Decentralized Voltage Control of Power Systems Using Multi-agent Systems

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Abstract—A comprehensive scheme based on decentralized control, partitioning, multi-agent systems, and fuzzy logic is presented in this paper for the voltage control of power systems. In our proposed smart self-healing method, two types of control agents are defined, namely master and local, which are applied in two steps. In the first step, the power system returns to the normal state after fault occurrence. Immediately after a fault detection in a power system, the system is divided into three subsystems using spectral graph partitioning. Partitioning is conducted based on reactive power flow in transmission lines. For each subsystem, a local control agent and a performance index (PI) are defined. Whenever the PI of a subsystem exceeds its threshold limit, the local control agent uses the Sugeno fuzzy system to intelligently select and apply control actions. In the second step as performed by the master control agent, the power system is transformed to an optimal state by solving the optimization problem. Simulations on a 39-bus New England reveal the effective performance of the proposed method.

Index Terms—Emergency voltage control, partitioning, multi-agent systems, fuzzy systems.

I. INTRODUCTION

According to the definition of Institute of Electrical and Electronics Engineers (IEEE) and International Council on Large Electric systems (CIGRE), voltage stability is the ability of power systems to retain stable and acceptable voltages in all buses following a fault occurrence [1]. Power systems are generally designed to supply an annual peak load without problems, and their protective system secures them from $N-1$ contingencies. Due to the low probability of cascading faults, no protection or control system is typically considered for these types of faults. However, unanticipated and cascade faults have occurred in the past, leading to voltage collapse [1], which makes an automatic control system necessary.

Recently, smart grids have quickly developed in power systems. One of the fundamental features of smart grids is self-healing. A self-healing grid is capable of power system monitoring and can identify disturbances and take required actions to restore the grid. Therefore, a smart grid can manage those issues which are too complicated for human operators. This safety structure in power systems can prevent many faults. Figure 1 shows five operation states existing in each power system: 1) optimal; 2) normal; 3) fragile; 4) fault; 5) post-fault. Based on these five states, a self-healing grid control is composed of four types of basic control as depicted in Fig. 1 and given as follows [2].

1) Preventive control: return the grid from a fragile state to a normal state. This control is a preventive measure and is activated prior to fault occurrence.
2) Emergency control: immediately return the grid to a normal state after fault occurrence. The process should occur quickly.
3) Restoration: restore the grid to its normal state after a fault (blackout).
4) Optimal control: return the grid to a state with a greater safety margin.

The present study concentrates on the emergency and optimal voltage control in self-healing grids. Emergency voltage control problems have been variously presented in many studies. These studies can be classified into centralized and decentralized control approaches. In centralized control approach, the model predictive control (MPC) is generally used to solve emergency voltage control problems. MPC contains three main blocks: control actions, trajectory prediction and an objective function. In this control approach, within a prediction horizon, the most appropriate control actions are applied to the power system [3]. The differences between various studies devoted to this subject are usually based on the type of the objective function or algorithm utilized to solve the optimization problem [4]-[16]. One of the advantages of MPC-based methods is the simultaneous utilization of existing control variables to solve emergency voltage control problems while determining an optimal operation point after a fault occurs. Thus, both emergency and optimal control are conducted at the same step in MPC. In addition, not only the steady-state points but also voltage variations dur-

Fig. 1. State and control of self-healing grid.
ing the trajectory are monitored and controlled by MPC. Despite the advantages associated with MPC-based methods, they are very time-consuming because of the optimization steps. Moreover, the methods proposed in [4]-[16] are centralized, and their implementations require the information obtained from the entire power system. Consequently, even a small fault/contingency during data transfer from one of the phasor measurement units may disturb the performance of the control method.

Today, fuzzy control theory has been used in many electrical engineering issues [17]-[21]. A new strategy based on the Takagi-Sugeno fuzzy controller is proposed in [17] for wide-area power systems. In [18], fuzzy inference systems (FISs) are employed to determine the required amount of load shedding to stabilize the system regardless of any voltage collapse. This method has a desirable operation speed due to the high decision-making speed of fuzzy systems. However, the method introduced in [18] merely uses load shedding to stabilize the voltage in power systems, and it should be the last action employed to ensure that consumer rights are not violated. This method is also centralized and suffers from certain limitations.

Recently, multi-agent systems (MASs) have been heavily developed. In the research of artificial intelligence, agent-based system technology has been hailed as a new paradigm for conceptualizing, designing, and implementing software systems. Agents are sophisticated computer programs that act autonomously on behalf of their users across open and distributed environments to solve an increasing number of complex problems. Increasingly, however, applications require multiple agents that can work together. An MAS is a loosely coupled network of software agents that interact to solve problems which are beyond the individual abilities or the knowledge of the problem solvers.

An MAS has the following two main advantages over a single agent or centralized approach:

1) An MAS distributes computation resources and capabilities across a network of interconnected agents. Whereas a centralized system may be plagued by resource limitations, performance bottlenecks, or critical failures, an MAS is decentralized and thus does not suffer from the “single point of failure” problem associated with centralized systems.

2) An MAS enhances the overall system performance, specifically in terms of computation efficiency, reliability, extensibility, robustness, maintainability, responsiveness, flexibility, and reuse.

In [22], [23], MASs are used for emergency voltage control, but both studies use centralized frameworks to solve problems. In [24], MASs are used to solve an emergency voltage control problem in an interconnected transmission system. The method introduced in [24] is also based on MPC, which is insufficiently fast to control a system.

To create a coordinated decentralized control, the power system should be partitioned to form a local control system in each subsystem. In [25], spectral graph partitioning, which is based on an active power flow in transmission lines prior to fault detection, is used to partition the system. Still, no solution has yet been provided to control the system against voltage collapse. In [26], spectral k-way partitioning method is applied to power system partitioning. However, this method only uses load shedding to control the system and, as previously mentioned, this control action should be the last measure to ensure that consumer rights are not violated.

A coordinated decentralized control for emergency voltage control in power systems is proposed in [27]. In this method, prior to fault occurrence, the 39-bus New England power system is initially divided into three subsystems based on electrical distance. In addition, a performance index (PI) is introduced for each subsystem, where PI is calculated based on the voltage deviations of the load buses in each subsystem, and the deviation of the reactive power is derived from the maximum reactive power limit on each generator. Whenever the integral of PI in a subsystem is greater than 1, the control system is activated, and the two parameters of capacitor and load shedding are used to control the voltage in the subsystem. The advantage of the method proposed in [27] is the speed of the control system, but it suffers from three shortcomings:

1) The system is partitioned before the fault occurs. If the fault in the power system is a line outage, the electrical distance matrix of the system will vary. Consequently, pre-fault partitioning does not render precise partitioning for these types of faults. In [28], this issue is solved by partitioning the system following fault occurrence based on an electrical distance matrix. However, disturbances resulting from generator outage or sudden load changes will not alter the electrical distance matrix.

2) The system is controlled only by switching on the capacitors or load shedding.

3) The control variables are applied unintelligently and step by step until the PI value becomes zero. Therefore, the number of required control steps will increase for restoring the grid to its normal state.

This study presents a smart self-healing grid control for emergency voltage control in two steps. In the first step, following fault detection, the system is immediately partitioned based on the reactive power flow in transmission lines. The system is partitioned so that each subsystem exhibits the lowest exchange of reactive power with its neighboring subsystems. Spectral graph partitioning is used here for power system partitioning. Control actions in this paper include altering the reference voltage of generators as well as switching the capacitors and load shedding. Load shedding is applied if no other options exist to prevent a voltage collapse in the power system. The exact values of the control variables are determined using a fuzzy control system. Membership functions (MFs) in fuzzy control are regulated based on the pre-assessment of the power system in offline mode. In the case of obligatory load shedding, load buses with the shortest electrical distances from fault locations are selected. It should be mentioned that control actions in each subsystem are coordinated using MASs when no connection exists between the subsystems. With the use of control actions determined by FISs, the power system is transferred to its normal state in the first step. In the second step, the teaching-learn-
ing-based optimization (TLBO) is used to return the power system to its optimal state.

The remainder of this paper is organized as follows. Section II addresses the problem of coordinated and emergency voltage control. Section III introduces the structure of the proposed self-healing grid control based on a decentralized control. Section IV evaluates the proposed method using several simulations on a 39-bus New England power system. Finally, Section V discusses the obtained results.

II. POWER SYSTEM MODEL

A model of a power system for emergency voltage control including a combination of algebraic and dynamic equations is expressed as:

\[ \dot{x} = f(t, x, y, u) \]

\[ 0 = g(x, y, u) \]

where \( f(\cdot) \) and \( g(\cdot) \) are dynamic and algebraic equations, respectively; \( x \) is the dynamic state variable; \( y \) is the algebraic output variable; \( u \) is the system control variables; and \( t \) is the time.

Since we intend to study the long-term voltage instability problem, the quasi-steady state (QSS) of generators suffices to investigate the behavior of the system [4], [15]. Hence, the differential equations of the system only include the equations of dynamic loads. This study uses an aggregated exponential recovery model, which is defined as [12], [13]:

\[ \frac{dx_{i,p}}{dt} = -\frac{x_{i,p}}{T_{i,p}} + P_{i,d}\left(V_{i}^{n} - V_{i}^{*}\right) \]

\[ P_{i,d} = (1 - n_{i,d}D_{shed}) \left( \frac{x_{i,p}}{T_{i,p}} + P_{i,d}V_{i}^{n}\right) \]

\[ \frac{dx_{i,q}}{dt} = -\frac{x_{i,q}}{T_{i,q}} + Q_{i,d}\left(V_{i}^{n} - V_{i}^{*}\right) \]

\[ Q_{i,d} = (1 - n_{i,d}D_{shed}) \left( \frac{x_{i,q}}{T_{i,q}} + Q_{i,d}V_{i}^{n}\right) \]

where \( V_{i} \) is the voltage of the \( \text{th} \) load; \( x_{i,p} \) and \( x_{i,q} \) are the state variables whose variations result in retrieval of active and reactive loads in the bus \( i \), respectively; \( P_{i,d} \) and \( Q_{i,d} \) are the active and reactive power of the \( \text{th} \) load, respectively; \( P_{i,d} \) and \( Q_{i,d} \) are the initial values of active and reactive power of the \( \text{th} \) load, respectively; \( D_{shed} \) is the load shedding step size equal to 0.05 p.u. in each bus; \( n_{i,d} \) is the number of load steps to shed in bus \( i \); \( T_{i,p} \) and \( T_{i,q} \) are the time constants for retrieving active and reactive power of the \( \text{th} \) load, respectively, and are assumed to be 60 s; and \( \alpha_{s}, \alpha_{r}, \beta_{s}, \beta_{r} \) are the constants denoting the amount of correlation between active and reactive loads in steady and transient voltage states, respectively.

In this paper, control variables include susceptances of capacitors, reference voltages of generators, and the amount of load shedding. Load shedding is applied only if no other options exist to prevent a voltage collapse in the power system.

III. PROPOSED SELF-HEALING GRID BASED ON DECENTRALIZED CONTROL

The structure of a self-healing grid based on decentralized control is presented in Fig. 2. As shown in Fig. 2, the proposed method is conducted in two steps, where Step 1 involves a decentralized emergency voltage control for restoring the system to its normal state, and Step 2 involves switching the system to an optimal mode. In decentralized control, a system is divided into several subsystems, each of which have its own local controller agent (LCA). LCA receives dynamic state variable \( x \) and the output \( y \) from its subsystem. And then it takes a few control actions in the shortest possible time to its subsystem based on PI calculated for each subsystem. In this figure, a master controller agent (MCA) supervises all LCAs to control the system and restore it to its optimal state. In the proposed optimal control, each LCA sends the data related to its subsystem, including \( x_{1}, y_{1}, \) and \( u_{1} \), to MCA. Then, MCA uses TLBO to determine the number of optimal control variables \( u^{*} \) required to restore the grid to its optimal state. Ultimately, each LCA applies the received \( u^{*} \) from MCA to its own subsystem.

In the proposed emergency control method, numerous preliminary simulations are conducted for each power system. Then, after the system status with different faults is identified, a preliminary knowledgebase of the system is collected in offline mode. This preliminary knowledge is the basis for defining MFs of the fuzzy system. Then, a fuzzy control system is created for each control variable. Following a fault occurrence, the power system is immediately divided into three subsystems using spectral graph partitioning. For each subsystem, a local control system is defined. Based on the PI value of each subsystem, the control system smartly determines and applies the values of control variables to the system based on FIS. Figure 3 depicts the algorithm proposed for emergency voltage control.

For transferring to the optimal state, data from all power systems are required. These data are transmitted from LCAs to MCA, and the optimal control variables are determined by MCA by solving the optimization problem with TLBO algorithm. Reducing the voltage deviations is the objective function in this step. To solve this optimization problem, TLBO is proposed although it is possible to apply other optimization algorithms such as the imperialist competitive or parti-
cle swarm optimization. The control variables in the optimal control step include alterations in the susceptance of capacitors and reference voltage of generators.

To determine the vulnerability of a grid to a voltage collapse, the PI introduced in [27] and [28] is used. According to outage, etc., alters the reactive power flow in the transmission lines. Consequently, PI can be expressed as:

$$PI = W_{rs} \sum_{i=1}^{N_{Li}} (V_{L,\min} - V_{Li}) + W_{pg} \sum_{i=1}^{N_{Gi}} (Q_{Gi} - Q_{Gi,max})$$  \hspace{1cm} (7)$$

where $V_{L,\min}$ is the minimum voltage limit; $Q_{Gi,max}$ is the maximum reactive power limit of the $i^{th}$ generator; $V_{Li}$ is the voltage of the $i^{th}$ load bus when the voltages are less than $V_{L,\min}$; $Q_{Gi}$ is the reactive power output of the $i^{th}$ generator when the reactive powers are greater than $Q_{Gi,max}$; $W_{rs}$ and $W_{pg}$ are the weighting factors equal to 1 and 2, respectively; and $N_{Li}$ and $N_{Gi}$ are the numbers of load and generator buses whose voltage and reactive power exceed their limits, respectively.

$$Q_{Gi,max} = \frac{V \cdot EFD_{\max} \cos(\delta - \theta) - V^2 \left\{ \sin^2(\delta - \theta) \frac{X_d}{X_q} - \cos^2(\delta - \theta) \right\}}{X_d}$$ \hspace{1cm} (8)$$

where $V$ is the output voltage of the generator; $EFD_{\max}$ is the maximum voltage of the generator excitation system; $\delta$ is the rotor angle; $\theta$ is the terminal voltage angle; and $X_d$ and $X_q$ are the reactances of the direct and quadrature axes of the stator, respectively.

Similar to [27], the timing of the control actions is determined when the PI value in each subsystem is greater than 1. Consequently, the control actions are automatically applied to the subsystem. The value of 1 is adopted from several simulations and the knowledge database obtained from the power system. The values for control variables are smartly determined based on the fuzzy system introduced in the following section. Capacitor switchings and reference voltages of generators are simultaneously applied to the power system. Load shedding is then used when the two other control variables are incapable of voltage restoration in the subsystem. Under this condition, load buses with the shortest electrical distances from the fault location are given priority because shedding these loads is highly effective in voltage improvement. To determine priorities, (9) and (10) can be used. Firstly, (9) is used to calculate the electrical distance matrix $D$, i.e., impedance matrix of the system. Then, (10) is used to select the bus loads with the maximum priorities for load shedding.

$$D = |Y_{bus}|$$ \hspace{1cm} (9)$$

$$Sort(D_{\theta}) \hspace{0.5cm} k = 1, 2, ..., N_{Li}$$ \hspace{1cm} (10)$$

where $Y_{bus}$ is power system impedance matrix; $N_{Li}$ is the number of bus loads in the subsystem $h$; and $D_{\theta}$ is the distance between the fault location $i$ and load number $k$. Then these distances are ordered from the smallest to the largest.

Whenever the PI value equals 0 in each subsystem, control actions are terminated. In addition, after 20 s, the emergency control system is deactivated. At this moment, the power system is restored from the fault state to the normal state. To restore the system to its optimal state, an optimization problem must be solved. Solving this optimization problem takes 240 s (four times the time constant) after the emergency control system is deactivated. In this stage, the power system is in the steady-state mode. Therefore, substituting the load model with the steady-state model is possible, and the QSS model can also be employed for generators. In this paper, the optimization problem is expressed as:

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Fig. 3. Proposed algorithm for a decentralized emergency voltage control in a self-healing grid.

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A. Power System Partitioning

Following a fault, the power system is divided into three subsystems using spectral graph partitioning. In our recent study [29], the power system is partitioned following the fault based on three matrices of admittance, active and reactive power flows in the transmission lines. It is attested that in the case of partitioning based on the reactive power flow in the transmission lines, the control variables which are critical factors for retrieving the voltage in the fault zone, e.g., generator buses, will be included in the fault zone and will speed up the voltage retrieval. Therefore, in this paper, the partitioning is based on a reactive power flow in the transmission lines following a fault. Partitioning is performed so that each subsystem has the least power exchange with its neighboring subsystems. In addition, each fault, which includes the line outage, increased or decreased load, generator outage, etc., alters the reactive power flow in the transmission lines. Spectral graph partitioning is explained in [16] and [30] and is also reviewed in Appendix A.

B. PI and Control Variables

To determine the vulnerability of a grid to a voltage collapse, the PI introduced in [27] and [28] is used. According to these references, the generator reactive power production is close to the maximum reactive power limit. In addition, the voltage magnitude in each bus plays a crucial role in voltage instability. Consequently, PI can be expressed as:

$$\text{PI} = W_{rs} \sum_{i=1}^{N_{Li}} (V_{L,\min} - V_{Li}) + W_{pg} \sum_{i=1}^{N_{Gi}} (Q_{Gi} - Q_{Gi,max})$$  \hspace{1cm} (7)$$
\[
\begin{align*}
\min VD &= \sum_{i=1}^{N_{L}} |V_i - V_i'| \\
\text{s.t. } g(x,u) &= 0 \\
h(x,u) &\geq 0
\end{align*}
\]

where \(VD\) is the voltage deviation of the system which should be minimized; \(V_i'\) is the desirable voltage of the bus which is assumed to be 1 p.u.; and \(N_{L}\) is the number of load buses. Control variables of the optimal state are susceptances of capacitors and reference voltages of generators. Finally, \(g\) refers to the equality equations such as the load flow and \(h\) refers to inequality equations such as limits of reactive power, voltage of generators, voltages of load buses, and limits of control variables. The variables \(g\) and \(h\) are fully described in Appendix A.

C. Fuzzy Inference System

The fuzzy control utilized in this paper is a Sugeno type. Regulating MFs is the most difficult part in the process of forming a fuzzy control system. Two general methods can be used to define the rules in a fuzzy system.

1) Extracting the rules out of the collection of input and output data such as the stock market forecasting for tomorrow’s prediction of an index status, the fuzzy system uses a set of input and output data for the past year to determine its fuzzy rules.

2) If the input and output datasets are not available, the knowledge of experts can be used. This requires a person with sufficient knowledge of the system who knows how influential any change in a control variable is on other system parameters. To this end, for the 39-bus system, offline calculations are employed to obtain the best knowledge empirically based on trial and error. Thus, for each fault (outage of a line or a generator), an offline simulation is conducted on the 39-bus system to obtain the rules empirically. The values for MFs are presented in Fig. 4.

For each control action (susceptance of capacitor \(B_{c,i}\), reference voltage of generator \(V_{r_{dc}}\) and \(n_{i,d}\)), five MFs are defined: four MFs of “very low (VL)”, “low (L)”, “medium (M)” and “high (H)” in triangular form, and one “very high (VH)” MF in trapezoidal form.

Fuzzy system rules for control actions are listed in Table I. It should be mentioned that the susceptances of capacitors and load shedding can both accept discrete values. Consequently, the output of fuzzy system is rounded to the closest discrete values for these control variables.

The smart selection of control actions based on the Sugeno fuzzy system boosts the solving speed and reduces the number of control actions compared to the unsophisticated utilization of control actions. This reduces the costs of the power system.

The proposed method is implemented on a 39-bus New England power system. All features and settings are based on this power system. Three subsystems in the proposed method are also considered [27]. Note that it is also possible to implement the proposed scheme by partitioning it into more subsystems, provided that the fuzzy rules are properly defined.

### Table I

| Rule | Control action |
|------|----------------|
| If IPI is VL, then \(V_{r_{dc}}\) is 1; if IPI is L, then \(V_{r_{dc}}\) is 1.05; if IPI is M, then \(V_{r_{dc}}\) is 1.075; if IPI is H, then \(V_{r_{dc}}\) is 1 | 0.5 |
| If IPI is VL, then \(B_{c,i}\) is 0.1; if IPI is L, then \(B_{c,i}\) is 0.2; if IPI is M, then \(B_{c,i}\) is 0.3; if IPI is H, then \(B_{c,i}\) is 0.4; if IPI is VH, then \(B_{c,i}\) is 0.5 | 1 |
| If IPI is VL, then \(n_{i,d}\) is 1; if IPI is VL, then \(n_{i,d}\) is 2; if IPI is VL, then \(n_{i,d}\) is 5; if IPI is VL, then \(n_{i,d}\) is 7.5; if IPI is VL, then \(n_{i,d}\) is 10 | 7.5 |

IV. Simulations

To evaluate the performance of the proposed self-healing control system, a 39-bus New England power system is studied, which is fully described in [31]. This system contains 10 generators. It is assumed that the reference voltage of each generator could change from 0.9 to 1.1 p.u. The maximum voltage of the generator excitation system is assumed to be 2 p.u.. Eight capacitors are used in buses 3, 4, 7, 8, 12, 15, 18, and 26 of the system with 0.1 increments from 0 to 0.5 p.u.. It is assumed that 10 buses (3, 4, 7, 8, 15, 16, 20, 23, 27, and 28) are available for load shedding. The maximum load shedding in each bus could reach up to 50% of the load existing in that bus. It is composed of 10 steps with each step size equal to 0.05 p.u.. It should be noted that the maximum voltage of the generator excitation system is equal to 2 p.u. due to the over-excitation-limiter performance. In addition, the values of reference voltages in all generators and capacitors in the basic state are equal to 1 and 0 p.u., respectively. Simulations are performed on MATLAB using an Intel Core i5, 2.86 GHz CPU.

Control variables are applied on the system every 5 s. Simulations are performed using two methods: 1) unsophisticated application of control variables (non-fuzzy); 2) application of control variables using the Sugeno fuzzy method (fuzzy). The results are then compared. In Table II, the step changes in control actions are listed with the non-fuzzy method. However, with the fuzzy method, the control actions are determined based on IPI. For example, assume IPI equals 1.5 in Subsystem 2. According to Fig. 4, the fuzzy method allocates 0.3 p.u. to the susceptance of the capacitor in one-step control. By contrast, with the same susceptance...
of capacitor in the non-fuzzy method, three control steps are required, which confirms that the fuzzy method is more economical.

In the optimal control step, MCA receives the required data \((x, y, u)\) from all LCAs. Then, MCA uses TLBO to determine the optimal control variables to transfer the power system to the optimal state. The initial population and number of iterations are assumed to be 40 and 400, respectively. TLBO algorithm is completely described in [32], and the effectiveness of TLBO is compared with the other population-based optimization algorithms according to the best solution, average solution, convergence rate, and computation effort. Results show that TLBO is more effective and efficient than the other optimization methods at solving different optimization problems.

In this section, two scenarios are investigated. Tripping the generator 32 (G32) is the first scenario. For the second scenario, lines 5-6 and 6-7 are simultaneously removed from the grid. In both cases, it is assumed that the fault occurs at 30 s.

**A. Scenario 1**

In this scenario, G32 is tripped at 30 s. Figure 5 shows that the outage of this generator without any control system leads to a voltage collapse in the power system. This figure presents the voltages of buses 11, 12, and 13 with high voltage drop as examples.

![Figure 5. System response after outage of G32 without any control actions.](image)

When G32 is tripped and the control system detects the fault, spectral graph partitioning immediately divides the power system into three subsystems as shown in Fig. 6. The system is immediately partitioned based on the reactive power flow in transmission lines after the fault occurs.

The IPI values for Subsystem 1 (IPI1) are presented in Fig. 7 for both methods. It can be seen that in both methods, IPI1 is greater than 1 at 35 s. Therefore, LCA1 is activated at this time. Based on Fig. 8, PI1 is zero at 40 s. This results from two switching control actions at 35 s and 40 s in Subsystem 1, respectively. Without the application of the fuzzy method, PI1 will be zero at 55 s. Thus, in the non-fuzzy method, the number of switching steps when applying control actions in Subsystem 1 is equal to 5 at 35, 40, 45, 50, and 55 s, respectively. Therefore, it can be concluded that when the fuzzy method is used, both the voltage recovery is accomplished in a shorter time and the number of steps to apply control actions to the system is reduced. This is an economically significant result.

**TABLE II**

| Control action | Step change (p.u.) |
|---------------|-------------------|
| \(\Delta V_{ref,i}\) | 0.1               |
| \(\Delta B_{ref,i}\) | 0.1               |
| \(\Delta n_{ref,i}\) | 1.0               |

For Subsystem 2, according to Fig. 9, the IPI values with the fuzzy and non-fuzzy methods reach a threshold value of 1 at 55 s and 50 s, respectively. Consequently, LCA2 is activated at the two times with the aforementioned methods. According to Fig. 10, applying control actions with the fuzzy and non-fuzzy methods reduces PI2 to 0 at 75 s and 85 s, respectively. It can be seen that the fuzzy method applies control actions in Subsystem 2 at 55, 60, 65, 70, 75 s, respectively, but with the non-fuzzy method, these measures are taken in eight time steps of 50, 55, 60, 65, 70, 75, 80, 85 s, respectively.

![Figure 6. Partitioning of power system after outage of G32.](image)

![Figure 7. IPI1 with fuzzy and non-fuzzy methods in Scenario 1.](image)
It should be noted that after G32 is tripped, the IPI value of Subsystem 3 does not reach 1 with either methods. Therefore, LCA3 is not activated with either method. In this scenario, the control system restores the grid from an emergency to a normal state without load shedding.

Figures 11 and 12 show the voltages of buses 11 and 12 in both methods, respectively. As can be seen in these figures, the voltage reaches nearly the same value in both methods. However, according to Figs. 7-12, two significant results are obtained: ① voltage control is faster with the proposed method (fuzzy method); ② fewer control actions are required with the proposed fuzzy method, which is economically significant. The number of control actions is 7 with the fuzzy method (2 and 5 steps in Subsystems 1 and 2, respectively). This number is 13 times with the non-fuzzy method (5 and 8 steps in Subsystems 1 and 2, respectively).

Now, after restoring the system from a fault state to a normal one, the proposed self-healing grid control should restore the system to an optimal state. This is accomplished using TLBO algorithm at 240 s after the emergency control system is deactivated. Figure 13 shows the voltage profile in both normal and optimal states.

B. Scenario 2

In this scenario, lines 5-6 and 6-7 are simultaneously out-
ed from the power system. Based on Fig. 14, this fault leads to voltage collapse without any control actions. Figure 15 shows the system partitioning based on a reactive power flow in the transmission lines after fault detection.

According to Fig. 16 and a comparison of IPI values in Subsystem 1 with the fuzzy and non-fuzzy methods, IPI1 will be greater than 1 at 50 s with both methods. Consequently, LCA of Subsystem 1 will be activated at 50 s with both methods. Figure 17 shows that PI1 will be 0 at 60 s with the fuzzy method. These results from three switching steps are used to apply control actions in the Subsystem 1 at 50, 55, 60 s, respectively. With the non-fuzzy method, the PI1 of Subsystem 1 will be reduced to 0 at 65 s when four steps of control actions are applied to Subsystem 1 at 50, 55, 60, 65 s, respectively.

According to Fig. 18, IPI2 in Subsystem 2 will reach the threshold limit of 1 at 35 s with the fuzzy or non-fuzzy method. Thus, LCA2 of Subsystem 2 will be activated at this time with either method. Figure 19 shows that PI2 reaches 0 at 60 s and 65 s with the fuzzy and non-fuzzy methods, respectively. With the proposed method, the control actions will be applied to Subsystem 2 at six time intervals of 35, 40, 45, 50, 55, 60 s, respectively. With the non-fuzzy method, seven time steps are required at 35, 40, 45, 50, 55, 60, 65 s, respectively.

It should be noted that with neither method does this fault shift IPI to 1 in Subsystem 3. Consequently, LCA3 will not be activated with either method. In this scenario, the control system returns the power system from an emergency to a normal state with two steps of load shedding at bus 7 with both methods.
Figures 20 and 21 show the voltage of buses 5 and 7 with both methods, respectively. Both methods nearly reach the same amount of voltage. With the fuzzy method, however, the retrieval speed is higher, and fewer control actions are employed. This is economically significant. The number of control actions with the proposed method is 9 (3 and 6 steps in Subsystems 1 and 2, respectively). The non-fuzzy method requires 11 steps of control actions (4 and 7 steps in Subsystems 1 and 2, respectively). The non-fuzzy method requires 11 steps of control actions (4 and 7 steps in Subsystems 1 and 2, respectively). Both methods nearly reach the same amount of voltage. With the fuzzy method, however, this method reduces the number of control actions in the system compared to the non-fuzzy method, which is economically significant. The number of steps employed. This is economically significant. The number of steps required in the subsystem. It is most influential on reducing the number of control actions required in the subsystem.

After restoring a fault state to the normal one, MCA should shift the power system to the optimal state. As in the previous scenario, the voltage profile in both normal and optimal states is shown in Fig. 22.

V. CONCLUSION

In this paper, a self-healing system is proposed for a coordinated voltage control based on spectral graph partitioning, MASs, FISs, and TLBO algorithm. The proposed method is based on the smart selection of control actions in each subsystem according to IPI values with an FIS. Results indicate that this method reduces the number of control actions in the system compared to the non-fuzzy method, which is an economically significant result. This paper shows that the proposed control method is decentralized and faster than centralized methods. This paper uses spectral graph partitioning based on a reactive power flow in the transmission lines after fault detection to determine the subsystems. The advantage of partitioning based on a reactive power flow in the transmission lines is that each control variable is allocated to the subsystem. It is most influential on reducing the number of control actions required in the subsystem.

APPENDIX A

A. Spectral Graph Partitioning

Each graph is composed of several vertices and edges. For example, graph $G = (V, E)$ is composed of a set of vertices $V = \{v_1, v_2, ..., v_n\}$, and $e_{ij} = (v_i, v_j)$ is the weight of the edge between vertices $v_i$ and $v_j$. The adjacency matrix for each graph is represented as $A = (e_{ij})$. In the graph partitioning problem, the goal is to partition the graph into $K$ subgraphs so that the overall weight of edges between subgraphs can be minimized as [30]:

$$C(P) = \min \left(1', A1\right) - \text{Trace}(n'A n) \quad (A1)$$

where $P = \{V_1, V_2, ..., V_K\}$ and $V_1, V_2, ..., V_K$ are the sets of vertices in each subgraph; $1_n$ is an $n$-vector with the sum of all entries equal to 1; and $n = (\pi_n)$ is an $n \times K$ matrix in which $\pi_{ij}$ is:

$$\pi_{ij} = \begin{cases} 1 & v \in V_j, \forall v \in V_j, j = \{1, 2, \ldots, K\} \\ 0 & v \notin V_j, \forall v \in V_j, j = \{1, 2, \ldots, K\} \end{cases} \quad (A2)$$

In addition, $n$ must be orthogonal (the diagonal matrix) and $\|n\|_F = \sqrt{n}$. The notation $\| \cdot \|_F$ denotes the Frobenius norm. In fact, the aforementioned conditions guarantee that each row of matrix $n$ has only one non-zero array,
which is equal to 1. After (A1) is solved, if $\pi_{ij}$ equals 1, it implies that bus $v$ is located in zone $j$.

Since in (A1), $I^*_{i}A_i$ is always a constant value, it can be rewritten as:

$$ C(P) = \max \text{Trace}(n^TAn) $$

s.t. $\pi_{ij} \in [0,1] \quad \forall v,j$

$$ \|n\|_F = \sqrt{n} \quad n \text{ is orthogonal} $$

(A3)

In graph partitioning, eigenvalues and eigenvectors are used to solve (A3). If $A$ is normalized so that the sum of each row is 1 and $e_{ij} = e_{ji}$, the largest eigenvalue for $A$ will be equal to 1.

Let $\lambda_1 > \lambda_2 > \ldots > \lambda_K$ be the largest eigenvalues of $A$ and $u_1, u_2, \ldots, u_k$ be the corresponding orthonormal eigenvectors. It is convenient to define:

$$ D = \text{diag}(\lambda_1, \lambda_2, \ldots, \lambda_K) $$

$$ U = [u_1, u_2, \ldots, u_k] $$

(A4)

where $UU^T=I_{K\times K}$ and $AU=DU$. $n$ is an orthogonal matrix whereby $\text{Trace}(nn^T)=n$, and since the largest eigenvalue of $A$ is equal to 1, we can obtain:

$$ \text{Trace}(nn^T) = \sum_{i=1}^{K} \pi_i A_{i\cdot} \leq \sum_{i=1}^{K} \pi_i A_{i\cdot} = \text{Trace}(nn^T) = n $$

(A5)

With the assumption that $n=UZ$ in which $Z$ is a $K \times K$ matrix, we can write:

$$ \text{Trace}(nn^T) = \text{Trace}(ZU^TUZ) = \text{Trace}(Z^TZ) = n $$

(A6)

$$ \text{Trace}(nn^T) = \text{Trace}(ZU^TAUZ) = \text{Trace}(Z^TDZ) $$

(A7)

Based on (A6) and (A7), if $D$ is equal to the identity matrix, the upper limit of (A5) and consequently the maximum of (A3) are obtained. The condition for holding this assumption is [30]:

$$ \min \|n - UZ\| $$

(A8)

B. Optimization Problem

The optimization problem is defined as:

$$ \min P_L - \sum_{i=1}^{n} V_i V_i^* $$

(A9)

$$ P_{Li} - \sum_{i=1}^{n} V_i V_i^* \cos(\theta_i - \theta_k - \alpha_k) = 0 \quad i = 1,2,\ldots,n-m $$

(A10)

$$ Q_{Li} - \sum_{i=1}^{n} V_i V_i^* \sin(\theta_i - \theta_k - \alpha_k) = 0 \quad i = 1,2,\ldots,n-m $$

(A11)

$$ I_d V_i \sin(\delta_i - \theta_k) + I_{d*} V_i \cos(\delta_i - \theta_k) - \sum_{i=1}^{n} V_i V_i^* \cos(\theta_i - \theta_k - \alpha_k) = 0 \quad i = n-m,\ldots,n-m+1 $$

(A12)

$$ I_d V_i \cos(\delta_i - \theta_k) - I_{d*} V_i \sin(\delta_i - \theta_k) - \sum_{i=1}^{n} V_i V_i^* \cos(\theta_i - \theta_k - \alpha_k) = 0 \quad i = n-m,\ldots,n-m+1 $$

(A13)

$$ E_{d*} - V_i \sin(\delta_i - \theta_k) - R_{d*} I_{d*} + X_{d*} I_{d*} = 0 \quad i = n-m+1,\ldots,n $$

(A14)

where $n$ and $m$ are the numbers of buses and generator buses, respectively. Equations (A10) and (A11) are equilibrium equations in the load buses, (A12) and (A13) are equilibrium equations in the generator buses, and (A14) and (A15) are algebraic equations in stators. The QSS equations are described in (A16) - (A21). Equation (A22) indicates thermal limits in any branch, (A23) describes the susceptance limitation, and (A24) and (A25) express the limitations of the reference voltages of the excitation system and voltage buses, respectively. Equations (A10) - (A21) are fully described in [33].

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