Leveraging Quantum Swarm Optimization for Voltage Stability Enhancement in Distribution Networks Incorporating Distributed Energy Resources

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ABSTRACT

The increasing integration of Distributed Energy Resources (DER) and renewable energy units into modern distribution systems introduces significant operational challenges, particularly related to voltage stability, network losses, and dynamic power-flow management. This study presents a Dynamic Distribution Network Reconfiguration (DDNR) strategy optimized using the Quantum Binary Particle Swarm Optimization (QBPSO) algorithm to enhance voltage stability and minimize operational costs in time-varying network conditions. The proposed multi-objective optimization simultaneously minimizes total operating cost and the aggregated voltage stability deviation (ΔVSI) by adaptively determining the optimal configuration of sectionalizing and tie switches across four dynamic load intervals. A modified IEEE 33-bus radial distribution network incorporating Photovoltaic (PV), Wind Turbine (WT), Diesel Generator (DG), and Battery Energy Storage System (BESS) units was employed to evaluate the method's effectiveness under 24-hour varying load profiles and simulated line disturbances. Simulation results in MATLAB R2022a using MATPOWER demonstrate that the QBPSO-based DDNR significantly outperforms both the initial configuration and the conventional Binary Particle Swarm Optimization (BPSO) approach. The total operating cost decreased from 3,346.47 to 2,314.11 USD, whereas the total ΔVSI improved from 50.638 to 39.2509. Moreover, the active and reactive load shedding was nearly eliminated, reduced from 429.405 kW and 303.3 kVAR to 0.000896 kW and 0.00521 kVAR, respectively. These results confirm that the proposed QBPSO method provides superior convergence, improved voltage-profile uniformity, and enhanced economic efficiency, thereby offering a robust and scalable solution for dynamic smart-grid operation and voltage-stability enhancement in future distribution networks.

Keywords-Dynamic Distribution Network Reconfiguration (DDNR); Quantum Binary Particle Swarm Optimization (QBPSO); voltage stability; power loss reduction; smart grid

I. INTRODUCTION

The provided sources strongly support the identified challenges in distribution networks. Authors in [1] comprehensively document traditional distribution issues, including voltage and thermal constraints, harmonics, overloading, and unbalanced loading, while noting that contemporary systems face additional complexity from the integration of Distributed Energy Resources (DER) [1]. Specifically, peak-load management challenges are addressed, demonstrating that "peak-load management of a distribution network has gained attention with increasing electric power consumption on the demand side" [2]. The evidence spans 10 studies from 2021–2024, with additional confirmation of reliability and economic efficiency challenges [3]. Demand-response solutions achieving a 33% peak-load reduction across residential users are demonstrated [4], whereas concerns about prosumer integration affecting network integrity are validated [5]. These studies collectively provide comprehensive coverage of operational challenges across various network types and consumer categories, offering robust evidence for the stated problems.

The evidence strongly supports these challenges across several dimensions. Power flow alterations are well-documented, with bidirectional flows creating "significant problems," including reduced power quality and equipment utilization issues [6-8]. Voltage stability risks are confirmed by multiple sources: voltage rise and reverse power-flow constraints at the point of common coupling were analyzed, demonstrating these effects under critical scenarios of low demand and peak generation [9]. Operational challenges are comprehensively documented, with large-scale DER deployment leading to network operational and efficiency issues, hampering passive network reliability and stability [10]. Voltage and angular stability, as well as power quality issues, are identified as key challenges from renewable integration. The evidence spans theoretical analysis, case studies, and comprehensive reviews, providing robust support for the stated challenges across multiple research groups and publication venues [11].

The evidence strongly supports Distribution Network Reconfiguration (DNR) as an effective solution for optimizing distribution networks. Recent studies demonstrate significant performance improvements, including voltage-profile enhancement from 0.918 to 0.922 p.u. and power-loss reduction from 0.6482 MW to 0.6052 MW on a 125-bus system [12], whereas similar benefits were validated on IEEE 33-bus systems across three load levels. The application of Particle Swarm Optimization (PSO) in DNR has been widely adopted [13], with enhanced binary PSO performance demonstrated on IEEE 33-bus, 69-bus, and 84-bus test systems [14]. Metaheuristic methods are generally preferred over conventional approaches due to their superior capability in solving complex combinatorial optimization problems [15]. Furthermore, a notable research gap remains in the area of dynamic reconfiguration, which has been explicitly identified as a key direction for future exploration [16, 17].

Building upon these prior advancements, this study aims to develop an enhanced control and optimization strategy for DNR by employing the Quantum Binary Particle Swarm Optimization (QBPSO) algorithm. The primary objective is to improve the Voltage Stability Index (VSI) and minimize the operational cost associated with power losses and voltage regulation. QBPSO leverages quantum-inspired principles to enhance both exploration and exploitation capabilities in discrete optimization problems, overcoming the premature convergence and parameter sensitivity limitations observed in conventional PSO-based methods. By integrating QBPSO with the AC Optimal Power Flow (AC-OPF), the proposed approach is expected to achieve more stable voltage profiles, reduced energy losses, and improved computational efficiency compared to traditional metaheuristic techniques.

II. PROBLEM FORMULATION

The Dynamic Distribution Network Reconfiguration (DDNR) problem involves altering the status of sectionalizing and tie switches in a radial distribution network without changing its topology. Unlike static reconfiguration, which is conducted only during system planning with constant load conditions, DDNR is performed at specific time intervals throughout the day to adapt to load variations, renewable generation, and system disturbances. This flexibility enables the distribution network to operate efficiently under changing operating conditions while maintaining voltage stability and minimizing operating cost.

A. Voltage Stability Index

Voltage stability is one of the most critical indicators of distribution network performance [18]. It describes the ability of the system to maintain bus voltages within acceptable limits under disturbances or increased loading. The VSI for each branch connecting sending bus i to receiving bus j is calculated as follows:

$$\mathrm{VSI}_{ij} = 1 - 4Z_{ij}^2((P_j^2 + Q_j^2)/V_i^4 \quad (1)$$

In (1), Z_{ij} denotes the line impedance (in p.u.), P_j and Q_j are the active and reactive powers flowing into the receiving bus j (in p.u.), and V_i is the sending-end voltage magnitude (in p.u.). Smaller VSI values indicate a higher risk of instability.

To quantify network-wide voltage performance, the total deviation of VSI from the ideal condition (VSI = 1) is minimized:

$$\Delta\mathrm{VSI} = \sum_{i=1}^{N_{branches}} \left|1 - \mathrm{VSI}_{ij}\right| \quad (2)$$

Equation (2) defines the aggregated voltage stability deviation (ΔVSI), which serves as the secondary objective in the optimization process. A smaller ΔVSI corresponds to a more stable voltage profile across the distribution network.

The VSI value ranges between 0 and 1, where smaller values indicate a higher risk of voltage instability. To improve the voltage profile across the entire network, the optimization process aims to minimize the total deviation of VSI values from their ideal condition, as formulated in (2).

B. AC Optimal Power Flow

The AC-OPF formulation is designed to minimize the total operating cost of the distribution network while ensuring that all technical and operational constraints are met. The objective function in (3) includes the total operating cost consisting of generation, load-shedding, switching, and penalty terms to maintain voltage and current within permissible limits.

$$\min F = \sum_{t=1}^{T}\left(C_{gen,t} + C_{shed,t} + C_{switch,t} + C_{penalty,t}\right) \quad (3)$$

The generation cost $C_{gen,t}$ is modeled as a quadratic function $a_i P_{G_{i,t}}^2 + b_i P_{G_{i,t}} + c_i$ for Diesel Generator (DG) units and as a linear function for Photovoltaic (PV), Wind Turbine (WT), and Battery Energy Storage Systems (BESS), based on their O&M and charging–discharging costs. The Time-of-Use (TOU) tariff ρ_t ranges between 0.09 and 0.18 USD/kWh, and penalty coefficients λ_V and λ_s are applied to discourage voltage and current violations.

Equations (4)–(5) ensure active and reactive power balance at each bus, whereas (6)–(7) maintain bus voltages within 0.95–1.05 p.u. and limit apparent power flow S_{ij} to its maximum rating S_{ij}^{max} . A radiality condition $N_b - N_1 - N_{loop} = 1$ is also enforced to ensure valid network topology during reconfiguration. The total cost function is combined with the voltage stability deviation term (ΔVSI) using weighting factors α and β to achieve a trade-off between economic efficiency and voltage stability.

$$P_G - P_D - P_{Loss} = 0 \quad (4)$$

$$Q_G - Q_D - Q_{Loss} = 0 \quad (5)$$

$$V_{min} \le V_i \le V_{max} \quad (6)$$

$$S_{ij} \le S_{ij}^{max} \quad (7)$$

The total cost component in (3) is combined with the ΔVSI in the multi-objective optimization, using weighting factors α and β, so that the optimization process does not minimize cost alone but balances both voltage stability and economic terms.

To support the reported total cost of 2,314 USD, the economic model explicitly includes hourly TOU tariffs ranging from 0.09 to 0.18 USD/kWh, quadratic generation cost for DG units (a = 0.004 USD/kW²h, b = 0.112 USD/kWh, c = 3.25 USD/h), a Value of Lost Load (VOLL) = 8.0 USD/kWh, and a switching cost = 0.05 USD per operation. The BESS model incorporates the State-of-Charge (SOC) dynamics, charge/discharge efficiency (n_{ch} = 0.95, n_{dis} = 0.95), and the energy-balance relation:

$$SOC_{t+1} = SOC_t + \left(n_{ch} P_{ch,t} - \frac{P_{dis,t}}{n_{dis,t}}\right) \Delta t / E_{cap}$$

subject to $0.2 \le SOC_t \le 0.9$ and $P_{ch,t} \cdot P_{dis,t} = 0$, with a rated capacity E_{cap} = 200 kWh and maximum charge/discharge power 50 kW. For reproducibility, each candidate topology generated by the QBPSO is evaluated through AC-OPF in MATPOWER 7.1 (MATLAB R2022a) to compute the total cost and ΔVSI. The optimization was executed on an Intel Core i7-12700H (32 GB RAM) system with rog (2025); the average runtime was approximately 28 s per interval (total ≈ 11 min for 24 intervals).

C. Quantum Binary Particle Swarm Optimization

The QBPSO algorithm is a modified version of the standard PSO specifically developed to handle discrete optimization problems such as switch configuration in distribution networks [18]. In this method, each particle represents a candidate network configuration, encoded in binary form to indicate the open or closed state of each switch.

$$mbest_k = \frac{1}{N}\sum_{t=1}^{N} Pbest_i^k \quad (8)$$

$$V_i^{k+1} = w.V_i^k + \alpha.c_1.r_1.\left(Pbest_i^k - X_i^k\right) + \beta.c_2 r_2.$$
$$\left(Gbest_i^k - X_i^k\right) + r_3(1-\alpha-\beta).(mbest^k - x_i^k) \quad (9)$$

$$sig\left(V_i^{k+1}\right) = \frac{1}{1+\exp(-V_i^{k+1})} \quad (10)$$

$$X_i^{k+1} = \begin{cases} 1 & \text{if } r_i^k < sig(V_i^{k+1}) \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

$$\min F_{total} = \alpha\left(\frac{F_{cost}}{F_{cost}^{max}}\right) + \beta\left(\frac{\Delta \mathrm{VSI}_k}{\Delta \mathrm{VSI}^{max}}\right) \quad (12)$$

The particle's movement through the search space is governed by the velocity and position update equations shown in (9)–(11), where the velocity V_i^{k+1} is updated based on the particle's previous velocity, its personal best position $Pbest_i$, and the global best position $Gbest_i$. The parameters w, c_1, and c_2 represent the inertia weight, cognitive coefficient, and social coefficient, respectively, whereas r_1 and r_2 are random values between 0 and 1 that introduce stochasticity to the search process. The updated velocity is then passed through a sigmoid transfer function to generate a binary value for the particle's new position X_i^{k+1}, representing a decision to open or close a switch. The optimization aims to minimize the total multi-objective fitness function given in (12), which simultaneously balances two competing objectives: minimizing the total operational cost and minimizing the overall deviation of the VSI. The weighting factors α and β determine the relative importance of economic efficiency and voltage stability in the optimization process. In this study, the main parameters of the QBPSO algorithm are defined to maintain a balance between exploration and exploitation throughout the optimization process. The population size is set to 20 particles and the optimization runs for a maximum of 50 iterations. The inertia weight w decreases linearly from 0.9 to 0.4 as the iteration progresses, following the linear scheduling formula $w = w_{max} - \left((w_{max} - w_{min}) \cdot iter\right)/iter_{max}$).

Both acceleration coefficients c_1 and c_2 are assigned a value of 2.0 to control the cognitive and social learning factors, respectively. The optimization process terminates when the maximum number of iterations is reached or when there is no improvement in the global best fitness value for ten consecutive iterations.

To evaluate the convergence behavior, a convergence curve representing the best fitness value versus the iteration count is analyzed. The results show that the fitness value improves rapidly during the first 20 iterations and gradually stabilizes after iteration 40, indicating convergence toward an optimal solution. Furthermore, ten independent runs were performed to assess the stability and robustness of the QBPSO results, showing minimal variation in the final objective values.

In the simulation scenario, a controlled line disturbance is introduced to evaluate the algorithm's performance under abnormal operating conditions. The disturbance is modeled on one of the main distribution feeders at $t = 0.3$ s where the line resistance R is increased by 20% and the reactance X by 10%. This condition represents a partial degradation of the feeder parameters and is used to assess the QBPSO's capability to maintain voltage stability and minimize operational costs under stressed network conditions.

The overall optimization process begins by inputting system parameters, defining switch search spaces, and modeling line disturbances. AC-OPF is performed to calculate initial costs, followed by QBPSO optimization for each time interval to determine the best configuration. The algorithm evaluates and updates solutions iteratively until convergence is reached, producing the optimal switch states that minimize both cost and VSI deviation.

D. System Model and Constraints

The system model utilized in this study is based on the modified IEEE 33-bus radial distribution network, which has been enhanced through the integration of various distributed generation units, including PV, WT, DG, and BESS. Each source operates within predefined capacity limits to ensure realistic operational behavior. To accurately represent time-dependent variations in demand, a 24-hour daily load curve is employed, allowing the model to capture real-time load dynamics and system responses to fluctuating consumption patterns. The operation of the network is governed by several technical constraints. Equation (13) defines the DG and BESS capacity limits, ensuring that their output remains within the minimum and maximum permissible generation boundaries:

$$P_{DG}^{min} \leq P_{DG} \leq P_{DG}^{max} \tag{13}$$

Equation (14) enforces voltage magnitude limits for each bus, maintaining voltages within acceptable operational thresholds to preserve system stability and power quality:

$$V_{min} \leq V_i \leq V_{max} \tag{14}$$

Equation (15) imposes line capacity restrictions, preventing the apparent power flow in any branch (S_{ij}) from exceeding its rated maximum value (S_{ij}^{max}) to avoid thermal overloading and potential equipment damage:

$$S_{ij} \leq S_{ij}^{max} \tag{15}$$

Additionally, a radiality constraint is applied to ensure that the network topology remains loop-free after reconfiguration, maintaining the fundamental radial structure of the distribution system. The overall system configuration, including the placement of PV, WT, DG, and BESS units, is illustrated in Figure 1, which serves as the reference model for all optimization and simulation analyses.

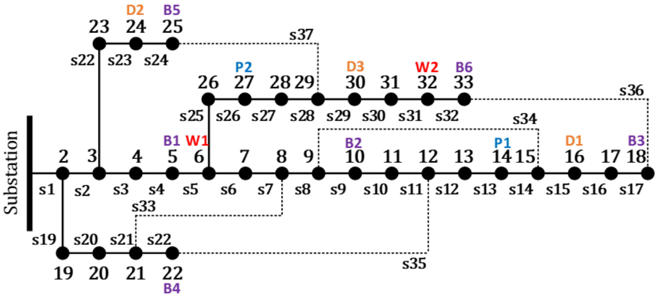

Fig. 1. Modified IEEE 33-bus distribution system integrated with PV, WT, DG, and BESS units.

III. RESULTS AND DISCUSSION

The proposed DDNR method was tested on the modified IEEE 33-bus radial distribution system, which was enhanced by the integration of several distributed generation and renewable energy units, including PV, WT, BESS, and DG sources. The generation capacities ranged from 200 kWh for the BESS units to 500 kW for the WT and DG units.

A 24-hour dynamic load profile was utilized to emulate realistic temporal variations in both active and reactive power demand, as illustrated in Figure 2. Each hourly interval was independently optimized to capture time-varying operating conditions within the distribution system. Line disturbances were simulated by increasing the resistance (R) and reactance (X) of selected network segments to represent degraded line performance caused by faults or aging infrastructure. All simulations were performed in MATLAB R2022a using the MATPOWER environment with base values of 12.66 kV and 100 MVA. Figures 3 and 4 show the active (P) and reactive (Q) load shedding curves under the base condition, whereas Figures 5–8 present the distribution network configurations after DDNR implementation with QBPSO at intervals 1, 2, 3, and 4, respectively.

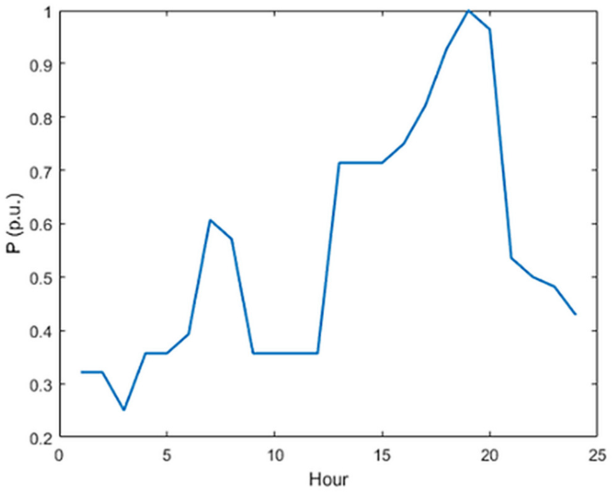

Fig. 2. 24-hour load curve of the distribution network.

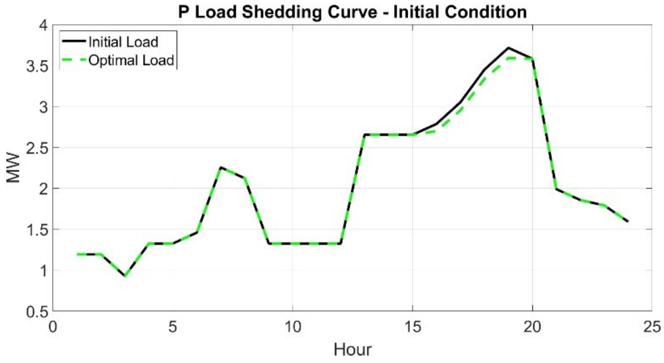

Fig. 3. Active (P) load shedding curve under base conditions.

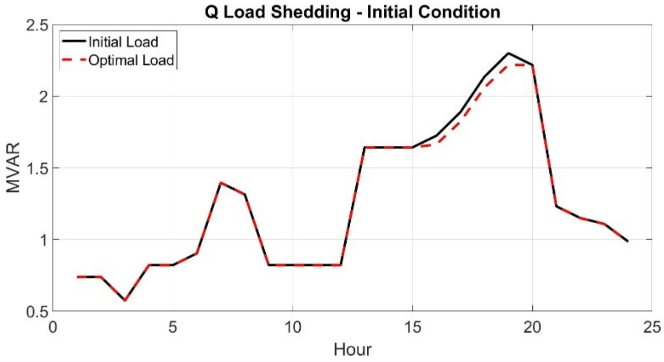

Fig. 4. Reactive (Q) load shedding curve under base conditions.

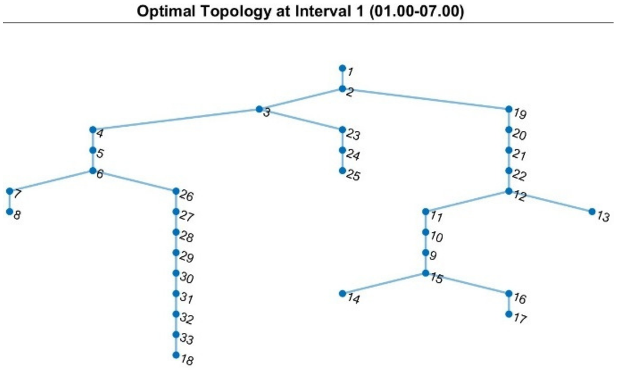

Fig. 5. Distribution network configuration after DDNR using QBPSO at interval 1.

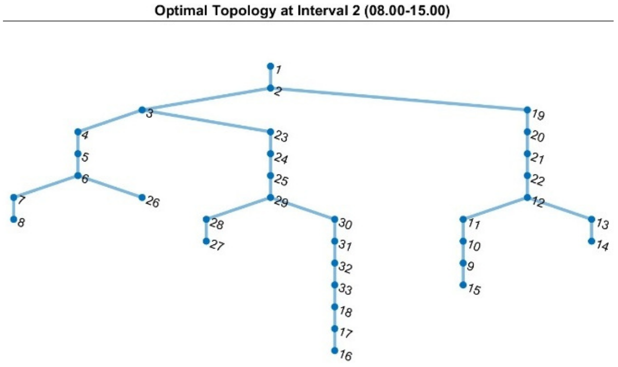

Fig. 6. Distribution network configuration after DDNR using QBPSO at interval 2.

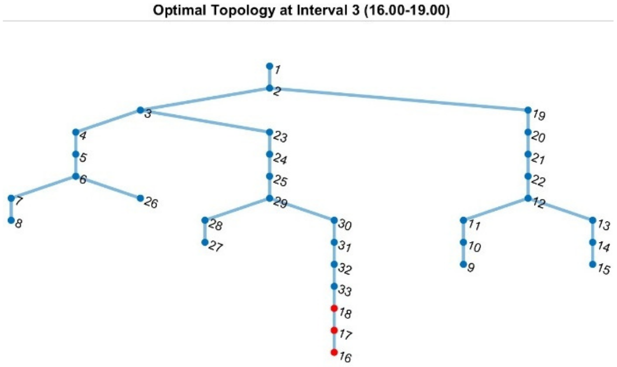

Fig. 7. Distribution network configuration after DDNR using QBPSO at interval 3.

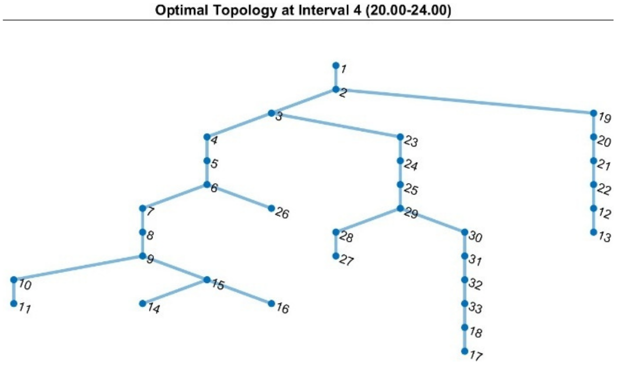

Fig. 8. Distribution network configuration after DDNR using QBPSO at interval 4.

Figures 9 and 10 illustrate the active (P) and reactive (Q) load-shedding curves obtained after implementing the DDNR optimization using the QBPSO approach. The results demonstrate that load shedding is nearly eliminated and the network maintains reliable power supply under dynamic conditions.

Quantitative comparisons summarized in Table I demonstrate significant improvements achieved by DDNR relative to the initial condition and conventional Binary Particle Swarm Optimization (BPSO). The total operating cost decreased slightly from 3,346.47 to 2,314.11 USD, which is comparable to the BPSO result (2,313.89 USD). Although the difference is very small (≈0.007%), the proposed QBPSO method demonstrates superior technical performance in terms of voltage stability and reduced load shedding, indicating improved reliability rather than economic superiority. Correspondingly, total active and reactive load-shedding values decreased from 429.405 kW and 303.300 kVAR to only 0.000896 kW and 0.00521 kVAR, indicating almost complete elimination of load curtailment. In addition, the total ΔVSI decreased from 50.638 to 39.2509, confirming that the proposed DDNR with QBPSO enhances voltage-stability margins more effectively than BPSO (39.6563). These results, consistent with the ΔVSI comparison trend shown in Figure 8, verify that QBPSO achieves faster convergence, better voltage-profile uniformity, and lower operational losses, thereby improving both technical and economic performance of the distribution network under dynamic loading conditions.

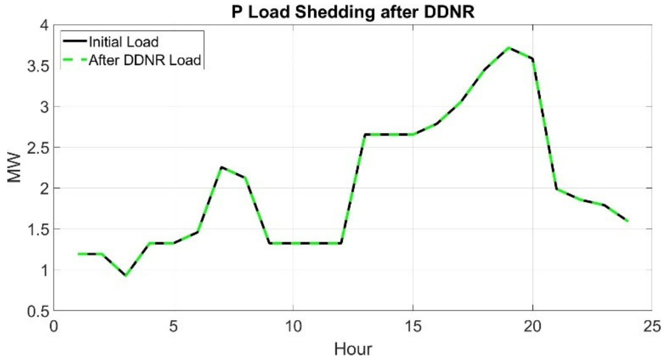

Fig. 9. Active (P) load shedding curve after DDNR using QBPSO.

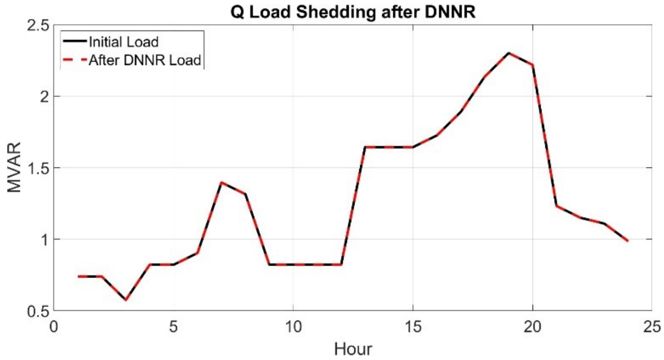

Fig. 10. Reactive (Q) load shedding curve after DDNR using QBPSO.

TABLE I. COMPARISON OF DDNR PERFORMANCE USING BPSO AND QBPSO

Parameter	Initial condition	DDNR with BPSO	DDNR with QBPSO
Cost (USD)	3,346.472	2,313.8937	2,314.1091
Total load shedding (kW)	429.405	0.00498	0.000896
Total load shedding (kVAR)	303.300	0.02902	0.00521
Total ΔVSI	50.638	39.65633	39.25087

IV. CONCLUSION

This study proposed a Dynamic Distribution Network Reconfiguration (DDNR) approach optimized using the Quantum Binary Particle Swarm Optimization (QBPSO) algorithm to enhance voltage stability and minimize operational cost in distribution systems with integrated Distributed Energy Resources (DER). The modified IEEE 33-bus test system, including Photovoltaic (PV), Wind Turbines (WT), Diesel Generators (DG), and Battery Energy Storage Systems (BESS), was simulated under 24-hour dynamic load conditions and line disturbances. The results demonstrated that the QBPSO-based DDNR achieved superior technical performance in terms of voltage stability and reliability, while maintaining operational costs comparable to the Binary Particle Swarm Optimization (BPSO) method. Specifically, the total operating cost decreased from 3,346.47 to 2,314.11 USD, whereas the aggregated voltage stability deviation (ΔVSI) improved from 50.638 to 39.2509. Moreover, active and reactive load shedding were nearly eliminated, confirming improved reliability and continuity of power supply. The proposed method effectively mitigates the impacts of faults and aging infrastructure by adaptively reconfiguring the network, maintaining voltage stability margins, and ensuring efficient power delivery. Consequently, the QBPSO-based DDNR framework provides a robust and scalable solution for smart-grid applications, supporting real-time reconfiguration and sustainable power-system operation under dynamic and uncertain conditions.

The main contribution of this work is not a new optimization algorithm, but a stability-oriented DDNR framework that explicitly formulates ΔVSI as an optimization objective within a multi-objective AC Optimal Power Flow (AC-OPF) under time-varying load and line disturbance conditions, and evaluates candidate topologies through a reproducible QBPSO–OPF coupling. Compared to conventional BPSO, the proposed approach achieves comparable operating cost while yielding lower ΔVSI and near-zero load shedding, indicating improved voltage robustness and operational reliability. Future work will strengthen comparative assessment through statistical validation over at least 30 independent runs to confirm convergence stability and performance significance, benchmark against additional recent metaheuristic algorithms, and extend the evaluation to larger and potentially unbalanced distribution networks.

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