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OPTIMIZATION OF DISTRIBUTED GENERATION PLACEMENT AND SIZING IN DISTRIBUTION SYSTEMS USING MULTI - OBJECTIVE DEEP REINFORCEMENT LEARNING

TỐI ƯU HÓA VỊ TRÍ VÀ CÔNG SUẤT CỦA NGUỒN PHÁT PHÂN TÁN TRONG HỆ THỐNG PHÂN PHỐI SỬ DỤNG THUẬT TOÁN HỌC TĂNG CƯỜNG SÂU ĐA MỤC TIÊU

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Abstract:

Distributed Generations (DGs) play a significant role in modern distribution systems by reducing power losses, improving voltage stability, and enhancing system reliability. However, determining the optimal placement and sizing of DGs is a complex problem with diverse objectives and vast search spaces. This paper introduces the Multi - Objective Deep Reinforcement Learning (MODRL) algorithm to address this challenge. The objective function is designed to optimize power losses, voltage deviation, and investment costs. The method is validated on 33-bus and 69-bus distribution systems, with results compared to traditional algorithms (GA, PSO) and modern approaches (COA, WOA, FA). The results demonstrate that MODRL outperforms other methods, achieving significant power loss reduction while providing the best voltage stability and the lowest investment cost.

Keywords:

Distributed Generation; Deep Reinforcement Learning; Distribution Systems; Optimization, Power Loss Reduction.

Tóm tắt:

Các nguồn phát điện phân tán đóng vai trò quan trọng trong các hệ thống phân phối hiện đại nhờ khả năng giảm tổn thất công suất, cải thiện ổn định điện áp và nâng cao độ tin cậy của hệ thống. Tuy nhiên, việc xác định vị trí và công suất tối ưu của DGs là một bài toán phức tạp với nhiều mục tiêu khác nhau và không gian tìm kiếm rộng lớn. Bài báo này giới thiệu thuật toán Học Tăng Cường Sâu Đa Mục Tiêu (Multi-Objective Deep Reinforcement Learning - MODRL) để giải quyết thách thức này. Hàm mục tiêu được thiết kế nhằm tối ưu hóa tổn thất công suất, độ lệch điện áp và chi phí đầu tư. Phương pháp được kiểm chứng trên các hệ thống phân phối 33 nút và 69 nút, với kết quả được so sánh với các thuật toán truyền thống như thuật toán di truyền, thuật tối tối ưu bầy đàn và các phương pháp hiện đại Thuật toán tối ưu Cuckoo, bầy cá voi, tối ưu bầy đom đóm. Kết quả thực nghiệm cho thấy MODRL vượt trội hơn các phương pháp khác, đạt được giảm tổn thất công suất đáng kể, đồng thời cung cấp độ ổn định điện áp tốt nhất và chi phí đầu tư thấp nhất.

Từ khóa:

Nguồn phân tán, Học tăng cường sâu, Hệ thống lưới phân phối, tối ưu hóa, giảm tổn thất công suất.

1. INTRODUCTION

Modern power systems are undergoing significant transitions from traditional centralized models to decentralized ones, driven by the rapid growth of renewable energy sources such as solar, wind, and other clean energy solutions. In the context of increasing energy demands, integrating Distributed Generations (DGs) into distribution networks has emerged as an effective solution. This integration not only alleviates the burden on transmission systems but also provides several technical and economic benefits. First, reducing power losses is one of the most notable advantages of DGs [1]. By delivering power directly to local consumption points, DGs minimize transmission losses, particularly in systems with long transmission lines or dispersed loads. Second, DGs contribute to improving voltage stability, ensuring that voltages at nodes within the network remain within permissible limits, thereby enhancing the quality of power supplied to users. Finally, the decentralized structure of DGs increases system reliability by reducing the risk of widespread outages during local failures [2].

However, to fully realize these benefits, determining the optimal placement and sizing of DGs is a complex problem. This challenge requires balancing multiple objectives, such as minimizing power losses, maintaining voltage stability, and optimizing investment costs, while adhering to technical constraints on voltage, capacity, and load. The non-linearity and dependency on system configurations make this problem difficult to solve using traditional methods. In recent years, metaheuristic algorithms and artificial intelligence have been widely applied to address this problem. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are popular methods due to their simplicity and ability to search large solution spaces [3]. However, these algorithms often converge prematurely to local optima, resulting in suboptimal performance in loss reduction and voltage improvement. More advanced methods, such as Coyote Optimization Algorithm (COA) [4], Whale Optimization Algorithm (WOA) [5], and Firefly Algorithm (FA) [6], [7] have significantly improved convergence performance but remain insufficiently robust for large or complex networks.

To overcome these limitations, this paper proposes the Multi - Objective Deep Reinforcement Learning (MODRL) algorithm [8], a modern approach combining reinforcement learning and deep neural networks. MODRL automates the solution search process while simultaneously optimizing multiple objectives. This approach promises superior performance in optimizing the placement and sizing of DGs, particularly in complex distribution networks. This paper will detail the problem, the proposed solution methodology, and the results of experiments conducted on two standard distribution networks, the 33-bus and 69-bus systems. Additionally, it compares the effectiveness of

MODRL with other algorithms such as GA, PSO, COA, WOA, and FA. Experimental results demonstrate that MODRL not only reduces power losses but also improves voltage stability and lowers investment costs, highlighting its significant potential for future applications in distribution systems.

2. PROBLEM DESCRIPTION

To optimize the placement and sizing of DGs in a distribution network, an objective function must be established to balance key criteria. In this context, the objective function is designed to simultaneously optimize three main factors: power losses, voltage deviation, and investment costs. This approach ensures not only the minimization of energy losses within the system but also the maintenance of voltage quality within permissible limits while optimizing the investment required for DG installation. These factors are incorporated into the following formula:

$$F(x) = W_1 \cdot P_{loss} + W_2 \cdot \sum_{i=1}^{N} (\triangle V_i)^2 + W_3 \cdot \sum_{k=1}^{K} C_{DG,k} \quad (1)$$

where:

• P_{loss} represents the power losses in the distribution network, a factor that must be minimized to improve system efficiency.

• $\triangle V_i = |V_i - V_{ref}|$ represents the voltage deviation at each node iii, playing a crucial role in ensuring the quality of power supply.

• $C_{DG,k} = C_{fixed} + C_{variable} \cdot P_{DG,k}$ is the investment cost of the k-th DG, including both fixed costs and variable costs dependent on the installed capacity .

The weights W_1, W_2, W_3 are used to adjust the priority levels among the objectives, ensuring flexibility in applying the objective function to systems under varying conditions. This method provides a comprehensive optimization framework, enabling an effective balance between technical performance and economic benefits in the operation of distribution networks [9] [10].

To ensure the feasibility and effectiveness of the optimization problem for the placement and sizing of DGs, technical constraints must be established alongside the objective function. These constraints are based on the physical and operational limits of the distribution network, including:

$$\text{DG Capacity: } P_{DG}^{min} \leq P_{DG,k} \leq P_{DG}^{max} \quad (2)$$

The capacity of each DG () must lie within a permissible range, defined by minimum and maximum limits. This constraint ensures that DGs are designed and operated in alignment with the practical capabilities of the equipment and the technical requirements of the system.

$$\text{Voltage at nodes: } V_{min} \leq V_i \leq V_{max} \quad (3)$$

The voltage at each node V_i must be maintained within permissible limits to ensure power quality and avoid operational issues such as under-voltage or over-voltage. This constraint plays a crucial role in ensuring voltage stability across the entire distribution network.

$$\text{Total DG Capacity: } \sum_{k=1}^{K} P_{DG,k} \leq P_{load} \quad (4)$$

The total installed capacity of all DGs ($\sum_{k=1}^{K} P_{DG,k}$) must not exceed the total load demand (P_{load}) of the system. This ensures that DGs are utilized effectively, avoiding excess capacity that could waste resources or negatively impact grid stability.

These constraints not only define the solution space for optimal placement and sizing but also ensure that the proposed solutions meet technical and operational requirements. Incorporating these constraints into the optimization problem enhances the performance of the distribution system while ensuring feasibility in practical implementation.

3. METHOD FOR SOLVING THE PROBLEM

To solve the problem of optimizing the placement and sizing of DGs in distribution networks, this paper employs the MODRL algorithm. This modern approach combines Reinforcement Learning (RL) and Deep Neural Networks (DNN), enabling the optimization of the objective function within the large and complex search space of distribution systems.

MODRL operates within a reinforcement learning environment, where an agent learns to make optimal decisions by continuously interacting with the environment. Each action taken by the agent affects the state of the environment and is evaluated through a reward mechanism. This process is repeated until an optimal solution is achieved. The basic structure of MODRL includes:

1. State: The system state at each step includes the voltage at nodes (V_i), the load power at nodes ($P_{load,i}$), and the current capacity of DGs ($P_{DG,k}$). This state is encoded into a feature vector that serves as the input for the deep neural network, enabling the model to learn critical patterns from the input data.

2. Action: Actions are defined as selecting the placement of DGs and determining their capacities. Actions are modeled as a vector and predicted by the neural network.

3. Reward: The reward is a numerical value reflecting the quality of an action. In this problem, the reward is calculated based on the value of the objective function:

$$R_T = -\left(W_1 \cdot P_{loss} + W_2 \cdot \sum_{i=1}^{N} (\Delta V_i)^2 + W_3 \cdot \sum_{k=1}^{K} C_{DG,k}\right) \quad (5)$$

where:

• P_{loss}: Power losses in the system.

• $\Delta V = |V_i - V_{ref}|$: Voltage deviation at the nodes.

• $C_{DG,k}$: Investment cost of the DG at position k.

Negative rewards encourage the agent to reduce power losses, improve voltage stability, and optimize investment costs.

4. Proximal Policy Optimization (PPO) Algorithm: PPO is a modern reinforcement learning algorithm designed to ensure stability and efficiency in policy updates. It maintains

a balance between exploring new solution spaces and exploiting potential solutions. PPO optimizes the following objective function:

$$L(\theta) = E[min(r_t(\theta) \cdot A_t, clip(r_t(\theta), 1 - \epsilon, 1 + \epsilon) \cdot A_t)] \quad (6)$$

where:

• $r_t(\theta)$: The probability ratio between the new policy and the old policy.

• A_t: The advantage estimate of an action.

• ϵ: A clipping parameter to prevent excessive policy changes.

The application of the MODRL algorithm to optimize the placement and sizing of DGs in distribution systems involves the following steps:

1. Initialize State: Capture the initial state of the system, including the voltage at nodes, loads at nodes, and the feasible locations for DG installation.

2. Predict Action: The agent uses a deep neural network to predict the optimal action, which includes selecting the placement and sizing of DGs.

3. Execute Action: Update the system state after executing the action, including adjustments to node voltages and DG capacities.

4. Calculate Reward: Compute the reward based on key criteria such as reducing power losses, improving voltage deviation, and optimizing investment costs.

5. Update Policy: Use the PPO algorithm to update the neural network based on the reward received, ensuring policy improvement.

6. Check Stopping Conditions: If convergence is achieved or the maximum number of iterations is reached, terminate the process. Otherwise, return to Step 1.

The MODRL approach leverages the PPO algorithm and deep neural networks to optimize the placement and sizing of DGs, enhancing the operational performance of distribution systems. With its ability to learn and adapt autonomously, MODRL serves as a powerful tool for addressing complex optimization problems in modern power systems.

4. TEST RESULTS

Table 1. Assumed Parameters for Fixed and Variable Costs of DG Installation

Parameter	Value
Fixed Cost (C_{fixed}) for installing each DG	200,000 USD/DG
Variable Cost ($C_{variable}$) per kilowatt of DG capacity	500 USD/kW

To evaluate the effectiveness of the MODRL algorithm in optimizing the placement and sizing of DGs, this method is tested on two standard distribution networks: the 33-bus and 69-bus systems. Table 1 presents the assumed parameters for fixed and variable costs associated with DG installation. Table 2 includes information on voltage limits, load capacities, and the range of DG capacities. Table 3 outlines the parameters related to comparison algorithms such as GA, PSO, COA, WOA, and FA. The entire testing process is implemented on the MATLAB platform, ensuring the accuracy and reproducibility of the results [11].

Table 2. Information on Voltage Limits, Load Capacities, and DG Capacity Range

Parameter	Value
Nominal Voltage ($V_{nominal}$)	12.66 kV
Total Load Capacity (33 nút)	$3.715 + j2.30$ MVA
Total Load Capacity (69 nút)	$3.80 + j2.69$ MVA
DG Capacity ($P_{DG,k}$)	0.5 MW − 2.0 MW
Maximum Number of DGs (K_{max})	03
Voltage Limits (V_{min}-V_{max})	0.90 − 1.05 p.u.
Objective Function Weights (w_1, w_2, w_3)	0.5; 0.3; 0.2

Table 3. Optimization Algorithm Parameters

Algorithm	Population Size	Maximum Iterations	Key Parameters
GA	50	100	Mutation rate: 10%, Crossover rate: 80%
PSO	30	150	Inertia weight: 0.5, Cognitive coefficient: 2.0, Social coefficient: 2.0
COA	40	100	Pack size: 15, Position change rate: 10%
WOA	50	100	Spiral adjustment factor: 1.5, Spiral adjustment factor: 50%
FA	30	150	Spiral adjustment factor: 0.2, Light intensity decay: 0.9
MODRL	1 (Agent)	500	PPO parameters: Clipping range $\epsilon = 0.2$, Update steps: 64, Learning rate: 0.001

Table 4. Optimization results of MODRL and other algorithms for the 33-bus distribution system

Algorithm	Locations of DGs (nodes)	Capacity of DGs (MW)	P_{loss}(kW)	P_{loss} Reduction (%)	V_{min} (p.u.)	ΔV_i (p.u.)	Investment Cost ($)
Initial	-	-	202.69	-	0.9131	0.056	-
GA [14]	11, 29, 30	1.50, 0.42, 1.07	106.3	47.55	0.9400	0.038	1,500,000
PSO [15]	13, 32, 8	0.98, 0.83, 1.17	105.3	48.05	0.9415	0.035	1,480,000
COA [16]	30, 14, 24	1.07, 0.75, 1.10	71.46	64.74	0.9687	0.024	1,320,000
WOA [17]	30, 14, 24	1.05, 0.74, 1.12	70.10	65.41	0.9695	0.021	1,310,000
FA [18]	30, 14, 24	1.02, 0.76, 1.10	69.30	65.81	0.9704	0.018	1,290,000
MODRL	30, 14, 24	1.03, 0.75, 1.10	69.00	65.96	0.9707	0.017	1,280,000

Table 5. Optimization results of MODRL and other algorithms for the 69-bus distribution system

Algorithm	Locations of DGs (nodes)	Capacity of DGs (MW)	P_{loss}(kW)	P_{loss} Reduction (%)	V_{min} (p.u.)	ΔV_i (p.u.)	Investment Cost ($)
Initial	-	-	224.89	-	0.9092	0.092	-
GA [14]	49, 50, 61	1.30, 0.80, 1.20	147.80	34.29	0.9305	0.042	1,750,000
PSO [15]	48, 64, 27	1.25, 0.95, 1.00	146.20	35.01	0.9321	0.038	1,710,000
COA [16]	61, 64, 27	1.20, 0.90, 1.15	101.50	54.85	0.9510	0.022	1,480,000
WOA [17]	61, 64, 27	1.22, 0.93, 1.10	99.50	55.74	0.9525	0.019	1,470,000
FA [18]	61, 64, 27	1.20, 0.92, 1.12	99.00	56.00	0.9530	0.018	1,465,000
MODRL	61, 64, 27	1.25, 0.95, 1.10	98.75	56.08	0.9540	0.015	1,450,000

4.1. The 33-bus distribution system

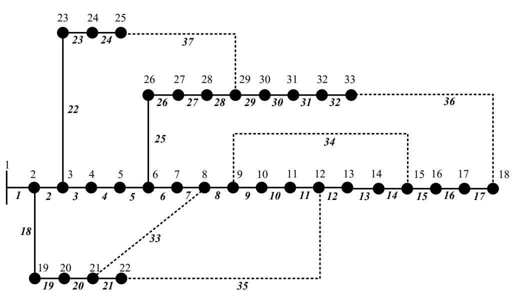

Figure 1. Diagram of the 33-bus distribution system

For the 33-bus system (Figure 1), the initial power loss is recorded as 202.6863 kW. The minimum voltage magnitude is 0.9131 p.u., and the maximum load carrying factor is 1.4024 p.u. [12], [13]. The optimal location and capacity of DGs determined by the proposed method are presented in Table 4. The results for the 33-bus system demonstrate that the MODRL algorithm achieves outstanding performance in reducing power losses, improving voltage stability, and optimizing investment costs. Before the installation of DGs, the initial power loss was 202.69 kW, with a minimum voltage of 0.9131 p.u., reflecting the inefficiency of the system. After applying MODRL, the power loss was significantly reduced by 65.96%, dropping to 69.0 kW. The minimum voltage also improved notably to 0.9707 p.u., ensuring high power quality and operational stability. Compared to other algorithms, MODRL excels in all aspects. Modern algorithms like FA and WOA achieved relatively high loss reductions of 65.81% and 65.41%, respectively, but they still fall short of MODRL in terms of total voltage deviation and investment cost. MODRL requires the lowest investment cost ($1,280,000), which is more economical than FA ($1,290,000) and WOA ($1,310,000), highlighting the economic efficiency of this algorithm.

4.2. The 69-bus distribution system

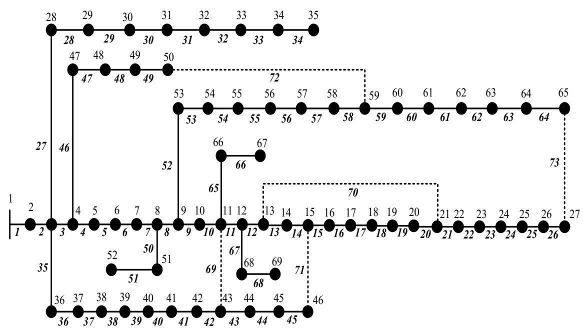

Figure 2. Diagram of the 69-bus distribution system

The 69-bus distribution network consists of 69 nodes, 73 branches, and a total load capacity of 3.802+j3.696 MW. The single-line diagram is shown in Figure 2. The initial power loss is 224.89 kW, and the minimum voltage is 0.9092 p.u.

The simulation results for the 69-bus distribution system are presented in Table 5. For the 69-bus system, MODRL continues to demonstrate its superior performance. Initially, the system's power loss was 224.89 kW, with a minimum voltage of 0.9092 p.u., reflecting unstable voltage conditions and significant losses. After applying MODRL, the power loss was reduced by 56.08%, down to 98.75 kW, the best reduction compared to other algorithms. The minimum voltage improved significantly to 0.9540 p.u., with a total voltage deviation of just 0.015 p.u., ensuring exceptional voltage quality. In terms of cost, MODRL also required the lowest investment ($1,450,000), lower than FA ($1,465,000) and WOA ($1,470,000). Traditional algorithms like GA and PSO achieved only moderate power loss reductions (34%–35%), highlighting their limitations when applied to large distribution networks. These results demonstrate that MODRL is not only technically more effective but also economically superior compared to other methods.

5. CONCLUSION

This paper introduced the MODRL method for optimizing the placement and sizing of Distributed Generations (DGs) in distribution networks. Experimental results on the 33-bus and 69-bus systems showed that MODRL achieved remarkable performance, reducing power losses by 65.96% and 56.08%, respectively, improving the minimum voltage, and minimizing the total voltage deviation. Furthermore, the method demonstrated the lowest investment cost compared to other algorithms such as GA, PSO, COA, WOA, and FA, highlighting its economic efficiency. With its automation capabilities, multi-objective optimization, and effective scalability to large networks, MODRL showcases significant potential for wide application, contributing to enhanced technical and economic efficiency in modern distribution system operations.

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