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RESEARCH ARTICLE

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Novel quantum-inspired firefly algorithm for optimal power quality monitor placement

Abstract The application of a quantum-inspired firefly algorithm was introduced to obtain optimal power quality monitor placement in a power system. The conventional binary firefly algorithm was modified by using quantum principles to attain a faster convergence rate that can improve system performance and to avoid premature convergence. In the optimization process, a multi-objective function was used with the system observability constraint, which is determined via the topological monitor reach area concept. The multi-objective function comprises three functions: number of required monitors, monitor overlapping index, and sag severity index. The effectiveness of the proposed method was verified by applying the algorithm to an IEEE 118-bus transmission system and by comparing the algorithm with others of its kind.

Keywords quantum-inspired binary firefly algorithm, topological monitor reach area, power quality

1 Introduction

With the advancement of the electrical energy industries, electric utility providers and end users have become increasingly concerned about power quality (PQ). Electrical PQ can be defined as the level through which utilization and delivery of electric power influence the performance of user equipment [1]. Generally, PQ problems are caused by PQ disturbances such as harmonics, voltage swell, voltage sag, and transients. Among these disturbances, voltage sag is the most frequent and harmful event. It causes heavy losses because of the failure or malfunction of sensitive industry equipment and loads. Therefore, monitoring voltage sag to mitigate the problem is crucial.

One way to monitor the voltage sag event is by installing power quality monitors (PQM) at each bus in the power system. Cristaldi et al. [2] proposed the installation of PQM at each bus and the linking of these PQM through a communication facility such as the Internet. However, this option is not cost effective as the cost increases with a larger number of PQM. This option also causes data redundancy [3]. Thus, the number of PQM should be decreased to boost the efficiency of the monitoring system. Since placing PQM at each bus is not feasible, optimal distribution of a number of PQM should be determined so that the installed PQM can monitor the entire system with minimum redundancy.

One of the first studies that aimed to obtain the optimum number and location of PQM introduced the covering and packing concept by using GAMS [3]. Another researcher used branch and bound algorithm, which divided the solution space into smaller spaces [4]. However, this algorithm might provide the wrong solution with the selection of a wrong branch in the earlier stages [5]. Meanwhile, meta-heuristic algorithms such as the genetic algorithm (GA) are employed in the optimal placement of PQM [6–8]. However, the GA requires long processing time to enable the convergence of the solution; thus, alternative techniques with better performance such as particle swarm optimization (PSO) [9] and gravitational search algorithm (GSA) [10] have been introduced.

The main purpose of this paper is to introduce a new algorithm known as quantum-inspired binary firefly algorithm (QBFA) to solve the problem of optimal PQM placement. This algorithm is a result of applying quantum behavior to the conventional firefly algorithm (FA) [11] to avoid premature convergence and improve efficiency [12–15]. The study is structured as follows. The basic principle

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of the FA is presented in the next section, followed by a brief explanation of the application of the algorithm in PQM placement. Subsequently, results from the QBFA based on simulation data are provided and discussed. Lastly, the conclusions are drawn.

2 Firefly optimization algorithm

2.1 Firefly algorithm

The FA was developed by Yang [11] based on the behavior of fireflies. Each particular species produces a unique pattern of flashing lights, which can be related with the objective function to be optimized through a particular formulation. For simplicity in describing the FA, three idealization rules are applied: ① All fireflies are unisex and therefore one firefly tends to be attracted to others regardless of their sex. ② Attractiveness is proportional to brightness; thus, for any two flashing fireflies, the brighter one tends to attract one that is less bright. As distance increases, the attractiveness decreases with decreasing brightness. A firefly tends to move randomly if no brighter firefly exists. ③ The brightness of a firefly is decided by the value of the objective function. For the maximization problem, the brightness is proportional to the value of the objective function, and other forms of brightness can be determined in a way similar to the fitness function in the GA. Based on these rules, the basic steps of the FA can be determined as shown in Fig. 1.

The attractiveness function $\beta(r)$ can be any monotonically decreasing function with the generalized form as follows [11]:

$$\beta(r) = \beta_o e^{-\gamma r^m} \ (m \geqslant 1), \tag{1}$$

where r is the distance between two fireflies, β_o is the attractiveness at $r = 0$ and γ is the light absorption coefficient. Next, the distance between any two fireflies i and j at x_i and x_j is the Cartesian distance r_{ij} [11]:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2}, \tag{2}$$

where $x_{i,k}$ is the kth component of the spatial coordinate x_i of ith firefly. The movement of a firefly i that is attracted to a brighter firefly j is decided by [11]:

$$x_i = x_i + \beta_o e^{-\gamma \ r_{ij}^2}(x_j - x_i) + phi\left(rand - \frac{1}{2}\right), \tag{3}$$

where the second term represents attraction and the third term corresponds to randomization with the randomization parameter phi and a uniformly distributed random number generator $rand$.

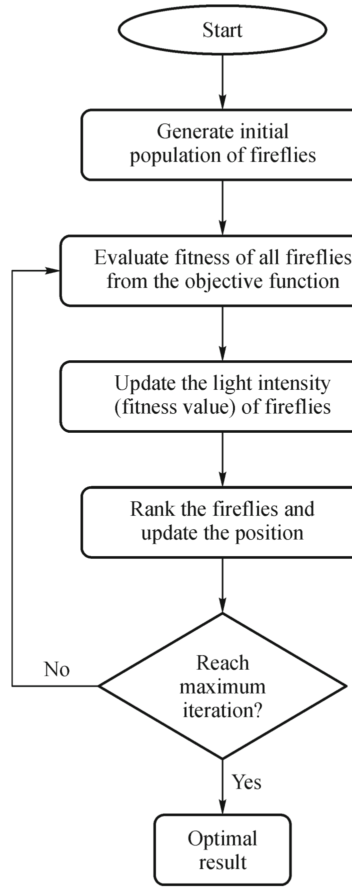

Fig. 1 Flowchart of firefly algorithm

This new FA can outperform other traditional algorithms such as the GA and PSO consistently in terms of efficiency and success rate [11].

2.2 Binary firefly algorithm

A binary firefly algorithm (BFA) was proposed by Sayadi et al. [16]. It is a discrete version of FA, which provides the output in binary number with either ‘1’ or ‘0’. When firefly i is attracted to firefly j, its position x_i changes from a binary to a real number. Therefore, sigmoid function $S(x_i)$ shown in Eq. (4) [16] is used to restrict the continuous output between zero and one. The value of $S(x_i)$ determines the probability of bit x_i becoming ‘1’ as shown in Eq. (5) [16].

$$S(x_i) = \frac{1}{1 + \exp(-x_i)}, \tag{4}$$

$$x_i = \begin{cases} 1, & \text{if } S(x_i) > rn, \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

where rn is a uniform random variable in interval [0,1].

2.3 Quantum-inspired binary firefly algorithm

The proposed QBFA is an efficient optimization technique inspired by the conventional BFA and the principle of quantum mechanics. The first quantum-inspired computing theory was proposed by Moore and Narayanan [17]. The quantum bit (Q-bit) is the smallest unit for quantum computing, which may be in the state of '1' or '0' or in a linear superposition of the two [13]:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle, \tag{6}$$

where α and β are complex numbers that specify the probability amplitudes of the corresponding states. $|\alpha|^2$ and $|\beta|^2$ indicate the probability that a Q-bit can be found in a '0' or a '1' state, respectively. Therefore, the states can be normalized to unity as follows [13]:

$$|\alpha|^2 + |\beta|^2 = 1. \tag{7}$$

The state of a Q-bit is updated through a quantum gate also known as a reversible gate, and can be represented as a unitary operator U. Types of quantum gates include NOT gate, controlled NOT gate, rotation gate, and Hadamard gate [18]. In this study, a rotation gate as shown in Eq. (8) is used because it has been applied to numerous heuristic search algorithms [12–15].

$$U(\Delta\theta_i) = \begin{bmatrix} \cos(\Delta\theta_i) & -\sin(\Delta\theta_i) \\ \sin(\Delta\theta_i) & \cos(\Delta\theta_i) \end{bmatrix}, \tag{8}$$

where $\Delta\theta_i$, $i = 1, 2, 3\ldots, n$, is the rotation angle of each Q-bit toward either 0 or 1 state depending on its sign.

This proposed rotation gate consists of two techniques, namely, the coordinate rotation gate and the dynamic rotation angle approach, which are used to update Q-bits and determine the magnitude of the rotation angle, respectively. Therefore, no pre-specified lookup table is necessary, and the rotation angle can be formulated as:

$$\Delta\theta_i = \theta \times \left(x_i + \beta_o e^{-\gamma r_{ij}^2}(x_j - x_i) + phi\left(rand - \frac{1}{2}\right)\right), \tag{9}$$

where θ is the rotation angle magnitude that decreases monotonously from $\theta_{\max}$ to $\theta_{\min}$ along the iteration. Then, the Q-bit individual string is updated based on the rotation angle and rotation gate as shown in Eq. (10) [13]. Lastly, the position of the firefly is updated by the probability of $|\beta|^2$ as shown in Eq. (11) [13].

$$\begin{bmatrix} \alpha_i(t+1) \\ \beta_i(t+1) \end{bmatrix} = U(\Delta\theta_i) \times \begin{bmatrix} \alpha_i(t) \\ \beta_i(t) \end{bmatrix}, \tag{10}$$

$$x_i = \begin{cases} 1 & if\ |\beta_i(t+1)|^2 > rn, \\ 0 & \text{otherwise}. \end{cases} \tag{11}$$

3 Application of FA for optimum PQM placement

Before the proposed QBFA is applied, the PQ monitor observability concept and the three common elements used in optimization, namely, decision vectors, objective function, and optimization constraints, have to be defined.

3.1 Monitor observability concept

The monitor observability concept is necessary in determining the PQM placement. This concept is used to ensure the observability of the entire power system. The monitor reach area (MRA) [4] is one of the conventional observability concepts that is only suitable for meshed networks. Therefore, in this study, the topological monitor reach area (TMRA) concept [19] is applied. The TMRA matrix is a combination of the MRA matrix and the system topology matrix (T) achieved by using operator 'AND' as shown in Eq. (12). TMRA is used to further restrict the monitor coverage to fulfill both the radial and meshed topologies. Similar to the MRA matrix, the TMRA matrix column is correlated to bus number, and its row is correlated to fault location. More details on TMRA can be found in the study conducted by Ibrahim et al. [19].

$$\mathrm{TMRA}(j,k) = \mathrm{MRA}(j,k) \cdot \mathrm{T}(j,k),\ \forall j,k. \tag{12}$$

3.2 Optimization decision vector

The optimization process explores the solution space as defined in the objective function through the bits manipulation of the decision vector subject to the system constraints. To satisfy the solution process, the monitor placement (MP) vector is introduced in this study to represent the binary decision vector (x_{ij}) in the optimization process. The bits of this vector indicate the need of the monitor to be installed at a particular bus in the power system. The dimension of the vector corresponds to the number of buses in the power system. A bit with the value of zero in the nth location in the MP vector indicates that no monitor is required at bus n, and a bit with the value of one indicates that a monitor should be installed at bus n. The MP vector can be described as [5]:

$$\mathrm{MP}(n) = \begin{cases} 1, & \text{if PQM is required at bus } n, \\ 0, & \text{otherwise}, \end{cases} \quad \forall n. \tag{13}$$

3.3 Objective function

The purpose of the optimization is to determine the minimum number of PQMs required by the optimal placement while maintaining the observability of any fault occurrence, which may lead to voltage sag events in the power system. Therefore, the objective function is formulated in such a way that determines the optimal number of required monitors as well as the optimal locations where the monitors can be installed. The number of required monitors (NRM) to be minimized [5] can be expressed as follows:

$$\mathrm{NRM} = \sum_{n=1}^{N} \mathrm{MP}(n). \tag{14}$$

At the same time, additional parameters are required to determine the best locations for installing the monitors. Thus, the monitor overlapping index (MOI) and the sag severity index (SSI) are employed to evaluate the suggested PQM placement in the optimization process [5]. The MOI refers to the level of overlapping in the PQM coverage as given by the suggested placement. This index value should be minimized to attain optimal PQM placement. The value can be calculated based on the following expression [5]:

$$\mathrm{MOI} = \frac{\sum(\mathrm{TMRA} \times \mathrm{MP}^{\mathrm{T}})}{\mathrm{NFLT}}, \tag{15}$$

where NFLT represents the total number of fault locations when all types of faults are considered.

Meanwhile, the SSI reflects the severity level of a specific bus on the voltage sag event because any fault occurrence can cause a significant drop in the voltage magnitudes of most of the buses in the affected system. As a result, the highest SSI value among those in the same NRM should be obtained to find the best PQM placement in the system. The severity level (SL) should be derived first based on the threshold t in p.u. before the SSI is calculated as follows [5]:

$$\mathrm{SL}^{t} = \frac{N_{\mathrm{SPB}}}{N_{\mathrm{TPB}}}, \tag{16}$$

where N_{SPB} is the number of phases that experience voltage sag with magnitudes below t in p.u., and N_{TPB} is the total number of phases in the system.

Subsequently, the SSI value is obtained by applying weighting factors for different SLs. The lowest t value has the highest weighting factor (k = 5) and vice versa. Thus, five threshold levels, namely, 0.1, 0.3, 0.5, 0.7, and 0.9 p.u. are included in this study. The SSI can be calculated as illustrated in Eq. (17) [5] where the number 5 and the value 15 refer to the weighting factor levels and the total weight, respectively. Lastly, the SSI values are stored in a matrix where the column indicates the bus number and the row indicates the fault type (F).

$$\mathrm{SSI}^{\mathrm{F}} = \frac{1}{15}\sum_{k=1}^{5} k \times \mathrm{SL}^{[1-(2k-1)/10]}. \tag{17}$$

However, the MOI and SSI should possess similar optimal criteria of either maximum or minimum to facilitate their combination. Consequently, the SSI matrix is modified to derive a minimum criterion in optimization similar to the case of minimization of MOI. Given that the maximum value of SSI element is one, minimization can be conducted by applying the complementary matrix of the SSI. The negative severity sag index (NSSI) is then introduced to evaluate the optimal placement of PQM in the system. The NSSI can be obtained by using Eq. (18) [5]. The lower the NSSI value, the better the arrangement of PQM in the system.

$$\mathrm{NSSI} = \frac{\sum \lfloor(\mathrm{ONE} - \mathrm{SSI}) \times \mathrm{MP}^{\mathrm{T}}\rfloor}{\mathrm{NFT}}, \tag{18}$$

where ONE is the matrix with all entries ‘1’ that has the same dimension as the SSI matrix, and NFT is the number of fault types.

All of the functions in Eqs. (14), (15), and (18) can be combined in a single objective function by employing the summation method because these functions have similar optimal criteria. Nonetheless, the objective functions should be independent from each other and must not influence one another in obtaining the optimal solution. The single multi-objective function used to solve the problem for the optimal placement of PQM is derived as follows [5]:

$$f = (\mathrm{NRM} \times \mathrm{MOI}) + \mathrm{NSSI}. \tag{19}$$

The MOI is inevitably given higher priority than the NSSI in the optimization process because the value derived through the multiplication between the NRM and the MOI is always greater than the NSSI. This idea is similar to the concept of the weighted sum method that is used extensively to solve multi-objective optimization problems [20].

3.4 Optimization constraints

The optimization algorithm should find the best solution while satisfying all the constraints used to define the optimal number of PQM in the system. The number of monitors that can detect the voltage sags resulting from the fault at a particular bus is the product of the multiplication between the TMRA matrix and the transposed MP matrix as shown in Eq. (20). The resulting matrix element corresponds to the number of monitors that detect the sag caused by the faults at a specific bus. If the value is zero, no monitor can detect the sag, whereas if the value is greater than one, more than one monitor can observe the fault. Therefore, the restrictions shown in Eq. (20) [5] must be satisfied to ensure that each fault is observed by at least one monitor.

$$\sum_{i=1}^{k} \text{TMRA}(k,i) \times \text{MP}(i) \geqslant 1 \, \forall k. \quad (20)$$

3.5 QBFA implementation steps for optimal PQM placement

The steps taken by the QBFA to obtain the optimal PQM placement in power systems are as follows:

1) Randomly initializing all entries of the MPs (firefly position x_{ij}) in the swarm within a feasible arrangement. Initializing all Q-bit individuals by setting them to $1/\sqrt{2}+\mathrm{j}(1/\sqrt{2})$.

2) Evaluating the performance of each MP vector based on the formulated objective function *f* as shown in Eq. (19).

3) Updating the light intensity and movement of the fireflies based on Eq. (3).

4) Updating the rotation angle $\Delta\theta_i\,(t+1)$ as well as the Q-bit individual $[\alpha\,(t+1), \beta\,(t+1)]$ based on Eqs. (9) and (10), respectively.

5) Updating the MP vector by bit updating $x_i\,(t+1)$ based on the criteria provided in Eq. (11).

6) Evaluating the new MP vector and reject those that do not fulfill the optimization constraints as shown in Eq. (20).

7) Repeating step 5) until all fireflies obtain their suitable positions and until the population size can be maintained at the same value.

8) Repeating step 2) until the optimization convergence criteria are achieved, in which case, the convergence criteria becomes the maximum number of iterations.

4 Results and discussion

An IEEE 118-bus transmission system is used to illustrate the effectiveness of the proposed QBFA optimization method in obtaining the optimal PQM placement. Three types of faults, namely, three-phase faults, double-line-to-ground faults, and single-phase-to-ground faults were simulated at each bus using DIgSILENT software to obtain the fault voltage matrix. The QBFA optimization technique is then compared with an existing method known as quantum-inspired gravitational search algorithm (QBGSA) [14] to exhibit the outstanding performance of QBFA in solving the same problem. Moreover, the BFA [16] is included in the comparison to demonstrate the improvement of the conventional method through quantum computing. In this study, the computer with Intel Core 2 Quad CPU and the RAM of 1.94 GB at 2.66 GHz is used to run the aforementioned algorithms.

For the optimization algorithms, the population size and number of maximum iterations are standardized to 70 and 200, respectively. To achieve improved performance, the randomization parameter *phi* used in the BFA are set to 1 with the decreasing factor of 0.99 in the following iteration, and the attractiveness β_o and light absorption coefficient γ are set to 1 and 0.001, respectively. In this work after some experimentation, γ is set to 0.001 as it gives a good performance for the optimization algorithm. The parameters of the QBFA are similar to those of the BFA with the magnitude of rotation angle decreasing monotonously from 0.05 π ($\theta_{\max}$) to 0.001 π ($\theta_{\min}$). All initial Q-bit individuals are set as $1/\sqrt{2}+\mathrm{j}(1/\sqrt{2})$. It means that one Q-bit individual represents the linear superposition of all possible states with the same probability [13]. Meanwhile, for the QBGSA, the initial gravity constant G_o is set to 100, and the best applying force K_{best} monotonously decreases from 100% (maximum K_{best}) to 2.5% (minimum K_{best}). The parameter τ is set to 8% of the total number of bits. The magnitude of the rotation angle and initial Q-bit individual are similar to those of the QBFA. The monitor coverage control parameter α_c = 0.85 p.u. is applied to all optimization processes.

An IEEE 118-bus system is a balanced transmission network with two voltage levels: 138 kV and 345 kV. In the system, 118 buses are interconnected by 177 lines, 34 generating stations, 20 synchronous condensers, and 9 transformers. The system data was provided by Christie [21].

After conducting 30 runs in this case study, the performances of the BFA, QBGSA, and QBFA in obtaining the optimal PQM placement solution for the 118-bus system were determined. The best, worst, and average values for each term are reported in Table 1. The algorithms are compared in terms of convergence rate (number of iterations necessary to converge), quality of optimal solution (fitness value), and time consumed in the optimization process. Figure 2 presents the convergence characteristics of the BFA, QBGSA, and QBFA for an IEEE 118-bus case study. The BFA converges in the shortest time but the optimal solution obtained is the worst compared with those obtained by using other algorithms. The minimum fitness value obtained via the BFA is 217.68 and the minimum number of PQM obtained via the BFA is 35 with the placement at buses 9, 14, 20, 23, 32, 34, 35, 37, 40, 41, 44, 46, 47, 52, 61, 65, 66, 68, 71, 73, 77, 79, 81, 84, 85, 86, 87, 90, 95, 98, 102, 103, 104, 108, and 110. This result can be accounted for by the premature convergence of the BFA.

Meanwhile, the QBFA and QBGSA have better convergence characteristics compared with the BFA, which proves that the QBFA and QBGSA can escape from premature convergence. Both algorithms have similar solutions for fitness values although the QBFA has slightly better performance than the QBGSA. However, the respective computational time and convergence rate for

Table 1 Performance of BFA, QBGSA, and QBFA in obtaining optimal PQM placement solution for a 118-bus system

Method	Quality (fitness)			Convergence (iterations)			Computational time/s		
	Best	Average	Worst	Best	Average	Worst	Best	Average	Worst
BFA	217.68	311.54	363.37	9	107.73	189	2.95	3.03	3.31
QBGSA	26.32	28.97	30.95	60	154.8	200	42.92	47.38	51.83
QBFA	26.26	28.97	31.06	43	101.43	186	31.39	32.53	33.75

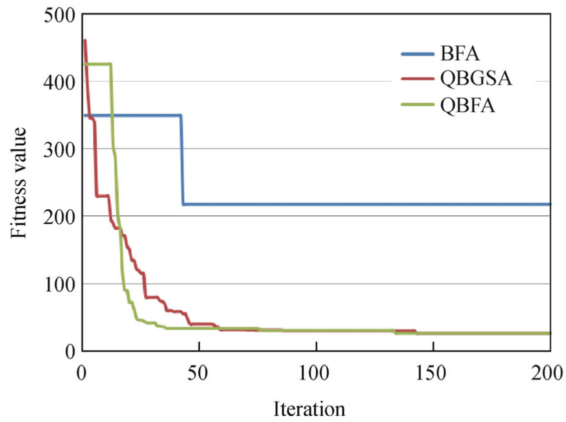

Fig. 2 Convergence characteristics of the QBFA, QBGSA and BFA for a 118-bus case study

the QBFA are significantly shorter and lower than the values for the QBGSA. For the QBGSA, the optimal number of PQM required to guarantee observability is 10 with the placement at buses 12, 22, 43, 54, 67, 71, 87, 93, 98, and 107. For the QBFA, the number of PQM required is 10 with the placement at buses 7, 22, 43, 55, 62, 71, 87, 93, 98, and 108. The results of the optimal PQM placement are illustrated in Fig. 3. Given that the minimum fitness value is obtained via the QBFA, the result is employed as the optimal solution for the PQM placement in this case study. Thus, it can be concluded that the QBFA is the most effective technique among the three algorithms because the QBFA has minimum fitness value, shortest computing time, and fastest convergence.

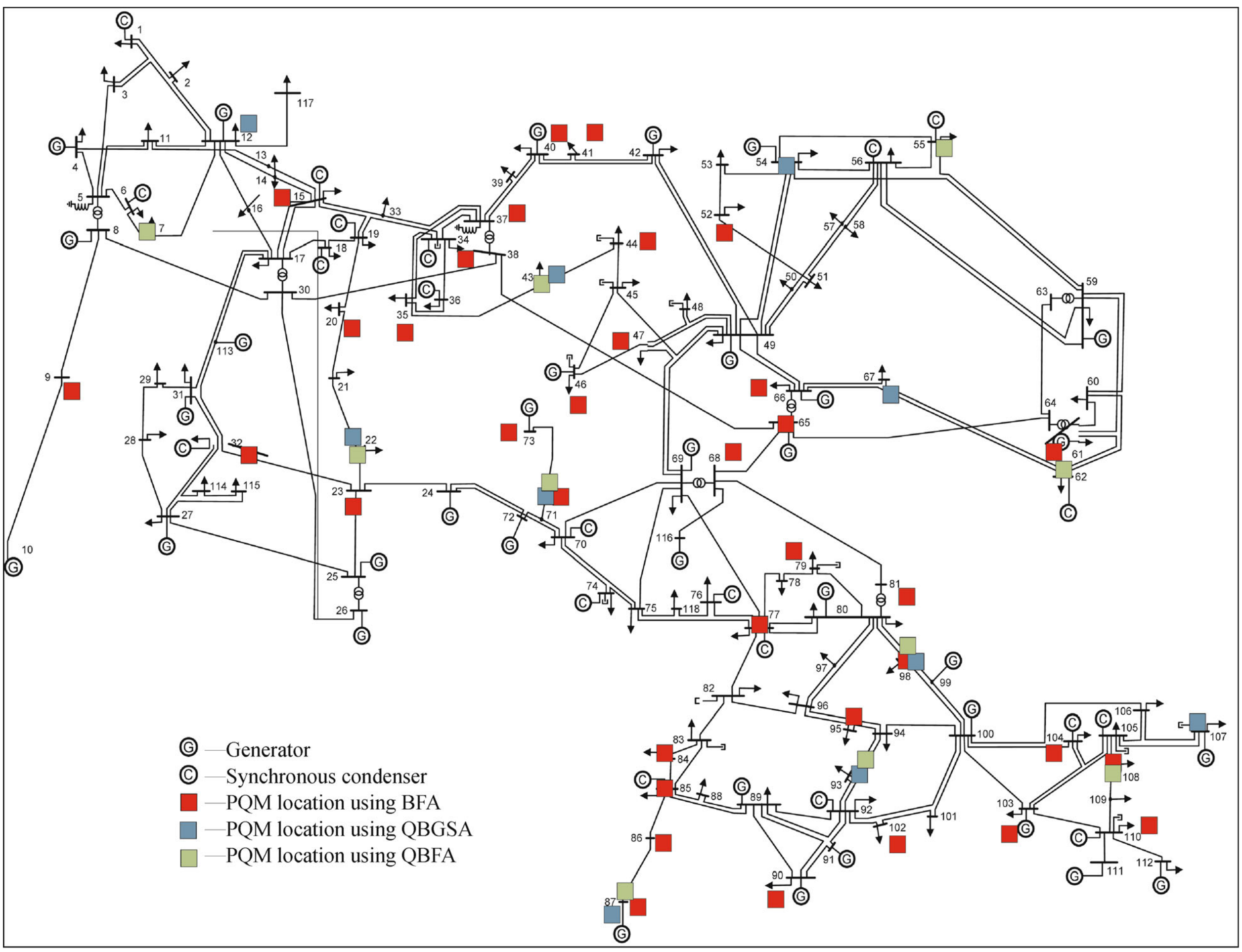

Fig. 3 Optimal location of PQM in a 118-bus power system based on different algorithms

5 Conclusions

In this study, a new method named QBFA has been presented to solve the multi-objective optimization problem for optimal PQM placement. The optimization problem formulation is mainly based on the TMRA concept and on the placement evaluation indices known as SSI and MOI. This method has been extensively tested on an IEEE 118-bus system, and the results have been compared with those from other existing methods such as the BFA and the QBGSA. In terms of performance, the QBFA is more effective in obtaining optimal PQM placement compared with the aforementioned optimization techniques.

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Notations

G_o	Initial gravity constant
K_{best}	Best applying force
r	Cartesian distance between two fireflies
x	Coordinate of firefly
phi	Randomization parameter
α_c	Monitor coverage control parameter
β_o	Attractiveness at $r = 0$
α	weighting factor for real part of Q-bit individual string
β	weighting factor for imaginary part of Q-bit individual string
γ	Light absorption coefficient
θ	Rotation angle

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