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Redundancy-based approach for optimal number and location of power quality monitors in distribution systems with binary imperialist competitive approach

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ABSTRACT

This article deals with optimal employment of power quality monitors (PQMs) in distribution networks on the basis of the idea of monitor reach area. The proposed model uses binary string, representing the installation mode of PQMs (Yes or No) in each bus of the network. In the current article, the binary version of the imperialist competitive algorithm (BICA) is used. Because it has the ability of enhancing the search potential with a rapid and secure convergence rate in the optimization process. The concept of redundancy is considered in this study. The overall cost function is formulated to optimize the two indices. The first one is the index of monitoring overlap, and the second one is the index of sag severity. Among the solutions that yield a full reachable power network and the objective function experiments the minimum value, the final optimal answer will be extracted through evaluating the redundancy. With an excellent redundancy with respect to other solutions, the buses of the system faced with faults are monitored more times, on an average. In the current research, DIGSILENT software is used in short-circuit analysis, whereas the BICA manages the optimization process. Simulation and comparison are performed on the 69-bus distribution system.

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Binary imperialist competitive algorithm (BICA); DIGSILENT software; monitor overlapping index (MOI); monitoring redundancy; power quality monitoring; sag severity index (SSI); topological monitor reach area (TMRA); voltage sag detection

1. Introduction

In recent years, we have faced with increasing micro-processors and power electronic devices in the customers' technology. So the sensitivity of these devices against power quality disturbances is increased. Therefore, it is an eminent issue that power quality indices with significant values than ever before satisfy the end-users. The power quality indices include a variety of types of disturbances. Many studies have focused on power quality improvement in the distribution system [1–3]. In [1], the improvement of voltage sag using multiple D-FACTS, in [2] the improvement of unbalancing using reconfiguration along with renewable energy resources, and in [3] the improvement of harmonics using passive filters, as power quality problems is analyzed. One of the most common types of disorders that are taking place is voltage dip (sag). It is caused by short-circuit faults, motor starting, sudden removal of large load, and an initial spurt of large capacitor banks into the power system. This voltage dip, according to its characteristics (magnitude and duration) has severe impacts. It is also affected due to critical voltage of the sensitive loads. It leads to failure, malfunction and forced outage of sensitive equipment, which imposes significant economic losses to industry owners. The DG and D-STATCOM are two useful devices that have ability to compensate drop voltage observed along with

distribution feeders [4]. The monitoring of the buses is faced with a sag in voltage amplitude and on the other hand analyzing the sags' characteristics (magnitude and duration) provides remarkable information. It can help power researchers and engineers to moderate such disturbances. This information covers the actual cause and main factors that lead to a dip in voltage magnitude. Thus, to ensure the accurate monitoring of the entire system, power quality monitors (PQMs) should be situated at all buses. Hence it is very costly and presents uneconomical planning. Therefore, new optimal placement methods are required to address the PQMs with the minimum number and suitable locations. It must perform in a way guarantees that voltage sag is detectable under any happening. Of course, it will be achieved using an efficient assignment approach. A few optimal allocation techniques of PQMs have been reported in the last few years. Generally, the techniques for the placement of voltage sag monitors comprise four fundamental methods, namely, monitor reach area (MRA), covering and packing, graph theory, and multivariable regression [5]. Since this article deals with optimal employment of PQMs in distribution networks on the basis of the idea of MRA, in the following studies, the articles which used this idea are reviewed. In 2003, Olguin et al. [6] proposed an MRA concept-based matrix method, which constructs a binary matrix to

obtain the observable area of the network from a given meter position. According to their proposed method, if a fault occurs only inside MRA, then the PQM is activated by the event. Thus, the MRAs of all feasible arrangements are concluded to express the optimization process in a formula. The procedure mentioned by [6] is performed using the binary MRA matrix, which is extracted through analysis of network's short circuits situated along with feeders in the electrical system. In the MRA-based methods, the heuristic optimization algorithms are used to determine the PQMs number and the best locations through optimizing the objective function. Many studies have reported the utilization of MRA method combined with heuristics algorithms for optimal placement of PQMs. In [7], the authors presented an MRA-based approach integrated with the sag severity index in solving the PQMs situation, whose optimization process is handled by GA algorithm. In a recently published study, the concept of fuzzy MRA has been introduced and it has been used for PQMs placement in a large transmission network [8]. The improved adaptive genetic algorithm (AGA) is presented by [9] to optimal allocation of PQMs based on the MRA and MRM matrices and redundant vector concepts. The PQMs location in transmission systems using the MRA matrix technique is a simple performance, but distribution systems with radial structure give the ill conditions that the MRA matrix generally could not respond. Under this condition, it will not guarantee the suitable number and locations, and often it yields only one PQM in the final solution. Thus, in 2011, Ahmad Ibrahim [10] proposed a novel idea of topological monitor reach area (TMRA) and used it to solve the optimal PQMs situation in distribution networks. Not only did the proposed TMRA technique use to allow for the observability's application to transmission systems but it was also used in radial distribution systems. In the TMRA, to get better flexibility of the search algorithm in viewpoints of sensitivity and economic capability, the *alpha* as a supervising parameter is introduced. It is added to the MRA method and controls the area monitors to provide more coverage. Authors in [11] presented and discussed an optimal solution in PQM placement in power systems using TMRA concept-oriented with particle swarm optimization (PSO) and artificial immune system techniques. The quantum-inspired particle swarm optimization (QPSO) was introduced by the same authors for PQM placement [12]. The adaptive QPSO (AQPSO) was also addressed for PQM placement on the basis of the MRA approach [13]. In [14], the quantum-inspired binary gravitational search algorithm (QBGSA) and in similar research by the same authors, the adaptive version of QBGSA is used for optimization process in PQMs placement using TMRA [15]. Solution a certain problem as a multi-objective problem is another approach in the solving of distribution system. In the recently published article [16],

the multi-objective-based optimal network reconfiguration using the crow search algorithm is presented and discussed. In addition, about PQM problem, some studies [17,18] have solved the PQMs optimal planning as a multi-objective problem. Author in [17] modeled this problem as a multi-objective problem to acquire a tradeoff between the data redundancy and the economic efficiency using Pareto optimal solutions obtained by AGA. In a recent published study about the PQMs placement, a non-dominated solution has been addressed. At the presented solution, the authors use a multi-objective evolutionary algorithm with tables and formulate it to satisfy two conflict aims simultaneously. They track two purposes: first try to reduce as much as possible the total cost of the PQMs and on the other side try to get the best level of the redundancy of measurements [18]. In this article, a new PQM location method on the basic of the binary version of imperialist competitive algorithm (BICA) is established to handle the optimization process. This research deals with optimal employment of PQMs in distribution networks on the basis of the idea of MRA. The first innovation of this study is using the DIGSILENT software combined with MATLAB program for the short-circuit process, which this technique increases the speed run of the simulation. In addition, the second innovation is using the binary format of imperialist competitive approach for solving this problem (PQMs placement) as the newest study which was not performed by others. The third innovation is considering the redundancy concept in this article and analyzing its effect on the results. With an excellent redundancy, the buses of the system faced with faults are monitored many times, on average and hence the level of power quality of system will be increased.

The main sections of this article are listed as follows:

- Section 2: PQM/meters (functions and installation).
- Section 3: Fundamental concepts about the residual fault voltage (FV) matrix, MRA, system topology and TMRA.
- Section 4: Objective function illustrate the minimizing the number of required monitors (NRMs), minimizing the monitor overlapping index (MOI) and maximizing the sag severity index (SSI).
- Section 5: Optimization techniques, imperialist competitive approach and its binary version.
- Section 6: Simulation and results.
- Section 7: Conclusion.

2. Functions and installation of PQM

When a three-phase system is needed to monitor and continuously supervised, there is an ideal option named PQM. It presents facilities in the measuring of fundamental parameters of power networks such as active and reactive powers, energy use, cost of power,

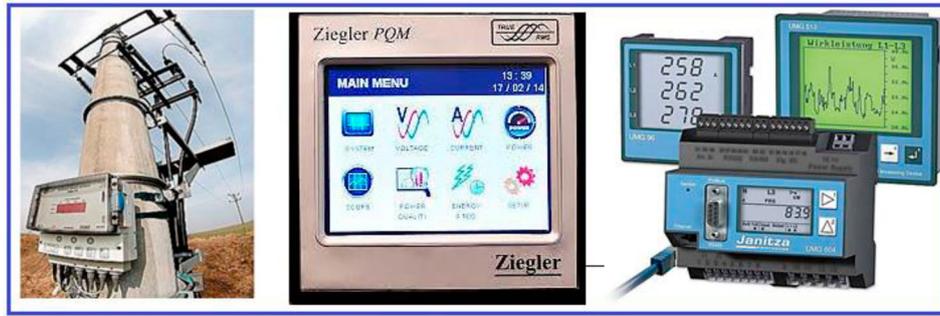


Figure 1. Schematic and how installation of several types of PQM.

power factor and frequency and initial quantities of bus voltages and feeder currents. In Figure 1, the schematic and how installing of several types of PQM is presented. PQM's application and the monitoring and metering function of a typical type are listed as follows:

- Providing to a meter of feeders in the distribution network, power transformers, synchronous generators in power plants, shunt capacitor banks and also induction electrical motors.
- Capability of utilization in LV and MV power networks.
- Technical and economic applications in commercial domain and industrials.
- Flexibly supply the control of demand load shedding, power factor, and so on.
- Analyzing of harmonic voltage and current content and obtain the THD (Total harmonic distortion) and TIF indices.
- Recording the event information (fault type, location and magnitude).
- Data capturing of waveforms.

3. Fundamental concepts

The main structure of optimal PQMs placement problem using the proposed approach is understanding of the monitor visibility concept. This principle is needed to explain the following concepts discussed earlier in Sections 3.1–3.4 as following sections: (1) residual FV matrix, (2) monitor reach area, (3) system topology, and (4) topology monitor reach area.

3.1. FV matrix

In the MRA-based approach of PQMs placement, the residual voltages at whole buses of the system for every kind of faults (single line-to-ground, two phases to ground, three-phase faults) and all fault cases are required. The residual voltage at each bus is valuable information in the formation of the MRA. Therefore, the residual voltages are necessary to be stored in a matrix called the FV matrix where the matrix columns represent bus number and the matrix rows relate to the simulated fault position. Then, the MRA matrix can be obtained by comparing all the FV matrix elements for

each phase with a threshold value. Each element of the MRA matrix is filled with 1 (one), when the bus residual voltage goes below or equal to α p.u. in any phase and with 0 (zero) otherwise. In the step of the short-circuit process about fault analysis, it is necessary to simulate all the various kinds of fault. This step is performed generally at each bus using the DIGSILENT software without fault impedance (i.e. zero amount for it) to form and conclude the FV matrix. Finally, the residual voltages as FV matrix are kept to employ in MRA formulation (see Figures 10 and 13 for simulation the short-circuit analysis with DIGSILENT software and calculate the FV matrix). In the FV matrix, the matrix column (j) is related to bus numbers of residual voltages, and its row (k) is correlated to the position of simulated fault for specific fault type [10,19]. To better understand the concept of FV, a simple power system is shown in Figure 2.

During a specific fault at bus 3, the voltage readings at each bus of the system are calculated and reported using DIGSILENT. These voltage values are matched with the 3rd row of the concluded FV matrix for the system, reported for completely fault analysis of the system as Figure 3.

3.2. MRA matrix

A particular area, in which every fault in that domain yields the voltage sag with the ability of capturing via

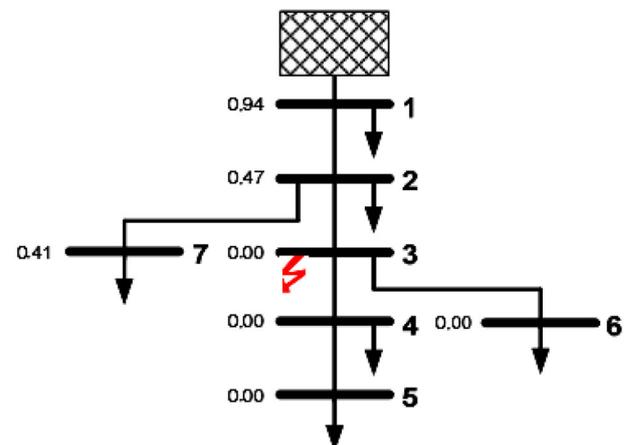


Figure 2. A simple distribution system with the radial structure.

0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.82	0.00	0.00	0.00	0.00	0.00	0.00
0.94	0.47	0.00	0.00	0.00	0.00	0.41
0.98	0.65	0.35	0.00	0.00	0.29	0.58
1.02	0.91	0.67	0.32	0.00	0.61	0.85
0.98	0.66	0.34	0.28	0.23	0.00	0.59
0.95	0.48	0.43	0.37	0.32	0.28	0.00

Figure 3. An example of the FV matrix.

a marked monitor, is defined as MRA [20]. The MRA matrix, which is the purpose of this section of the current article, is a matrix in a binary format. In this matrix, the $MRA(j, k) = 1$ signifies that point k is seen (observable) by installed PQM at bus j , whereas $MRA(j, k) = 0$ identifies that point k is outside of the coverage area of the installed PQM at bus j . Each element of this binary matrix is computed by making a comparison between any FV matrix elements with an entrance value. This value defines a threshold voltage which is represented by the α parameter. If the residual bus voltage of FV matrix is less or equal to α p.u., then $MRA(j, k) = 1$ and otherwise, if residual voltage of FV matrix is more than α p.u. at all phases, then $MRA(j, k) = 0$ is expressed as follows:

$$MRA(j, k) = \begin{cases} 1 & \text{if } FV(j, k) \leq \alpha \text{ p.u. at any phase} \\ 0 & \text{if } FV(j, k) > \alpha \text{ p.u. at all phases} \end{cases} \quad (1)$$

To better understand the concept of the MRA matrix, give attention to the simple distribution grid with radial topology as shown in Figure 2. Its FV matrix is obtained in Figure 3. In this specific example, the voltage of threshold is assigned at $\alpha = 0.9$ p.u., and as results of the formation of the MRA matrix-based Equation (1), it yields the MRA matrix as shown in Figure 4.

3.3. System topology matrix (T)

Fundamentally, the T matrix is obtained via a similar analysis accomplished in the MRA matrix and in the FV matrix. Comparison is the base of computation. In the T matrix, the column elements are related to bus number, and rows denote the fault location. When a direct path connects the slack bus (the bus to which one generator is connected) to a particular bus in the system, so the matrix is filled with 1 (one) and otherwise filled with

1	1	1	1	1	1	1
1	1	1	1	1	1	1
0	1	1	1	1	1	1
0	1	1	1	1	1	1
0	0	1	1	1	1	1
0	1	1	1	1	1	1
0	1	1	1	1	1	1

Figure 4. An example of the MRA matrix.

0 (zero) [21]. When a fault occurs in a particular bus, namely faulted bus, it becomes a cut vertex that splits into various vertices of the same component as many adjacent edges. Three examples of a highlighted row for a radial system with a single source, a radial system with two sources (feeding in doubly format), and a meshed system are presented in Figure 5. For instance, during fault at bus 3, depending on the number's feeders connected to this bus, the system graph can be separated into several sections. By investigating the connectivity status between the main bus (slack) and with the others (other nodes) under the mentioned criteria, the T matrix elements are then will be filled with "1" or "0". As shown in Figure 5 (a), the system has only one power source at bus 1, so clearly, there is one path that joints the generator bus (bus 1) to buses 1, 2 and 3, and it is not the same for the rest. Therefore, for the third row of the T matrix (because of occurring fault at third bus), value "1" will belong to the first column until to the third column and "0" will belong to the columns that come after it. As indicated in Figure 5(b), in this case, the bus number 4 and 5 have been connected to the second power source and thus, for the third row of T matrix value "1" will belong to the first column until to the fifth column. In the last case, in a system with mesh topology, as pictured in Figure 5(c), value "1" will belong to the entire columns due to infeasible connections between the source bus and the others. These examples are designed only with supposing happening fault at the third bus of the system. So it should be repeated for whole buses similarly to extract the information about system topology through complete T matrix.

3.4. Topology monitor reach area matrix

The TMRA is suggested to expand its usage to cover the distribution and transmission systems' fault analysis. The TMRA matrix is produced on the basis of the inner product of vectors concept and is illustrated as follows [10]:

$$TMRA(j, k) = MRA(j, k) \cdot T(j, k) \quad (2)$$

4. Problem formulation

The three main parts of a typical optimization problem are decision vector, objective function and constraints. Therefore each item has been illustrated about the optimal solution of PQM placement.

4.1. Decision vector

Monitor placement (MP) vector, which is tracked by the optimizer program, can be represented by a decision vector filled with values of "0" and "1". So the decision vector has a binary format that each bit indicates the position of the sag detector. In another word, the sag

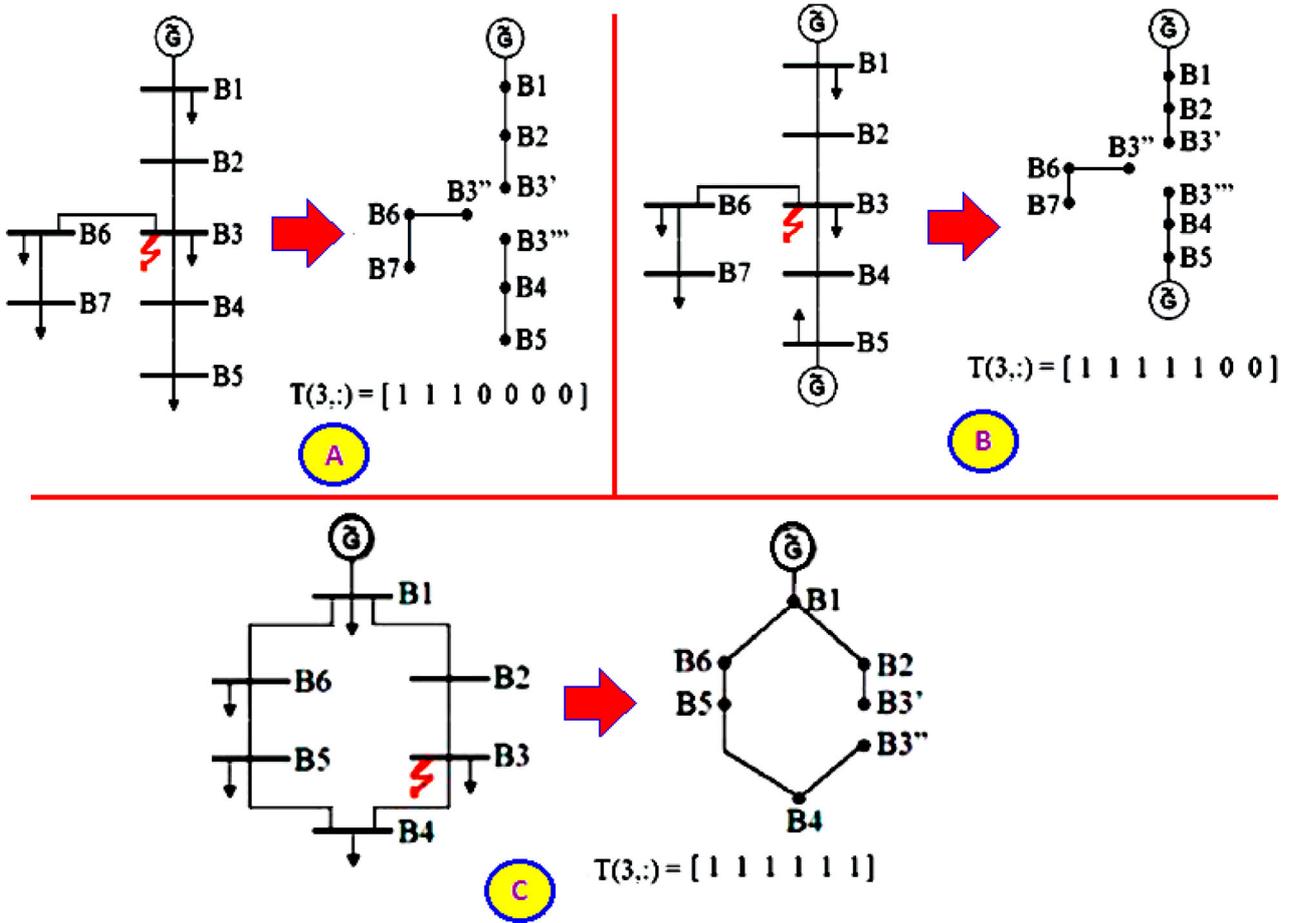


Figure 5. Example of fault analysis and T matrix extraction under different topologies [10]. (A) A radial-based single-fed system, (B) a radial-based doubly fed system, and (C) a meshed-based single-fed system.

detectors are the PQMs which are installed in the network. If $MP(n) = 1$, it points out that one voltage sag detector (i.e. dip monitor) must be situated at bus n , whereas a value of "0" means that no monitor is needed for bus n . So MP vector is illustrated as relation coming after [13]:

$$MP(n) = \begin{cases} 1 & \text{if monitor is required at bus } n \\ 0 & \text{if monitor is not required at bus } n \end{cases} \quad (3)$$

4.2. Objective function

The PQM optimization problem discussed in this study deals with three objective functions that are addressed as follows.

4.2.1. Minimizing the NRM

The first objective function is to minimize the number of situated monitors (NSM), which is addressed as (4):

$$NRM = \sum_{n=1}^{N_{bus}} MP(n) \quad (4)$$

4.2.2. Minimizing the MOI

The placement of monitors in a power system will result in different overlaps of monitor's coverage areas for different arrangements. Here, it is important to note

that these overlaps indicate the monitors which record the same fault occurrence in a power system. So these overlaps should be minimized. The overlaps can be calculated by multiplying TMRA matrix and transposed MP vector. If all the elements in the obtained results are 1, it implies that there is no overlap of the monitor's coverage. Thus, MOI can be introduced to evaluate the best monitor arrangement in a power system. Among the optimal solutions obtained from the viewpoint of economic analysis, a few monitor arrangements with high-level score will be selected based on technical view using a new index named as MOI. This technical based selection considers the overlaps which are issued by monitor coverage areas under different situated topologies in PQMs placement in the power system. Hence, it is essential to consider these overlaps and try to minimize them because they represent the number of sag detectors reporting the same fault occurrence. The index that clarifies the overlaps as a quantity value can be determined using the inner product of vectors concept and is extracted as follows by the inner product of both TMRA matrix and a vector which itself is the transposition of MP vector:

$$MOI = \frac{\sum (TMRA * MP^T)}{NFLT} \quad (5)$$

By considering all of kinds of fault, the entire locations that faults occur in which is determined. It is marked as NFLT value in equation (5). A lower MOI index represents situated PQMs with the better arrangement than others under that condition of system topology [12].

4.2.3. Maximizing the SSI

If several monitor configurations experiment the same MOI values, then in the next step of evaluating MP, a new index will be introduced to employ in the allocation process. This new index is pointed out as SSI that signifies the severity level (SL) of a particular bus regarding voltage sag where every fault that happens at this bus concludes a severe drop in all buses' voltage of the system. Thus, first it is needed to assess the SL. The SL is the total number of phases faced with voltage sags (N_{SPB}) under amplitude below t p.u. with considering three phases in the total feeders and buses of the understudy system (N_{TPB}), the SL is extracted as bellow [14]:

$$SL^t = \frac{\sum N_{SPB}}{\sum N_{TPB}} \quad (6)$$

Under different SLs, the weighting factors are utilized to determine the SSI.

Finally, the SSI is determined by weighting factors applied for different SLs.

$$SSI^F = \frac{1}{15} \sum_{k=1}^5 k * SL^{(1-\frac{2k-1}{10})} \quad (7)$$

Notably, the lowest t value is appointed with the maximum weighting factor and vice versa. Five different threshold values are considered as 0.1, 0.3, 0.5, 0.7 and 0.9 per unit in this research. Finally, the results of the SSI are saved in a two dimensions array. The rows of this array are related to the kinds of event (i.e. short circuits, interruptions and other faults), and bus numbers are represented by columns of this matrix. When SSI has a higher value, it reflects a pleasurable configuration of sag detectors (i.e. dip monitors). Considering both criteria, i.e. the SSI and the MOI give a reasonable solution. To merge the SSI with the MOI, and introduce an applicable index, first, it is needful to compute them under the same optimal criteria. This criterion would be maximum or minimum. In our study, the SSI index calculation must be revised to satisfy its level at the smallest one in the optimization procedure, as the case of the MOI. It is worth noting that the highest value of SSI matrix elements experiments "1" value. So, the suitable index can be extracted by the use of a complementary matrix of SSI. As a result, a negative severity sag index (NSSI) is proposed to assess the most pleasurable configuration of PQMs. The NSSI index is determined by multiplying the complementary format of SSI matrix by a vector resulted from the transposition of the MP. By considering the NFT, which counts

the fault types, the NSSI index is made clear as follows [14]. When NSSI meets its minimum value, it means that the best organization of PQMs is obtained.

$$NSSI = \frac{\sum [(1 - SSI) * MP^T]}{NFT} \quad (8)$$

Since the three mentioned objective functions have the same optimal criteria, therefore with a combination of them, the single objective function for minimizing of the proposed problem is extracted as follows:

$$f = (NRM * MOI) + NSSI \quad (9)$$

4.3. Optimization constraint

The only constraint in optimizing process in this problem is a controlling key named redundant vector or R . This controlling key enumerates the monitors detecting voltage sags issued from a fault at a particular bus, and must not be zero. This controlling key is obtained by the multiplication of the TMRA array by transposing of the MP array. So this constraint is formulated as follows [15]:

$$R = TMRA * MP^T \quad (10)$$

The structure of the redundant vector is similar to a column vector which has n rows. The rank of rows of R vector i.e. n is equal with the fault points counted in solving process using DIGSILENT software. The $R(j)$ of each element in the R vector clarifies that each fault point how many times is monitored. Here $R(j) = 0$ identifies that the monitoring of j th fault point is not provided. When each element in the R vector experiments the values with higher than or equal to 1, it means that situated monitors observe whole fault points under a fault condition in the system. To meet the governing requirements in the proposed problem and deduce optimal solutions, BICA is used in the optimization process. In practice, the obtained optimal solutions will be available by the decision-maker to only select a final solution, and it is accepted as the final implementable topology. Among the answers in which the objective function f meets its lowest value and on the other hand whole network is observed by the monitors, the optimal solution is exacted by assessing redundancy rd , which its definition is clarified as:

$$rd = \sum_{i=1}^M R(i)/M \quad (11)$$

The worth of each element of obtained vector in the previous step of the analysis, i.e. redundant vector R is denoted by $R(i)$, which is used in Equation (10), and M is the sum of all counted fault points in fault analysis. The greater rd is, the more times the fault points are monitored in the system, on average. While the

objective function meets its minimum point, the individual arrangement which faced with the highest level of rd is selected as the optimal solution. Redundancy index rd experiments the values in a range of $[1, \min(\text{NRM})]$, which makes clear that each point affected by fault experiments the monitoring once at least and the maximum level of monitoring that it will be meet is equal with $\min(\text{NRM})$ times.

5. Imperialist competitive algorithm

5.1. Classical approach

Imperialist Competitive Algorithm (ICA) is a new evolutionary technique inspired by imperialistic competitions [22]. This algorithm has been used in many studies in the electrical engineering field to solve the related problems. For instance for power system stability improvement [23] or for harmonic compensation [24], the utilization of ICA is reported. In this method, each solution has an array format named one country. In the optimization solving of an N_{var} -dimensional problem, each country is a horizontal vector with a length of N_{var} . And the cost of it is determined through the cost function of variables $(P_1, P_2, P_3, \dots, P_{N_{var}})$ as follows:

$$\text{Cost}_i = f(\text{country}_i) = f(P_1, P_2, P_3, \dots, P_{N_{var}}) \quad (12)$$

$P_1, P_2, P_3, \dots, P_{N_{var}}$ are variables that must be optimized. Identification of the best country (an empire with more potent than others) is the purpose of this algorithm. The best country is one that has a lower cost. To start this algorithm, it is needed to generate some countries ($N_{country}$). So the random matrix of countries is generated as follows:

$$\text{COUNTRY} = \begin{bmatrix} \text{country}_1 \\ \text{country}_2 \\ \text{country}_3 \\ \vdots \\ \vdots \\ \vdots \\ \text{country}_{N_{country}} \end{bmatrix} \quad (13)$$

In this algorithm, all individuals are grouped into several empires. In the first step, some of the more powerful countries are candidate as the initial imperialists and the remaining less powerful are colonies of them and, under two criteria, are dispersed among the imperialists. The first criterion is position and the second one is the power of imperialists. The power corresponds to the inverse of their cost values. The number of imperialists is denoted by N_{imp} , and the colonies related to each imperialist is clarified by N_{col} that sum of them is $N_{country}$. According to the second criterion, which is the power of imperialists, each country is allocated to an empire. To accomplish this goal, the normalized cost

(Cn) of an imperialist is extracted as (14):

$$C_n = f_{\text{cost}}^{\text{imp},n} - \max_i(f_{\text{cost}}^{\text{imp},n}) \quad (14)$$

where $f_{\text{cost}}^{\text{imp},n}$ denotes the cost of the n th imperialist. According to the imperialists' power or normalized cost, which is calculated as (15), the initial colonies are dispersed among empires, and for the n th empire, it is extracted as (16):

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right|. \quad (15)$$

$$NC_n = \text{round}(P_n, N_{Col}) \quad (16)$$

In the next step, according to absorption policy as the main central part and heart of the current approach and as a strategy to transfer countries to their better position with their minimum cost value, the imperialist countries absorb the colonies towards themselves. The movement of colonies toward pertinent imperialist in the second phase of the optimization process is shown in Figure 6, which d denotes the imperialist and colony distance, and x represents a random value uniformly distributed between 0 and $\lambda \times d$. So that λ is a controlling parameter that is close to 2. V is a vector that has unity length, and its start point is the previous location of the colony, and its direction is toward the imperialist place.

$$\vec{X}_{\text{new}} = \vec{X}_{\text{old}} + U(0, \lambda \times d) \times \vec{V} \quad (17)$$

In equation (18), a random quantity of deviation θ , is introduced, and on the basic of it, the movement's direction is updated. This updating is made to enhance the searching operator through developing the search region in the nearby of the imperialist.

$$\theta \approx U(-\gamma, +\gamma) \quad (18)$$

Where γ represents a controlling parameter that chooses an arbitrary value and, under its effect, the random searching space of colonies nearby the imperialist will be modified. In most simulation, the θ value close to $\pi/4$ is suitable. Under this condition, the movement of colonies toward pertinent imperialist is changed, as shown in Figure 7.

The last and, of course, the most prominent step in ICA is the competition of imperialistic in which all empires attempt to take into command other empires' colonies. As a result of the gradually power reduction of the weaker empires, their colonies will be diminished and delivered to the stronger ones. This competition is performed by picking the weakest colony of the weakest empire and delivering it to the appropriate empire, established upon competition among all empires. To simulate this performance, first, the

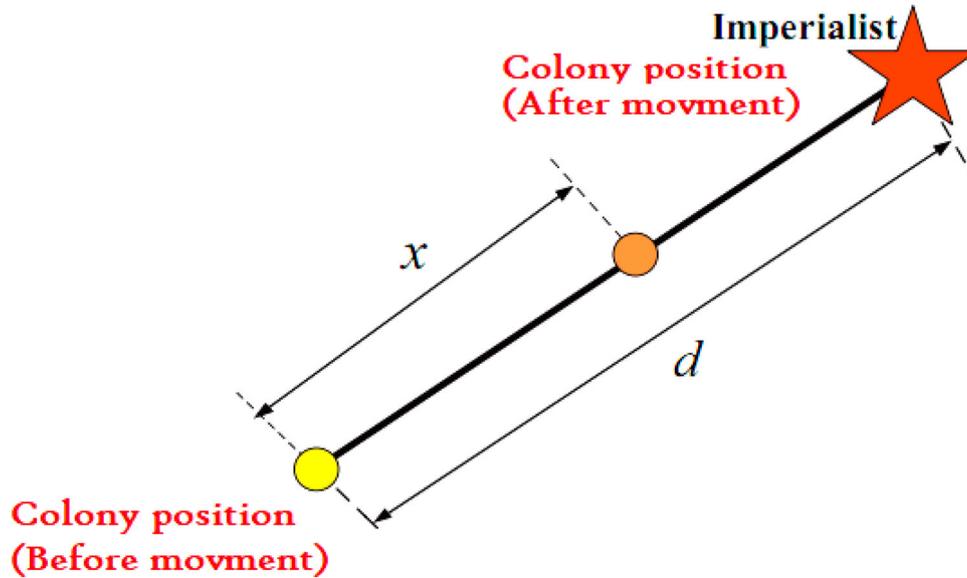


Figure 6. The movement of colonies toward pertinent imperialist.

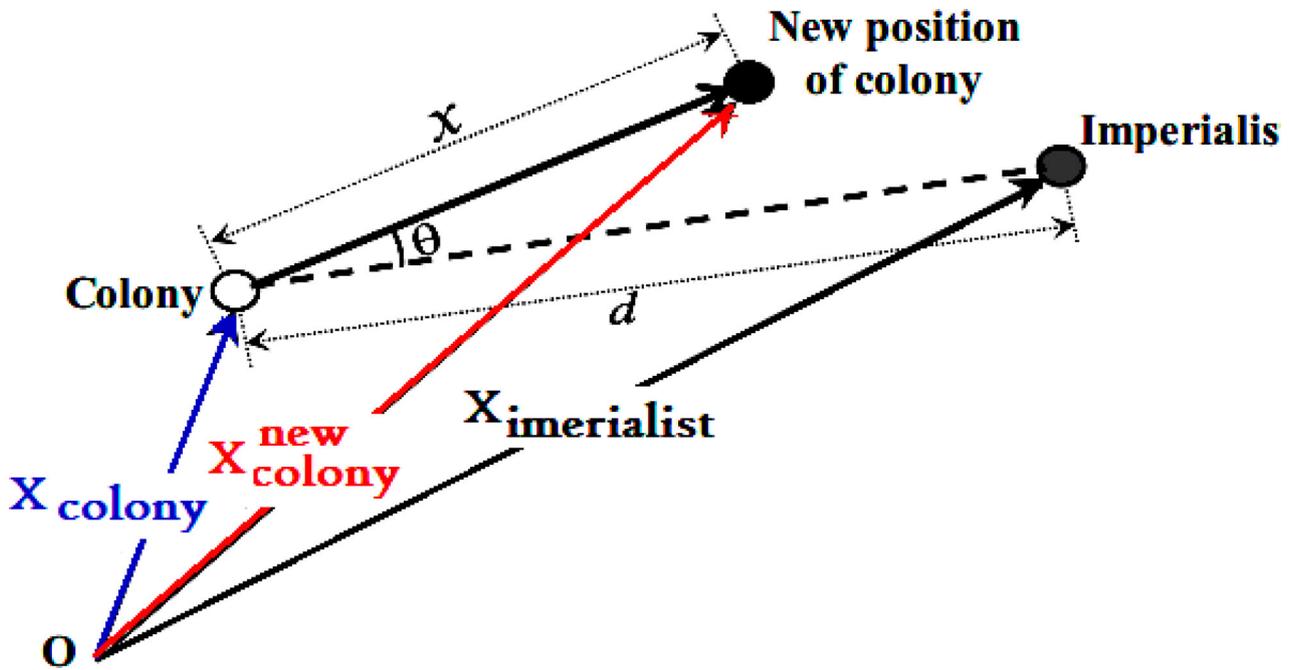


Figure 7. The movement of colonies toward pertinent imperialist considering θ angle.

ownership probability must be extracted by taking into account the empire’s total power.

The empire’s total power is concluded by adding imperialist power to an arbitrary percentage of the mean power of its colonies as follows:

$$T.C_n = Cost(imperialist_n) + \xi \times \text{mean}\{Cost(\text{colonies of empire}_n)\} \quad (19)$$

$T.C_n$ is the total cost of an empire, ξ is a minimal positive value which is supposed to be 5% in this study, and it describes the duty of colonies in calculating the net power of an empire.

The total normalized cost of an empire is determined as (20):

$$N.T.C_n = \max_i(T.C_i) - T.C_n \quad (20)$$

Finally, the possession probability is calculated for each empire as:

$$Pp_n = \frac{N.T.C_n}{\sum_{i=1}^{N_{imp}} N.T.C_i} \quad (21)$$

Using the possession probability of each empire, the vector of possession probability is built as follows:

$$Pp_n = [Pp_1 \quad Pp_2 \quad Pp_3 \quad \dots \quad Pp_{N_{imp}}] \quad (22)$$

The random vector R with the same size of P vector is built after:

$$R = [r_1, r_2, r_3 \dots r_{N_{imp}}] \quad (23)$$

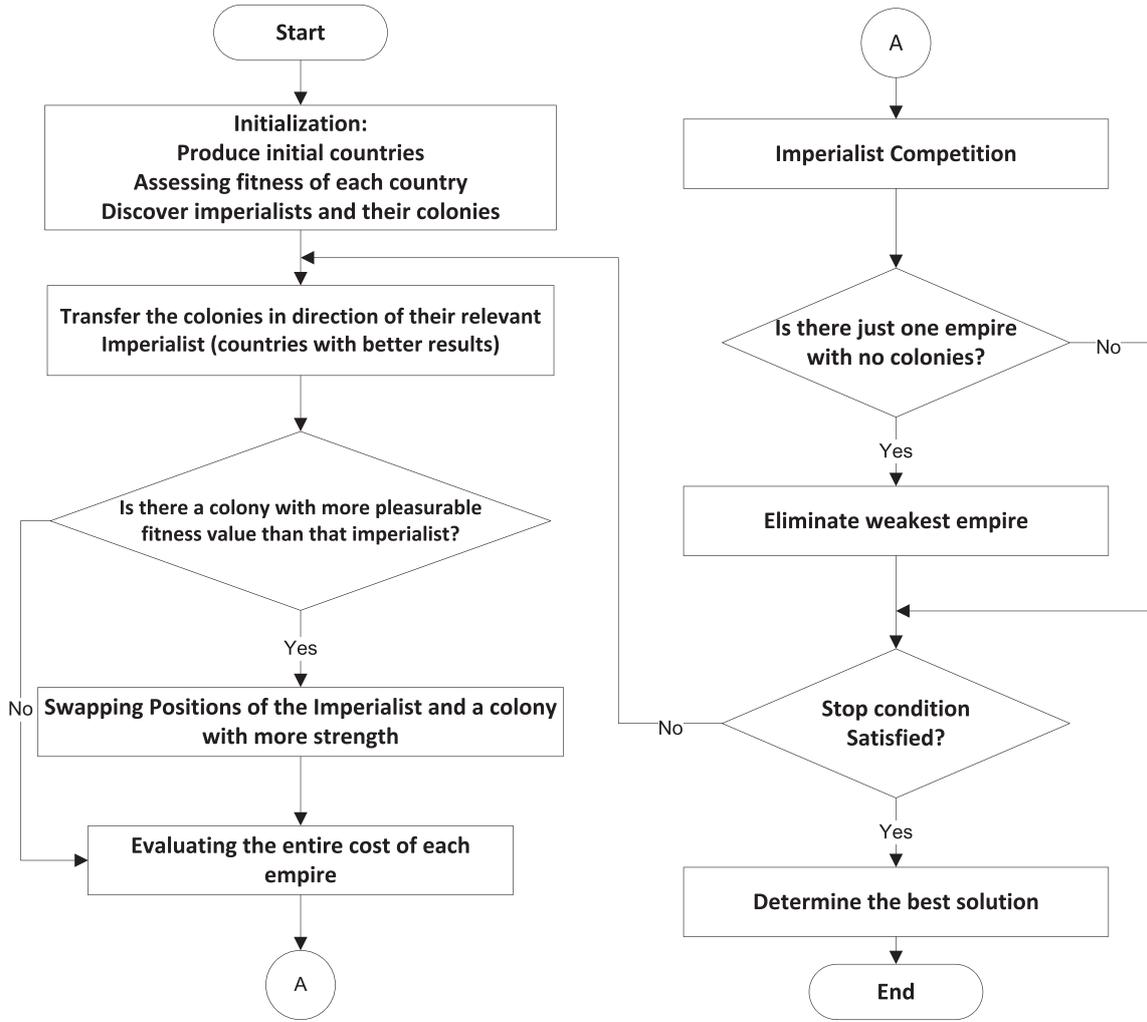


Figure 8. The flowchart of ICA.

Which each r_i experiments a uniform distribution between 0 and 1. Finally, the D vector will be built, and for the empire that has the most D index value, the mentioned colonies will accrue to that empire, and it will be more powerful.

$$\begin{aligned}
 D &= Pp_n - R \\
 &= \begin{bmatrix} Pp_1 - r_1 & Pp_2 - r_2 & Pp_3 - r_3 & \dots \\ Pp_{Nimp} - r_{Nimp} \end{bmatrix} \\
 &= \begin{bmatrix} D_1 & D_2 & D_3 & \dots & D_{Nimp} \end{bmatrix} \quad (24)
 \end{aligned}$$

This process will be repeated until to state where to remain only one empire and, the rest of the countries are its colonies.

Figure 8 shows the flowchart of ICA.

5.2. Binary ICA

As discussed further in section 4.1, the MP vector is a binary decision vector where the bit value $MP(n) = 1$ indicates the installation of PQM, and the 0 value means the not installation of PQM. The deamination of 0 and 1 values in each bit is the function of the optimization algorithm. Therefore in this study, we have

the binary optimization problem that we can use from binary version of the ICA algorithm. So in this section, the binary version of ICA is explained in detail. In this study, the solution vector size is limited as the possible number of buses which is situated by PQMs. This array is described as under relation:

$$\text{Country} = \begin{bmatrix} \text{Bus}_1 & \text{Bus}_2 & \text{Bus}_3 & \dots & \text{Bus}_N \end{bmatrix} \quad (25)$$

where N indicates the number of buses that are possibly appropriate for PQM situation. Bus_i is 1 or 0 according to its condition. Each country is met a cost that is determined as (26):

$$\text{Cost} = \sum_{i=1}^N S(n) \quad (26)$$

The mechanism of assimilation of ICA under the version of binary framework differs from that of the continuous one. A new probability-based logical operator under the BICA version is presented as follows [25]:

$$i \oplus j = \begin{cases} i & x < \frac{1}{3} \\ j & x \geq \frac{1}{3} \end{cases} \quad (27)$$

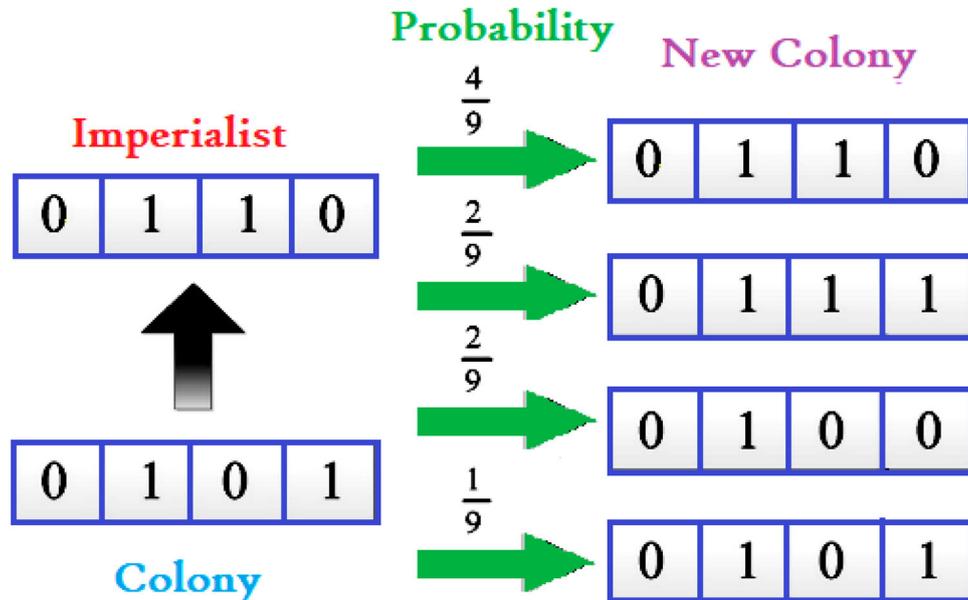


Figure 9. The motion of colonies in the direction of relevant imperialist in newly assimilation mechanism.

Table 1. Truth table of the new probability-based logical operator.

Colony variable (i)	Imperialist variable (j)	Result probability	
0	0	0	0
0	1	0	1
1	0	1	0
1	1	1	1

Where i and j indicate binary numbers and x represents a random variable that has a uniform distribution. In the newly proposed model of assimilation, i and j have, respectively, corresponded to the colonies and imperialists. Thus, the possibility of a variable to match the imperialist value is two times the colony itself. Table 1 shows the proposed operator truth table.

As shown in Table 1, if the first variables experiment exactly the second variables, then the result is equal to them. Therefore, the designed logical operator based on the proposed probability associated with new assimilation model, transfers the colonies to their new positions. Figure 9 shows the newly proposed assimilation procedure, which tests two different sample countries. Each country, imperialist and colony, keeps under control four binary variables. As shown in Figure 9, the first and the second bits are identical in two different sample countries. Hence, the first and the second bits of new colonies are the same as imperialist (or colony). The third bit of imperialist experiments "1" value, while the third bit of colony experiments "0" value. As presented in Table 1, the chance of the third bit to meet "1" is two times that of staying 0. Similarly for the fourth bit, the chance of being as imperialist's fourth bit, is two times that of being as colony's fourth bit. Thus the new colony can experiment with four possible positions because of two different bits between colony and imperialist. As indicated in Figure 9, the chance of the new colony to be the same as imperialist is $4/9$, while it is $1/9$ for being as the colony.

5.3. BICA for optimal PQM placement

Using the BICA, an algorithm for the optimal placement of PQMs is described in the following steps:

Step 1: Calculating the voltage, current, and other electrical parameters in steady-state using power flow, and in fault duration using short-circuit analysis

Step 2: While fault analysis, at first SL is computed, and the matrix of SSI is concluded. The short-circuit results are saved as an integrated form in the frame of the MRA matrix.

Step 3: Relying on network topology, the T matrix is extracted, and with the attention of the result of MRA in step 2, and combining with the T matrix, it forms the TMRA.

Step 4: The vectors of the solution, i.e. the MP vectors, which are equal to countries' matrix in ICA, are initialized in a random manner.

Step 5: Investigation of the MP vectors from the point of view constraints is accomplished. If not satisfied, so it should manipulate the MP vectors until constraints' satisfaction is obtained.

Step 6: Total evaluation indices regarding to the problem of MP, such as NRM, MOI, and NSSI, are computed.

Step 7: Assessment of the MP vectors' performance with the attention of objective function (f) using analyzed indices. In this step, for each country, it is computed and saved.

Step 8: All individuals are grouped into several empires. In this step, some of the more powerful countries, according to calculated fitness values in the previous action, are chosen as the initial imperialists and the remaining less power are colonies of them and are dispersed among imperialists based on their position and power.

Step 9: The movement of colonies toward pertinent imperialist is performed according to absorption policy.

Step 10: Making the imperialistic competition. To do this, first the possession probability should be calculated using (Equation (20)).

Step 11: The vector of possession probability using the correspondent value of each empire is concluded through (Equation (21)).

Step 12: The D vector is built through (Equation (23)), and the empire that has the most D index value, the mentioned colonies will accrue to that empire, and it will be more powerful.

Step 13: Updating process, i.e. each MP vector to meet a new situation is brought up to date based on criterion presented using new binary probability-based logical operator (Equation (26)).

Step 14: Steps 5–13 will be repeated again until convergence is acquired, where there is just one empire with no colonies and the weakest empire is eliminated and the best solution is achieved. Upon convergence, the optimal PQM placement is obtained.

The overall sequence of instructions in the optimal monitor allocation using BICA in the framework of a flowchart is indicated in Figure 10. As shown in this figure, the proposed program for optimal placement of PQMs is based on the coordination between MATLAB and DIGSILENT. The short-circuit analysis is performed using DIGSILENT software, and the evaluation indices are calculated using MATLAB software. The BICA optimization tool is programmed in a MATLAB environment.

6. Simulation and results

The 69-Node IEEE test system is a distribution system with a balanced radial topology fed by an upstream grid to feeder nominal voltage at 12.66 kV. The system with 69 buses is linked together through 73 branches associated five tie lines in its topology. The information and data of feeder's impedance and requested power by each bus of this system is reported in [26]. Figure 11 indicates the topology of this system. The performance of BICA is compared with that of other heuristic optimization techniques, namely, BPSO [11], QBPSO [12,13], BGSA [14], and QBGSA [15], to display the impressiveness of the BICA optimal monitor situation. Parameters of BICA in the optimization process are standardized, where initial country, initial imperialists and numbers of decades are set to 100, 10 and 300, respectively. The maximum iteration is set at 150. Three-phase faults, double line-to-ground faults, and single phase-to-ground faults were simulated at each bus in the test systems with 0Ω fault impedance. The FV analysis results as a matrix is extracted with the proposed method in a DIGSILENT environment as indicated in Figure 12.

In the following, a comparative study with the existing methods is used for the location of PQM devices. In Tables 2–4, the comparison of the proposed method by BPSO [11], QBPSO [12,13], BGSA [14] and QBGSA [15] without redundancy is presented. Of course, the redundancy is the novelty of this research. In addition, Figure 13 represents the convergence characteristics of BPSO, BGSA, QBPSO and QBGSA and its comparison with BICA for the 69-bus system. Since the nature of the proposed problem in this study is binary (selection “1” or “0” for placing or not the PQMs), so the Binary Imperialist Competitive Approach is suggested for the optimization process. Of course, the main reason for suggesting the Imperialist Competitive Approach is related to its ability to avoid the algorithm falling into the local optimum answers.

Table 2 lists the worst, average, best and standard deviation values extracted under different optimization techniques discussed in this research. These results are compared from the points of view convergence rate and quality of the optimal solution. As listed in Table 2, BICA displays the most precise optimal solution relative to the other optimization techniques because it experiments the lowest fitness function value of 16.54 and the lowest standard deviation value of 0.63. BPSO experiments the worst performance due to the highest fitness function value of 35.89.

Figure 13 indicates the characteristics of convergence characteristic of discussed techniques in

Table 2. Performance of BPSO, QBPSO, BGSA, QBGSA and BICA in obtaining the optimal PQM placement solution for the 69-bus system without redundancy at $\alpha = 0.85$.

Method	Convergence rate (iterations)				Fitness value			
	Best	Average	Worst	SD	Best	Average	Worst	SD
BPSO [11]	11	25.8	55	11.51	35.89	47.65	62.32	6.07
QBPSO [12]	30	84.3	145	39.64	18.37	20.44	23.32	1.54
BGSA [14]	137	143.8	149	3.91	19.85	23.95	35.53	3.81
QBGSA[15]	48	111.2	150	30.33	18.28	19.94	23.03	0.77
BICA	37	96	147	20.45	16.54	19.23	21.34	0.63

Table 3. Performance comparison of different algorithms in PQM placement.

Method	Convergence speed	Results accuracy	Comment
BPSO	4	5	The worst
BGSA	5	4	The nearly worst
QBPSO	1	3	The medium
QBGSA	2	2	The medium
BICA	3	1	The best

Table 4. Performance of BPSO, BGSA, QBPSO, QBGSA and BICA in optimizing monitors in the 69-bus test system for α at 0.85.

Method	Fitness values	Number of PQMs	Optimal arrangement
BPSO [11]	35.89	12	1,5,6,29,31,35,38,44,48,49,64 and 69
QBPSO [12]	18.37	8	1,6,29,32,37,41,48 and 57
BGSA [14]	19.85	8	1,6,26,30,34,38,49 and 64
QBGSA[15]	18.28	8	1,6,29,32,36,38,48 and 57
BICA	16.54	8	1,6,29,32,36,41,48 and 57

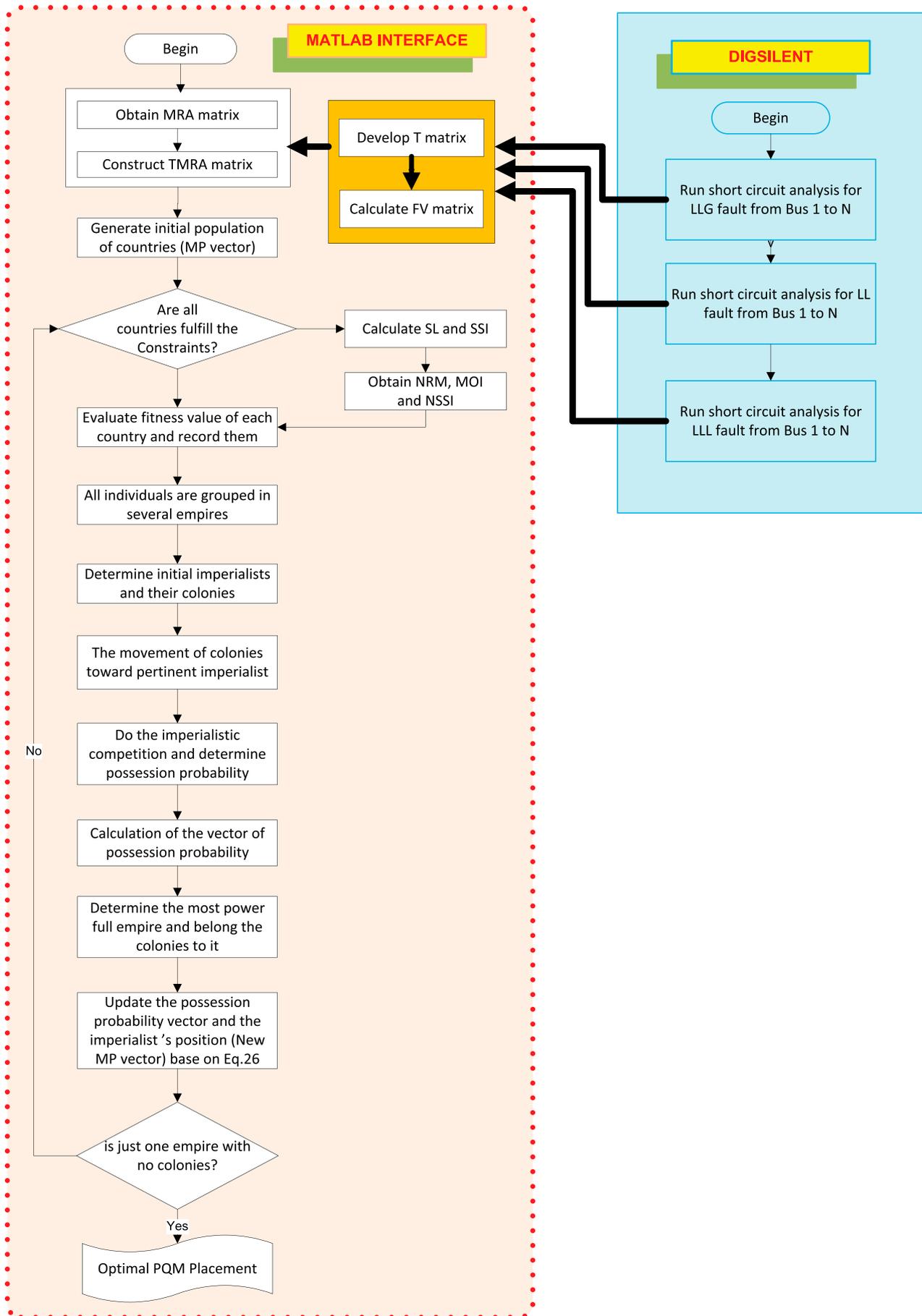


Figure 10. Implementation of BICA in MATLAB interface and coordination with DIGSILENT interface.

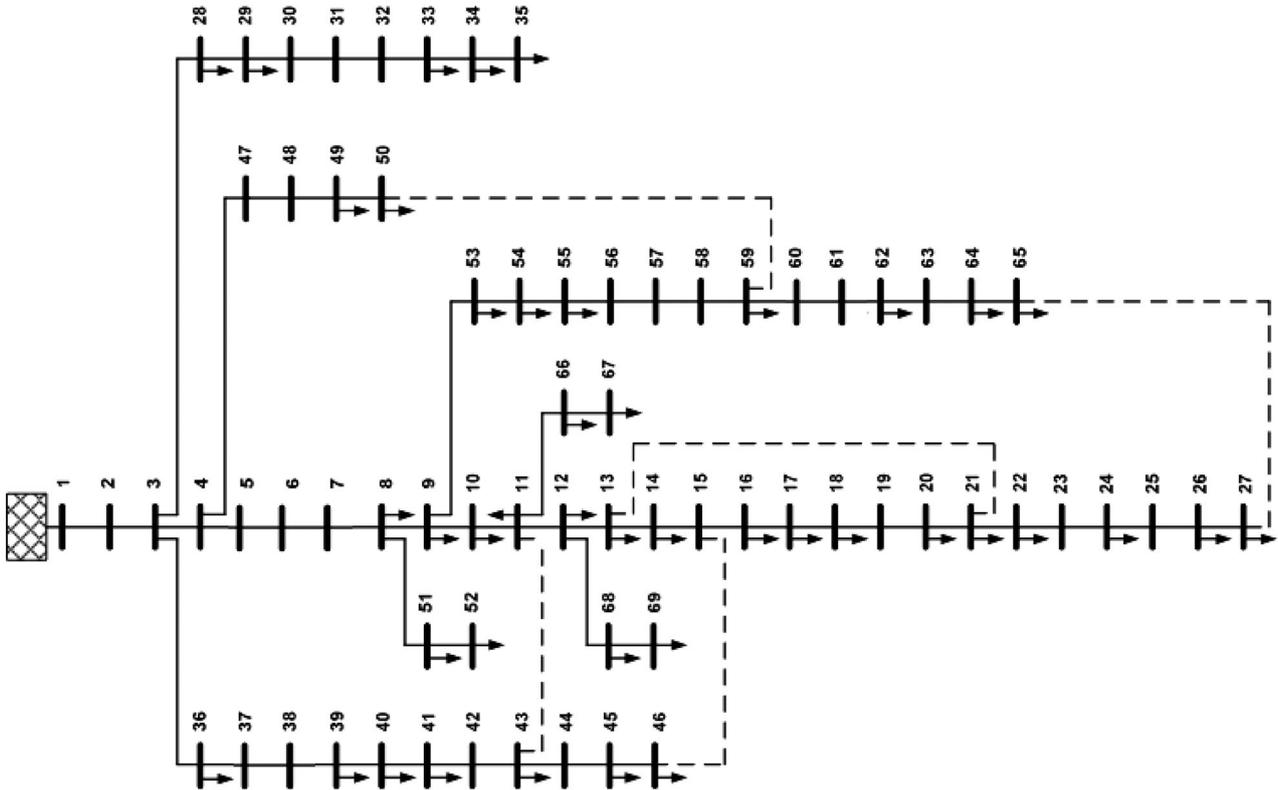


Figure 11. Single line diagram of 69-bus IEEE distribution test system

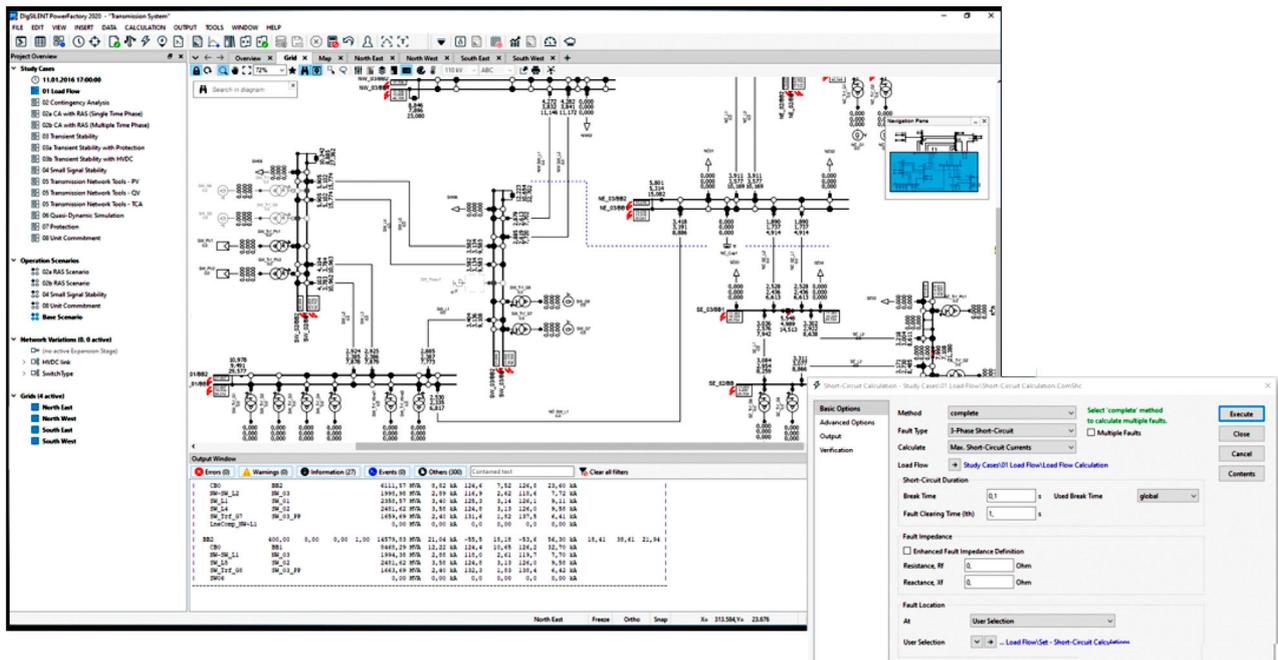


Figure 12. Short-circuit analysis in the DIGSILENT environment to form FV matrix.

optimizing monitors under test system with current topology. The results of Figure 13 clear that the fastest convergence compared with the other methods is achieved by QBPSO. Initially, BPSO closely experiments a convergence rate that is similar to that of QBPSO. However, a premature convergence is seen by BPSO, which occurs after a few times. With two viewpoints, at first, ability to overcome the premature convergence challenge and at second, ability to supply an

enhanced optimal solution, QBPSO and QBGSA and BICA demonstrate a significant enhancement in the solution with respect to BPSO and BGSA. It also is evident that from Figure 13, BGSA experiments the slowest convergence. However, from the point of view of accuracy, BGSA is more pleasurable than BPSO, which this fact is concluded from the standard deviation results shown in Table 2. By investigating all the optimization techniques which are utilized in the PQM

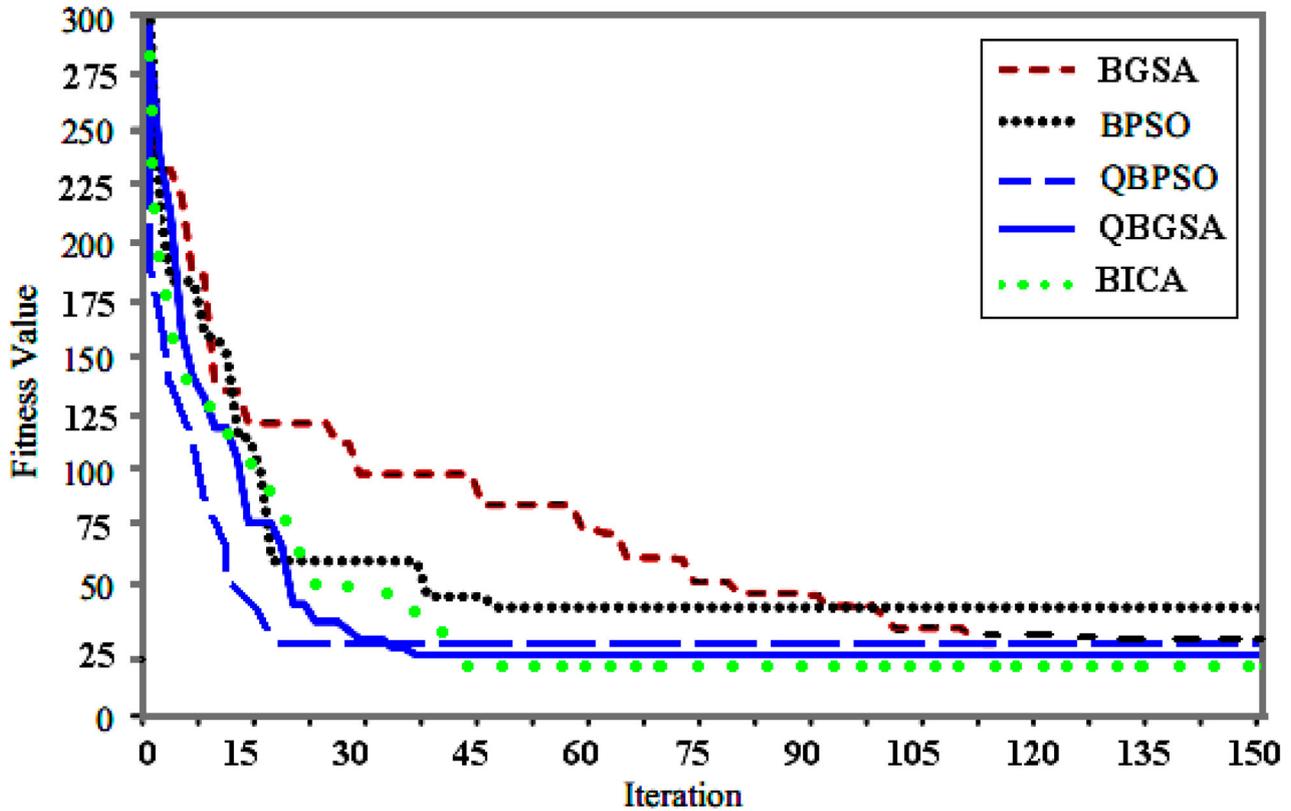


Figure 13. Convergence characteristics of BPSO, BGSA, QBPSO and QBGSA for the 69-bus system.

placement, from viewpoints of statistical quantities, accuracy and standard deviation, BICA presents the most desirable optimal solution. By the results shown in Figure 13, it is clear that BICA experiments the slowest convergence regarding the QBPSO and experiments the fastest convergence respect to QBGSA. However, BICA, due to high accuracy and the low standard deviation, is better than QBPSO and QBGSA. From the obtained results, it evident that the BPSO and QBPSO exhibit the fastest convergence compared with the BICA (11 and 30 iterations compared with 37 in term of best convergence rate); however, BICA has the most accuracy and the lowest standard deviation and also does not have the problem of premature convergence. In Table 3, in accord with convergence speed and results accuracy, the ranking order of methods are listed and shows that BICA has a good position compared with the others.

Table 4 exhibits the number and location as an optimal answer in PQMs optimizing for the 69-bus system. BICA concludes that the 69-bus system should experiment eight monitors which must be situated at buses 1, 6, 29, 32, 36, 41, 48, and 57 relying on the lowest best fitness value.

Table 5 lists a comparison of the results of the BICA, in the 69-bus test system, in terms of fitness value, number of PQMs, iteration numbers and optimal configuration under different α values.

Figure 14 shows the optimal configuration of PQMs obtained by BICA with considering redundancy in IEEE 69-bus distribution test system at buses 1, 6, 29, 32, 36, 41, 48 and 57.

Table 5. Performance of BICA in obtaining the optimal PQM placement solution for the 69-bus system for different values α .

α Values	Fitness values	N_{PQM_s}	Iteration	Optimal arrangement
0.85	16.54	8	37	1,6,29,32,36,41,48 and 57
0.75	24.67	11	42	1,6,15,29,32,34,38,41,48,50 and 58
0.65	31.25	11	51	1,6,13,29,30,35,37,42,49,52 and 57
0.55	36.42	15	64	1,5,6,14,29,32,33,35,37,41,48,49,52,57 and 67
0.45	47.94	17	78	1,5,6,7,10,15,29,30,33,34,37,38,41,48,49,56 and 69

As seen in Table 5, it was evident that the fitness value experiments a decreasing trend from 24.67 ($\alpha = 0.75$) to 31.25 ($\alpha = 0.65$). This decreasing trend may be because at these two values, the number of PQMs has the same value, that is, 11. By decreasing the α value, PQMs meet a growing numbering and the coverage area provided by each monitor will be small.

To analyze and investigate the considering and no considering redundancy effects modeled by (11) on the performance of BICA on convergence rate and accuracy fitness value of the optimal solution, Table 6 makes a comparison in terms of the worst, average, best and standard deviation values obtained after performing 25 runs at $\alpha = 0.85$. As indicated by the results shown in Table 6, BICA guarantees the most precise optimal answer when the redundancy is modeled in the analyzing program because it has the lowest fitness function value of 16.54 and the lowest standard deviation value of 0.63 compared with those of 17.34 and 0.74,

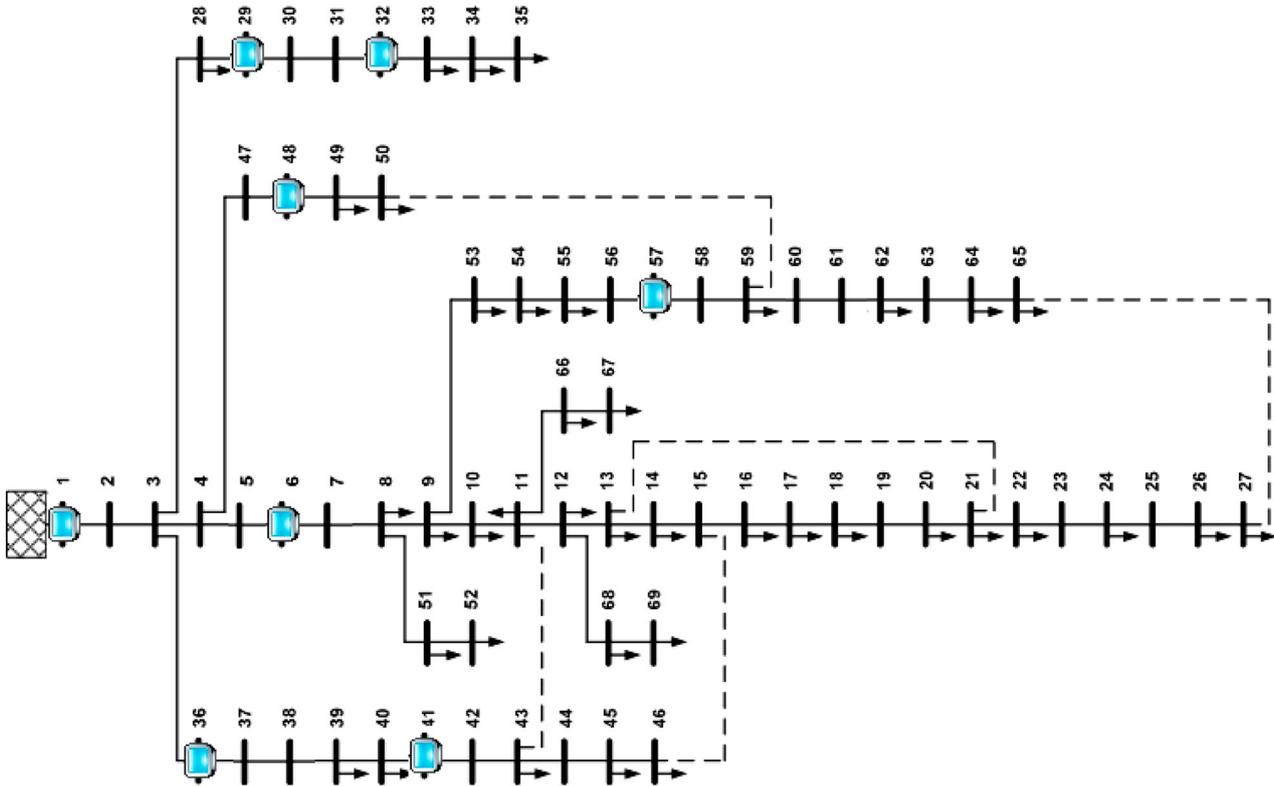


Figure 14. An optimal PQMs placement in the IEEE 69-bus system.

Table 6. Effect of redundancy on the performance of BICA in optimizing monitors for the 69-bus system at $\alpha = 0.85$.

Method	Convergence rate (iterations)				Fitness value			
	Best	Average	Worst	SD.	Best	Average	Worst	SD.
With redundancy	37	96	147	20.45	16.54	19.23	21.34	0.63
Without redundancy	35	84	134	18.87	17.34	19.87	21.85	0.74

Table 7. Results of redundancy under different values α .

α Values	Num. of PQMs (N_{PQM})	Redundancy (rd)	rd/N_{PQM}
0.85	8	5.6208	0.7026
0.75	11	6.1952	0.5632
0.65	11	6.1952	0.5632
0.55	15	6.7965	0.4531
0.45	17	6.9751	0.4103

respectively, in case of no considering redundancy. In addition, this indicates that added computation due to redundancy modeling in the optimization problem affects the needed iteration number for convergence of problem and also influences the fitness function value. Owing to additional computation in case of considering redundancy as a result, the needed iteration number for convergence of problem is increased.

Table 7 lists the BICA results for the 69-bus system, including the redundancy value (rd) and the ratio of redundancy to installed PQMs, (rd/N_{PQM}) under different values α .

Table 7 represents the redundancies that experiment with the remarkable values such that its lowest level is 5.6208. It is cleared in Table 7 that the redundancy has a direct relation to α and also to the number of

Table 8. Analysis of system indices in optimal managing of monitors for the 69-bus system with and without redundancy different values α .

α Values	Without redundancy				With redundancy			
	MOI	SSSI	PQMs	Fitness	MOI	SSSI	PQMs	Fitness
0.85	1.132	1.324	8	17.34	1.112	1.592	8	16.54
0.75	1.128	1.464	11	25.78	1.108	1.656	11	24.67
0.65	1.118	1.521	11	28.94	0.987	1.713	11	31.25
0.55	1.105	1.623	15	34.65	0.912	1.878	15	36.42
0.45	1.004	1.689	17	45.23	0.901	1.912	17	47.94

monitors. The higher the number of detectors, it yields to the higher redundancy and hence the fault points faced with more times monitoring and so they are much observed on the whole. By decreasing the α value, it is added to PQMs. The issue of this increase is that each PQM's coverage area gets smallish. The ratio of rd/N_{PQM} in Table 7, corresponded with the MRA, is reduced with the decline of the voltage sag threshold. Thus, the lower threshold of the voltage sags is considered, the smaller MRA and consequent the higher number of monitors. Finally, Table 8 lists the analysis results of the system's indices in terms of the MOI and the SSI, N_{PQM} and fitness values in optimal managing of monitors for the 69Bus system with and without redundancy different values α .

In this table, the effect of considering redundancy and the effect of the threshold of the voltage sags on the MOI and SSI indices are evaluated. Thus, the lower the threshold of the voltage sags, the smaller the MOI and the higher the number of monitors required and finally avoids overlapping in the monitoring scheme.

In addition, the modeling of redundancy reduces the MOI that it is because that each PQM's coverage area becomes small.

7. Conclusion

In this article, a new PQM location method on the basis of the binary version of imperialist competitive algorithm is established to handle the optimization process. It manages the optimization process using the optimal number and location of PQMs to obtain optimal monitor overlapping as well as satisfies the sag severity index at the highest level. This method relies on the concept of redundancy, and the greater redundancy is, the more times the points affected by faults are observed in the system, on the whole. In this article, DIGSILENT software is used for short-circuit analysis, whereas the optimization process is managed by the BICA. The algorithm is applied to IEEE 69-bus distribution systems. For different voltage sag thresholds, the effect of considering redundancy on optimal number, configuration, the MOI and SSI indices are analyzed. In addition, fitness values and iteration numbers are computed and compared with results of BPSO, BGSA, QBPSO and QBGSA, utilized earlier by others. The results show that BICA provides the most desirable allocation of sag detectors compared with the other optimization techniques. Other advantages of BICA cover the fast convergence, low time of simulation and run, ability to attain global either minimum or maximum point (of course it depends on objective function). The BICA-based proposed approach also experiences the standard deviation nearly with the amount of zero. Two effects are analyzed. First, the considering of redundancy and, second, the effect of the voltage sag thresholds on the MOI and SSI indices. Thus, the lower the threshold of the voltage sags, the smaller the MOI and the higher the number of monitors required and finally avoids overlapping in the monitoring scheme. In addition, the modeling of redundancy reduces the MOI that it is because that each PQM's coverage area becomes small. When voltage threshold reduces from 0.85 to 0.45, without redundancy the MOI index decreases from 1.132 to 1.004, whereas under molding of redundancy, the corresponding values are improved in such away whose values are 1.112 and 0.901. In addition, it is seen due to decreasing in the voltage threshold from 0.85 to 0.45, the number of PQM are increased from 8 to 17. It is cleared from results that the redundancy has a direct relation to voltage threshold and also to the number of monitors. The higher the number of PQMs, it yields to the higher redundancy and hence the fault points need more monitoring and so they are much observed on the whole. By decreasing the voltage threshold value, PQMs are increased as it is because each PQM's coverage area gets smaller. When voltage threshold reduces from 0.85 to 0.45, the

redundancy values are changed from 5.6208 to 6.9751, and this means that the ratio of rd/NPQM reduces from 0.7026 to 0.4103 which represented the adequacy of the proposed PQM configuration.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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