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Original Research Article

Dynamic Load Reactive Power Optimization Based on Convolutional Neural Network VGG16 Model

DUAN Jun-peng[1], YANG Chen-chen[2], HE Peng[3], XU Ke-wei[3], LI Guo-you[1], WANG Jia-fu[1]

1 Chuxiong Power Supply Bureau of Yunnan Power Grid Co.，Ltd.，Chuxiong 675009，China；

2 Faculty of Electric Power Engineering，Kunming University of Science and Technology，Kunming 650500，China；

3 Electric Power Research Institute of Yunnan Power Grid Co.，Ltd.，Kunming 650217，China.

Abstract: In reactive power optimization of distribution network, in most cases, the processing of load data is often only for the specific data under a certain operation condition, so it is difficult to classify and process the data of multiple working conditions in a certain operation stage. To solve the above problems, an optimization method basedon convolutional neural network VGG16 (visual geometry group network) is proposed. Firstly, it is classified according to the capacity proportion of transformer in the station area, and three kinds of scenes of light, medium and high are obtained. Then, particle swarm optimization algorithm is used to optimize each kind of scene, and the corresponding optimization strategy is obtained. The effectiveness of this method to solve the problem of dynamic reactive power and voltage in the substation area is verified by simulation.

Keywords: Dynamic reactive power optimization; Distribution network; VGG16, Image processing; Reactive power compensation.

1. Introduction

Based on the background of the development of distribution network construction in our country, there are problems such as aging of the lines after long-term operation of equipment. At the same time, the transformation speed of the distribution network is relatively slow. Therefore, during the peak electricity consumption in the simulated substation area, the voltage difference between the head and end of the substation area is mostly above 40V, which affects the user's electricity experience[1]. In response to the above issues, reactive power optimization is carried out on the distribution network to obtain optimization strategies, thereby increasing the terminal voltage of the substation, reducing the voltage difference between the beginning and end, and improving the power quality of users.

Traditional research on reactive power optimization in distribution network substations often focuses on static reactive power optimization under a certain operating condition. However, the load in the substation is constantly changing, and a single load operating situation cannot cover the overall operating scenario of the actual operating situation in the substation. There is a limited amount of research on dynamic reactive power optimization in the distribution station area in existing literature. For example, in reference [2], a two-stage dynamic reactive power optimization method was proposed to address the problem of dynamic reactive power optimization in the power system. By using different two-stage objective functions, the mathematical calculation scale can be reduced. Reference [3] proposes a scenario based dynamic reactive power optimization method for active distribution networks in response to the reactive power optimization problem caused by the integration of distributed power sources. This method uses K-means clustering and Monte Carlo simulation sampling algorithms to cluster the samples into three typical scenarios, and then dynamically optimizes the reactive power

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of IEEE33 nodes with the objective function of minimizing network loss. Reference [4] addresses the problem of dynamic reactive power shortage in distribution networks by improving the hybrid leapfrog algorithm and combining it with the K-means clustering algorithm to solve the reactive power optimization problem. Reference [5] is based on the dynamic load changes of 10kV transmission lines in a certain substation area throughout the year. K-means clustering is used to classify the dynamic loads, and the daily average load is used as sampling data. The dynamic load changes throughout the year are classified into 6 categories, and optimization strategies are obtained for each category to reduce network losses and costs, and improve voltage levels. Reference [5] uses the daily average load of the substation area for a whole year as simulation data, and only obtains the total load of all nodes in the substation area for each scenario. The specific load to nodes is allocated based on percentages. Although it improves the practicality and reference value compared to static reactive power optimization problems, it is insufficient in simulating the actual operating conditions of the substation area.

In response to the existing problems in literature research, this paper adopts the convolutional neural network VGG16 model, using the transformer capacity of each node in the substation area as sampling data for classification. The load data of each node in the three scenarios are set to be 65% below the rated capacity of the transformer, 65%-75% of the rated capacity of the transformer, and 75% above the rated capacity of the transformer[6-8]. The overall classification is divided into three categories, Then, the particle swarm optimization algorithm is used to optimize the reactive power of each scenario, obtaining the optimization strategy for each scenario, thereby achieving the processing of dynamic reactive power optimization in the substation area[7]. The specific steps are as follows:

Step 1: Determine the load data information of each node based on the rated capacity percentage of the transformer corresponding to the 37 nodes in the substation area.

Step 2: Select 100 types of load data for each category and use the VGG16 model for learning and training.

Step 3: The final decision is to classify it into three scenarios. Subsequently, a set of load data will be randomly selected, and the trained VGG16 will automatically determine which scenario it belongs to.

Step 4: Directly derive compensation strategies based on scene classification.

2. Introduction to Convolutional Neural Network VGG16 Model

The structure of VGG is a type of CNN (Convolutional Neural Networks) composed of pooling layers and convolutional layers. Its principle is to stack weighted fully connected or convolutional layers onto 16 layers, hence it is called VGG16. Compared with other convolutional neural network models, VGG16 has a simpler structure but stronger applicability, making it more suitable in many fields. Its structural diagram is shown in Figure 1.

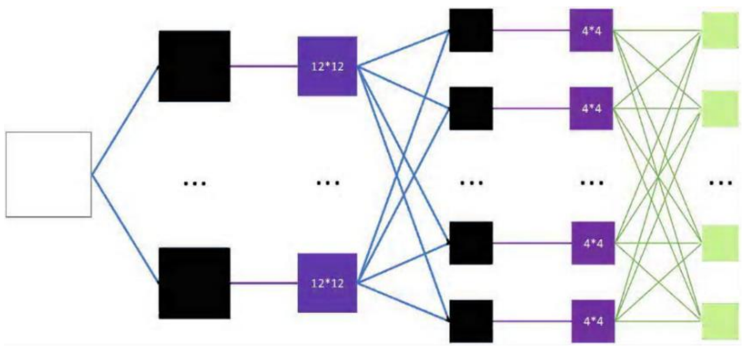

Figure 1 VGG16 convolutional neural network structure diagram.

The structure diagram starts from the left and any image that needs to be classified is input into the VGG model network. The white squares in the diagram are convolutional layers, which are used to generate a new matrix. The matrix stores the updated parameter values for each training, and the best parameter values are found during the continuous training process. The black blocks are pooled, and through convolutional layer processing, some feature information is generated, but this information may be duplicated. To simplify the calculation process, the role of pooling is to summarize similar feature information and select the average or maximum value of the feature area. The dark gray squares are fully connected layers that connect the weights of each layer to the last layer. The light gray blocks are the prediction layer, whose function is to convert the previously output information into category probabilities, thereby achieving classification.

This article uses the VGG16 model to classify dynamic load data, trains the VGG16 model through the dataset, and then puts any operating condition in the substation area into the model to determine which type of condition it belongs to, and obtains the corresponding reactive power optimization strategy.

3. Dynamic Load Handling of Substation Distribution Network

The simulation object selected in this article is a 37 node distribution network model under a 10kV line in a certain substation area. The load model is classified according to the percentage of transformer capacity corresponding to each node. The load model is divided into three categories:

(1) The selection of load data accounts for 65% -75% of the rated capacity of the transformer. Under this operating condition, the load belongs to the most economical operating situation. In this operating situation, the system may experience reactive power loss for factories and large village nodes, which corresponds to the normal period of real civil electricity.

(2) The load data is selected to be lower than 65% of the rated capacity of the transformer. In this operating scenario, the load belongs to the lowest economic operating scenario, and the system reactive power will not be insufficient. This situation corresponds to the low valley period of real civil electricity.

(3) The third scenario combines the actual situation of a selected station area, Among the 37 nodes in the substation, 7 nodes have transformer rated capacities higher than 100kVA, and the load data is selected to be higher than 75% of the rated capacity of the transformer; In addition, the electricity consumption of residents in the Taiwan area is also relatively high, and it is set to be 75% higher than the rated capacity of the transformer. Under this operating condition, the distribution network may experience reactive power loss, and the voltage at the end of the line may be lower than the normal voltage value. Therefore, reactive power optimization of the network is necessary to improve the terminal voltage of the substation area through compensating reactive power strategies. This situation corresponds to the peak hours of actual civilian electricity.

The VGG16 convolutional neural network model is used to train and classify the load data in the substation area, with a sample size of 100 for each class. Figures 2 to 4 show the operating load of each node in three different load scenarios, with the horizontal axis representing the number of nodes in the network at 37 nodes and the vertical axis representing the actual capacity of the corresponding node transformer. After training with sample data, the VGG16 convolutional neural network model forms a classification memory for the load data of 37 nodes in the substation area. Subsequently, the load data of any working condition in the substation area is taken and placed into the VGG16 convolutional neural network model. It will automatically determine which of the three scenarios this situation belongs to, and decide whether to perform reactive power compensation based on the scenario. If compensation is required, a corresponding compensation strategy will be determined.

4. Dynamic Reactive Power Optimization of Distribution Network

4.1 Objective Function

This article divides the load operation situation in the substation area into three categories, mainly considering the goal of minimizing node distribution network losses for reactive power optimization of the distribution network. The objective function is as follows:

$$\min F = MIN\left\{P_{loss} = \sum_{k=1}^{n} g_{k(i,j)}\left[U_i^2 + U_j^2 - 2U_iU_j\cos\theta_{ij}\right]\right\} \quad \text{(Eq.1)}$$

In Eq.1, P_{loss} represents the active power loss of the entire distribution station area; $g_{k(i,j)}$ is the line conductivity between node i and node j; U_i is the voltage assignment of node i; U_j is the voltage assignment of node j; θ_{ij} is the phase difference between node i and node j.

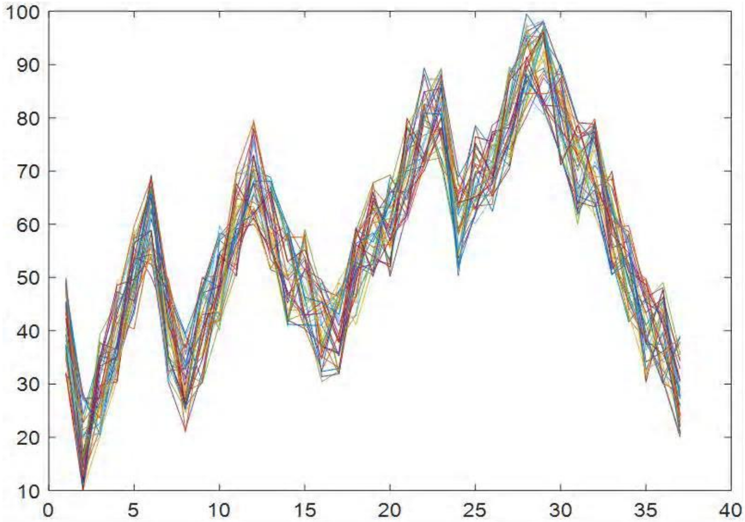

Figure 2 Load classification scenario 1.

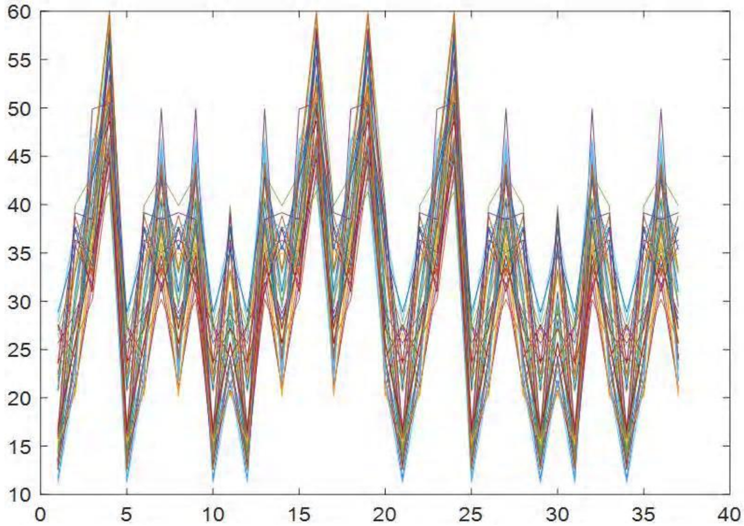

Figure 3 Load classification scenario 2.

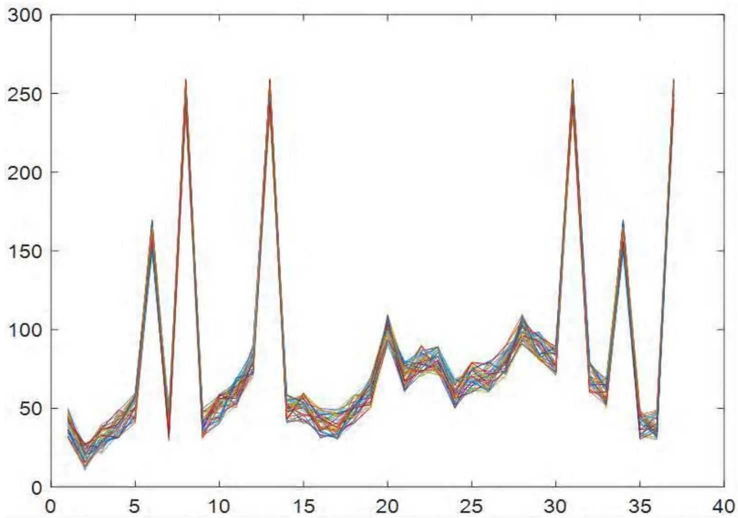

Figure 4 Load classification scenario 3.

4.2 Constraint Condition

4.2.1 Equation Constraints

Each node in the substation should meet the balance of active and reactive power, so the equation constraint is the power balance equation:

$$\begin{cases} P_i - \sum_{j=1}^{n} U_i U_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) = 0 \\ Q_i - \sum_{j=1}^{n} U_i U_j \left(G_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij} \right) = 0 \end{cases} \quad \text{(Eq.2)}$$

In Eq.2, P_i injects active power into node i; Q_i injects reactive power into node i; U_i is the voltage of node i; θ_{ij} is the voltage phase angle difference between node i and j; G_{ij}, B_{ij} represents the real and imaginary parts of the elements in the node admittance matrix; n is the total number of nodes in the system.

4.2.2 Inequality Constraint

Inequality constraints for controlling variables:

$$Q_{i\min} \le Q_i \le Q_{i\max} \quad \text{(Eq.3)}$$

Among them, $Q_{i\min}$ is the upper limit of the compensation output of the capacitor reactive power compensation device, and $Q_{i\max}$ is the lower limit of the compensation output of the capacitor reactive power compensation device.

The inequality constraints for state variables are:

$$U_{i\min} \le U_i \le U_{i\max} \quad \text{(Eq.4)}$$

Among them, $U_{i\min}$, $U_{i\max}$ represents the upper and lower limits of node voltage. Figure 5 shows the PSO algorithm flowchart.

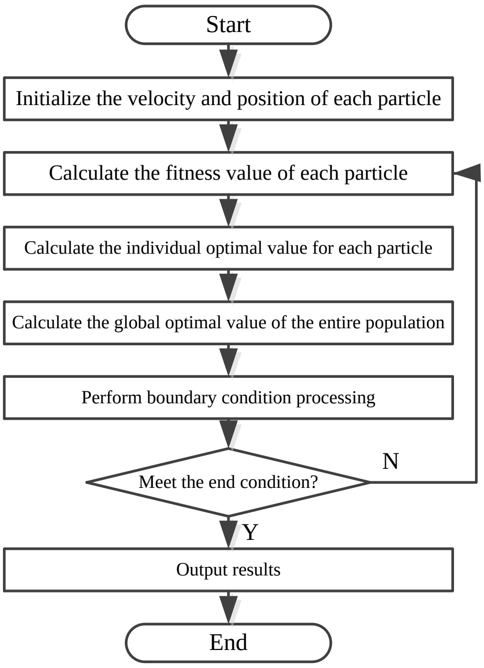

Figure 5 PSO algorithm flowchart.

5. Example Analysis

This article selects the reactive power optimization object as a 37 node distribution station area model in a certain substation area. The specific structure diagram is shown in Figure 6. The neural network VGG16 model is used to first process the dynamic load data of the substation area, and then the particle swarm optimization algorithm is used to optimize the reactive power for each scenario. Using the daily load data of 10kV transmission lines in this substation area in 2021 as simulation data, combined with the user types in this substation area, classification scenario optimization is carried out. As the second type of situation belongs to the low valley period of residential electricity consumption, there is no reactive power shortage. Therefore, reactive power optimization is mainly carried out for the first and third types of situations, and corresponding reactive power optimization strategies are obtained. The voltage situation of nodes before and after optimization is compared.

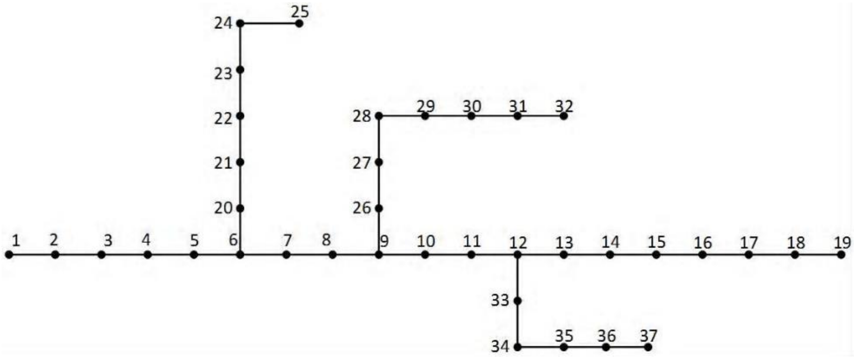

Figure 6 Structural diagram of distribution station area.

5.1 Optimization of the First Type of Scenario

This scenario corresponds to the residential electricity level period, where some factories are working and residential electricity is in normal condition. Some nodes at the end of the line may have low voltage. The particle swarm optimization algorithm is used to optimize reactive power for this type of scenario.

Figure 7 shows the comparison of node voltages before and after optimization, with the horizontal axis representing the number of nodes and the vertical axis representing the corresponding voltage values of nodes. The voltage value of the first section of the substation is 10.5kV. Before optimization, the voltage values of nodes 6, 13, and 37 were relatively low. After reactive power compensation, the voltage value of each node has increased.

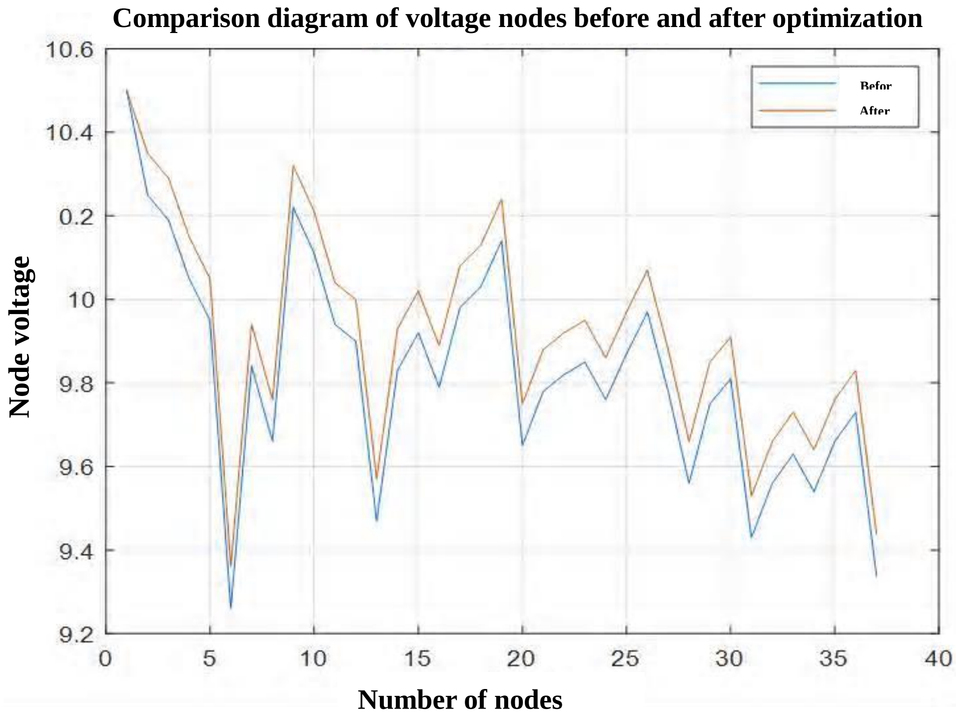

Figure 7 Comparison of node voltages before and after optimization in Scenario 1.

According to the particle swarm optimization algorithm, the compensation strategy is shown in Table 1.

Table 1 Compensation strategy for Scenario 1.

Node number	Compensation capacity / Kvar	Node number	Compensation capacity / Kvar
6	100.1	14	86.1

5.2 Third Category Scenario Optimization

This scenario corresponds to the peak period for residential use, with a total of 4 factories working in the substation area and residential electricity consumption also in peak conditions. There are many nodes at the end of the line that may experience low voltage. The particle swarm optimization algorithm is used to optimize reactive power for this type of scenario.

Figure 8 shows the comparison of node voltages before and after optimization, with the horizontal axis representing the number of nodes and the vertical axis representing the corresponding voltage values of nodes. Due to the peak electricity consumption in this scenario, the voltage values of each node are relatively low. Before optimization, the voltage values of nodes 6, 8, 13, 31, and 37 were all low, with two nodes having voltage values below 9kV. After reactive power compensation, the voltage values of each node were increased.

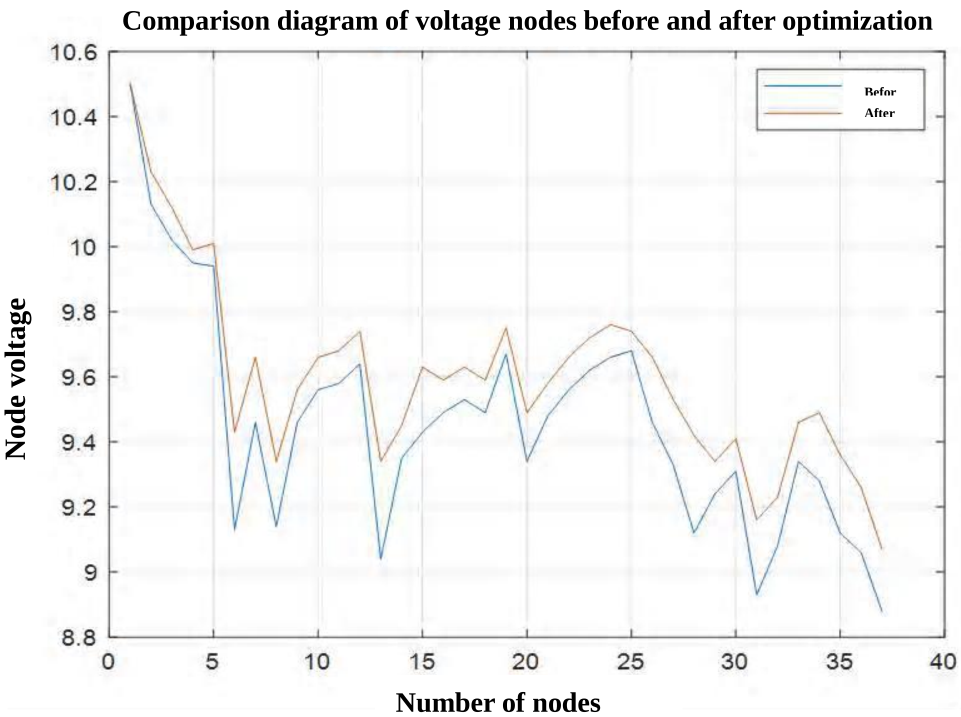

Figure 8 Comparison of node voltages before and after optimization in scenario three.

According to the particle swarm optimization algorithm, the compensation strategy is shown in Table 2.

Table 2 Compensation strategy for Scenario 2.

Node number	Compensation capacity / Kvar	Node number	Compensation capacity / Kvar
7	112.1	13	98.3
21	123.8	29	109.4
37	140.6		

6. Conclusion

This article considers the reactive power optimization strategy for the dynamic load data of the distribution network in the distribution station area. A dynamic load data classification based on the convolutional neural network VGG16 model is established, and the particle swarm optimization algorithm is used for reactive power optimization. The optimization strategy is obtained, and the following conclusion is drawn: compared with the static reactive power optimization of the distribution network, the dynamic load data is classified based on the convolutional neural network VGG16 model, Being able to simulate the actual operating conditions of the substation area comprehensively, and then optimize reactive power through particle swarm optimization algorithm to obtain corresponding optimization strategies. Compared with before optimization, the node voltage has been improved to a certain extent.

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