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Impact of Smart Grid Technology on Power Distribution Efficiency

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Abstract. Traditional smart grids lack real-time data analysis capabilities when processing large-scale data, resulting in insufficient timeliness of power dispatching and fault response. Low load forecasting accuracy affects the accuracy of distribution dispatching and reduces distribution efficiency. This paper proposed a solution that combined PSO (Particle Swarm Optimization) and SVR (Support Vector Regression). PSO optimizes power resource dispatching and minimizes energy consumption under constraints by adjusting the operating status of equipment. SVR predicts future loads through regression analysis of historical load data to provide accurate support for distribution planning. The paper applied the PSO to hyperparameter and penalty factors to improve prediction accuracy. According to the PSO optimization and SVR prediction results, the power grid dispatching plan is adjusted in real time, and the power flow and equipment load are dynamically adjusted to ensure the smooth operation of the system under different loads and improve dispatching efficiency. The experimental results show that the average MSE (Mean Square Error) of SVR under different samples is 0.30, and the average MAE (Mean Absolute Error) is 0.45, with high prediction accuracy. After PSO optimization, the energy saving rate and load balancing rate of the dispatching system under high load conditions increased by 5% and 10% respectively, the dispatching time was shortened by 15 seconds, and the fault response time was shortened by 15 seconds, with higher dispatching efficiency and real-time performance.

Key words. Distribution Efficiency, Particle Swarm Optimization, Smart Grid, Support Vector Regression, Load Prediction

1. Introduction

A. Importance of Context and Subject Matter

The application of smart grid technology is profoundly changing the operation mode and resource allocation of power systems. As one of the core technologies of modern power grids, smart grids integrate information and communication technologies with energy technologies to form a highly automated power management system [1,2]. The key is to achieve reasonable energy allocation and dynamic balance of power supply through accurate load forecasting and efficient resource scheduling, so as to meet the increasingly complex power demand scenarios and provide strong technical support for building a green and low-carbon energy system [3,4]. The smart grid schematic diargam is shown in Figure 1.

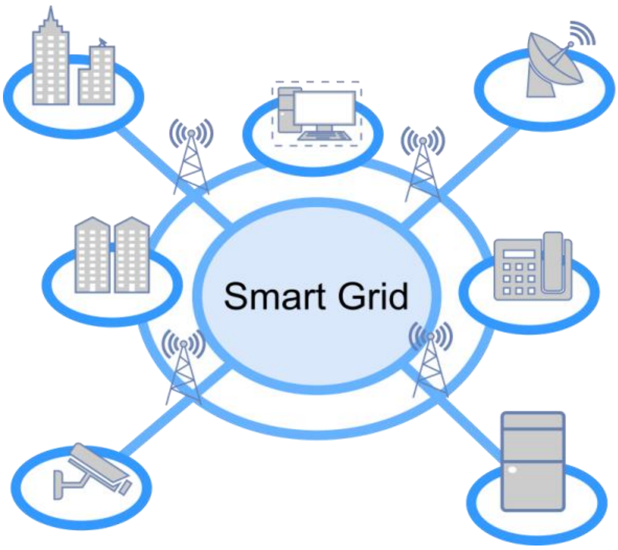

Figure 1. Smart grid schematic diagram.

The current smart grid system has been widely used in power scheduling and resource optimization, but its performance in complex scenarios is still insufficient. Traditional technologies rely on fixed models and linear methods to process power grid data [5,6], ignoring the nonlinear characteristics of power load that change dynamically with multiple factors such as time, weather, and user behavior [7,8], and the prediction results lack accuracy. Especially when peak loads or emergencies occur, existing methods make it difficult to quickly adjust power distribution, which may cause problems such as uneven power supply or equipment overload [9,10].

Smart grids process massive amounts of real-time data, and existing data analysis tools are difficult to match actual needs in computing efficiency [11,12]. When the grid operation environment becomes more complex, with large-scale access to new energy and widespread use of distributed power sources [13,14], the data processing speed and decision-making efficiency of existing methods can be significantly limited. This hysteresis affects the dynamic response capability of the power grid and may also lead to waste of power resources and increase in system operating costs [15,16].

Traditional load forecasting models are mostly based on historical data analysis, but often ignore the deep correlation between environmental variables and user behavior characteristics [17,18]. This method is difficult to adapt to the complex and changeable actual scenarios in power grid operation, resulting in a large deviation between the prediction results and the actual demand, which to a certain extent affects the scientificity and reliability of dispatching decisions [19,20]. Traditional smart grid technology has limitations in nonlinear problem modeling, real-time data processing efficiency, load forecasting accuracy, etc. It is necessary to solve these core bottlenecks by improving technical models and optimization algorithms to better meet the efficient operation requirements of modern power systems.

This study explores how to use intelligent optimization algorithms and machine learning models to redefine the efficiency standards of distribution systems. In the modern power grid environment, data-driven scheduling and load forecasting have become key, and a single algorithm or traditional model is difficult to cope with complex demands and dynamic changes. The study integrates PSO and SVR, innovatively constructs a comprehensive model that can dynamically adapt to variable load demands, and realizes intelligent resource scheduling and precise control of power flow. The innovation of the study is to establish an efficient and flexible distribution optimization method that can deeply mine multi-source data and adjust the power grid operation strategy in real time. PSO is used to optimize the operating status of power grid equipment and minimize system energy consumption while meeting constraints. Compared with traditional genetic algorithms, PSO has better global search capabilities and lower computational complexity; Compared with the traditional PSO-SVR model, the main difference is that a more sophisticated hyperparameter tuning strategy is adopted, which combines real-time load forecasting with dynamic scheduling optimization to improve the accuracy and efficiency of the distribution system in practical applications. combined with SVR, it provides accurate load data support for power grid dispatching. Through multi-algorithm collaborative optimization, a closed-loop improvement from data to decision-making is achieved, allowing the distribution system to achieve efficient operation and stable control under high load and dynamic demand scenarios, providing more practical theoretical and methodological support for smart grid technology.

B. Related Work

In smart grid research, many scholars have proposed various methods to improve the efficiency of power distribution and the accuracy of power dispatching. Some studies proposed load forecasting methods based on neural networks, using historical load data to train models and make forecasts [21,22]. Sun C proposed a short-term load prediction framework, in which the learning module automatically obtained the relationship between variables, and can also effectively deal with time and spatial dependence, with excellent prediction accuracy on the data set [23]. These methods have high computational complexity when processing large-scale data, resulting in inaccurate prediction results. Some studies have proposed a power dispatch optimization method based on genetic algorithm, which has achieved certain distribution optimization effects by optimizing the operating status of each device in the power grid [24,25]. Wang X proposed an improved optimal dispatch strategy for hybrid ship power system based on genetic algorithm, which is used to optimize the coordinated work of diesel generators, energy storage systems, propulsion systems, dynamic loads and photovoltaic power generation devices, and to a certain extent improves the performance of dispatch optimization and global optimization capabilities [26]. This method relies on a lot of computing time and cannot respond to load changes in real time, which affects its application in actual power grids. Although current research has proposed a variety of improvement schemes, most methods have problems such as complex calculations, poor real-time performance, and insufficient prediction accuracy. A more efficient and accurate solution is needed.

Some scholars have tried to apply SVR [27,28] into smart grids to solve the shortcomings of traditional methods. Some scholars have used SVR to optimize smart grids and achieved good prediction results, showing high accuracy in load forecasting [29,30]. Yao H explored the application of SVR model in cooling load prediction, and used crystal structure algorithm and reptile search algorithm to optimize and improve the accuracy of the model. The SVR model combined with the optimization algorithm can effectively obtain the nonlinear relationship between building parameters and cooling load [31]. These methods still face the problem of adaptability when dealing with complex power grid environments, especially when the power grid load changes greatly, the prediction accuracy and scheduling efficiency may decrease. The prediction accuracy and dispatching efficiency may decrease. In the modern power grid environment, a single algorithm or traditional model is difficult to cope with complex demands and dynamic changes. This study integrates PSO and SVR to innovatively construct a comprehensive model that can dynamically adapt to variable load demands and realize intelligent resource scheduling and precise flow control.

2. Methods

A. PSO Algorithm Optimizes Load Scheduling

PSO [32] is used to optimize the scheduling of power resources in the distribution system. The fitness function is defined, and PSO adjusts the operating status of each device. The system minimizes energy consumption and improves distribution efficiency under the premise of satisfying constraints.

1) Definition of Fitness Function and Constraint Setting of PSO Algorithm

When the PSO algorithm optimizes the load scheduling of the distribution system, it is necessary to construct a reasonable fitness function to evaluate the quality of the solution. The design of the fitness function directly affects the convergence and accuracy of the optimization process, and must accurately express the energy efficiency and constraints of the system; for the power resource scheduling problem, the fitness function can be expressed as the following formula:

$$F\left(\mathbf{x}\right)=\alpha\cdot\sum_{i=1}^{N}C_iP_i+\beta\cdot\sum_{j=1}^{M}L_j\left(x_j\right) \quad (1)$$

C_i is the power consumption coefficient of the equipment, P_i is the power output of the equipment i, L_j is the load constraint, x_j is the adjustment variable of the load demand, and α and β are weight factors. In this way, the fitness function considers the minimization of energy consumption and also integrates the constraints of load demand to ensure that the scheduling plan minimizes energy consumption while meeting the constraints of power grid operation.

The constraints in load scheduling include the maximum power output limit of the equipment, the power transmission capacity limit of the power grid, and the time sequence change constraint of the load demand; the maximum power output of equipment i is $P_{i_{\max}}$, and the constraint based on the maximum power output can be expressed as:

$$P_i\le P_{i_{\max}},\quad \forall i=1,2,\cdots,N \quad (2)$$

The load demand of the distribution system should meet the fluctuation range of the real-time load. Assuming that the load demand range is $L_{\min}\le L_j\le L_{\max}$, the dispatch output of each device can be further constrained to meet the changes in real-time load demand.

2) Particle Update and Scheduling Optimization Process

The particles are updated and the speed and position are constantly adjusted to find the optimal solution of the fitness function. In the power resource scheduling problem, the position of the particle represents the scheduling state of the power equipment, and the speed of the particle represents the adjustment direction and amplitude of the equipment state. The particle's position vector is $\boldsymbol{x}=\left(x_1,x_2,\cdots,x_N\right)$, the velocity vector is $\boldsymbol{v}=\left(v_1,v_2,\cdots,v_N\right)$, N is the number of devices, and the PSO update formulas are as follows:

$$v_i\left(t+1\right)=w\cdot v_i\left(t\right)+c_1\cdot r_1\cdot\left(p_i-x_i\left(t\right)\right)+c_2\cdot r_2\cdot\left(g_i-x_i\left(t\right)\right) \quad (3)$$

$$x_i\left(t+1\right)=x_i\left(t\right)+v_i\left(t+1\right) \quad (4)$$

w is the inertia weight, c_1 and c_2 are acceleration constants, r_1 and r_2 are random numbers, p_i is the historical optimal position of the i th particle, and g_i is the optimal position of the group. The PSO adjusts the speed and position of the particles to efficiently search for an optimized load scheduling scheme.

The update of particles in scheduling optimization is calculated based on fitness. The position of particles can be adjusted to a more appropriate load range under load overload to avoid energy waste. PSO also needs to dynamically adjust the scheduling status of each device to ensure a smooth transition of the device load and avoid power shortages or equipment damage caused by sudden load changes.

PSO combines load forecast information in optimization and uses historical load data and real-time load demand to adjust the search strategy of particles. Dynamic adjustment of the search space of particles can quickly respond to fluctuations in load demand. PSO can quickly adjust the operating state of the equipment, and use the feedback mechanism to optimize the scheduling strategy, so that the system can achieve smooth operation under different load demand conditions.

The advantage of PSO lies in its strong global search [33] capability. The introduction of randomness can avoid falling into the local optimal solution and provide a more reliable solution in the case of large-scale power scheduling. Combined with the results of power grid load forecasting, the application of PSO algorithm in power scheduling improves the accuracy of scheduling, enhances the adaptability of the system in actual operation, and can flexibly respond to power distribution needs under different working conditions.

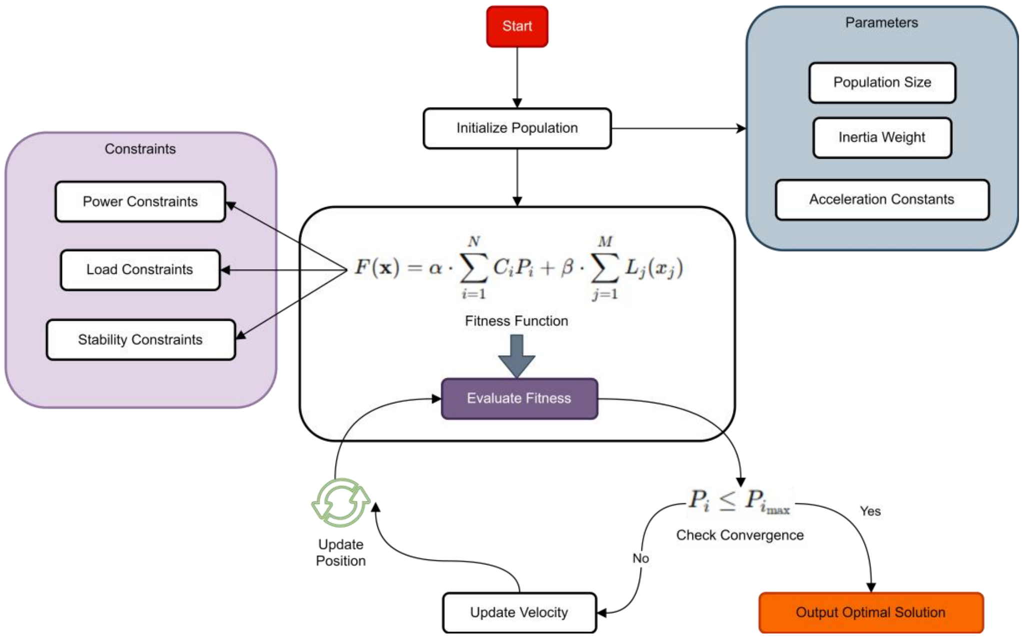

Figure 2. PSO optimization process.

The PSO's application process is consisely shonwn in Figure 2. The initial solution is generated by initializing the particle swarm, and the performance of each particle is evaluated by the fitness function. The fitness function combines the power constraints, load constraints and system stability constraints in the power system to ensure that the optimization process meets the actual operation requirements. The algorithm updates the speed and position of the particles according to the evaluation results, and adjusts the particle position to make it closer to a better solution. The inertia weight and acceleration constant in the update process control the movement of the particles to improve the search efficiency. The algorithm checks whether the convergence conditions are met. If the conditions can be met, output the optimal solution, otherwise, continue to iterate.

B. SVR Algorithm for Load Forecasting

1) Construction and Training of Load Forecasting Model

The historical load data were subjected to the regression analysis. Let the historical load data be $D=\{(x_1,y_1),(x_2,y_2),\cdots,(x_N,y_N)\}$, where x_N represents the input features of the historical time period and y_N represents the corresponding load value. Appropriate features can be selected as input data to improve the accuracy of load forecasting, and they can be standardized to ensure that the model can converge smoothly at different feature scales; preprocessing of data reduces the impact caused by dimensional differences.

In the stage of building a load forecasting model, the goal of SVR is to optimize the hyperplane to minimize the error between the predicted value and the actual value. Given an input vector and a target output, the SVR model obtains the optimal hyperplane by solving the following optimization problem:

$$\min_{\boldsymbol{w},b,\epsilon} \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{N}\epsilon_i \quad (5)$$

$\boldsymbol{w}$ is the normal vector of the hyperplane, b is the bias term, C is the penalty factor, and ϵ_i is the error tolerance, which represents the deviation between the predicted value and the actual value. The goal of this optimization problem is to balance the complexity of the model and the degree of fit of the training data to ensure that the regression model finds a suitable balance between accuracy and generalization ability.

SVR introduces kernel functions in real training to solve the nonlinear regression problem. Common kernel functions include the radial basis function kernel, and the calculation formula is:

$$K(x,x') = \exp\left(-\frac{\|x-x'\|^2}{2\sigma^2}\right) \quad (6)$$

The kernel technique enables SVR to effectively handle nonlinear relationships. The load forecasting can more accurately obtain the complex patterns of load data and avoid the limitations of simple linear regression in dealing with nonlinear problems.

SVR has a strong mapping capability for high-dimensional feature space and can effectively handle nonlinear relationships. Power grid load data usually has complex nonlinear patterns. By selecting appropriate kernel functions, SVR can extract key trends and laws under limited samples. SVR performs relatively stably in a small amount of training data, avoiding overfitting, and is suitable for the data characteristics in power grid load forecasting.

2) Regression Analysis and Result Output of Load Forecasting

The new load data is analyzed by regression and the predicted value is generated. In practical application, the load data of the current period is input. SVR can output the corresponding load forecast value as the load prediction result for a period of time in the future. SVR predicts future load requirements based on patterns learned from historical data.

The output of SVR in the prediction is expressed by the following formula:

$$\hat{y} = \boldsymbol{w}^{\mathrm{T}}\phi\left(x\right)+b \quad (7)$$

The above method allows SVR to accurately predict the future load demand within a given period of time and provide accurate load data support for the distribution dispatching system. SVR analyzes the temporal characteristics and change patterns of historical load data, and can predict the load demand of the power system in the future period. This prediction result can help power companies optimize the dispatch of power resources, improve the stability of the power grid, and reduce the risk of power shortage caused by load fluctuations.

C. PSO and SVR Algorithm Parameter Tuning

1) Kernel Function Parameter Optimization

The selection and parameter setting of kernel function in SVR play a crucial role in prediction accuracy. It is necessary to optimize the kernel function parameters in SVR to improve performance. The common kernel function is radial basis function [34,35], and its performance is affected by kernel width. Using PSO algorithm, the optimal kernel function parameters can be efficiently searched, which can improve the prediction accuracy of SVR model to a certain extent.

The PSO algorithm simulates the process of bird flocks foraging for global search; each particle represents a possible solution and is updated by its position and velocity. For kernel function parameter optimization, the goal of the PSO algorithm is to minimize the SVR prediction error. In each iteration, the position of the particle is $\boldsymbol{p}_i = \left(\sigma_i\right)$, and the goal is to find the optimal σ so that the following optimization problem is optimally solved:

$$\min_{\sigma}\frac{1}{N}\sum_{i=1}^{N}\left(y_i - f\left(x_i;\sigma\right)\right)^2 \quad (8)$$

$f\left(x_i;\sigma\right)$ represents the SVR prediction function based on the current σ parameters, y_i is the actual value, x_i is the input feature, and N is the number of samples. The particle swarm evaluates the fitness value of each particle position and guides the movement of particles through the fitness function, so that the particles gradually approach the optimal kernel function parameters.

If the algorithm converges to a local minimum value, it may lead to suboptimal solutions, thus affecting the overall optimization effect. Each particle continuously updates its position and speed in PSO optimization in order to find the best kernel function parameters in the search space. This change effectively avoids the local optimal solution problem that traditional methods may face, and improve SVR's ability to fit load data and prediction accuracy.

2) Penalty Factor Optimization

The penalty factor in SVR [36,37] also has a profound impact on the prediction effect of the model. The penalty factor controls the tolerance for training error and affects the degree of fit of the model to the training data. Smaller values allow for larger training errors, but may also lead to underfitting; larger penalty factor values can lead to overfitting of the model. Reasonable selection of the penalty factor value is very important for the adaptability of SVR.

The PSO algorithm is also applied to this process to accurately select the penalty factor. Explore the different $\left(C,\sigma\right)$ pairs in the search space, and evaluate the fitness of the particles to find the best parameter combination. The objective function is:

$$\min_{C,\sigma}\frac{1}{N}\sum_{i=1}^{N}\left(y_i - f\left(x_i;C,\sigma\right)\right)^2 + \lambda C \quad (9)$$

λ is a regularization parameter used to control the impact of the penalty factor on the model. This objective function takes into account the model fitting error and the regularization term. PSO uses the global search strategy to optimize C and σ in turn to optimize the prediction accuracy and adaptation of SVR.

The particle position and velocity at each iteration can be updated. The position of the particle represents the current parameter combination $\left(C,\sigma\right)$, and the speed determines the jumping distance of the particle. Continuous iteration enables the particle population to find the global optimal solution, and the optimized parameters give SVR higher prediction reliability in load prediction tasks.

The penalty factor of SVR is effectively optimized after

PSO optimization. In the actual power grid load prediction, this optimization can provide high precision prediction results under the variable load demand, and provide reliable data support for the subsequent distribution dispatching.

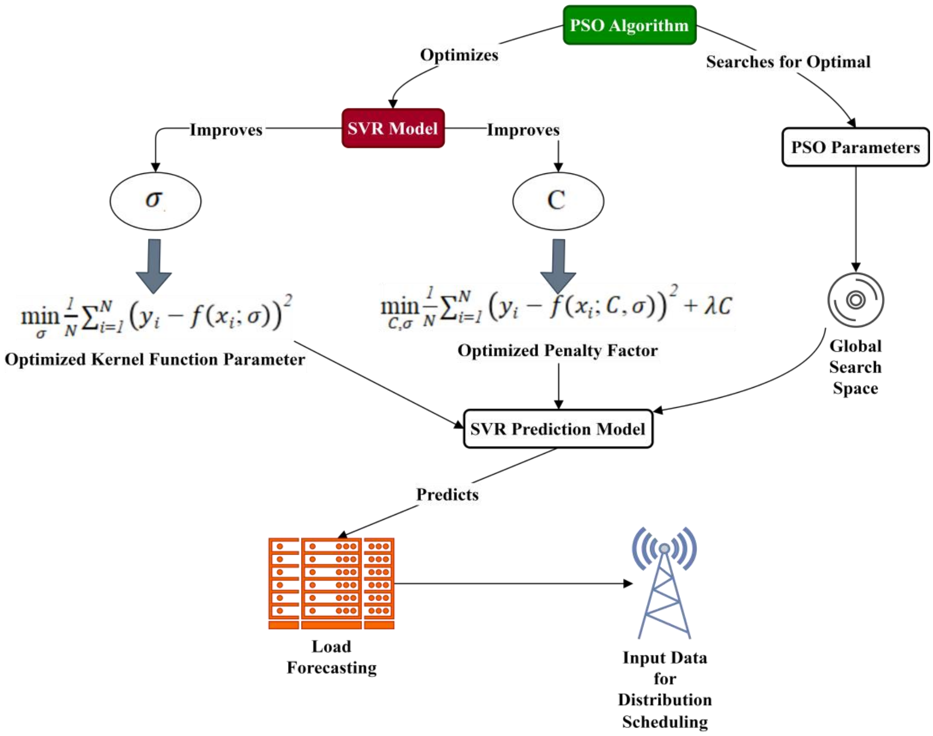

Figure 3. PSO and SVR collaborative workflow.

Figure 3 shows the collaborative working process of PSO and SVR in power grid load forecasting. PSO optimizes the kernel function parameters and penalty factors of SVR through global search to improve the prediction accuracy of SVR; the optimized kernel function parameters and penalty factors respectively improve the ability to fit the data and avoid the risk of overfitting. The parameter-optimized SVR can accurately predict the future power grid load and provide reliable data support for distribution scheduling; the load forecast results become the input data for distribution system scheduling, ensuring that the power grid can operate efficiently and smoothly under different load demands. By combining PSO optimization with SVR, this solution effectively improves the dispatching efficiency of the power distribution system, allowing the power grid to respond quickly when facing dynamic load demands.

D. Dynamic Dispatching Optimization and Load Adjustment Implementation

1) Power Flow Adjustment

The real-time adjustment of power flow direction is a key step to ensure the smooth operation of the distribution system. Real-time load forecasting obtains the future load change trend, and combined with the current power grid status, determines the load demand of each area and equipment. The PSO optimization results are used to reasonably dispatch power resources to ensure that the power grid can effectively respond under different load demands.

The adjustment process of power flow involves multi-objective optimization problems. The goal is to minimize distribution losses and ensure the stability of the power grid. The objective function of the system is defined as follows:

$$\min_{P_{ij}} \sum_{i=1}^{N}\sum_{j=1}^{N}\left(r_{ij}P_{ij}^2 + q_{ij}\right) \quad (10)$$

P_{ij}^2 represents the square of the power flow from node i to node j, r_{ij} is the line resistance between node i and node j in the power grid, and q_{ij} is the corresponding reactive power loss. Dynamically adjusting the power flow and optimizing the objective function can ensure the minimization of energy loss. Under the premise of meeting the load demand, optimizing power distribution can improve the distribution efficiency and system stability to a certain extent.

In actual implementation, PSO adjusts the power flow in real time and connects the load demand with the actual state of the power grid. When the load demand of a certain part increases, the PSO algorithm adjusts the power flow according to the current power grid topology and equipment operation status, so that the power is allocated from the lightly loaded area to the heavily loaded area. This process can respond to load demand fluctuations in real time and reduce power waste caused by power imbalance.

2) *Dynamic Adjustment of Equipment Load*

Dynamic adjustment of equipment load is an essential part of improving the dispatching efficiency of distribution system. Based on load forecasting and power flow adjustment, dynamic adjustment of equipment load ensures that each equipment can be optimally configured according to real-time conditions under different load demands. Based on real-time data and forecast results, a constraint-based optimization model is used to adjust the load of each equipment.

Assume that there are multiple devices in the power grid, and the load of each device can be represented by $L_i(t)$. The goal is to adjust the device load so that the system can minimize the total energy consumption while satisfying various operating constraints. The device load optimization problem can be expressed as:

$$\min_{L_i(t)} \sum_{i=1}^{M} \left(\alpha_i L_i(t)^2 + \beta_i \right) \quad (11)$$

$L_i(t)$ represents the load of device i at time t, and α_i and β_i are the load weight coefficients of the device. The load of the device is adjusted in real time to optimize the operating status of the device, ensuring that each device can operate efficiently and avoiding device damage or performance degradation caused by load imbalance.

The algorithm optimizes and adjusts the load of each device according to the real-time load demand and the state of the power grid to achieve dynamic adjustment of the equipment load. Equipment load adjustment needs to take into account the changes in the current load, and also needs to perform forward-looking scheduling according to the state of the power grid to ensure that the system's load fluctuations can be responded to smoothly. The algorithm adjusts the load distribution of each device during optimization. The system can respond quickly when the load increases or decreases, and adjust the load of the equipment to minimize the total energy consumption of the system and improve scheduling efficiency.

Combining the PSO optimization results with the future load data predicted by SVR, the dynamic adjustment of equipment load can track the changes in load demand in real time, adjust the operating status of power grid equipment, reduce energy waste, and improve the dispatching efficiency of the distribution system. This strategy ensures that the power grid can operate in an efficient and stable manner when facing different load demands, providing support for the long-term stability and efficient operation of the power system.

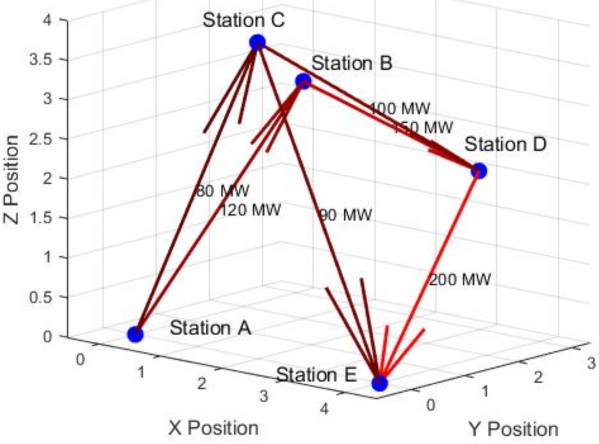

Figure 4. Topology of power transmission network.

Figure 4 shows the topology of power transmission network between substations. Arrows connect different nodes, representing the transmission path of power. The color of the arrows reflects the size of the power flow. The arrows with larger flow are redder. The data also marks the power flow of each line. The intuitive display of these power flows and flows can clearly show the distribution of power between nodes in the distribution system, helping to analyze the power dispatching efficiency and system stability under different load demands.

3. Method Effect Evaluation

A. *Evaluation of Hyperparameter Adjustment Effect and Load Forecasting Accuracy*

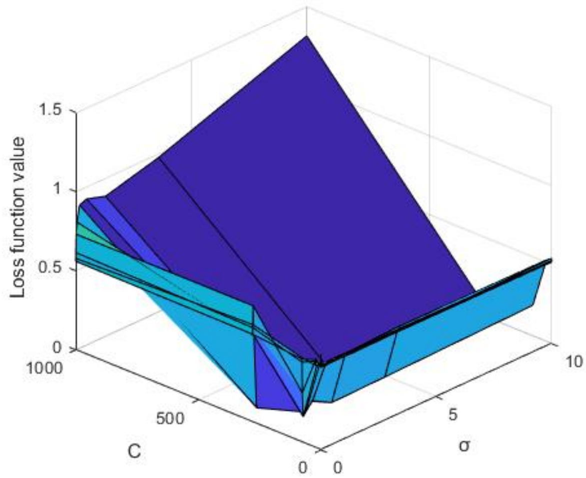

Figure 5. SVR hyperparameter adjustment.

Figure 5 shows the prediction error of the SVR model under different hyperparameter combinations. The determining factors are the kernel width parameter σ and the penalty factor C, and the z-axis represents the loss function value. As C and σ change, the error value shows a certain pattern. When C is too large or too small, the error value is high, and the model may be overfitting or underfitting; under certain specific C and σ combinations, the error is small, indicating that the model has a good fitting effect and high prediction accuracy. This data change can help find the appropriate hyperparameter range, which helps provide guidance for parameter tuning of the SVR model and ensure the accuracy and stability of load forecasting. Optimizing these parameters can significantly improve the accuracy of load forecasting in the distribution system, thereby optimizing the efficiency of power dispatching.

Table 1. Hyperparameter adjustment.

Experiment No.	C Value	σ Value	Optimization Effect
1	1	0.01	Poor
2	10	0.05	Medium
3	20	0.1	Medium
4	50	0.5	Good
5	100	1	Optimal
6	200	2	Good
7	500	5	Medium
8	1000	10	Poor

Table 1 shows the hyperparameter adjustment results under 8 different combinations of C and σ values. By comparing the optimization results of each group of experiments, it can be seen that the changes in the optimization results show a certain pattern. Experiment 5 (C =100, σ =1) performed best among all experiments, with the best prediction performance and the smallest error, and was considered to be the optimal hyperparameter combination. Other combinations performed poorly and failed to provide ideal optimization results.

MSE and MAE are used as the main evaluation indicators to evaluate the load forecasting accuracy of the SVR model. MSE can quantify the average deviation between the predicted value and the true value. The smaller the MSE value, the higher the prediction accuracy of the model; MAE provides the average absolute value of the prediction error, which more intuitively reflects the actual error size of the model. These two indicators are used for comprehensive evaluation to fully understand the prediction performance of SVR.

The experiment compares SVR with popular prediction models such as XGBoost (eXtreme Gradient Boosting), LightGBM (Light Gradient Boosting Machine) and GBR (Gradient Boosting Regression). The hyperparameters of each model can be optimized to ensure their best performance in the task. The evaluation is based on the same data sample to ensure the fairness and consistency of the results; the MSE and MAE values of each model are calculated during the experimental phase to analyze the accuracy and error of each model in load forecasting. The data set used in the experiment comes from a power grid operator in a certain region. The historical load data covers information such as daily load, weekly load and seasonal load changes, with a total of more than 5,000 records. The data set includes load changes in different time periods, weather conditions, holidays and other factors. It has high diversity and representativeness and can reflect the real fluctuation characteristics of the power grid load. All datasets used have been properly anonymized in the experiments and have been authorized for use by the relevant data providers. To ensure the robustness of the evaluation results, a 10-fold cross validation was used to divide the data set into 10 subsets. Nine of the subsets were used for training each time, and the remaining subset was used for testing. This process was repeated 10 times to ensure that the prediction model with the best performance was selected.

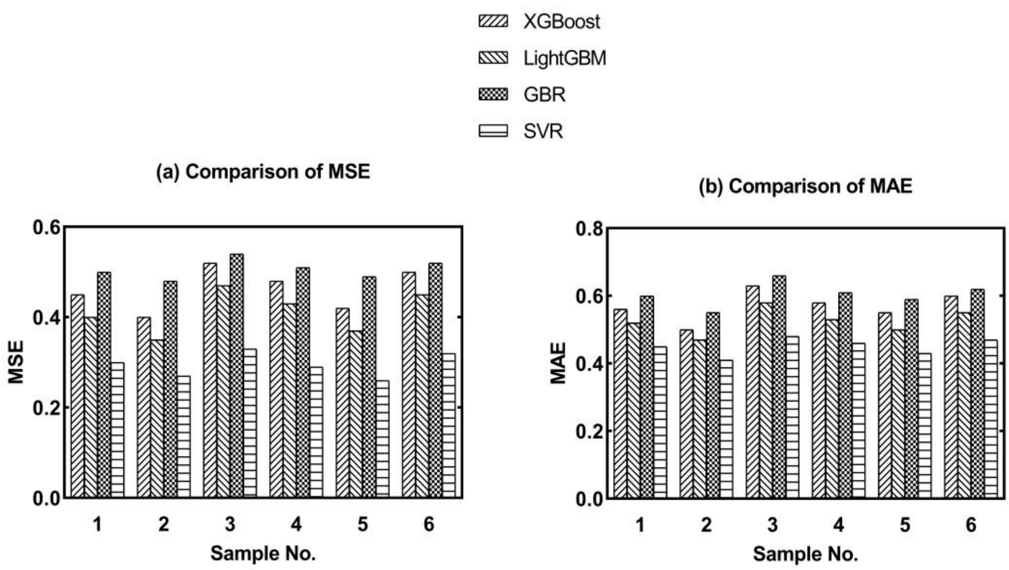

Figure 6. Comparison of MSE and MAE of different models.

Figure 6 shows the MSE and MAE performance of XGBoost, LightGBM, GBR and SVR on different samples. The SVR algorithm shows the best prediction accuracy in both indicators. The MSE and MAE values are lower than those of other algorithms, with an average MSE of about 0.30 and an average MAE of 0.45. The error value of SVR is relatively stable and always remains in a low range, indicating its accuracy and reliability in load forecasting tasks. In contrast, XGBoost, LightGBM, and GBR have large errors in performance in different samples, and the MSE and MAE values are generally high, showing the shortcomings of these algorithms in load forecasting. XGBoost and GBR exhibit MAE above 0.6 in some samples, while SVR remains below 0.5, proving its advantage in prediction accuracy. It can see the superior performance of SVR in power grid load forecasting through these data. After parameter tuning, it can provide more accurate load forecasting results and improve the efficiency and stability of power dispatching.

B. Fitness Value Change and Evaluation of Dispatching Efficiency

Table 2 shows the changes in fitness values in particle swarm optimization, combined with confidence intervals and p-values for analysis. The best fitness value drops from 450 to 200, and the average fitness value and the worst fitness value also show a corresponding downward trend. This change shows that PSO can effectively optimize the load scheduling scheme and gradually approach the optimal solution. The values of the confidence interval show that as the optimization process progresses, the fluctuation of the fitness value gradually decreases, and the system stability and optimization effect are improved. Comparing the p-values of different iterations, it is found that from the 50th iteration, the optimization effect is statistically significant, $p < 0.05$, and the improvement of the optimization effect at the 100th, 150th and 200th iterations is more significant, $p < 0.02$. These results verify the effectiveness of PSO in load scheduling optimization and prove the ability of the algorithm to gradually improve system performance and save energy and reduce consumption in the process of power resource optimization. The PSO algorithm gradually optimizes the scheduling scheme and improves the scheduling efficiency and stability of the system.

The energy saving rate and load balancing rate are used as the main evaluation indicators to evaluate the scheduling efficiency in the distribution network. The energy saving rate is used to measure the percentage of energy consumption reduction under the optimized scheduling scheme compared with the traditional scheduling method; the load balance rate reflects the reasonable distribution of power resources among various devices to ensure the balance and stability of load distribution. The evaluation can compare the power scheduling before and after PSO optimization. Based on the results of the traditional scheduling method and the PSO optimization method, the energy saving rate and load balance rate are calculated respectively to quantify the advantages of the optimization algorithm in improving scheduling efficiency. The same distribution network environment is used in the experiment to ensure the consistency of the comparison of different scheduling methods. Through multiple rounds of experimental verification, the performance of the scheduling scheme after PSO optimization in energy saving and load balancing is analyzed, and a direct comparison is made with the scheduling method before optimization to comprehensively evaluate the efficiency of the scheme.

Table 2. Changes in fitness values with Confidence Intervals (CI).

Iteration	Best Fitness Value (95% CI)	Average Fitness Value (95% CI)	Worst Fitness Value (95% CI)	p-value
20	450 (±10)	460 (±12)	480 (±15)	<0.1
50	300 (±8)	320 (±9)	350 (±11)	<0.05
100	250 (±7)	265 (±6)	280 (±10)	<0.02
150	230 (±6)	240 (±5)	260 (±9)	<0.01
200	200 (±5)	210 (±4)	230 (±8)	<0.01

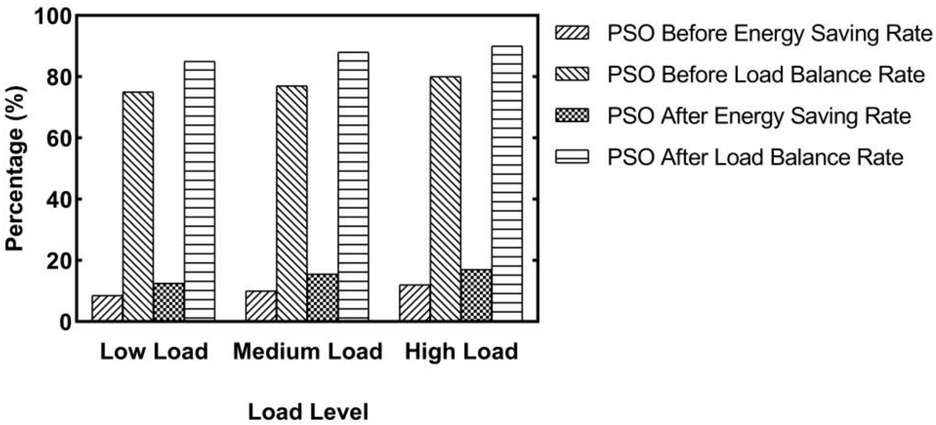

Figure 7. Comparison of energy saving and load balance before and after PSO optimization.

Figure 7 shows the changes in energy saving rate and load balance rate before and after PSO optimization under different load conditions. After PSO optimization, the energy saving rate and load balance rate increased by 4% and 10% respectively at low load. Under medium load conditions, the energy saving rate and load balance rate increased by 5.5% and 11% respectively. The energy saving rate and load balancing rate at high load increased by 5% and 10%. These changes show that the PSO optimization method has a preliminary effect at low load, and the optimization effect is also more significant at medium and high load, which improves the scheduling efficiency and stability of the system. PSO optimization effectively reduces energy waste and, to a certain extent, ensures that power resources are more evenly distributed when load fluctuations are large, thus improving the overall performance of the system.

C. *Real-time Analysis*

The real-time performance of the power dispatching system is evaluated mainly through two indicators: dispatching time and fault response time. Dispatching time measures the time required from load forecasting to dispatching decision completion, reflecting the system's response speed when facing load changes. Fault response time evaluates how quickly the system can complete fault detection, diagnosis and recovery dispatch after a fault occurs, ensuring the stable operation of the power grid. In the evaluation, the dispatching system before and after PSO optimization is compared, and the dispatching time and fault response time are recorded respectively. The system's ability to cope with sudden load fluctuations or faults before and after optimization is analyzed experimentally to evaluate its real-time response capability. The experiment can cover different load conditions to ensure the comprehensiveness of the evaluation results. Compared with the dispatching system before PSO optimization, the advantages of PSO optimization scheme in improving the real-time performance of dispatching can be verified.

Figure 8 shows the changes in scheduling time and fault response time before and after PSO optimization under different load levels. As the load level increases, the scheduling time and fault response time before PSO optimization both increase. Compared with before PSO optimization, the scheduling time and fault response time after PSO optimization are significantly reduced. Under low load conditions, PSO optimization reduced the dispatch time and fault response time by 10 seconds each; under medium load conditions, both were reduced by 10 seconds after optimization; under high load conditions, the dispatch time was reduced by 15 seconds and the fault response time was also reduced by 15 seconds. From these data, PSO optimization has greatly improved the system's dispatching time and fault response speed, and the optimization effect is more prominent under high load conditions, showing the real-time advantage of this method in the dispatching of distribution systems, which helps to ensure that the system can operate efficiently and stably under various load conditions.

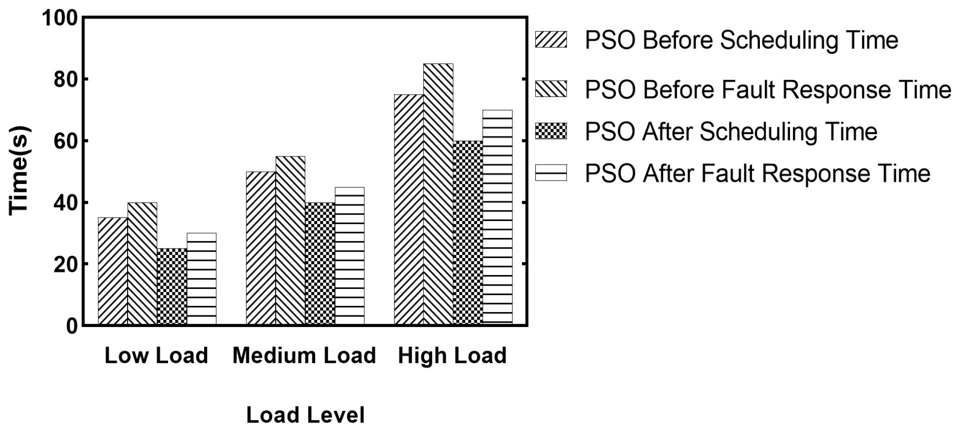

Figure 8. Comparison of scheduling time and fault response time before and after PSO optimization.

4. Conclusions

The power grid dispatch optimization scheme combining PSO and SVR proposed in this paper effectively solves the real-time and load forecasting accuracy problems of traditional smart grid technology when processing large-scale data. PSO can be used to optimize the scheduling of power resources, minimize energy consumption and improve distribution efficiency while meeting various constraints. SVR can be used for load forecasting, providing accurate data support for power grid scheduling and ensuring the scientificity and accuracy of the scheduling plan. The experimental evaluation compared the performance of the system before and after PSO optimization. The results showed that the optimization scheme showed significant advantages in dispatching efficiency, load balance and real-time performance. After refined hyperparameter adjustment and real-time load forecasting, the joint optimization of PSO and SVR effectively improved the real-time performance of the power grid dispatching system, shortened the dispatching time and fault response time, and enhanced the emergency response capability and stability of the system. The evaluation results of multiple indicators prove that this optimization scheme not only ensures the efficient operation of the power grid, but also achieves the rational use of energy and real-time dispatch response.

The grid dispatching scheme based on PSO and SVR optimization provides new ideas for load forecasting and dispatching optimization of modern smart grids, and provides an effective solution for improving grid operation efficiency, reducing energy consumption and increasing system response speed. Future research can further explore the combination with other intelligent optimization algorithms and prediction models. In addition to PSO, ant colony algorithm, differential evolution algorithm, simulated annealing algorithm and grey wolf optimization algorithm can also be applied to power grid dispatch optimization. These algorithms have different search strategies and exploration capabilities. They can be combined with PSO according to the characteristics of the problem to improve the optimization effect or overcome the local optimal problem of PSO in certain scenarios, thereby improving the adaptability and stability of the system in more complex environments. In the delay problem in real-time systems, power grid dispatch optimization requires processing a large amount of dynamic data. Real-time calculations and decisions may cause system delays and affect dispatch efficiency. How to reduce delays while ensuring optimization effects will be a key direction for further research.

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Author Contribution

[Dong Lv]: Developed and planned the study, performed experiments, and interpreted results. Edited and refined the manuscript with a focus on critical intellectual contributions.

[Yuanqing Pan, Yijie Xia]: Participated in collecting, assessing, and interpreting the date. Made significant contributions to date interpretation and manuscript preparation.

[Xiaolin Liu, Lingjie Wu]: Provided substantial intellectual input during the drafting and revision of the manuscript.

Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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