M}^{+}$ is an explanation, if it contains only a single disorder.
- Minimality: a cover $D_I$ of $\mathbf{M}^{+}$ is an explanation, if it has the minimal cardinality among all covers of $\mathbf{M}^{+}$.
- Irredundancy: a cover $D_I$ of $\mathbf{M}^{+}$ is an explanation, if it has no proper subsets that also cover $\mathbf{M}^{+}$.
- Relevancy: a cover $D_I$ of $\mathbf{M}^{+}$ is an explanation, if it contains the disorders that causally associate with at least one of the manifestations of $\mathbf{M}^{+}$.

The selection of the parsimony criterion depends on the characteristics of every diagnosis problem. The irredundancy and the minimality criteria are widely used in many problems. In this work, as suggested in [28], the irredundancy criterion is used. It is worth noting that to find the solution for **P** is an NP-hard problem, where NP-hard is a measure of the complexity of an algorithm. Specifically, problems for which the time of execution grows exponentially as the problem size increases are referred to as NP-hard [27]. However, in the case under analysis and due to the radial configuration of the MV network, it is possible to significantly reduce the dimension of the problem. The explanations of a CTC must be selected only among the $m$ devices located upstream; the remaining devices are disregarded. This characteristic notably reduces the problem size. In order to calculate the explanations of $\mathbf{M}^{+}$, the interactive algorithm presented in [21] is used.

### *B. Solution of the fuzzy model*

After the explanations have been calculated, their plausibility is evaluated by a plausibility criterion (11), (12) that is founded on the proposals of [23]-[25] and [28].

$$P(d_i) = \vee \left\{ \underset{j=1,n}{\vee} \left[ \wedge \left( \mu c_{ij}^{+}, \mu_{m_j}^{+} \right) \right], \underset{j=1,n}{\vee} \left[ \wedge \left( \mu c_{ij}^{-}, \mu_{m_j}^{-} \right) \right] \right\} \tag{11}$$

$$P(\mathbf{D}_s) = \sum_{i=1}^{nd} \frac{P(d_i)}{nd} \tag{12}$$

The first part of (11) evaluates the consistency among the *"more-or-less" certain* manifestations of $d_i$ and the *"more-or-less" certainly present* manifestations. The second part of (11) evaluates the consistency among the *"more-or-less" impossible* manifestations of $d_i$ and the *"more-or-less" certainly absent* manifestations. Here, the algebraic sum (13) and its dual, the algebraic product (14), are selected to evaluate the t-conorm ($\vee$) and t-norm ($\wedge$), respectively. These operators are special cases of a more general family of parameterized norms, known as Hamacher norms. They were chosen by following the guidelines presented in [32]. The algebraic sum is an adequate operator because it reflects the contribution of every component to their union. This characteristic is used to model the following intuitive reasoning: the plausibility of $d_i$ must increase, as more of its *"more or less" certain* manifestations arise. The algebraic sum has been used and suggested in many engineering applications [32]-[34].

$$\mu_{A\vee B}\left(x\right)=\mu_{A}\left(x\right)+\mu_{B}\left(x\right)-\mu_{A}\left(x\right)\cdot\mu_{B}\left(x\right) \tag{13}$$

$$\mu_{A\wedge B}\left(x\right)=\mu_{A}\left(x\right)\cdot\mu_{B}\left(x\right) \tag{14}$$

Equation (12) evaluates the relative plausibility of the *s*-th explanation, where *nd* is the number of disorders of each explanation. It is noted that this equation "penalizes" multiple disorder explanations. This is intuitively satisfactory, because these explanations are generally less plausible. The results of (12) are ranked and presented to the operator. The explanation that maximizes (12) is the solution of the OC in ERT. However, all explanations are presented in order to provide a general outlook of the plausible solutions. In this way, the operator is fully informed to make a final decision.

In some instances, the delay between the occurrence of an outage and the reception of the respective CTCs may be large, e.g., if a fault occurs in a residential feeder during early hours. If, in addition, the weather conditions are adverse, a second fault could happen as well. For such a case, it is necessary to actualize $\boldsymbol{\mu}\mathbf{C}^{+}$ (using the RT data from the second fault) before processing any CTC, by resorting to (15).

$$\mu c_i^{+}=\begin{cases}\mu c_i^{+}\left(f_1\right) & if \quad \mu c_i^{+}\left(f_1\right)\geq \mu c_i^{+}\left(f_2\right)\\ \mu c_i^{+}\left(f_2\right) & if \quad \mu c_i^{+}\left(f_1\right)< \mu c_i^{+}\left(f_2\right)\end{cases} \tag{15}$$

Here, $\mu c_i^{+}(f_1)$ and $\mu c_i^{+}(f_2)$ are computed with the RT data from the first and second fault, respectively, and $\mu c_i^{+}$ is the actualized value for the *i*-th protective device.

## V. RESULTS

In this section, the ERT model is used to improve the results obtained with the RT model proposed in [1]. Three cases have been analyzed for the feeder of Fig. 2. Only the HV/MV SE is monitored in RT by SCADA.

### A. Case 1

A single line-to-ground fault is simulated on the zone protected by F2403. The results of the RT model are shown on Table II, which indicate that there are two candidate devices. Therefore, the ERT model should be used to end the inference of the OC. It is firstly assumed that a CTC has been received from the zone protected by F1364, and that the linguistic qualifier selected by the operator is "*almost certain*". Table III shows the six explanations inferred by the ERT model. These results are more conclusive than those of Table II. Then, it can be stated that F2403 is the operated protective device. To verify how the plausibility of the solution increases as more data become available, it is assumed that a second CTC is received from the zone protected by F1377. The linguistic qualifier selected by the operator is "*likely*". Using both CTCs, the results of Table IV are obtained. Six explanations arise here, too, but two of them imply the operation of two protective devices. These latter explanations are discarded, because only one fault has been detected ($\Delta P$, $I_{sc}$). Besides, their plausibility is very low. The plausibility of operation of F2403, F1355 and F1303 has risen as expected, because they are covers of the CTCs received. It is also noted that F1759, F1331 and F1364 have been discarded, as expected as well, because they do not cover the CTC received from zone F1377. These last results reinforce the appropriateness of choosing F2403 as the operated protective device.

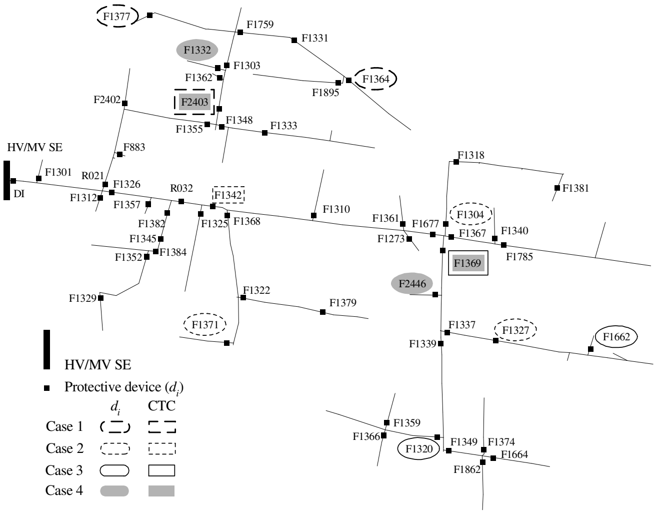

Fig.2 Test feeder

TABLE II

| $\Delta P$ | $I_{sc}$ | $d_i$ | $I_{i\ L}^{P}$ | $I_{i\ U}^{P}$ | $I_{i\ L}^{I}$ | $I_{i\ U}^{I}$ | $I_{i\ L}^{Q}$ | $I_{i\ U}^{Q}$ | $\mu c_{i\ L}^{+}$ | $\mu c_{i\ C}^{+}$ | $\mu c_{i\ U}^{+}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 57 | 500 | F2403 | 0.66 | 0.83 | 0.65 | 0.77 | 0.20 | 0.31 | 0.64 | 0.68 | 0.72 |
| | | F1677 | 0.80 | 0.90 | 0.22 | 0.48 | 0.20 | 0.31 | 0.55 | 0.59 | 0.64 |

TABLE III

| $d_i$ | Explanations | | | | | |
|---|---|---|---|---|---|---|
| | $\mathbf{D_1}$ | $\mathbf{D_2}$ | $\mathbf{D_3}$ | $\mathbf{D_4}$ | $\mathbf{D_5}$ | $\mathbf{D_6}$ |
| F2403 | 1 | 0 | 0 | 0 | 0 | 0 |
| F1355 | 0 | 1 | 0 | 0 | 0 | 0 |
| F1303 | 0 | 0 | 1 | 0 | 0 | 0 |
| F1759 | 0 | 0 | 0 | 1 | 0 | 0 |
| F1331 | 0 | 0 | 0 | 0 | 1 | 0 |
| F1364 | 0 | 0 | 0 | 0 | 0 | 1 |
| $P(\mathbf{D}_s)$ | 0.47 | 0.27 | 0.17 | 0.15 | 0.10 | 0.06 |

TABLE IV

| $d_i$ | Explanations | | | | | |
|---|---|---|---|---|---|---|
| | $\mathbf{D_1}$ | $\mathbf{D_2}$ | $\mathbf{D_3}$ | $\mathbf{D_4}$ | $\mathbf{D_5}$ | $\mathbf{D_6}$ |
| F2403 | 1 | 0 | 0 | 0 | 0 | 0 |
| F1355 | 0 | 1 | 0 | 0 | 0 | 0 |
| F1303 | 0 | 0 | 1 | 0 | 0 | 0 |
| F1377 | 0 | 0 | 0 | 1 | 1 | 1 |
| F1759 | 0 | 0 | 0 | 1 | 0 | 0 |
| F1331 | 0 | 0 | 0 | 0 | 1 | 0 |
| F1364 | 0 | 0 | 0 | 0 | 0 | 1 |
| $P(\mathbf{D}_s)$ | 0.58 | 0.35 | 0.23 | 0.10 | 0.07 | 0.05 |

### B. Case 2

A single line-to-ground fault is simulated on the zone protected by F1342. The results of the RT model are shown on Table V. In this case there are also two candidate devices and the certainty of operation of F1355 is greater than that one corresponding to F1342. It is firstly assumed that a CTC is received from the zone protected by F1304; the qualifier selected is "*almost certain*". Four explanations are inferred by the ERT and are presented on Table VI. These results are more conclusive than those of Table V. Then, it is acceptable to affirm that F1342 is the operated device. If CTCs are received from the zones protected by F1327 and F1371, and if the qualifiers "*almost certain*" and "*likely*" are selected, the results shown in Tables VII-VIII will be attained, respectively. It is noted that some explanations imply the operation of two or three protective devices. These latter explanations are calculated only to obtain a complete outlook of all plausible solutions. However, they may be discarded, because only one fault was detected. Here, the plausibility of operation of F1342 has increased, too, thus confirming that it is the operated protective device.

TABLE V

| $\Delta P$ | $I_{sc}$ | $d_i$ | $I_i^P{}_L$ | $I_i^P{}_U$ | $I_i^I{}_L$ | $I_i^I{}_U$ | $I_i^Q{}_L$ | $I_i^Q{}_U$ | $\mu c_i^+{}_L$ | $\mu c_i^+{}_C$ | $\mu c_i^+{}_U$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 83 | 650 | F1355 | 0.94 | 0.97 | 0.10 | 0.40 | 0.20 | 0.31 | 0.57 | 0.61 | 0.64 |
| | | F1342 | 0.68 | 0.84 | 0.34 | 0.56 | 0.20 | 0.31 | 0.54 | 0.59 | 0.64 |

TABLE VI

| $d_i$ | Explanations | | | |
|---|---|---|---|---|
| | $\mathbf{D}_1$ | $\mathbf{D}_2$ | $\mathbf{D}_3$ | $\mathbf{D}_4$ |
| F1342 | 1 | 0 | 0 | 0 |
| F1326 | 0 | 1 | 0 | 0 |
| F1677 | 0 | 0 | 1 | 0 |
| F1304 | 0 | 0 | 0 | 1 |
| $P(\mathbf{D}_s)$ | 0.41 | 0.19 | 0.07 | 0.06 |

TABLE VII

| $d_i$ | Explanations | | | | | |
|---|---|---|---|---|---|---|
| | $\mathbf{D}_1$ | $\mathbf{D}_2$ | $\mathbf{D}_3$ | $\mathbf{D}_4$ | $\mathbf{D}_5$ | $\mathbf{D}_6$ |
| F1342 | 1 | 0 | 0 | 0 | 0 | 0 |
| F1326 | 0 | 1 | 0 | 0 | 0 | 0 |
| F1677 | 0 | 0 | 1 | 0 | 0 | 0 |
| F1304 | 0 | 0 | 0 | 1 | 1 | 1 |
| F1337 | 0 | 0 | 0 | 1 | 0 | 0 |
| F1327 | 0 | 0 | 0 | 0 | 1 | 0 |
| F1369 | 0 | 0 | 0 | 0 | 0 | 1 |
| $P(\mathbf{D}_s)$ | 0.65 | 0.34 | 0.13 | 0.07 | 0.06 | 0.06 |

TABLE VIII

| $d_i$ | Explanations | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\mathbf{D}_1$ | $\mathbf{D}_2$ | $\mathbf{D}_3$ | $\mathbf{D}_4$ | $\mathbf{D}_5$ | $\mathbf{D}_6$ | $\mathbf{D}_7$ | $\mathbf{D}_8$ | $\mathbf{D}_9$ | $\mathbf{D}_{10}$ |
| F1342 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1326 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1677 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1368 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| F1371 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| F1304 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| F1337 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| F1327 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 |
| F1369 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| $P(\mathbf{D}_s)$ | 0.72 | 0.39 | 0.10 | 0.08 | 0.07 | 0.06 | 0.06 | 0.05 | 0.05 | 0.05 |

### C. *Case 3*

A single line-to-ground fault is simulated on the zone protected by fuses F1369. The results of the RT model are shown on Table IX, indicating two candidate devices, F1369 and F1303. It is firstly assumed that a CTC is received from the zone protected by F1662; the qualifier selected is "*likely*". Table X depicts seven explanations. These results are more conclusive than those of Table IX. Then, it is acceptable to affirm that F1369 is the operated device. Table XI shows the results for the case when a second CTC is received from the zone protected by F1320 and the qualifier "*almost certain*" is selected. Here, there are ten explanations, but -this time- many of them imply the operation of two protective devices. Like above, they are discarded as well. The plausibility of operation of F1369 has risen, which confirms that it is the operated protective device.

TABLE IX

| $\Delta P$ | $I_{sc}$ | $d_i$ | $I_i^P{}_L$ | $I_i^P{}_U$ | $I_i^I{}_L$ | $I_i^I{}_U$ | $I_i^Q{}_L$ | $I_i^Q{}_U$ | $\mu c_i^+{}_L$ | $\mu c_i^+{}_C$ | $\mu c_i^+{}_U$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 30 | 400 | F1369 | 0.72 | 0.81 | 0.79 | 0.86 | 0.20 | 0.31 | 0.68 | 0.73 | 0.78 |
| | | F1303 | 0.24 | 0.62 | 0.97 | 0.98 | 0.25 | 0.37 | 0.54 | 0.59 | 0.64 |

TABLE X

| $d_i$ | Explanations | | | | | | |
|---|---|---|---|---|---|---|---|
| | $\mathbf{D}_1$ | $\mathbf{D}_2$ | $\mathbf{D}_3$ | $\mathbf{D}_4$ | $\mathbf{D}_5$ | $\mathbf{D}_6$ | $\mathbf{D}_7$ |
| F1369 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1677 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| F1342 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| F1326 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| F1337 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| F1327 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| F1662 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| $P(\mathbf{D}_s)$ | 0.22 | 0.11 | 0.11 | 0.07 | 0.07 | 0.03 | 0.02 |

TABLE XI

| $d_i$ | Explanations | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\mathbf{D}_1$ | $\mathbf{D}_2$ | $\mathbf{D}_3$ | $\mathbf{D}_4$ | $\mathbf{D}_5$ | $\mathbf{D}_6$ | $\mathbf{D}_7$ | $\mathbf{D}_8$ | $\mathbf{D}_9$ | $\mathbf{D}_{10}$ |
| F1369 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1342 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1677 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1326 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1339 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| F1337 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| F1327 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 |
| F1662 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| F1320 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |
| $P(\mathbf{D}_s)$ | 0.62 | 0.34 | 0.32 | 0.23 | 0.12 | 0.10 | 0.10 | 0.08 | 0.06 | 0.06 |

### D. *Case 4*

In this case, it is assumed that a single line-to-ground fault occurs on the zone protected by F2403. A few minutes later, a second single line-to-ground fault occurs on the zone protected by F1369. There are no CTCs received in the lapse between the first and second faults. The results of the RT model for these faults are the same ones shown in Tables II and IX. Therefore, there are four candidate devices, namely, F2403, F1677, F1369 and F1303. After the second fault is detected, two CTCs are received from the zones protected by F1332 and F2446. The qualifiers selected are "*certain*" and "*almost certain*", respectively. Using these CTCs and (15), the explanations of Tables XII-XIII are attained. The results are more conclusive than those of Tables II and IX. Then, it is confirmed that F1369 and F2403 are the operated protective devices.

TABLE XII

| $d_i$ | Explanations | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $\mathbf{D}_1$ | $\mathbf{D}_2$ | $\mathbf{D}_3$ | $\mathbf{D}_4$ | $\mathbf{D}_5$ | $\mathbf{D}_6$ | $\mathbf{D}_7$ | $\mathbf{D}_8$ |
| F2403 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 |
| F1369 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| F1677 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| F1342 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| F1326 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| F1355 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| F1332 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| F2446 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| $P(\mathbf{D}_s)$ | 0.59 | 0.54 | 0.47 | 0.47 | 0.45 | 0.44 | 0.44 | 0.40 |

TABLE XIII

| $d_i$ | Explanations | | | | | | |
|---|---|---|---|---|---|---|---|
| | $\mathbf{D}_9$ | $\mathbf{D}_{10}$ | $\mathbf{D}_{11}$ | $\mathbf{D}_{12}$ | $\mathbf{D}_{13}$ | $\mathbf{D}_{14}$ | $\mathbf{D}_{15}$ |
| F2403 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1369 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1677 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| F1342 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| F1326 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| F1355 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| F1332 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| F2446 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| $P(\mathbf{D}_s)$ | 0.39 | 0.32 | 0.32 | 0.32 | 0.32 | 0.29 | 0.28 |

## VI. CONCLUSIONS

In this work, an approach aiming at inferring the OC in ERT has been presented. The methodology improves the initial results obtained by the RT model proposed in [1]. In this sense, both models are complementary. The methodology provides a sound mathematical framework for the integration of all the data available at every stage of the process: RT data, ERT data (CTCs) and the expert knowledge of distribution operators. In this way, the uncertainty of the results is reduced and they are dynamically improved as more data are being received. At every stage, all the plausible solutions are calculated, ranked and presented to the operator. With this, a complete outlook of possible options is obtained, which allows the operator be fully informed to make proper operative decisions. Thus, the methodology contributes to the improvement of the outage management process, which has a positive impact on QS. Results have been proven satisfactory, which encourage for a further practical implementation.

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