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A comprehensive fuzzy-based scheme for online detection of operational and topological changes

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ABSTRACT

Operational modes and topological changes affect power flow in the power systems. As a result, a broad spectrum of protection issues may happen in the power system. So, both the operational and topological changes should be detected fast to prevent blackouts. On the other hand, the existing detection schemes are complex in analyzing and implementation. Therefore, there is a need for an online scheme to identify the network's topology and operation mode simultaneously without complex computations and additional communication infrastructures. To this end, a comprehensive scheme is proposed in which the changes are detected by analyzing the power flow obtained from the network. For this purpose, line outage contingencies and operation modes are defined in rules to be used in a fuzzy inference system (FIS) as a decision-making tool. The proposed scheme can be implemented on existing lines as a communication infrastructure and determines the network’s status in an online manner. Also, in comparison to the existing schemes, the proposed scheme reduces the complexity and the computational burden. The proposed scheme is implemented on IEEE 8-bus system and the results proved its efficiency.

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1. INTRODUCTION

Transmission lines play a vital role in the power system, as they transfer electric power from power plants to the users [1]. Planned events such as maintenance operations or unplanned events, such as short circuit faults, which are the most common type of faults in the power system, can lead to line outage contingencies. Moreover, the single-line outage, if not detected and treated quickly, may result in multiple line outages in a few minutes and eventually lead to a costly blackout in less than one hour [2]. On the other hand, the protection system would encounter some problems due to the acceleration of the microgrid technology development in distribution networks and changes in the amount and direction of power flow levels at different modes of operation (i.e., grid-connected and islanded) [3], [4]. When a microgrid is operating without a connection to the main network, it is said to be operating in islanded mode [5]. When the network is in grid-connected mode, an external grid is connected to the main grid to feed the loads. Thus, the power flow value obtained by the measurements devices in islanded mode will be much smaller in comparison with the grid-connected mode.

The operational and topological changes in the networks will encounter the protection system to some protection problems due to variations in the level of the power. So, applying a scheme to detect the network’s status both operational and topological for subsequent adaptive actions and preventing protection problems is mandatory. There have been lots of methods to detect the networks' operation mode known as island detection methods. These methods utilized non-phasor measurements of network parameters and characteristics analyses [6]–[15], or phasor measurements data obtained from phasor measurement units (PMUs) [16]–[18].

In literature [6], [7] the wavelet transform is utilized for island detection. Wavelet transform and S-transform are applied on features that are extracted from the negative sequence component of the voltage signal for islanding detection [6]. Analysis of the transient signals of voltage generated during non-islanding events is used for islanding detection [7]. Extraction of signal energies in different levels of discrete wavelet transform is utilized as features and used in a decision tree as a classifier to identify the islanding condition.

Marchesan *et al.* [8] utilized frequency oscillation estimation to distinguish the islanding from other events in distribution systems. To this end, a small window of data is used to estimate the oscillation of frequency, which leads to a significant reduction in islanding detection time. Voltage unbalances and total harmonic distortion detection along with reactive power variation are utilized for island detection in [9]. The reactive power variation is only used when the islanding condition is detected by voltage unbalance and total harmonic distortion that leads to improvement in islanding detection performance and resolved power quality problems. Also, in other research, voltage unbalance and voltage total harmonic distortion from all phases are used for islanding detection [10].

Chen *et al.* [11] utilized the correlation factor between the reactive power disturbance and frequency variation along with three criteria including voltage variation, voltage unbalance, and rate of change of frequency to improve the detection time for island detection. Also, in study [12] an islanding detection algorithm based on reactive power control is proposed that provides the reactive power reference for the distributed generation (DG). This helps the system to keep the consistency of the frequency variation due to active and reactive power mismatches and consequently accelerate the islanding detection speed.

Moreover, in study [13] an islanding detection technique is proposed that is based on the derivation of components of the voltage signals as islanding detection factor. The island detection factor is compared with the preset threshold that is the steady-state value of voltage during a normal situation (non-islanding). If this value is greater than the preset threshold, the network is in islanding condition.

Guo *et al.* [14] proposed a component analysis method for islanding detection that improves the traditional rate of change of frequency technique that is not reliable for the time-varying process in fault and noisy situations. The technique obtains data from PMUs for system monitoring. To this end, a simple control procedure is used to monitor the transients. Therefore, by offline modeling and online monitoring, the islanding situation is detected. As a recent non-phasor based method, the islanding mode is detected using the rate of change of power technique based on the terminal voltage of the DG [15].

Also, lots of research have been introduced for island detection that are based on phasor measurements. In study [16] frequency difference and the change of voltage angle difference are utilized for island detection. Data are collected by the frequency disturbance recorder that is a single-phase PMU. To this end, the sensitivity analysis is performed on the thresholds of the frequency deviation and angle deviation, and the insensitive interval of the two mentioned thresholds is obtained to set the final threshold for decision making of islanding or non-islanding.

Recently, in studies [17], [18] some phasor-based methods have been provided to detect the islanded mode. the method employed the angle difference between positive and negative sequence phase angle of the voltage signal and angle difference under a normal scenario to detect the islanded conditions [17]. Also, in study [18] a predictive model is used for islanding detection based on measuring phasors obtained from the real-time system. The measurements are used as inputs of an artificial neural network for initiating the model that is designed based on the occurrence of islanding in terms of probability to estimate the probability of the islanding.

On the other hand, there are methods to detect the networks' topological changes known as line outage detection methods including non-phasor measurements of network parameters and characteristics analyses [19], and phasor measurements data [20]-[34]. In study [19] a line outage detection algorithm is proposed that used a divide-based procedure. First, the distribution network is divided into sub-networks, which communicate with their neighbors with separate control areas. Then a load estimation procedure is applied across the control areas of each sub-network to detect the outage independently by voltage magnitude measurements.

Direct current (DC) and alternating current (AC) models of power flow are utilized to estimate the locations of lines that are under outage [20]. Line outages are modeled using power flow equations by the magnitude and angle of voltage that are obtained by PMU. Also, the losses corresponding to the post-outage of lines are modeled and used in the power flow equations. Finally, a regularized least square method is used to solve the model and to estimate the locations of lines that are under outage.

Babakmehr *et al.* [21] considered the power network as a single graph and initialized the mathematical formulation of the power line outage detection problem using the DC power flow model. Then, a sparse representation-based formulation is applied for this problem. The data to be used in the sparse outage vector are obtained by PMUs. Based on the sparse vector representation the line outage is detected.

Alam *et al*. [22] proposed an algorithm for the detection of line outage that is based on a comparison of the current phasor measurements. To this end, the phasors of current that are obtained from power flow simulation for some line outage contingencies are stored in matrix form. When an actual outage happened, the real-time data of current phasors that are obtained from PMU are compared with the stored values for detection purposes. By utilizing the virtual adaptive observers that applied on voltage phasor angle obtained from the PMUs, the connectivity status between buses is monitored to detect the line outage contingency [23]. The power network is modeled by the weighted Laplacian matrix and the lines' admittance value could be estimated. If the admittance values decayed to zero, the line is in outage status.

As the other study, a scheme is proposed in [24] to detect line outages based on changes in impedance matrix due to voltage phasor variations in outage conditions. So, calculation of changes in impedance matrix due to each single line outage is performed in an offline manner, stored, and compared with online data for outage detection. In study [25] a methodology is proposed that is based on the state estimation. This method utilized a sparse vector to model the network using the voltage angle values corresponding to pre-outage and post-outage to find the variations in network topology and to estimate the power system status. Also, in study [26] an algorithm has been developed for the online detection of line outage contingencies. The proposed algorithm is based on a parameter namely line current distribution factor. This factor is the ratio of changes in current due to fault to the base case current flow through the line that is stored as a matrix in an offline manner. In the proposed algorithm, the current passing through the line is monitored by PMU and compared with the line current distribution factor for detection purposes. Moreover in study [27], an algorithm is proposed that utilized an estimation of the pre-outage power flow of lines for detection purposes. Line outage can be detected based on the phasor angle difference at the observable buses with respect to the pre-outage angles.

Several studies [28]–[31] solved the line outage problem by some probability-based methods. In study [28] a scheme is proposed that is based on the variations of the angles between the voltage of the bus and the injected active power. To this end, the statistical models from pre and post-outage of the angle variations are extracted. Then, the scheme evaluates the probability of a normal condition against the abnormal condition continuously. Under normal conditions, system outputs follow a common distribution of probability. When an outage occurred, the density of the probability function changes. The line is detected in outage condition when the statistics cross the pre-defined threshold. In other words, line outage can be detected by continuous online monitoring and comparing the probability of every outage scenario with the offline pre-defined threshold value. Also, a method is proposed that utilized the linearized model of the AC power flow with current and voltage phasor data to detect the most probable location of line outages [29]. In this method, a comparison procedure between the variations in observed and calculated values in the phase angles of voltage and active power flowing through the lines is performed to detect the locations of lines under outages. Moreover, the changes in network power injection at each bus are modeled by the probability distribution of generation and demand [30]. Then, the model is used to relate the distribution's probability of the injected power and the voltage angles through a mapping procedure. Finally, a decision-maker is used to observe the sequence of changes in bus voltage phase angle in the condition of change due to a line outage. In addition, a probability-based method is proposed that is based on a stochastic search method to estimate the probability of line outage occurrence [31]. To this end, the voltage phasor angle at each bus is measured and sent to the control center for detection purposes.

The dynamics of the power system are utilized to model the system by voltage phase angle measurements [32]. The model is applied in the dynamic CuSum test that is used to obtain the behavior of the system in transient situations. If any of the test statistics crosses a pre-determined threshold, then the corresponded line is considered under outage.

Several studies [33], [34] presented state-of-the-art approaches in line outage detection. Machine learning is used to locate line outages in [33]. To this end, a feature extraction method is used to obtain the dynamic characteristics of voltage phase angles when the topology changes. Also, in study [34] a methodology is proposed that is based on the phasors of current. In this algorithm, the currents of buses for various line outage cases are obtained from the simulations and are stored. In the case of an actual outage, the currents of buses from PMUs are compared with the previously stored values for line outage detection.

In the above mentioned studies the complexity, high computational burden and not being cost-effective can be considered as the research gap. In other words, both existing operational and topological detection methods suffer from complex detection algorithms to analyze, heavy mathematical computations especially for large-scale networks, or expensive hardware such as PMU that must be installed in the network. More importantly, the lack of a comprehensive detection scheme to cover the detection of both the operation modes and line outage contingencies leads to a need for a less complex, less computational burden and cost-effective detection scheme to detect both the operation modes and lines' status simultaneously. For this purpose, this study provides a comprehensive and practical scheme that ensures the detection of both operating modes (grid-connected or islanded) and the topological changes (line outage contingencies). The detection of operational and topological changes is performed utilizing data that are obtained in an online manner. Applying the proposed scheme, any changes in the network's operation mode and single-line outage contingencies are detected in the control center utilizing a fuzzy inference system (FIS) as an artificial intelligence (AI) tool to overcome the complexity and high computational burden of existing methods based on the current and voltage data obtained from the network without the need to any additional measurement devices. The transformation of the network's data is performed under existing power lines, and consequently, the status of the network can be determined cost-effectively.

In this paper, first, the details of the proposed detection scheme are explained. Then the detection procedure of the network's operation mode and topology which are all designed as a computer program is explained. Finally, the effectiveness of the proposed scheme for the detection of the network's operation mode and single-line outage contingencies is evaluated. To summarize, the main contribution of this paper is introducing a cost-effective, less complex, and less computational burden intelligent scheme to detect both modes of operations and network topology in an online manner simultaneously.

The paper is structured: the explanations of the proposed detection scheme are provided in section 2. The FIS approach for the detection procedure is addressed in section 3. The results of implementing the proposed detection scheme on a sample network are illustrated in section 4. Finally, the conclusion is remarked in section 5.

2. PROPOSED DETECTION SCHEME

For protection purposes, there is a need for a comprehensive scheme with the capability of detecting both modes of operation and lines' status in an online manner. This paper proposes a scheme based on an AI tool for detecting the single-line outage contingencies and the network mode of operation. The AI tool applied in the proposed detection scheme is a FIS which determines the operational and topological status of the network as the pre-defined scenarios. The data used for the FIS is independent of the extra communication devices and relies on existing power lines as communication infrastructure for receiving input data from the network for the detection procedure.

In the proposed scheme, local data are measured by current transformers (CTs) and potential transformers (PTs) and sent to the control center. In the control center, the obtained data are analyzed to determine the final status of the network's scenario. The proposed scheme concentrated on AI for analyzing data to determine the mode of operation and topology simultaneously. Figure 1 provides the proposed scheme's procedure in detail.

According to Figure 1, the scheme is designed in a way that performs in an online manner. The signals from relays are obtained and divided into two separate detection procedures. The first procedure transforms the analog signals to digital signals utilizing the relays to find the power flow passing through the lines' circuit breakers (CBs) and make the decision if any line is in outage condition or not. In the second procedure, the analog data are utilized to obtain the total power flowing through the lines. This value determines the operation mode of the network. Finally, the results of both procedures are used as inputs of a FIS as a decision-making tool to detect the operational and topological changes of the network and determine the final status of the network's scenario.

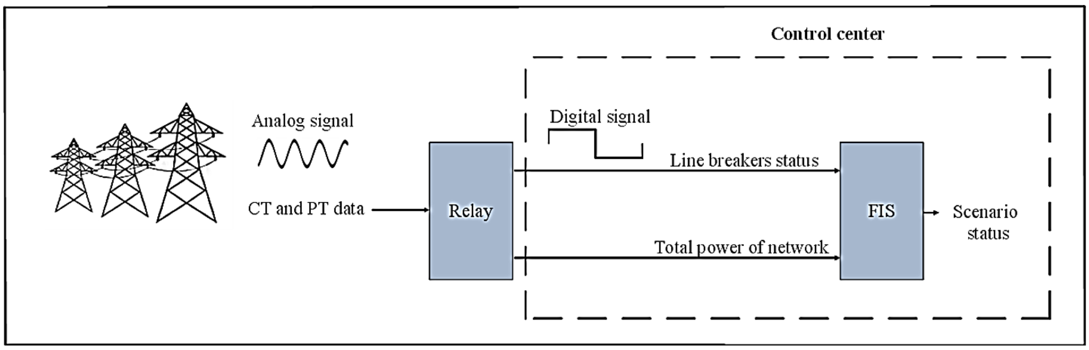


Figure 1. The proposed detection scheme

3. FUZZY APPROACH FOR DETECTION PROCEDURE

FIS has been widely applied for making the decision [35]. The key advantage of FIS is complete consistency and always giving the same outputs when receives the same inputs [36]. In this paper, a scheme based on FIS is proposed for the detection procedure of the network's operation mode and single-line outage contingencies. A typical FIS consists of three components including fuzzification, fuzzy inference engine, and defuzzification as shown in Figure 2 [37]. In FIS, numerical input variables go through the fuzzification block and are converted to linguistic variables to act as the input of the inference engine. These fuzzy inputs are converted to fuzzy outputs utilizing the fuzzy inference engine by defining the rules. Finally, in the defuzzification block, they are converted to numerical values as the output of the system. A fuzzy set A in X={x_1, x_2, …, x_n} as the universe of discourse is defined [38],

$$A = \{(x.\mu_A(x))\} \qquad x \in X \tag{1}$$

where $\mu_A(x)$ is the grade of membership x in A and μ_A: $X \rightarrow [0,1]$, is called the membership function (MF) [38]. Therefore, inputs and output are defined as MFs in FIS. A FIS is made of a collection of several rules of the type IF-THEN [39],

$$\text{If } x_1 \text{ is } A \text{ and } x_2 \text{ is } B. \text{then } Y \text{ is } C \tag{2}$$

where x_1 and x_2 are inputs and C is the output [39]. This type of rule is utilized for detection purposes in the proposed detection scheme. Therefore, x_1 and x_2 can be defined as two inputs of the proposed scheme corresponded to the operation mode and line's status. Also, C can be defined as the goal output which is the scenario index. The application of FIS for the detection of operational and topological changes is explained.

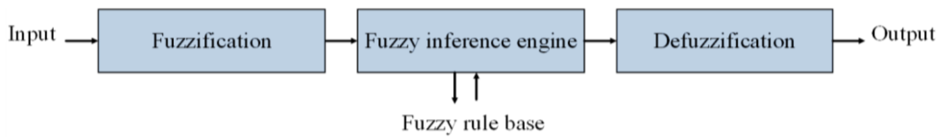


Figure 2. Functional blocks of a FIS

3.1. FIS for operation mode detection

The real-time data corresponded to currents and voltages obtained from the CTs and PTs are aggregated as analog signals using a relay to be used for operation mode detection. As aforementioned, some networks are capable of working at two different operation modes (i.e., grid-connected and islanded). In islanded mode, the network is working by DGs located at different busses to feed the loads. When the operation mode is changed to grid-connected, the network is connected to an external grid to retain the capability of feeding the loads. In such a situation, the power flowing through the network increases significantly. By knowing the total power level passing through the lines, the operation mode can be detected. So, this parameter, which is obtained as the analog data, is used as one of the inputs of the FIS in the proposed detection scheme.

3.2. FIS for line status detection

In the proposed detection scheme, there is a need for digital data as input of the FIS to detect the status of the lines. For this purpose, data are obtained from the CTs and PTs located at each end of the lines as analog signals and converted to digital signals in the relay. To utilize the digital signals for the detection of the lines' status, the CBs' status of the lines (open or closed) must be defined as binary values. For this purpose, first, the active power flowing through a CB is defined using a DC approximation as (3) [40]:

$$F_{ij} = B_\varepsilon(\theta_i - \theta_j) \tag{3}$$

where F_{ij} indicates the active power flowing through each CB of the line between bus i and j with the phase angle of θ_i and θ_j. Also, $B\varepsilon$ indicates the susceptance of the line. Then, a binary value namely U_{ij} is defined for the status of each CB located at the line, as (4) [40]:

$$F_{ij} = U_{ij}B_\varepsilon(\theta_i - \theta_j) \tag{4}$$

As can be interfered from (4), when the value of U_{ij} is "1" the CB is in the closed condition and the power flows through the line (normal status of the line), whereas "0" value indicates the CB of the line is in the open condition and there is no power flowing through the line (line outage contingency). For the sake of clarity, a scheme diagram of the line's CBs, which receives the data at both ends of the corresponding buses and pre-processes them in the control center for the line's status detection procedure, is shown in Figure 3. As it can be seen from Figure 3, the power flowing through the line's CBs is received by the relays. Then data are sent to the control center to be used by a FIS as a decision-making tool to determine the line's status. To consider the two CBs located at each end of the line and determine the final status of the binary variable U_{ij} to use as the other input of the FIS, a logic gate is used as shown in Figure 3.

Also, communication infrastructure is necessary to transform data from the network to the control center for analyzing and decision–making procedures. Power line carrier communication (PLCC) is a widely used telecommunication technology that uses the existing electrical transmission line as a medium to transmit data [41]. Power transformation along with communication are the two tasks of PLCC. A modem is responsible to transmits and receives data through the transmission line [42]. Utilizing the PLCC, data is sent by the modulator and at the receiver's side, a demodulator is responsible to retrieve data [42]. The frequency shift technique is utilized for keying the binary data into a carrier signal and coupling it onto the power line by the PLC modem (PLM). Finally, the other PLM at the receiver's side will detect the signal and convert it to binary data [42].

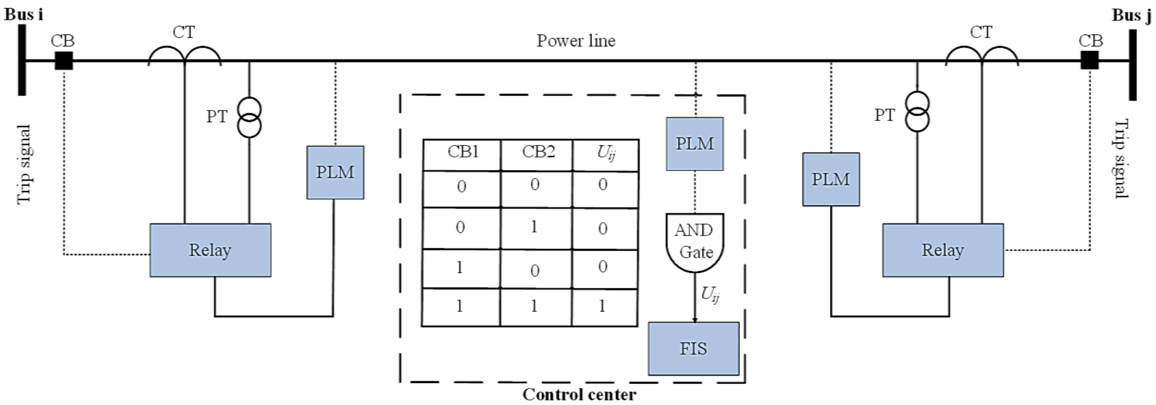


Figure 3. The schematic diagram for the procedure of the line's status detection

4. IMPLEMENTATION OF THE PROPOSED DETECTION SCHEME
4.1. Network under study

The IEEE 8-bus system that is shown in Figure 4 is utilized to implement and evaluate the proposed detection scheme [43]. The network operates at 300 MVA rates. Moreover, the network can be operated as the grid-connected mode by connecting to the external grid with a capacity of 400 MVA. Also, a wind energy farm (WEF) can be connected to bus 5 that includes four wind turbine generators (WTGs) of 2.5 MVA which makes the capacity of the total power of WEF to 10 MVA rates [43]. The IEEE 8-bus system parameters are available in [44].

4.2. Design and application of FIS

As above mentioned, in this study, FIS is the selected AI tool to be used for detection purposes. To this end, in the proposed scheme, a FIS structure is designed and used for the detection of both the networks' modes of operation and the single-line outage contingencies. Consequently, the network's status can be determined as the output of the FIS. There are two types of FIS namely Mamdani and Takagi-Sugeno (TS). The TS type is similar to the Mamdani type, and the difference is that the output is a crisp function of the input variables rather than a fuzzy proposition that appears in the Mamdani type [45]. So, the TS type is chosen for the fuzzy part of the proposed detection scheme.

The inputs which are used in the FIS for detection purposes, are "LBK-ST" and "TOTAL-POWER" which are corresponded to the lines' CBs' status and the network's total power, respectively. Also, the output is "SCE-INDEX" which is corresponded to the pre-defined indices of the network scenarios including operational and topological changes. Since the simple implementation and fast computations, the triangular MFs are used for the inputs of the FIS.

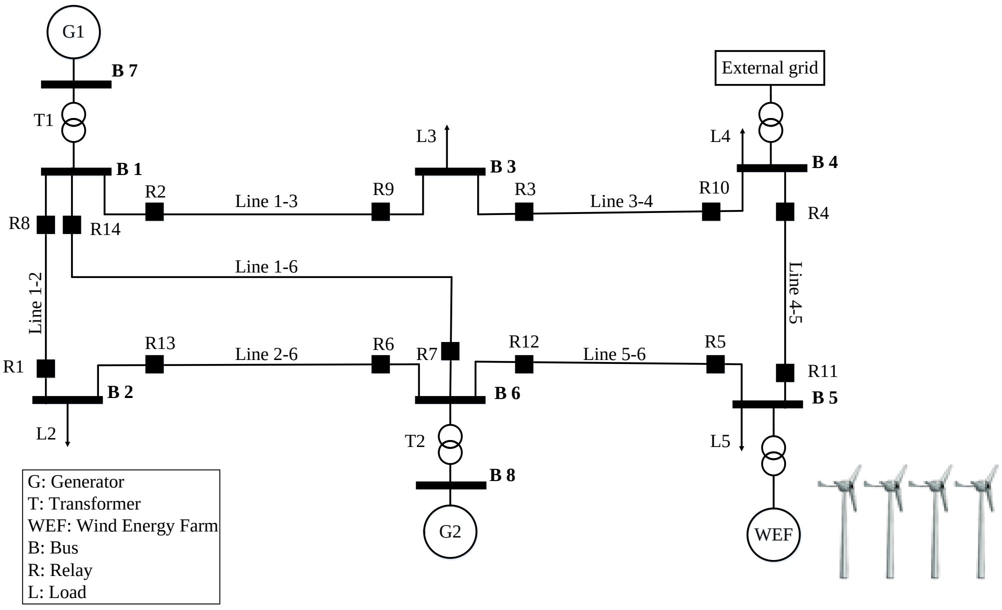


Figure 4. IEEE 8-bus system

For this purpose, the "LBK-ST" as one of the inputs is defined by MFs "low" and "high" with the range of (−1, 0, 1) and (0, 1, 2), respectively. MF "low" means the line is in outage condition and MF "high" indicates the normal status of the line. The "TOTAL-POWER" as the second input receives the MFs namely "low", "medium" and "high" with the range of (0,300), (300,310), and (310,710) respectively. These MFs correspond to islanded mode, islanded mode with WEF, and grid-connected mode, respectively. The associated triangular MFs for the three pre-defined operation modes are defined:

$$\mu_{low}(x) = \begin{cases} 0 & x \leq 0 \\ \frac{x}{150} & 0 < x \leq 150 \\ \frac{300-x}{300-150} & 150 < x < 300 \\ 0 & x \geq 300 \end{cases} \tag{5}$$

$$\mu_{medium}(x) = \begin{cases} 0 & x \leq 300 \\ \frac{x-300}{305-300} & 300 < x \leq 305 \\ \frac{310-x}{310-305} & 305 < x < 310 \\ 0 & x \geq 310 \end{cases} \tag{6}$$

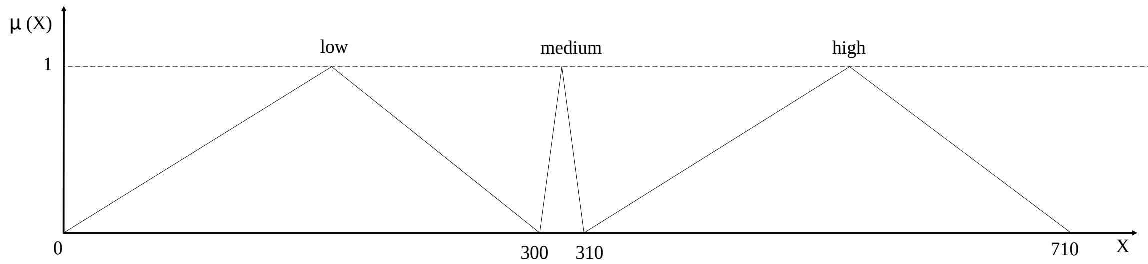
$$\mu_{high}(x) = \begin{cases} 0 & x \leq 310 \\ \frac{x-310}{510-310} & 310 < x \leq 510 \\ \frac{710-x}{710-510} & 510 < x < 710 \\ 0 & x \geq 710 \end{cases} \tag{7}$$

Also, the MFs correspond to the status of the lines' CBs are defined:

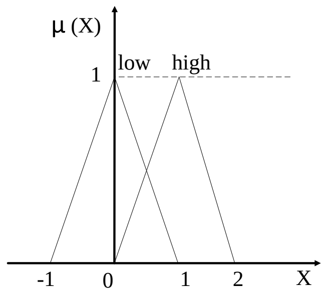
$$\mu_{low}(x) = \begin{cases} 0 & x \leq -1 \\ x+1 & -1 < x \leq 0 \\ 1-x & 0 < x < 1 \\ 0 & x \geq 1 \end{cases} \tag{8}$$

$$\mu_{high}(x) = \begin{cases} 0 & x \leq 0 \\ x & 0 < x \leq 1 \\ 2-x & 1 < x < 2 \\ 0 & x \geq 2 \end{cases} \tag{9}$$

According to the MFs defined for the CBs' status and the power flow level in (5)-(9), the graphs of MFs for inputs of the FIS are shown in Figure 5. Figure 5(a) indicates the MFs of power flow level. In addition, Figure 5(b) shows the MFs corresponding to the CBs' status.



(a)



(b)

Figure 5. Graph of MFs (a) power flow level and (b) CBs' status

Based on the status of these MFs, the rules in the FIS for the proposed detection scheme are formulated for the IEEE 8-bus system as shown in Table 1. It is to be noted that the linguistic terms L, M, and H which are used in Table 1 are corresponded to "low", "medium", and "high" MFs, respectively. As can be seen in Table 1, each scenario corresponds to the one single-line outage contingency in a specific network operation mode. A fuzzy logic designer is used to design and test the FIS for modeling the system behaviors under operational and topological changes. The designer in Figure 6, shows the status of lines' CBs and the total power as inputs and the index of the pre-defined scenario as the output.

Table 1. Fuzzy rules for IEEE 8-bus system

SCE-INDEX	LBK-ST (Line 1-2)	LBK-ST (Line 1-3)	LBK-ST (Line 3-4)	LBK-ST (Line 4-5)	LBK-ST (Line 5-6)	LBK-ST (Line 2-6)	LBK-ST (Line 1-6)	TOTAL-POWER
1	L	H	H	H	H	H	H	L
2	H	L	H	H	H	H	H	L
3	H	H	L	H	H	H	H	L
4	H	H	H	L	H	H	H	L
5	H	H	H	H	L	H	H	L
6	H	H	H	H	H	L	H	L
7	H	H	H	H	H	H	L	L
8	L	H	H	H	H	H	H	M
9	H	L	H	H	H	H	H	M
10	H	H	L	H	H	H	H	M
11	H	H	H	L	H	H	H	M
12	H	H	H	H	L	H	H	M
13	H	H	H	H	H	L	H	M
14	H	H	H	H	H	H	L	M
15	L	H	H	H	H	H	H	H
16	H	L	H	H	H	H	H	H
17	H	H	L	H	H	H	H	H
18	H	H	H	L	H	H	H	H
19	H	H	H	H	L	H	H	H
20	H	H	H	H	H	L	H	H
21	H	H	H	H	H	H	L	H

Figure 6 shows that the output obtained after defuzzification is in terms of scenario index. These are numerical values vary from 1 to 21 corresponding to SCE-INDEX1 to SCE-INDEX21. Each scenario corresponds to a single-line outage contingency in a pre-defined operation mode. So, by knowing the status of the lines and the value of total power flowing through the network, the topological and operational status of the network can be detected. The selection of the network's scenario index is performed by fuzzy logic toolbox using the graphical user interface (GUI) in MATLAB software and the results are shown in Figure 7. In this Figure, the SCE-INDEX2, SCE-INDEX9, and SCE-INDEX16 are selected when line 1-3 is under outage and the network is in islanded mode, islanded mode with WEF and grid-connected mode, respectively.

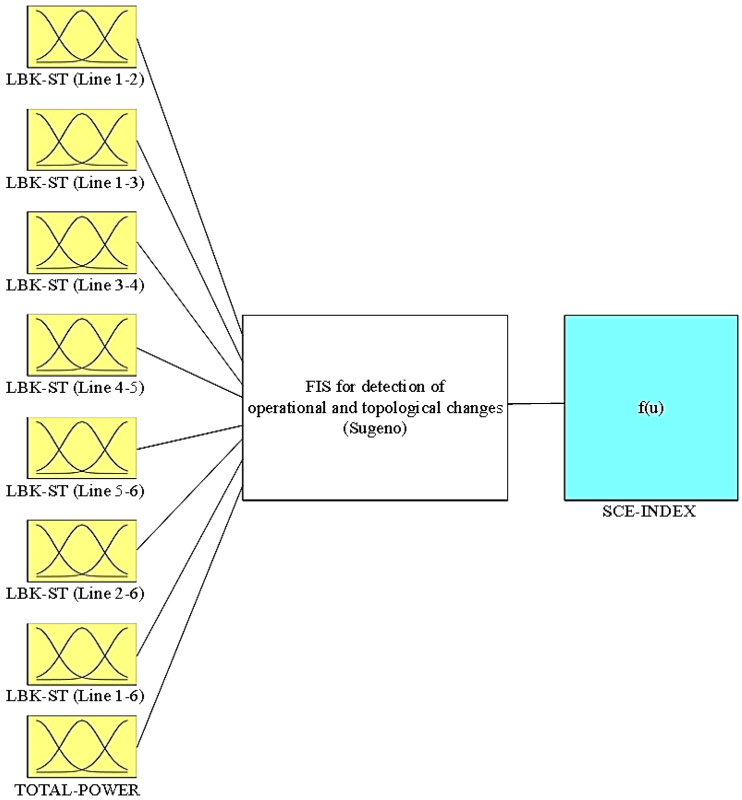
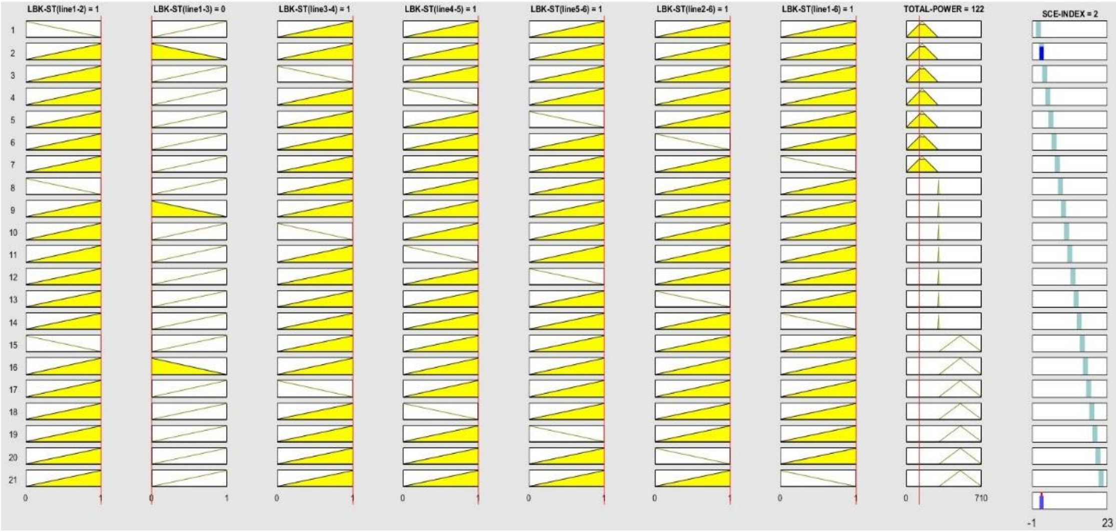
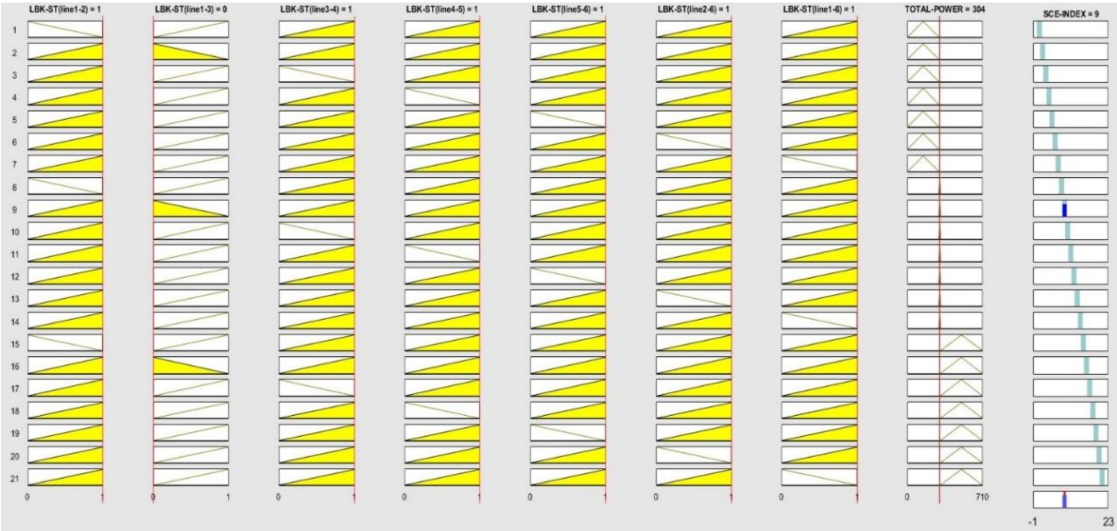


Figure 6. Fuzzy logic designer for detection of operational and topological changes

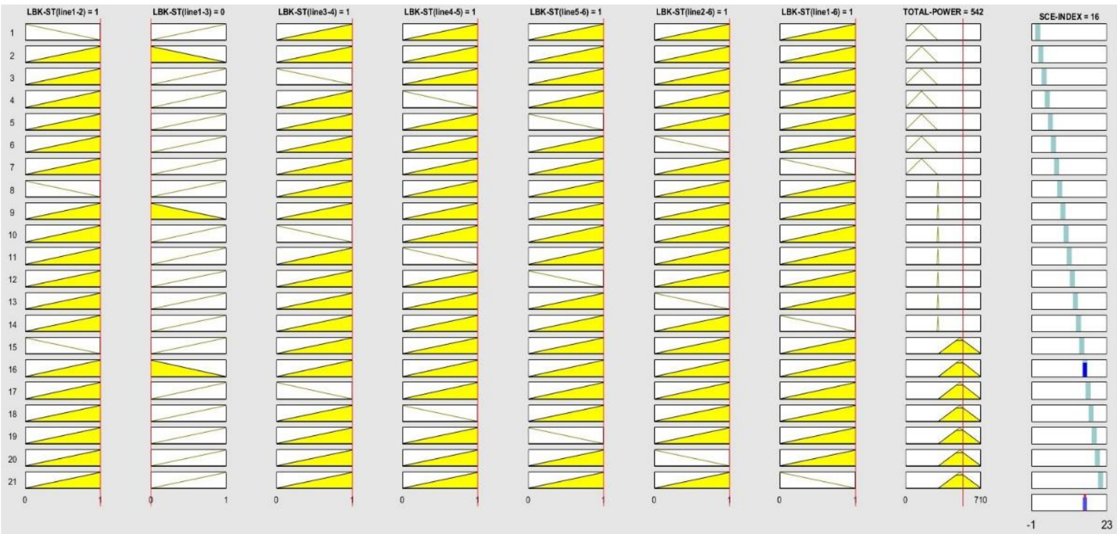
In Figures 7(a), 7(b), and 7(c), the first eight columns represent the inputs, and the last column represents the output. Inputs are the status of the lines' CBs and the value of the total power of the network. Also, the output is the related scenario index. As it is shown in Figures 7(a), 7(b), and 7(c), a text block of FIS with 21 scenarios including single-line outage contingencies at the three pre-defined operation modes (i.e., islanded mode, islanded mode with WEF, and grid-connected mode) is used for assessment of the FIS in the proposed detection scheme. It is shown in Figure 7(a), that if the CBs of line 1-3 be open and 122 MVA electric power flowing through the network, the FIS output indicates the scenario index 2 that is defined for line 1-3 outage at islanded mode as per Table 1. Also, the selection of the scenario indices 9 and 16 are shown in Figures 7(b), and 7(c) respectively. In Figure 7(b), scenario index 9 is selected when the network is in islanded mode along with the connection of WEF while line 1-3 is under outage. At this condition, the power flowing through the network is in the range of [300,310]. So, by the selection of 304 as the network power when the CBs of line 1-3 are open (line 1-3 is in outage condition), index 9 is selected by the FIS as the output. Moreover, when the loads exceed and the network is unable to feed the loads, the network is connected to the external grid. At this condition, the power flowing through the network is raised to the range of [310,710]. Figure 7(c) corresponds to this situation. As can be seen from this figure, the FIS output shows scenario index 16 when the network power is 542 MVA and line 1-3 is in outage condition. To clarify, the performance of the FIS for detection purposes is presented in Table 2. So, according to the performance of the FIS, the network's status both operational and topological can be determined accurately.



(a)



(b)



(c)

Figure 7. Network status selection in IEEE 8-bus system (a) scenario 2, (b) scenario 9, and (c) scenario 16

Table 2. Performance of the FIS

Operational mode	Total power (MVA)	Number of outage line							
		1-2	1-3	3-4	4-5	5-6	2-6	1-6	
Islanded mode	0-300	1	2	3	4	5	6	7	Scenario index
Islanded mode with WEF	300-310	8	9	10	11	12	13	14	
Grid-connected mode	310-710	15	16	17	18	19	20	21	

4.3. Method comparison

Generally, the detection methods in the power system can be divided into operational and topological methods. In both categories, some methods are based on non-phasor measurements and analysis of the network's parameters such as current and voltage, and some methods are based on analysis of phasor measurements including the angle of networks' parameters. The non-phasor measurement-based methods suffer from a high computational burden for final decision-making. On the other hand, the phasor measurement-based methods suffer from complexity and expensive implementation due to the utilization of PMUs.

To illustrate the superiority of the proposed method to the existing detection methods there is a comparison given in Table 3. According to the comparison characteristics that are listed in Table 3, less computational burden and reduction in complexity to analyze the networks' parameters that are obtained from existing measurement devices in the network utilizing the FIS for the detection procedure are the two significant characteristics that the proposed method benefits from them. Also, the proposed method utilizes the advantage of certainty of FIS since gives the same output by receiving the same inputs according to the pre-defined fuzzy-based rules.

Moreover, the advantage of the PLCC technology is the capability to use existing power lines for communication and data can be sent without any additional wiring or Ethernet-based infrastructures or PMUs that are expensive in implementation. So, regardless of the probable defects on transferring data such as noise that may mix with the communication signal and can be solved easily using filters or isolation circuits, no need for additional communication infrastructures due to using the PLCC technology is the other advantage of the proposed detection method. This characteristic is remarked as "cost-effective" in Table 3.

In addition, the simultaneous detection of both the operational and topological status of the network in an online manner can be considered as an advantage of the proposed method. Finally, as a vital advantage, the proposed detection method can be extended to more possible scenarios of the network such as double or multiple line outage contingencies just by defining the related fuzzy-based rules in the FIS to cover all possible outage contingencies that can be considered for future works.

Table 3. Characteristics comparison of the existing methods and the proposed method

Characteristic	Detection methods				
	Operational		Topological		Proposed method
	Non-phasor measurement-based [6]–[15]	Phasor measurement-based [16]–[18]	Non-phasor measurement-based [19]	Phasor measurement-based [20]-[34]	
Less computational burden	×	✓	×	✓	✓
Less complexity in analyzing data	✓	×	✓	×	✓
Cost-effective	✓	×	✓	×	✓

✓: In accordance with the characteristic ×: Not in accordance with the characteristic

5. CONCLUSION

This paper proposed a scheme to detect the operational changes and line outage contingencies using local data obtained from existing measurement devices. These data are analyzed at the control center and utilized to detect the occurrence of line outage or changes in the network's operation mode. One of the advantages of the proposed scheme is the simultaneous detection of both operational and topological changes. Also, the proposed scheme reduces the complexity of the existing detection methods and the computational burden utilizing the FIS as an AI tool. Moreover, as a vital advantage, the proposed detection scheme is based on transferring data through the existing power lines and there is no need for extra devices for implementing wireless and Ethernet technologies or PMUs which makes the proposed scheme cost-effective. To evaluate the proposed comprehensive detection scheme, MATLAB software is utilized to simulate the FIS. As a consequence of the results obtained from the FIS, the proposed detection scheme can successfully determine the accurate operational and topological status of the network based on real-time data in an online manner.

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