Failure Section Identification in Smart Distribution Network Based on IFIAPN Considering the Auto-reclosing and DG

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Abstract. This paper proposes a fault location method for smart distribution networks based on the intuitionistic fuzzy inhibitor arc Petri net (IFIAPN) technique that employs discrete evidence such as the status of protective devices and fault indicators (FIs) to estimate the faulted section. To eliminate the possible false fault section estimations and pinpoint the actual faulted location, an IFIAPN algorithm is improved. It amends the certainty and uncertainty of the information according to the action logic of the protection system and the direction of fault propagation. The authors further utilize the directional fault indicator to cope with the impact on the bidirectional power flows caused by distributed generation, and introduce the inhibitor arc to represent the action characteristics of auto-reclosing to optimize the diagnostic model. The proposed method can precisely determine the fault location in distribution systems with many laterals and sub-laterals in the presence of distributed generators (DGs). Finally, feasibility, fault tolerance, and effectiveness of the proposed method are verified by the IEEE 33 node feeder distribution system.

1. Introduction
With smart grids in evidence, also grow auto-reclosing and distributed generator (DG) penetration in smart distribution systems [1]. On the one hand, the application of the automatic reclosing can significantly improve the reliability of power supply, and on the other hand, because DGs are connected to the distribution network, the structure and operation mode of the distribution network are changed, and the magnitude and direction of the fault current are affected so that the original protection strategy of the traditional distribution network may no longer be applicable.

Model-based Petri net methods have been applied in fault location identification [2]-[4]. The paper [5], which is based on a well-designed Petri net that captures the modeling details of the distribution network protection system, adopts matrix operations to detect and identify data transmission failures and faults in the distribution network. But the model is too large, prone to combinatorial explosion. In [6], a multi-factor hierarchical Petri net model is presented to solve problems of mal-operation or failure to trip protection relay and circuit breaker when fault diagnosis information is unclear. Furthermore, discrete multi-source data based on a fuzzy Petri net are employed to estimate the fault section [7]. The fault identification methods mentioned above have achieved improved the accuracy and speed of fault location to a certain extent. But there are still some shortcomings, such as the prior studies that have primarily focused on protection and circuit breaker information, which do not consider the influence of DG and auto-reclosing on fault location.

To better address the above issues, we sought to investigate a reasonable fault location identification approach based on IFIAPN, which can fully explore and utilize the logicality of alarm information that encompasses information from reclosers, relay protection, and switch devices, and fault indicators.
Taking into account the impact of recloser and DG on the distribution network, the inhibitor arc and fault indicator are introduced to optimize the IFIAPN model.

2. Basic concepts

2.1. Definition Petri net with inhibitor arc

The Petri net with inhibition arc is formed by adding an arc connecting the place and transition on the basis of the prototype Petri net. As shown in Fig. 1, $IA$ means the inhibitor arc. If the place is marked with a token which is shown as $\bullet$, the transition $t$ will not be fired. Conversely, the transition $t$ will be fired when meeting the ignition trigger conditions and there is no token in. Hence, this arc only controls the transition that meets enabling the conditions, and once the transition occurs, the inhibition arc will not have any effect on the change of the identification value.

![Figure 1. The model of Petri net with inhibitor arc](image)

2.2. Definition of intuitionistic fuzzy inhibitor arc Petri net

Intuitionistic Fuzzy Inhibitor Arc Petri Net (IFIAPN) is an octet [8], as show in (1).

$$IFIAPN = \{P, T, \lambda, W, I, O, M_0, IA\}$$  \hspace{1cm} (1)

Where, $P = \{p_1, p_2, \ldots, p_n\}$ represents a collection of finite places or called propositions. $T = \{t_1, t_2, \ldots, t_m\}$ represents a collection of finite transitions or called rules. $\lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_m\}$ represents the firing thresholds in IFIAPN. $\lambda_j = (\alpha_j, \beta_j), j = 1, 2, 3, \ldots, m$, is the intuitionistic fuzzy set. The value $\alpha_j \geq 0$ and $\beta_j \geq 0$ indicate the certainty and uncertainty of transition, respectively. $W$ is the weight of the connecting arc. If $p$ is the input place for transition $t$, then $W = W_j(p, t), 0 \leq W_j(p, t) \leq 1$; If $p$ is the output place for transition $t$, then $W = W_i(t, p) = (\mu_i, \gamma_i), \mu$ and $\gamma$ denote the certainty and uncertainty of transition $t$, respectively. $I$ is an $(n \times m)$-dimensional input matrix. If place $p_i$ is an input for transition $t_j$, then $I_{ij}$ is equal to the weight of the input arc. Otherwise, $I_{ij} = 0, i = 1, 2, \ldots, n, j = 1, 2, \ldots, m$. $O$ is an $(n \times m)$-dimensional output matrix. If place $p_i$ is an output for transition $t_j$, then $O_{ij}$ is equal to the weight of the output arc. Otherwise $O_{ij} = 0, i = 1, 2, \ldots, n, j = 1, 2, \ldots, m$. $M_0 = [M_0(p_i)], i = 1, 2, \ldots, n$, represents the initial state of the place $p_i$ and $M_0(p_i) = (\mu, \gamma), \mu$ and $\gamma$ denote the certainty and uncertainty of place $p_i$, respectively. $IA$ means the inhibitor arc.

2.3. Definition of reasoning operators

To facilitate the description of reasoning rules and speed up the calculation in algebraic matrices, we defined four operators. Suppose $A, B,$ and $C$ are all intuitionistic fuzzy matrices and $a_y \in A, b_y \in B, c_y \in C$.

1) Direct multiplication operator $\circ : C = A \circ B \Leftrightarrow c_y = (a_y \cdot b_y)$.
2) Addition operator $\oplus : C = A \oplus B \Leftrightarrow c_y = \max(a_y, b_y)$.
3) Multiplication operator $\otimes : C = A \otimes B \Leftrightarrow c_y = \max(\sum_{k \leq j} a_{yk} \cdot b_{yj})$.
4) Comparison operator $\left< : C = A \left< B \right> \Rightarrow c_y = \begin{cases} 1, & \text{if } a_y \geq b_y, \\ 0, & \text{otherwise} \end{cases}$.
3. Proposed methodology for fault location identification

3.1. IFIAPN Optimization Model Considering Auto-reclosing and DG

This paper uses the fault indicator (FI) with directional information to handle DG's effect on bidirectional power flow in the distribution network. A simple distribution feeder diagram with protection devices and directional fault indicator (DFI) [9] is shown in Fig. 2. Assume that a short-circuit fault occurs in Sec3 of Fig. 2, DFI3, DFI2, DFI1, and the upstream switch S3 will be triggered. The main feeder and the downstream DG contribute to the fault current. In general, the protection direction is specified to be the same as the energization direction in the radial topology of the distribution networks. Accordingly, the DFI5 detects the reverse fault current from downstream to upstream and is not set off, and keeps in the passive status can avoid unnecessary alarm information uploading and reduce the interference to maintenance personnel.

After a fault occurs in this distribution network, the protective devices such as recloser, circuit breaker, and switch are triggered and disconnect the fault point. Under the premise of installing auto-reclosing, the line with a transient fault can restore power supply in a short time. Consequently, regarding recloser information as the key to start the diagnostic model, judging whether the distribution network has an instantaneous fault or a permanent fault based on the recloser information. The IFIAPN optimization model is established based on Fig. 2 and the distribution network protection configuration rules, as shown in Fig. 3, where $XP$ consists of three categories including $MP$, $NP$, and $RP$, which represent the main protection, near backup protection, and remote backup protection, respectively. $p_0 = 1$ means the closing is successful, and the fault is transient, then there is no need to perform IFIAPN fault diagnosis. But the fault scenario's occurrence cannot be ignored, and the subsequent fault analysis is required. $p_0 = 0$, it expresses the closing fails, or the equipment fails, and the fault is permanent. So, it is necessary to carry out the IFIAPN model for fault reasoning based on other alarm information. In this way can we reduce the computation burden and speed up the troubleshooting time.

![Figure 2. Schematic of a distribution feeder with protective devices and fault indicators.](image)

![Figure 3. IFIAPN optimization model](image)
3.2. Parameter settings

3.2.1. Setting the Identification Values and Weights for Alarm Information
The identification values of fuzzified information and their corresponding weights for the fault diagnosis in this work are calculated based on statistical databases relevant to the correct operating rates and reliability of protective devices and alarm indicators are given in Table 1 [10][11].

Table 1. Identification values and corresponding weights for alarm information.

| Protective devices | Identification values | Weights |
|--------------------|------------------------|---------|
| Main protections   | (0.9913, 0.006294)     | 0.5096  |
| switches           | (0.9833, 0.006188)     | 0.4904  |
| Near backup protections | (0.7903, 0.007868) | 0.6061  |
| switches           | (0.8358, 0.00728)      | 0.3939  |
| Near backup protections | (0.6939, 0.008991)   | 0.6013  |
| switches           | (0.7375, 0.008251)     | 0.3987  |
| Fault Indicator    | (0.9, 0.1)             | 0.5     |

3.2.2. Setting the identification values of non-existent alarm information
Suppose \((\mu_2, \gamma_2)\) is the identification value when there is alarm information, an \((\mu_3, \gamma_3)\) is the identification value when the alarm information does not exist. If we judge that one of the protection or corresponding switch alarm information is missing, the relationship is as follows:

\[
\begin{align*}
\mu_3 &= w \times \mu_1 \\
\gamma_3 &= \frac{\gamma_1}{w}
\end{align*}
\]

where \(w\) is used to express greater uncertainty in a refusal and maloperation event of the protection or switch, and its value is equal to the corresponding weight. If the protection alarm information and the corresponding switch information are both missing, the identification value of lost information can be taken as \((0.2, 0.6)\) to ensure the fault tolerance of the model. The identification value of the output arc connected to the intermediate place is set to \((0, 1)\), and the identification value of the output arc connected to the terminal place is set to \((0.95, 0.025)\). Considering the adverse effect of a pair of protective system miscoordination and the failure of a fault indicator, and guarantee the accuracy of diagnosis results, we presume that the transition threshold value is \((0.2, 0.7)\).

4. Reasoning rule of IFIAPN

(1) Suppose the initial state of the place is \(M_{x M}^0\), calculate the input intuitionistic fuzzy value of \(\eta_{x M}^k\):

\[
\eta_{x M}^k = I_{x M}^k \odot M_{x M}^k
\]

(2) Compare the transition threshold value with the \(\eta_{x M}^k\) to obtain the transition set of \(\varphi_{x M}^k\) that can fire the transition:

\[
\varphi_{x M}^k = \eta_{x M}^k \setminus \lambda_{x M}^k
\]

(3) Calculate the input intuitionistic fuzzy value of \(\psi_{x M}^k\) that can stimulate the transition based on the obtained set of \(\varphi_{x M}^k\):

\[
\psi_{x M}^k = \eta_{x M}^k \odot \varphi_{x M}^k
\]

(4) Calculate the confidence value of the place \(M_{x M}^{k+1}\) obtained after \((k+1)\) iterations:

\[
M_{x M}^{k+1} = E_{x M}^k \odot \psi_{x M}^k \odot M_{x M}^k
\]

(5) If \(M_{x M}^{k+1} = M_{x M}^k\), end the iterative reasoning and output \(M_{x M}^{k+1}\), otherwise, let \(k = k+1\), and return the step (4).

The output confidence of the final place is the certainty and uncertainty of the failure section.

(6) Use the measure function to calculate the failure probability:
where $E$ represents the failure event, $(\mu, \gamma)$ represents the confidence of the final place. $E$ is deemed to be faulty when $f(E) > \theta$. Among them, $\theta$ is the fault threshold. And to ensure the accuracy of the fault diagnosis result, the certainty of the fault should be much greater than the uncertainty, so $\theta$ is set to 0.75 in this paper.

We give the first case analyses to clarify the specific IFIAPN diagnosis model and detailed calculation process. Assuming that a single-phase short-circuit fault occurs on Sec3 in Fig. 2. The dispatch center receives the signal statuses from Rcl, MR3, and S3, DFI1, DFI2, and DFI3 detect the fault currents. If the protective system operated appropriately and all the alarm information is correct. According to the alarm information, we can get Rcl=0, which means the recloser fails to close and has a permanent fault on the distribution system. Therefore, the IFIAPN fault diagnosis model for Sec3 is established. The inference process is clearly as follows:

1. Input matrix $I$ with weights:
   \[
   I = \begin{bmatrix}
   0.5096 & 0.4904 & 0 & 0 & 0 & 0 & 0 \\
   0 & 0 & 0.5 & 0.5 & 0 & 0 & 0 \\
   0 & 0 & 0 & 0 & 1 & 0 & 0 \\
   0 & 0 & 0 & 0 & 0 & 1 & 0 
   \end{bmatrix}
   \]

2. Output matrix $O$ with confidence:
   \[
   O = \begin{bmatrix}
   (0,1) & (0,1) & (0,1) & (1,0) & (0,1) & (0,1) & (0,1) \\
   (0,1) & (0,1) & (0,1) & (0,1) & (1,0) & (0,1) & (0,1) \\
   (0,1) & (0,1) & (0,1) & (0,1) & (0,1) & (0,1) & (0.95,0.025) \\
   (0,1) & (0,1) & (0,1) & (0,1) & (0,1) & (0.95,0.025) 
   \end{bmatrix}
   \]

3. Transition threshold matrix $\lambda$:
   \[
   \lambda = [(0.2,0.7) (0.2,0.7) (0.2,0.7) (0.2,0.7)]^T
   \]

4. The intuitionistic fuzzy set $M_0$ of the initial places:
   \[
   M_0 = [(0.9913,0.006294) (0.9833,0.006188) (0.9,0.1) (0.95,0.05) (0,1) (0,1)]^T
   \]

5. The matrices obtained after iterative calculations are:
   \[
   M_1 = [(0.9913,0.006294) (0.9833,0.006188) (0.9,0.1) (0.95,0.05) (0.9874,0.006242) (0.925,0.075) (0,1)]^T
   
   M_2 = [(0.9913,0.006294) (0.9833,0.006188) (0.9,0.1) (0.95,0.05) (0.9874,0.006242) (0.925,0.075) (0.938,0.03109)]^T
   
   M_3 = [(0.9913,0.006294) (0.9833,0.006188) (0.9,0.1) (0.95,0.05) (0.9874,0.006242) (0.925,0.075) (0.938,0.0311)]^T
   
   By $M_3 = M_2$, the inference calculation ends. The fuzzy confidence value of Sec3 is (0.938, 0.0311), that is the certainty of Sec3 failure is 0.938, and the uncertainty is 0.0311. Refer to (17), the failure probability of Sec3 is $f(\text{Sec}_3) = 0.9685$.

5. Cases analysis

![Figure 4. IEEE 33 node feeder distribution system with DG at nodes 11 and 30.](image-url)
We use the IEEE 33-node feeder test system [12] to further verify the effectiveness of the proposed strategy. The diagram of the system is shown in Fig.4. Due to space limitations, we test two examples in this system, including single, and multiple complex failures such as alarm information loss, protection and switch refusal or misoperation, and information chaos. The detailed fault information, diagnosis results, and failure analysis are summarized in Table 2.

| No. | alarm information                      | Candidate sections | Reasoning results this method | Fault probability | Fault analysis |
|-----|----------------------------------------|--------------------|--------------------------------|-------------------|---------------|
| 1   | Rcl2, Rcl3, Rcl4, S3, S5, DFI1, DFI5, DFI6, MP3, MP5, NP6 | Sec3               | 0.5639 0.66                   | 0.4316            | Sec3: failure; Sec5 failure; MP6, Rcl4, and S6 failed action; DFI3 signal lost. |
|     |                                        | Sec5               | 0.7511 0.09                   | 0.9316            |               |
|     |                                        | Sec6               | 0.6016 0.09                   | 0.9214            |               |
| 2   | Rcl2, Rcl4, MP3, MP5, NP6, DFI1, DFI3, DFI6, S3, S4 | Sec3               | 0.5639 0.66                   | 0.4316            | Sec3: failure; S6 failed action; |
|     |                                        | Sec5               | 0                      | 0.085            | RP6 lost; S6 mal |
|     |                                        | Sec6               | 0.5867 0.081                | 0.9061            |               |
|     |                                        | Sec8               | 0.3772 —                    | 0.1341            |               |

Taking the scenario of No.1 as an example for detailed failure analysis. The alarm information for this fault is: \{Rcl2, Rcl3, Rcl4, S3, S5, DFI1, DFI5, DFI6, MP3, MP5, NP6\}. We can get a suspected fault candidate set: \{Sec3, Sec5, Sec6\} by topology analysis and alarm information logical reasoning. Accordingly, the fault diagnosis model is first established. The probability of failure shows that Sec5 and Sec6 are actual failure sections. After analysis, recloser#4 fails, and the main protection of Sec6 does not act, then the NP6 acts, but the switch S6 associated with it refuses to move, causing the fault spread to section#3. The main protection of Sec3 and the remote backup protection of the Sec5 act to cut off the fault. Sec3 is the fault propagation area, but the dispatching center does not receive the fault signal from DFI3, which illustrates that the alarm information from the fault indicator DFI3 is lost.

6. Conclusion
This proposed method can accurately identify faulty equipment at one time by adopting the improved IFIAPN algorithm and can diagnose faults even in complex situations involving protection and equipment malfunction, refusal to move, and missing alarm information, thereby improving the fault tolerance and effectiveness of the approach. The inhibitor arc tuple is introduced to indicate the reclosing action information and reduce the ambiguity of the diagnostic model. The direction fault indicator is adopted to eliminate DG’s influence on the fault diagnosis of the distribution network. This method has a broad application prospect and strong practicability.

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