OPTIMIZING POWER DISTRIBUTION NETWORK RECONFIGURATION WITH QUANTUM PSO: INCORPORATING SOLAR POWER AND ELECTRIC VEHICLES

TỐI ƯU HÓA TÁI CẤU TRÚC MẠNG PHÂN PHỐI ĐIỆN VỚI QUANTUM PSO: KẾT HỢP NĂNG LƯỢNG MẶT TRỜI VÀ XE ĐIỆN

Nguyen Thanh Hoan[1], Truong Viet Anh[2], Nguyen Tung Linh[3,*], Nguyen Huu Vinh[1], Truong Dinh Nhon[2]

DOI: http://doi.org/10.57001/huih5804.2024.359

ABSTRACT

The solar energy source (PV) is rapidly developing in Ho Chi Minh City, along with the promising increase in electric vehicle (EV) charging stations connected to the distribution grid. Ensuring the reliability of power supply and power quality is becoming a significant concern. To meet this demand, the problem of grid reconfiguration to minimize losses and optimize the use of renewable energy, considering the integration of EV charging stations, has become an essential approach in grid operation management. Various algo-rithms have been explored for the grid reconfiguration problem, with Particle Swarm Optimization (PSO) being highly regarded and still actively developed for application today. In this study, the Quantum-PSO (QPSO) method is proposed to enhance the global search performance and convergence ability of PSO by incorporating concepts from quantum mechanics. The QPSO method was tested alongside Binary PSO and PSO on the same grid model to compare these methods. The results have been applied and verified on the IEEE 33-bus grid model, with parameters adjusted for distribution grid re-configuration, in two scenarios: before and after the integration of solar en-ergy and EV charging stations, confirming the accuracy and reliability of the proposed method.

Keywords: *PSO, Binary PSO, Quantum PSO, QPSO, Power losses, Particle Swarm Opti-mization, Anomaly Detection, Reconfiguration Power Distribution Networks.*

TÓM TẮT

Nguồn năng lượng mặt trời (PV) đang phát triển nhanh chóng tại Thành phố Hồ Chí Minh, cùng với sự gia tăng đầy hứa hẹn của các trạm sạc xe điện (EV) kết nối với lưới điện phân phối. Đảm bảo độ tin cậy của nguồn cung cấp điện và chất lượng điện năng đang trở thành một mối quan tâm đáng kể. Để đáp ứng nhu cầu này, vấn đề tái cấu trúc lưới điện nhằm giảm thiểu tổn thất và tối ưu hóa việc sử dụng năng lượng tái tạo, có tính đến sự tích hợp của các trạm sạc EV, đã trở thành một phương pháp quan trọng trong quản lý vận hành lưới điện. Nhiều thuật toán đã được nghiên cứu cho vấn đề tái cấu trúc lưới điện, trong đó Tối ưu hóa bầy đàn (PSO) được đánh giá cao và vẫn đang được phát triển tích cực để ứng dụng ngày nay. Trong nghiên cứu này, phương pháp Quantum-PSO (QPSO) được đề xuất để nâng cao hiệu suất tìm kiếm toàn cục và khả năng hội tụ của PSO bằng cách kết hợp các khái niệm từ cơ học lượng tử. Phương pháp QPSO đã được thử nghiệm cùng với Binary PSO và PSO trên cùng một mô hình lưới điện để so sánh các phương pháp này. Kết quả đã được áp dụng và kiểm chứng trên mô hình lưới điện IEEE 33 nút, với các thông số được điều chỉnh cho tái cấu trúc lưới điện phân phối, trong hai kịch bản: trước và sau khi tích hợp năng lượng mặt trời và trạm sạc EV, khẳng định tính chính xác và độ tin cậy của phương pháp đề xuất.

Từ khóa: *PSO, Binary PSO, Quantum PSO, QPSO, tổn thất điện năng, tối ưu hóa bầy đàn (PSO), phát hiện bất thường, tái cấu trúc mạng lưới phân phối điện.*

[1]Ho Chi Minh City Power Corporation, Vietnam
[2]Ho Chi Minh City University of Technology and Education, Vietnam
[3]Electric Power University, Vietnam
[*]Email:linhnt@epu.edu.vn
Received: 30/8/2024
Revised: 07/11/2024
Accepted: 28/11/2024

1. INTRODUCTION

In the context of the NetZero development trend, the increasing presence of distributed generation (DG) sources such as rooftop solar power (PV) and electric vehicle (EV) charging stations has introduced several challenges related to harmonics, local source-load imbalances, and increased losses in the distribution network (DN). To mitigate these losses, reduce operational costs, and enhance reliability, distribution network reconfiguration (DNR) is considered a low-cost method and has garnered significant attention [1]. Regarding the optimization of switch configurations in the system to improve the Voltage Profile (VP) and reduce power losses (PL), study [2] applied the Simplified Particle Swarm Optimization (SPSO) algorithm. Building on this, study [3] proposed a multi-objective optimization model to determine the optimal location and capacity of DGs based on renewable energy sources (RES), battery energy storage systems (BESS), and circuit breakers (CB), incorporating demand response (DR) programs. In the pursuit of improving system structure, paper [4] introduced the Improved Heap-Based Optimization (IHBO) algorithm, aiming to en-hance global search capability in reconfiguring the distribution system and allocating distributed generation sources. Additionally, study [5] utilized comprehensive search methods such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) on the IEEE 33-bus network. To further improve reliability and reduce power losses, paper [6] optimized the distribution grid structure using the PSO method, while paper [7] proposed a decentralized control strategy employing MFO-PI and 2DOF-PI controllers for Microgrids (MG), including energy storage systems (BESS) and photovoltaic systems (PV).

Regarding the application of Distributed Generation (DG) to achieve technical, environmental, and commercial benefits in power systems, study [8] focuses on this aspect. Following that, paper [9] introduced the Quadratic Unconstrained Binary Optimization (QUBO) method to minimize losses in the distribution network through a quantum annealing model. Paper [10] further focused on network reconfiguration to reduce power losses using the Adaptive Quantum-Inspired Evolutionary Algorithm (AQiEA) and compared its performance on the IEEE 33-bus system. Studies [11, 12] also contributed to this field by Intelligent Water Drop algorithm and Hybrid Grey Wolf optimizer method to tackle multi-objective optimization problems. Finally, paper [13] proposed a development process for mixed integer nonlinear optimization problem is solved using a heuristic technique "A-MWOA". Additionally, other studies like [14] concentrated on the definition, technology, and optimization techniques for DG, including the application of energy storage systems. The Grey Wolf Optimizer (GWO) algorithm was applied in paper [15] to solve the Distribution Network Reconfiguration (DNR) problem, while dynamic reconfiguration was implemented in paper [16] to optimize the scheduling of energy production from DG sources and manage energy storage systems, aiming to reduce operational costs and optimize voltage stability. Also in [17] multi-objective approach for the optimal allocation of electric vehicle charging stations (EVCS), focusing on user satisfaction, integration of renewable energy, and power system stability through a System Dynamics model, k-means clustering, and GA-PSO under an IEEE 33-node framework. To address the DNR problem more effectively, study [18] combined PSO with the Shuffled Frog Leaping Algorithm (SFLA), while paper [19] developed the Adaptive Particle Swarm Optimization (APSO) algorithm with self-adjusting parameters to enhance the search for optimal solutions. Lastly, paper [20] introduced the firework explosion mechanism into the Artificial Bee Colony (FW-ABC) algorithm to overcome the shortcomings of traditional ABC, improving both exploitation efficiency and convergence speed.

In this study, the proposed method is implemented using a Quantum PSO variant, which applies quantum mechanics principles to update the PSO algorithm, aiming to improve convergence speed, enhance global search capabilities, and reduce computational load. In addition, the study also applies the PSO and Binary Particle Swarm Optimization (BPSO) methods to compare the different approaches. The simulation results are carried out on the IEEE 33-bus test system under various conditions, such as changes in load, output power of PV, and EV charging stations. Following the general introduction, Section 2 describes the multi-objective optimization model for the distribution network, Section 3 details the proposed method, Section 4 presents the results, and Section 5 concludes the study.

2. OBJECTIVE OPTIMIZATION IN DISTRIBUTION NETWORK

2.1. IEEE 33-node distribution network model

The proposed method is applied for evaluation on the IEEE 33-bus distribution system model shown in Fig. 1 [18].

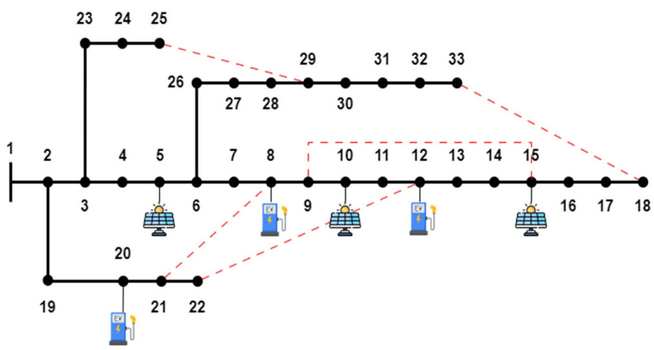


Fig. 1. IEEE 33-node distribution network model

The system includes three solar PV sources with average capacities as follows: node 5 with a capacity of 500kW, node 10 with a capacity of 400kW, and another source at node 15 with a capacity of 300kW. Additionally, there are electric vehicle (EV) charging stations at node 8 (load capacity of 300kW), node 12 (load capacity of 400kW), and node 20 (load capacity of 200kW).

2.2. Objective Function

Distribution network reconfiguration is part of a complex multi-objective optimization problem. The objective functions include network performance variations based on load deviation, voltage drop, and power loss reduction [16].

Load's variance:

$$OF_1 = \min \sum_{i=1}^{N} \left(\frac{S_i}{S_{imax}}\right)^2 \quad (1)$$

the power on branch i is represented by the values S_i and S_{imax}, corresponding to the actual and maximum values, respectively, with the total number of closed branches being k.

Voltage deviation:

$$OF_2 = \min \sum_{j=1}^{N} \left(\frac{U_j - U_{js}}{U_{js}}\right)^2 \quad (2)$$

U_j is the actual voltage at node j; U_{js} is the rated voltage at node j, and N is the total number of nodes.

Power loss:

$$OF_3 = \min \sum_{i=1}^{n} (P_i + Q_i) \quad (3)$$

where P_i is the real power loss on branch i, and Q_i is the reactive power loss on branch i.

In this study, the proposed method uses the main objective function as Power Loss (OF3), while also considering voltage drop across the grid (OF2). Instead of combining the objective functions into a single equation with weights, which could reduce the accuracy of the optimization goal, the study opts to keep the objective functions separate. This method will be further refined in the next development phase to handle multi-objective optimization more effectively.

3. METHODOLOGY

The methods implemented include basic PSO, Binary Particle Swarm Optimization (BPSO) [21], and the proposed Quantum PSO, to evaluate the performance among these methods. The input data used is based on the standard IEEE 33-bus model in the Matlab R2023b environment, with the initial positions and capacities of PV and EV points selected randomly.

3.1. Basic PSO Algorithm

Particle Swarm Optimization (PSO) is an optimization algorithm based on the behavior of organisms in a swarm. Each potential solution to the problem is considered a "particle" in the search space. Each particle has a position and velocity, representing its current state and direction of movement in the search space. The goal of PSO is to find the best position (global maximum or minimum) that particles can achieve by moving through successive generations. The standard PSO velocity and position update equations are shown in (4) and (5), as referenced in [6].

Velocity Update:

$$v_i^m(t+\Delta t) = \omega v_i^m(t) + c_1\phi_1\left(P_{Li}^m - x_i^m(t)\right) + c_2\phi_2\left(P_{gi} - x_i^m(t)\right) \quad (4)$$

$v_i^m(t)$: The current velocity of particle m at time t.

$x_i^m(t)$: The current position of particle m at time t.

P_{Li}^m: The local best position that particle m has achieved.

P_{gi}^m: The global best position that the entire swarm has achieved.

ω: Inertia weight, which controls the impact of the previous velocity on the current velocity.

c_1, c_2: Cognitive and social factors, which influence the extent to which a particle is attracted to the local and global best positions.

ϕ_1, ϕ_2: Random variables uniformly distributed between 0 and 1, which introduce randomness into the search process.

Position Update:

$$x_i^m(t+\Delta t) = x_i^m(t) + v_i^m(t+\Delta t) \quad (5)$$

The new position of particle mmm at time t + Δt is determined by adding the updated velocity to the current position.

3.2. BPSO Algorithm

Binary Particle Swarm Optimization (BPSO) is designed to handle optimization problems where the search space is discrete, specifically binary space. In BPSO, each particle has a position vector and a velocity vector, with the elements of the position vector being binary values (0 or 1). As in study [21], the probability-based approach for velocity (6) and the position update (7) are cited below.

Velocity Update: similar to equation (4) in the PSO algorithm.

Velocity-to-Probability Conversion:

$$S\left(v_i^m\left(t+\Delta t\right)\right)=\frac{1}{1+e^{-v_i^m(t+\Delta t)}} \tag{6}$$

$S\left(v_i^m(t+\Delta t)\right)$*: This is a sigmoid function* that converts *velocity into a probability.*

Position Update:

Once the probability is obtained, the particle's position is updated by comparing it with a random value:

$$x_i^m(t+\Delta t)=\begin{cases}1 & \text{if rand}()<S\left(v_i^m(t+\Delta t)\right)\\ 0 & \text{if rand}()\geq S\left(v_i^m(t+\Delta t)\right)\end{cases} \tag{7}$$

rand():A random number selected in the range from 0 to 1.

3.3. QPSO Algorithm

Quantum Particle Swarm Optimization (QPSO) is an advanced variant of the PSO algorithm, developed to enhance the global search performance and convergence capability of PSO by applying concepts from quantum mechanics. In QPSO, instead of having a fixed velocity, particles move based on a quantum probability distribution function, allowing them to explore the search space more effectively and avoid getting trapped in local extrema. Following the quantum model representation in [9] and [10], this study considers a new approach for updating position and velocity in equations (8-10).

Quantum Motion Position Update

The positions of particles are updated based on the quantum probability distribution, determined by the following equation:

$$x_i^m(t+1)=P_m(t)+\beta\left|M_i^m(t)-x_i^m(t)\right|\cdot\ln\left(\frac{1}{u}\right)\cdot\text{sign}\left(v_i^m(t)\right) \tag{8}$$

$x_i^m(t+1)$: The new position of particle m at time t + 1.

$P_m(t)$: The weighted average between the local best position and the global best position.

$$P_m(t)=\alpha P_{Li}^m+(1-\alpha)P_{gi} \tag{9}$$

α: Adjustment parameter between the local and global positions, typically a random value between 0 and 1.

$M_i^m(t)$: The average position of all particles.

β: Adjustment parameter, determining the influence of the quantum average position.

$\ln\left(\frac{1}{u}\right)$: The logarithm of the reciprocal of a random number u (with u uniformly distributed between 0 and 1).

$\text{sign}(v_i^m(t))$: The sign function of the quantum velocity (assumed).

Quantum Velocity Update Formula

In some QPSO models, the quantum velocity can be expressed as follows:

$$v_i^m(t+1)=\beta\cdot\left(P_m(t)-x_i^m(t)\right)\cdot\ln\left(\frac{1}{u}\right) \tag{10}$$

$v_i^m(t+1)$: The new quantum velocity at time t + 1.

β: Adjustment parameter.

$P_m(t)-x_i^m(t)$: The quantum distance between the current position and the quantum average position.

$\ln\left(\frac{1}{u}\right)$: The logarithm of the reciprocal of a random number.

Quantum motion in QPSO allows particles to explore a larger search space and escape from local extrema, which classical PSO may struggle with.

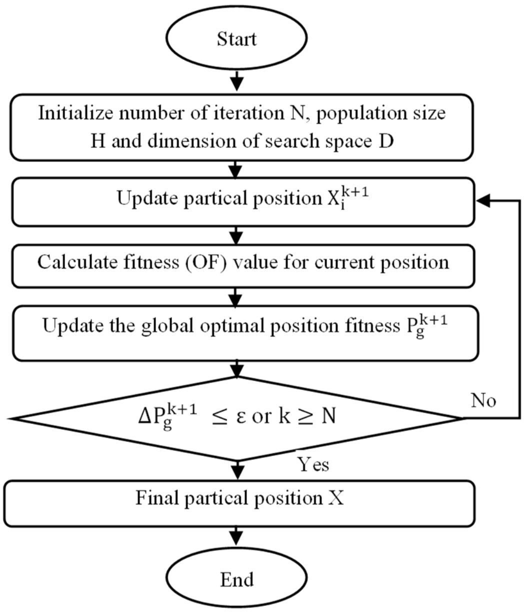


Fig. 2. QPSO Algorithm Flowchart

The use of a quantum probability distribution function allows particles to "jump" to different regions in the search space in a non-linear manner, improving the convergence to the global optimum. The QPSO algorithm flowchart is illustrated in Fig. 2.

4. RESULTS AND DISCUSSION

The proposed method has been simulated using the IEEE 33-bus power grid model, which includes solar PV sources and EV charging stations, to evaluate the effectiveness of the proposed algorithm and compare it with other methods. Table 1 shows that the network loss before reconfiguration, in two cases without PV and EV sources was 208.46kW, and with PV and EV sources was 190.12kW decreases to 138.93kW and 130.97kW after reconfiguration using the QPSO method, representing a reduction of approximately 33.355% and 31.11%, respectively. Compared to the PSO and BPSO methods, QPSO shows significantly improved results.

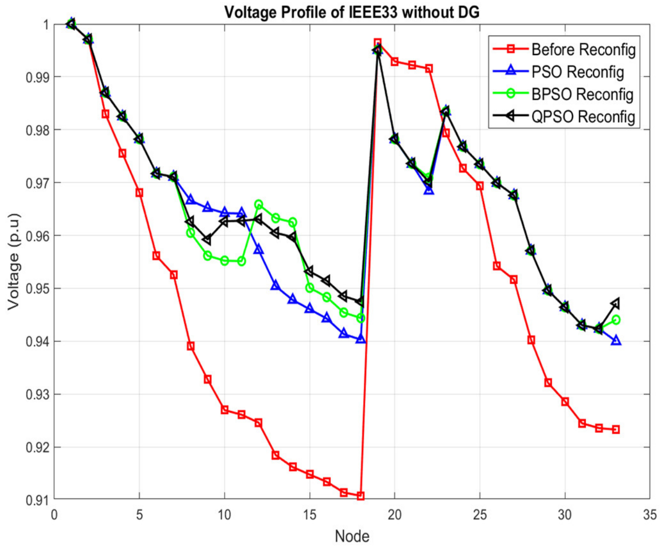
Table 1. Simulation results

No	Method	Case	Open switches	P_{losses} (kW)	Voltage deviation/p.u
0	None	Before reconfiguration without PV-EV	8–21, 9–15, 12–22, 18–33, 25–29	208.46	0.089
0	None	Before reconfiguration with PV-EV	8–21, 9–15, 12–22, 18–33, 25–29	190.12	0.066
1	PSO	After reconfiguration without PV-EV	7–8, 11–12, 32–33, 9–15, 25–29	142.13	0.060
2	PSO	After reconfiguration with PV-EV	6–7, 9–10, 14–15, 32–33, 25–29	136.83	0.056
3	BPSO	After reconfiguration without PV-EV	7–8, 11–12, 14–15, 32–33, 25–29	140.58	0.057
4	BPSO	After reconfiguration with PV-EV	7–8, 8–9, 32–33, 9–15, 25–29	135.38	0.055
5	QPSO	After reconfiguration without PV-EV	7–8, 9–10, 14–15, 32–33, 25–29	138.93	0.057
6	QPSO	After reconfiguration with PV-EV	7–8, 11–12, 14–15, 31–32, 25–29	130.97	0.066

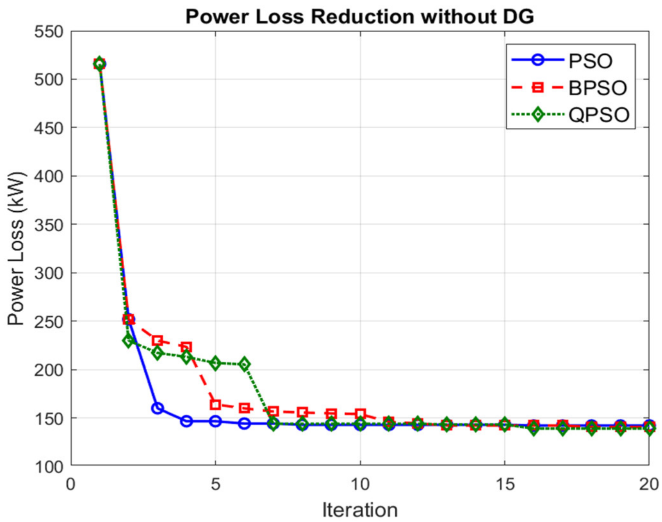
Between the two cases considered, it is also shown that distributed generation (DG) has helped reduce network losses and voltage drop. The results of applying the optimization methods are also compared based on convergence time, as shown in Table 2, with QPSO achieving the best convergence time.

Table 2. Results of reconfiguring the grid without DG

Method	P_{losses} (kW)	P_{losses} Reduction (%)	Min Voltage (pu)	Time (s)
Before Reconfiguraction	208.45	-	0.91075	-
PSO	142.13	31.8163	0.93996	10.45
BPSO	140.58	32.5622	0.94234	10.01
QPSO	138.93	33.355	0.94234	8.25



a)



b)

Fig. 3. a) Voltage Profile graph of the IEEE 33-bus network without DG; b) Power Loss graph over time without DG

Load balancing and voltage deviation have improved, with network stability shown in Fig. 3, indicating effective reconfiguration. The losses before and after reconfiguration using QPSO, for the grid without PV and EV charging stations, were 208.45kW and 138.93kW, respectively, a reduction of about 33.355%. In the case of the grid with PV and EV charging stations, which contributes to reducing losses and voltage drop, the optimal grid configuration results shown in Table 3 indicate that QPSO performs significantly better than PSO and BPSO, with a 31.1106% reduction in losses and a convergence time of 8.46 seconds.

Table 3. Results of reconfiguring the grid with DG

Method	Plosses (kW)	Plosses Reduction (%)	Min Voltage (pu)	Time (s)
Before Reconfiguraction	190.12	-	0.93402	-
PSO	136.83	28.0319	0.94369	14.89
BPSO	135.38	28.7911	0.94447	12.72
QPSO	130.97	31.1106	0.9343	8.46

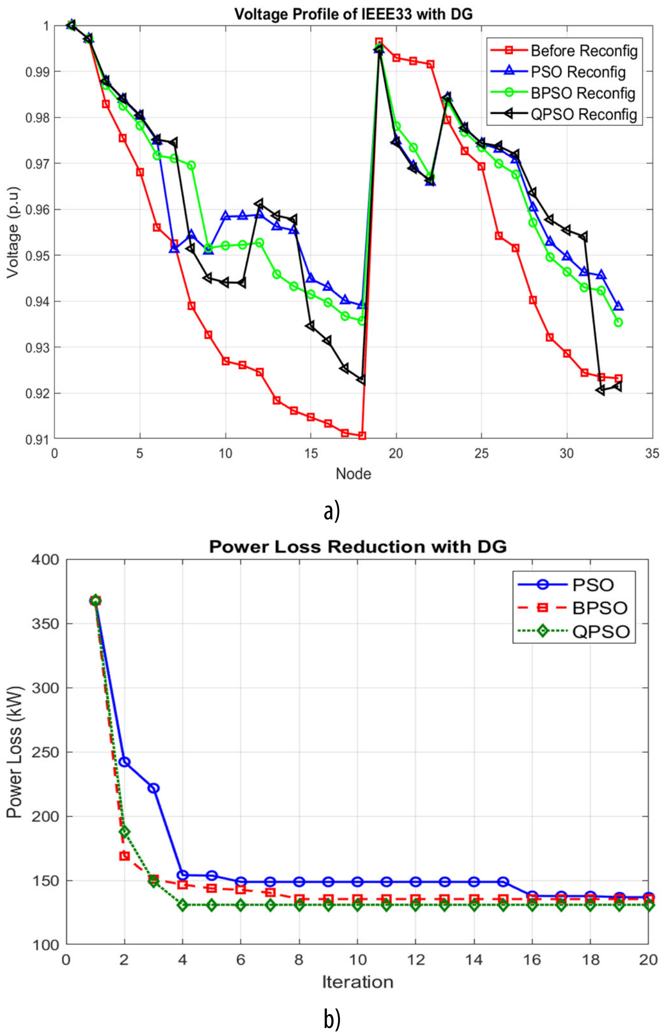


Fig. 4. a) Voltage Profile graph of the IEEE 33-bus network with DG; b) Power Loss graph over time with DG

Table 4. Comparison of the results of different methods

Method	Opened switches	P_{loss} (kW)	Min Node Voltage (p.u)
Before reconfiguration	8–21, 9–15, 12–22, 18–33, 25–29	190.12	0.9340
Proposed method - QPSO	7–8, 11–12, 14–15, 31–32, 25–29	136.83	0.9388
Chen [20]	7–8; 9–10; 14–15; 25–29; 32–33.	139.55	0.9379
Liu [17]	7–8; 9–10; 14–15; 25–29; 32–33.	139.57	0.9378

The results are also compared with the studies by Chen [20] and Liu [17], showing that the open/closed switches are the same. The simulation results are presented in Table 4.

5. CONCLUSION

In this study, a method combining the characteristics of quantum mechanics simulation in the form of a quantum probability distribution function is used to update the positions and coordinates of particles, replacing the conventional principles in swarm optimization algorithms, referred to as QPSO. This method simplifies optimization calculations, results in faster convergence times, and enhances global optimal search capabilities. The PSO, BPSO, and QPSO methods were applied to the IEEE test grid for scenarios before and after the inclusion of solar power (PV) sources and electric vehicle (EV) charging stations. The simulation results show that the proposed method is faster in computation and yields better results in reducing power losses and voltage drops compared to the other two methods. In future research, the authors will consider evaluating multi-objective problems without combining objectives into a single equation, as well as expanding the scope of grid considerations and improving the effectiveness of the method.

REFERENCES

[1]. Tran Dinh Long, *Quy hoach phat trien nang luong va dien luc*. Science and Technics Publishing House, Hanoi, 1999.

[2]. Milad R. B., Alireza J., Alireza S. F., "Reconfiguration of distribution network for improving power quality indexes with flexible lexicography method," *Electric Power Systems Research*, 230, 110172, 2024. https://doi.org/10.1016/j.epsr.2024.110172

[3]. Mustarum M., Tambi T., Waode Z., Gamal A. N. M., Agustinus L., Abdul D., Marwan M., "Optimizing network reconfiguration to reduce power loss and improve the voltage profile in the distribution system: A practical case study," *e-Prime Advances in Electrical Engineering Electronics and Energy,* 8, 100599, 2024. https://doi.org/10.1016/j.prime.2024.100599

[4]. Taha H. A., Alham M. H., Youssef H. K. M., "Multi-Objective Optimization for Optimal Allocation and Coordination of Wind and Solar DGs, BESSs and Capacitors in Presence of Demand Response," *IEEE Access*, 10, 16225-16241, 2022.

[5]. A. M. Shaheen, A. M. Elsayed, A. R. Ginidi, R. A. El-Sehiemy, E. E. Elattar, "Improved Heap-Based Optimizer for DG Allocation in Reconfigured Radial Feeder Distribution Systems," *IEEE Systems Journal*, 16, 4, 6371-6380, 2022. doi: 10.1109/JSYST.2021.3136778.

[6]. Tran Quang Tho, Truong Viet Anh, "Optimization of current controller For grid-connected inverters using a pso algorithm," *Journal of Technical Education Science*, Ho Chi Minh City University of Technology and Education, 40, 68 - 75, 2017.

[7]. Omar K., Haitham A., Yassine B., Naim B. A., Mohamed C., "Power System Reconfiguration in Distribution Network for Improving Reliability Using Genetic Algorithm and Particle Swarm Optimization," *Appl. Sci.*, 11, 3092, 2021. https://doi.org/10.3390/app11073092.

[8]. Suresh V., Pachauri N., Vigneysh T., "Decentralized control strategy for fuel cell/PV/BESS based microgrid using modified fractional order PI controller," *Int. J. Hydrog. Energy*, 46, 4417-4436, 2021.

[9]. Farrokhabadi M., Lagos D., Wies R. W., Paolone M., Liserre M., Meegahapola L., "*Microgrid Stability Definitions, Analysis, and Examples*," *IEEE Trans. Power Syst.*, 35, 13-29, 2020.

[10]. Yisah Y. A., Sadiq Thomas, Mohammed S. Haruna, Sikiru O. Anaza, "Distributed Generation (DG): A Review," in *2021 1st International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS),* Abuja, Nigeria, 1-5, 2021. doi: 10.1109/ICMEAS52683.2021.9692353.

[11]. Rama Prabha D., Jayabarathi T., Umamageswari R., Saranya S., "Optimal location and sizing of distributed generation unit using intelligent water drop algorithm," *Sustain. Energy Technol Assess*, 11, 106-113, 2015.

[12]. Sanjay R., Jayabarathi T., Raghunathan T., Ramesh V., "Mithulananthan, N. Optimal a location of distributed generation using hybrid grey Wolf optimizer," *IEEE Access*, 5, 14807-14818, 2017.

[13]. Uniyal A., Sarangi S., "Optimal network reconfiguration and DG allocation using adaptive modified whale optimization algorithm considering probabilistic load flow," *Electr. Power Syst. Res.*, 192, 106909, 2021.

[14]. Linh N. T., "A Novel Combination of Genetic Algorithm, Particle Swarm Optimization and Training and Learning-Based Optimization for Distribution Network Reconfiguration in Case of Faults," *Engineering, Technology & Applied Science Research (ETASR)*, 14, 1, 12959-12965, 2024. doi.org/10.48084/etasr.6718.

[15]. Truong Hoang Bao Huy, Thanh Van Tran, Dieu Ngoc Vo, Ho Thi Thao Nguyen, "An improved metaheuristic method for simultaneous network reconfiguration and distributed generation allocation," *Alexandria Eng. J.*, 61, 8069–8088, 2022.

[16]. Shaheen A., Elsayed A., Ginidi A., El-Sehiemy R., Elattar E., "Reconfiguration of electrical distribution network-based DG and capacitors allocations using artificial ecosystem optimizer: Practical case study," *Alexandria Eng. J.*, 61, 6105-6118, 2022.

[17]. Liu J. P., Zhang T. X., Zhu J., Ma T. N., "Allocation optimization of electric vehicle charging station (EVCS) considering with charging satisfaction and distributed renewables integration," *Energy*, 164, 560-574, 2018.

[18]. Linh N. T., Long P. V., "A Novel Solution Method for the Distribution Network Reconfiguration Problem based on an Objective Function and considering the Cost of Electricity Transmission," *Engineering, Technology & Applied Science Research (ETASR),* 13, 6, 12366-12372, 2023. doi.org/10.48084/etasr.6568

[19]. Hop D. C., Van Hop N., Anh T. T. M., "Adaptive particle swarm optimization for integrated quay crane and yard truck scheduling problem," *Computers & Industrial Engineering,* 153, 107075, 2021. doi: 10.1016/j.cie.2020.107075.

[20]. Chen X., Wei X., Yang G., Du W., "Fireworks explosion based artificial bee colony for numerical optimization," *Knowledge-Based Systems*, 188, 105002, 2020.

[21]. Firdaus A. A., Soeprijanto A., Priyadi A., Putra D. F. U., Aryani N. K., Dina N. Z, "Distribution Network Reconfiguration with Binary Particle Swarm Optimization to Reduce Power Loss in Kuta," in *2022 International Seminar on Intelligent Technology and Its Applications (ISITIA),* Surabaya, Indonesia, 332-337, 2022. doi: 10.1109/ISITIA56226.2022.9855345.

THÔNG TIN TÁC GIẢ

Nguyễn Thanh Hoan[1], Trương Việt Anh[2], Nguyễn Tùng Linh[3], Nguyễn Hữu Vinh[1], Trương Đình Nhơn[2]

[1]Tổng công ty Điện lực TP. Hồ Chí Minh

[2]Trường Đại học Sư phạm kỹ thuật Thành phố Hồ Chí Minh

[3]Trường Đại học Điện lực