Optimal Monitoring Allocation by Considering Voltage Sags Locating and Disturbance Tolerance

SUN Haotian1, DU Xiaotong1, YI Hao1, ZHUO Fang1, LUO Shanshan2, ZHANG Jun3, WANG Xinxiang4, and LI Yongheng4

1. Xi'an Jiaotong University, Shaanxi, Xi'an, 710049 2. Jiangsu Electric Power Company Research Institute, Jiangsu, Nanjing, 210000 3. State Grid Jiangsu Electric Power Cooperation, Jiangsu, Nanjing, 210000 4. Golden Cooperate information & automation technology Co., Ltd, Nanjing, 210000

***Abstract*—This paper presents a bi-level optimal allocation for voltage-sag monitors with the consideration of fault locating and disturbance tolerance ability. In the first level, a binary linear programming model is proposed for both symmetrical and asymmetrical faults. A binary gravity search algorithm (BGSA) is applied for solving the binary optimization problem. In the second level, to select the optimal allocation among all feasible solutions, the disturbance tolerance ability is modeled and quantified based on fuzzy inference. Allocation-level disturbance tolerance indexes are then obtained to determine the ultimate monitoring allocation. The IEEE 39-bus test system is used for the validation of proposed method.**

***Index Terms*—BGSA, disturbance tolerance, fault locating, fuzzy inference, MRA (Monitor Reach Area), optimal allocation, voltage-sag monitor.**

I. INTRODUCTION

VOLTAGE sags are one of the most important issues of Power Quality(PQ) [1]. To detect the occurrence of them, voltage-sag monitors are installed at several buses in the power system. With the consideration of economy, accuracy and robustness of the proposed allocation scheme, it is required to have minimal number of monitors installed properly so as to detect voltage sag events caused by any types of faults at any buses under the existence of disturbances. Many optimal allocation algorithms have been proposed in past. Reference [2] presents an approach based on MRA and binary linear programming for three-phase symmetrical fault. The asymmetrical faults are taken into consideration to generalize the aforementioned MRA method in [3]. Reference [4] optimizes monitoring allocation with the criterion of fault location (FL) ability. An optimization method based on the propagation law of voltage sags is developed in [5].

In this paper the monitoring allocation optimizing lies in two aspects: 1) locating ability of faults causing voltage sag is closely related to the allocation scheme so the former should be considered in the optimization of the latter; 2) given that the measurement from voltage-sag monitor can be affected the voltage disturbance, the impact from the latter should be attenuated as much as possible by the allocation algorithm.

In this context, the methodology developed in this work applies a bi-level optimization: first an improved MRA-based method is used to obtain several possible solutions; second a disturbance tolerance evaluation model is established to calculate the quantified tolerance indexes of each solution obtained previously, among which the allocation with the highest tolerance index value is selected ultimately. These two levels of optimization are discussed in section II and III respectively. A simulation analysis is given in section IV to validate the proposed algorithm.

II. FIRST LEVEL OPTIMIZATION: IMPROVED MRA-BASED METHOD

In the first level of optimization, 4 MRA matrices are established corresponding to 4 types of faults: 1) three-phase

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SUN Haotian is with the Electrical Engineering Department, Xi'an Jiaotong University, Xi'an, Shaanxi 710049 China. (phone: +86 130-8758-7594; e-mail: sunhaotian@stu.xjtu.edu.cn).

DU Xiaotong is with the Electrical Engineering Department, Xi'an Jiaotong University, Xi'an, Shaanxi 710049 China. (e-mail: doxato@stu.xjtu.edu.cn).

YI Hao is with the Electrical Engineering Department, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, China. (e-mail: yi_hao@xjtu.edu.cn).

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symmetrical fault (LLL); 2) single-line grounded fault (LG); 3) line-to-line fault (LL); 4) line-to-line grounded fault (LLG). Redundancy coefficients are defined to improve the performance of voltage sags locating; and the BGSA is used to calculate the possible solutions.

A. Improved MRA-based Method

1) Voltage vulnerability matrices

The residual voltage V_{kf} of bus *k* is defined as the minimum value among the three-phase voltages (in p.u.) of bus *k* after some type *t* of fault occurred at bus *f*, as in (1).

$$V_{kf,t} = \min\left(V_{kf,t'}^{(a)}, V_{kf,t'}^{(b)} V_{kf,t}^{(c)}\right) \quad (1)$$

Wherein $V_{kf,t'}^{(a)}, V_{kf,t'}^{(b)} V_{kf,t}^{(c)}$ are the voltages of three phases at bus *k* after fault type *t* occurred at bus *f* which can be calculated by power system analysis theory. Given that faults caused by unbalanced voltage sags are asymmetrical, the positive, negative, and zero sequence impedance matrices (noted Z_1, Z_2, Z_0 respectively) are needed for the symmetrical components analysis. $\alpha = e^{j120°}$denotes the complex rotation operator. It is assumed that all pre-fault positive-sequence voltages are 1.0 p.u. which is reasonable for power system short circuit studies [4]. The fault resistances are also assumed to be zero, which indicates that the bolted faults occurred.

Based on the assumptions above, voltage vulnerability matrices of each type of fault can be derived [6].

a) Three-phase symmetrical fault (t=LLL)

$$V_{a,b,c} = 1 - \frac{Z_1}{diag(Z_1)} \quad (2)$$

b) Single-line grounded fault (t=LG)

$$V_a = 1 - \frac{Z_1 + Z_2 + Z_0}{diag(Z_1 + Z_2 + Z_0)} \quad (3)$$

$$V_b = \alpha^2 - \frac{\alpha^2 \cdot Z_1 + \alpha \cdot Z_2 + Z_0}{diag(Z_1 + Z_2 + Z_0)} \quad (4)$$

$$V_c = \alpha - \frac{\alpha \cdot Z_1 + \alpha \cdot Z_2 + Z_0}{diag(Z_1 + Z_2 + Z_0)} \quad (5)$$

c) Line-to-line fault (t=LL)

$$V_a = 1 + \frac{Z_2 - Z_1}{diag(Z_1 + Z_2)} \quad (6)$$

$$V_b = \alpha^2 + \frac{\alpha \cdot Z_2 - \alpha^2 \cdot Z_1}{diag(Z_1 + Z_2)} \quad (7)$$

$$V_c = \alpha + \frac{\alpha^2 \cdot Z_2 - \alpha \cdot Z_1}{diag(Z_1 + Z_2)} \quad (8)$$

d) Line-to-line grounded fault (t=LLG)

$$V_a = 1 + \frac{(Z_2 - Z_1) \cdot diag(Z_0) + (Z_0 - Z_1) \cdot diag(Z_2)}{D} \quad (9)$$

$$V_b = 1 + \frac{(Z_2 - Z_1) \cdot diag(Z_0) + (Z_0 - Z_1) \cdot diag(Z_2)}{D} \quad (10)$$

$$V_c = 1 + \frac{(Z_2 - Z_1) \cdot diag(Z_0) + (Z_0 - Z_1) \cdot diag(Z_2)}{D} \quad (11)$$

$$D = \sum_{\substack{i,j=\{0,1,2\} \\ i \neq j}} diag(Z_i) \cdot diag(Z_j) \quad (12)$$

Wherein $diag(\cdot)$ denotes the diagonal elements of the matrix in parenthesis.

2) Binary linear problem with constraints

The residual voltage $V_{kf,t}$ of every bus *k* after 4 types of faults *t* at fault position *f* are calculated to form the 4 voltage vulnerability matrices so that the MRA matrices can be established respectively as in (13).

$$MRA_{kf,t} = \begin{cases} 1, & V_{kf} \leq V_{threshold} \\ 0, & V_{kf} > V_{threshold} \end{cases} \quad (13)$$

Where 4 MRA matrices can be obtained, corresponding to 4 types of faults: $t = LLL, t = LG, t = LL, and\ t = LLG.$

Besides, a binary decision vector $\boldsymbol{x} = [x_1\ x_2 \ldots x_N] \in \{0,1\}^N$ is also defined as in (14).

$$x_i = \begin{cases} 0, & no\ monitor\ installed\ at\ i \\ 1, & a\ monitor\ installed\ at\ i \end{cases} \quad (14)$$

The binary linear programming problem is thus formed as in (15) and (16).

$$\min \sum_{k=1}^{N} x_k\ s.t. \quad (15)$$

$$\boldsymbol{x} \cdot \boldsymbol{MRA}_t = R_t \cdot \boldsymbol{ones} \quad (16)$$

Wherein R_t are the redundancy coefficients. $\boldsymbol{ones}$ is the matrix whose elements are all one.

For the asymmetrical faults (*t=LG, LL, and LLG*), all positive, negative and zero sequence matrices are used in the aforementioned calculations whereas for the three-phase symmetrical fault, only positive components are adopted, which signifies that insufficient information is obtained from the system. In this case, it requires to acquire more information from monitoring recording and measurement. Therefore, proper redundancy should be added in the allocation scheme by increasing the coefficient R_{LLL}. Researches gives that $R_{LLL} = 2$ is sufficiently large for fault locating[7].

For the accurate voltage-sag locating, R_t are evaluated as in (17).

$$R_{LLL} = 2\ and\ R_{LG} = R_{LL} = R_{LLG} = 1. \quad (17)$$

B. Problem-Solving based on BGSA

BGSA is a raising stochastic searching algorithm and has a good performance for solving large-scaled optimization problems[8]. To apply this algorithm, both best and worst functions for agent *i* are defined as in (19) and (20); equivalent mass for agent *i* is also defined to fit the problem as in (18).

$$M_i(k) = \frac{m_i(k)}{\sum_{j=1}^{M} m_j(k)}, m_i(k) = \frac{fit_i(k) - worst(k)}{best(k) - worst(k)} \quad (18)$$

$$\begin{cases} best(k) = \min_{j} fit_j(k) & (19) \\ worst(k) = \max_{j} fit_j(k) & (20) \end{cases}$$

Wherein *k* is the iteration time, *fit(k)* is the fitness function defined by (15) and (16).

After each iteration, the equivalent interaction between agent i and j is calculated as in (21); the equivalent velocity and position are updated as in (22) and (23), and they converge to the optimal solution successively. Thus, the solution with acceptably minimum error can be obtain after several iterations.

$$\boldsymbol{F}_{ij} = G(k)\frac{M_i^2}{|\boldsymbol{X}_i - \boldsymbol{X}_j|}\left(\boldsymbol{X}_j(k) - \boldsymbol{X}_i(k)\right) \tag{21}$$

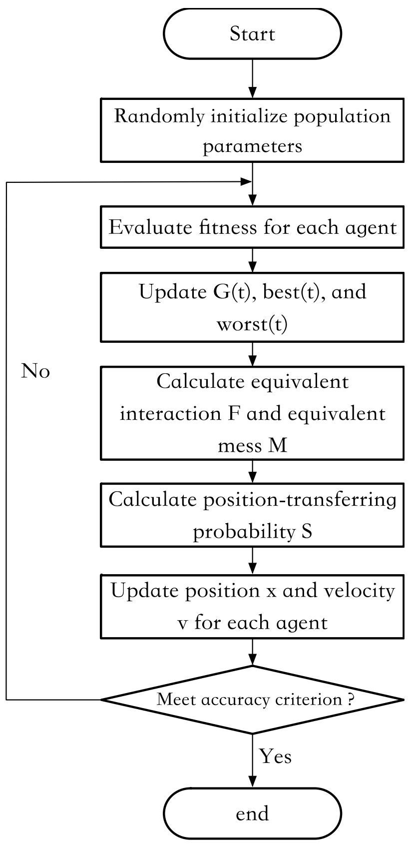


Fig. 1. Numerical presentation of applied Mamdani inference model

$$\boldsymbol{v}_i(k+1) = rand \cdot \boldsymbol{v}_i(k) + \frac{\boldsymbol{F}_i(k)}{M_i(k)} \tag{22}$$

$$\boldsymbol{X}_i(k+1) = \begin{cases} \overline{\boldsymbol{X}_i(k)}, & rand < S(\boldsymbol{v}_i(k)) \\ \boldsymbol{X}_i(k), & otherwise. \end{cases} \tag{23}$$

Wherein $\boldsymbol{F}_i$ is the resultant interaction of agent i; $S(\boldsymbol{v}_i(k))$ is the position-transferring probability and is defined as in (24).

$$S(\boldsymbol{v}_i(k)) = |tanh(\boldsymbol{v}_i(k))| \tag{24}$$

The flowchart of BGSA algorithm is presented in Fig. 1.

III. SECOND LEVEL OPTIMIZATION: DISTURBANCE TOLERANCE-BASED COMPARATIVE METHOD

In the second level of optimization, the disturbance tolerance indexes for each bus and finally for the whole allocation schemes are established and evaluated based on fuzzy inference model.

A. Single-Bus Disturbance Tolerance Index

Disturbance tolerance is in positive correlation to the Euclidean metric between the theoretical detected voltage after fault (V_{kf}) and the threshold voltage ($V_{threshold}$). In the case

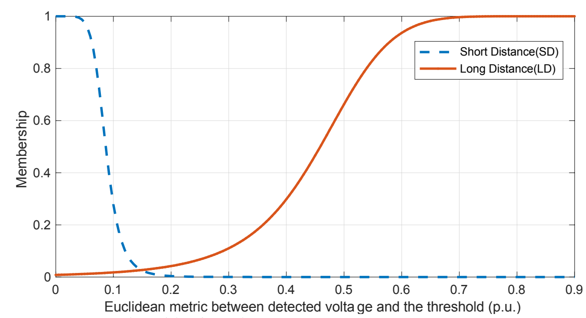


Fig. 2. Input membership function

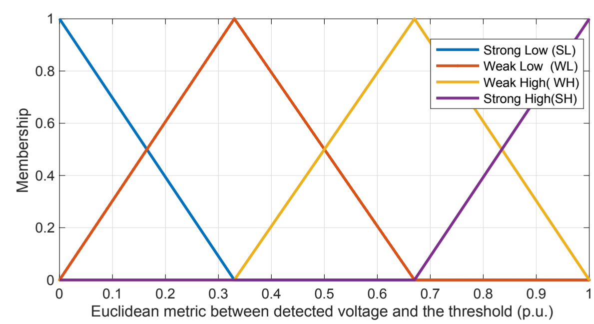


Fig. 3. Output membership function

where the theoretical voltage in some monitor is quite close to the pre-set threshold voltage, some small disturbance can make the detected voltage flip over the threshold and can result in mis-operations.

In order to quantify such tolerance, the average and minimum distances are defined for all 4 types of faults based on this Euclidean metric, as in (25) and (26). The average distance $D_{ave}^{(k)}$ reflects the average disturbance tolerance ability of bus k of every possible fault position, and the minimum distance $D_{min}^{(k)}$ implies the worst case for bus k.

$$D_{ave}^{(k)} = \frac{1}{N}\sum_{f=1}^{F} |V_{kf} - V_{threshold}| \tag{25}$$

$$D_{min}^{(k)} = \min_f |V_{kf} - V_{threshold}| \tag{26}$$

A Mamdani fuzzy inference model is established by defined the input and output membership functions as in Fig. 2 and Fig. 3.

The Input membership function consists of two curves for "short distance (SD)" and "long distance (LD)" respectively. These two curves are in shape of gaussian membership function. With the consideration that the measuring error caused by disturbance are typically less than 10%, SD membership function is designed to give a large membership value at very small distance and attenuate exponentially membership values at around 0.1 which accounts for 10% error. The LD membership function is designed in the same manner but in opposite increasing trend.

The output membership function is formed of 4 triangular membership functions, which is reasonable since any value of tolerance index is equiprobable within the interval of [0, 1].

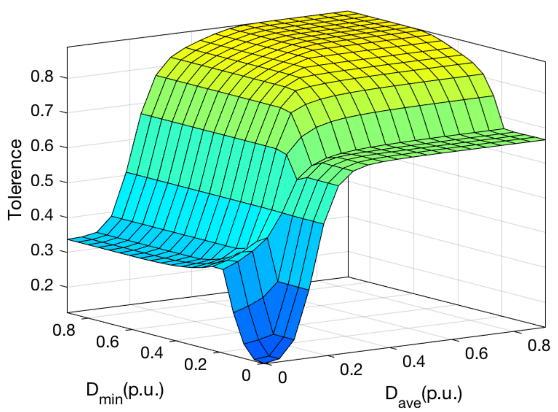


Fig. 4. Numerical presentation of applied Mamdani inference model

The Mamdani inference rules are also defined to obtain the output as in Table I, in which 4 IF-THEN rules are defined based on the aforementioned input variables D_{min} and D_{ave}. In this model, the min-max inference and centroid defuzzification strategy is adopted.

The 3-D numerical representation is illustrated in Fig. 4.

By calculating the membership of "short distance (SD)" and "long distance (LD)" for both input variables D_{ave} and D_{min}, the quantified index $T_{t,k}$ for bus *k=1,2…N* with specific fault type *t* is obtained within the range [0,1], as in (27).

$$\mathbf{T_t} = [T_1 \quad T_2 \quad \dots \quad T_k \quad \dots \quad T_N] \tag{27}$$

B. *Allocation Disturbance Tolerance Index*

The allocation-level disturbance tolerance index for the first level optimized solution m can be defined as the minimum value among the 4 types of fault cases of the average bus-level tolerance indexes for the buses selected in this solution, as in (28) and (29)

$$TOL_m = \min_t \frac{\sum_{k=1}^{N} T_k \cdot x_m^{(k)}}{\sum_{k=1}^{N} x_m^{(k)}} \tag{28}$$

$$= \min_t \frac{\mathbf{T} \cdot \mathbf{x_m}'}{\mathbf{x_m} \cdot \mathbf{x_m}'} \tag{29}$$

Wherein *t=LLL, LG, LL, and LLG* respectively.

The ultimate solution can be selected by comparing the quantified allocation-level disturbance tolerances.

The total algorithm can be made by combining the two algorithms proposed in section II and section III, as in Fig. 5.

TABLE I
FUZZY INFERENCE RULES

D_{ave} \ D_{min}	SHORT DISTANCE (SD)	LONG DISTANCE (LD)
SHORT DISTANCE (SD)	Strongly Low (SL)	Weakly Low (WL)
LONG DISTANCE (LD)	Weakly High (WH)	Strongly High (SH)

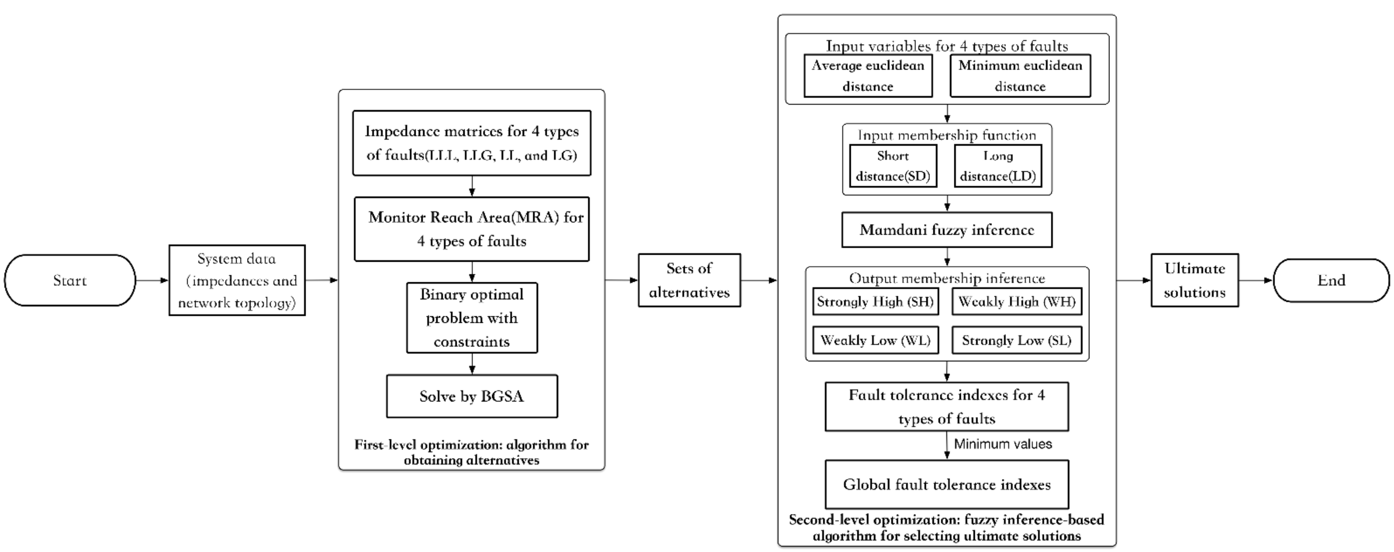
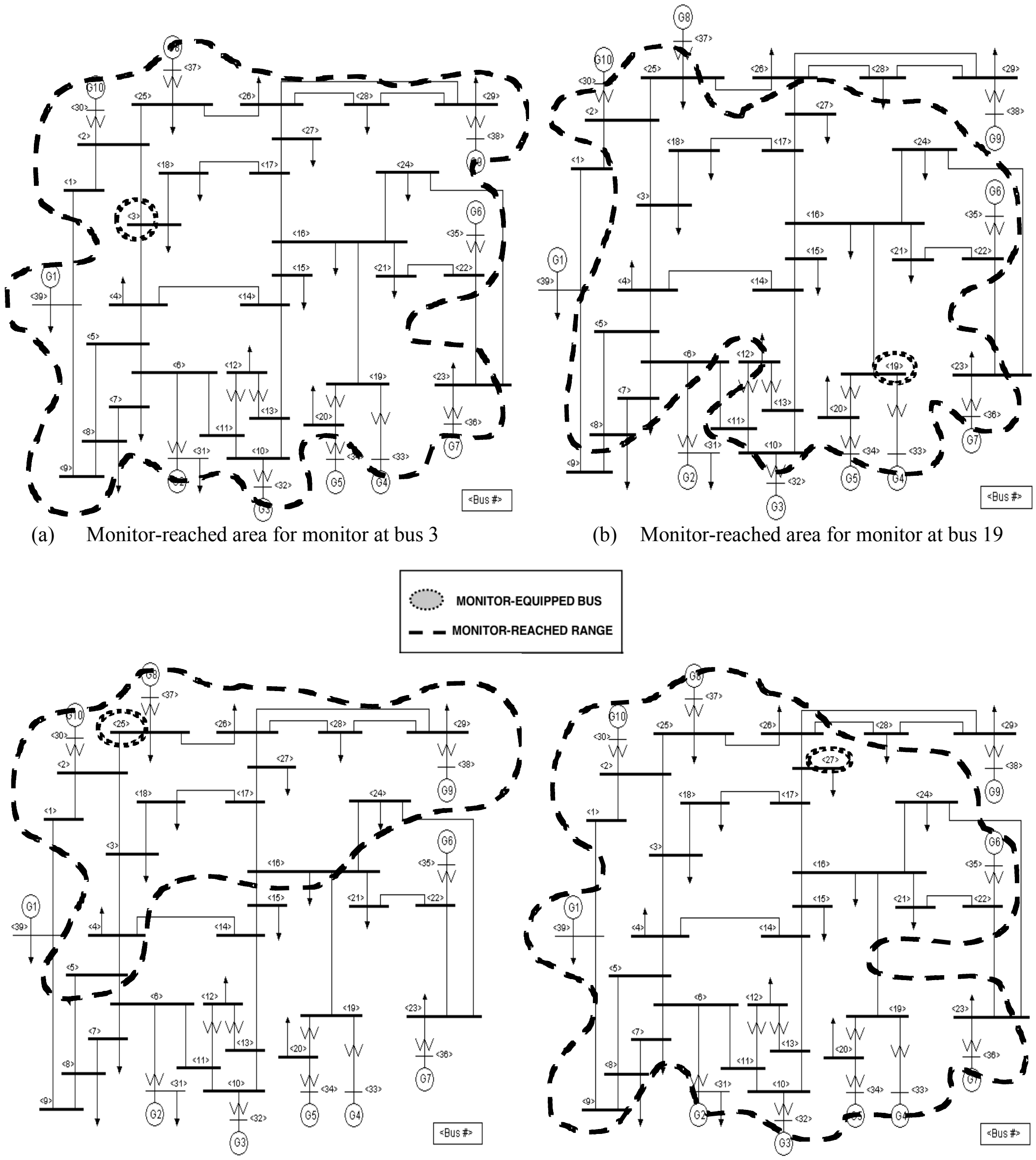


Fig. 5. Flowchart of the proposed bi-level optimal allocation algorithm



(a) Monitor-reached area for monitor at bus 3

(b) Monitor-reached area for monitor at bus 19

(c) Monitor-reached area for monitor at bus 25

(d) Monitor-reached area for monitor at bus 27

Fig. 6. Optimal allocation illustration

IV. SIMULATION ANALYSIS

Using the proposed method, the optimal allocation for the IEEE 39-bus test system is obtained under MATLAB. To demonstrate without losing generality, 0.85p.u. is taken as the voltage-sag threshold in the simulation. For the BGSA, the number of populations is set to 50 and the maximum iteration is 1000.

After the first-level optimization, 104 possible solutions remain. After the second-level optimization, only 1 possible solution is left: bus 3, bus 19, bus 26, and bus 27, with the allocation-level disturbance tolerance index of 0.5806.

The test system is then simulated under PSCAD. By simulating LLL and LLG fault occurring from bus 20 to bus 30 successively, it is observed that asymmetrical faults (LLG) can be detected by at least 1 monitor (at least 1 monitor records a residual voltage less than 0.85 p.u.) and the symmetrical fault (LLL) can be detected by 2 monitors (at least 2 monitors record a residual voltage less than 0.85). The simulation results validate the feasibility of pre-calculated allocation.

V. CONCLUSION

In this paper, a bi-level optimized allocation is obtained:

1) by establishing an improved MRA problem and solving on BGSA;

2) by quantifying the disturbance tolerance and selecting the ultimate solution with the highest tolerance index value.

Through simulated calculation on IEEE 39-bus system, the feasibility and efficiency of proposed method is validated.

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SUN Haotian was born in Shandong province, China, on 14 January, 1996. He received B.Sc. degree in electrical engineering from Xi’an Jiaotong University, Xi’an, China, in 2017. He is Master Candidate in electrical engineering in Xi’an Jiaotong University since 2017.

His current research interests include voltage sag, power system fault analysis and power quality analysis.