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Adaptive Unscented Kalman Filter Dynamic State Estimation Method for Distribution Network Based on Dynamic Interval Optimization

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Abstract. With the rapid development of smart grid technology, the distribution network, as the core part of the power system, is facing more and more challenges. Traditional distribution network state estimation methods are mostly based on static models, which dynamic changes such as load fluctuations and equipment failures in the power grid. In order to improve the accuracy and real-time performance of dynamic state estimation of distribution network, this paper proposes an adaptive unscented Kalman filter dynamic state estimation method of distribution network based on dynamic interval optimization. This unscented Kalman filter can deal with nonlinear and multivariable dynamic systems. Through dynamic interval, it accurately estimates the running state of dynamic state estimation of distribution demand during distribution operation constructs the mathematical of dynamic state estimation based on this demand. To improve the accuracy and real-time performance of dynamic state estimation in distribution networks, this paper proposes an adaptive unscented Kalman filter dynamic state estimation method based on dynamic interval optimization. Improved UKF refers to adaptive UKF based on dynamic interval optimization, which enhances adaptability to nonlinear systems and dynamic disturbances by adjusting the noise covariance matrix and filtering gain in real-time. This algorithm uses a dynamic interval optimization strategy to automatically adjust UKF parameters to adapt to real-time changes in the operating status of the distribution network, significantly improving estimation stability and accuracy. Compared with traditional methods, the estimation error of the proposed adaptive unscented Kalman filter method is reduced by about 18%, and the computational efficiency is improved by 25%. This paper further discusses the application prospect of this method in large-scale distribution network, and puts forward the future optimization direction, such as the applicability in multi-level and multi-regional distribution network and the parallel optimization of the algorithm. This method has high practical value and intelligence level of distribution network. The experiment shows that compared with traditional UKF, this method reduces the maximum error from 5.45% to 2.47% in a 50 node network, shortens the average computation time from 4.2 seconds to 3.1 seconds, and reduces the fault recovery time to less than 3 seconds.

Key words. Maximum correntropy criterion, Sigma points, Non-Gaussian noise, Load transients, Fault recovery time, Multi-level distribution network

1. Introduction

With the intelligence and complexity of the power system, the distribution network is an important link of power transmission and distribution, and its accurate monitoring and dynamic estimation of its running state have become increasingly critical. Traditional distribution network state estimation methods mostly rely on static models, which makes it difficult to cope with the rapid changes of modern distribution networks under load fluctuations and equipment failures [1]. Especially after the connection of new loads, such as distributed energy and smart home appliances, the operating environment of the distribution network is more complex. Therefore, how to obtain the running state of the distribution network in real-time and accurately in the dynamically changing power grid environment has become an important topic in power system dispatching and management.

Distribution network dynamic state estimation (DSE), a technology that reflects the changes in the power grid operating state in real-time, has become a key tool to ensure the power grid's stable operation and efficient dispatch [2]. Compared with traditional static estimation methods, dynamic state estimation can consider the influence of load fluctuations, equipment failures, and other external disturbances and provide more accurate power grid operation information [3]. However, dynamic state estimation faces many challenges, including nonlinear system modeling, measurement noise, computational complexity, and other issues, which often make it difficult for existing algorithms to maintain high estimation accuracy and computational efficiency when dealing with large-scale distribution networks.

Traditional state estimation methods, such as EKF and UKF, although well applied in simple distribution networks, often face significant challenges in complex and dynamically changing distribution systems. Traditional methods typically rely on linearization and fixed noise assumptions, which can lead to significant estimation errors and lack sufficient adaptability in nonlinear systems and time-varying environments [4].

The dynamic interval optimization method can flexibly respond to the nonlinear characteristics and environmental changes of the system based on the actual operating status of the distribution network by adjusting the filtering parameters of the UKF in real time [5]. This method improves estimation accuracy, enhances robustness, and optimizes computational efficiency, providing a more accurate and reliable solution for efficient state estimation of distribution networks and meeting the dynamic and precise monitoring needs of smart grids.

As a powerful nonlinear state estimation method, Unscented Kalman Filter (UKF) can better deal with nonlinear characteristics and complex dynamic processes in distribution networks, so it has been widely used in dynamic state estimation of distribution networks. UKF solves the limitation of traditional Kalman filters in nonlinear systems by introducing unscented transform, improving state estimation accuracy. However, in practical applications, the UKF algorithm is highly sensitive to the selection of parameters. If the parameters are not set properly, it may lead to unstable estimation accuracy or excessive computational overhead. Therefore, how to optimize the UKF algorithm to improve its adaptability in dynamic environments is an important issue.

This paper proposes an adaptive UKF dynamic state estimation method based on dynamic interval optimization. Through a dynamic interval optimization strategy, this method automatically adjusts the parameters in the UKF algorithm so that it can adapt to the changes in the distribution network running state in real-time and significantly improves the stability and accuracy of estimation. This method provides a new solution for improving the dynamic state estimation accuracy and operation efficiency of the distribution network and lays a foundation for the future development of smart grid.

Existing research has optimized battery state estimation through adaptive UKF, but has not solved the problem of parameter drift under dynamic loads; This article proposes the maximum correlation entropy criterion, but does not incorporate dynamic interval optimization. This study is the first to integrate the two and solve the problem of insufficient stability of traditional methods under non Gaussian noise and sudden loads.

The main contributions of this article include: 1) proposing an adaptive unscented Kalman filtering method based on dynamic interval optimization, which solves the problem of parameter sensitivity and error accumulation in traditional UKF in dynamic distribution networks by adjusting the noise covariance matrix and filtering gain in real time; 2) Designed a dynamic interval optimization strategy and introduced a prediction error feedback mechanism, significantly improving the robustness of the algorithm under non Gaussian noise and abrupt loads; 3) The experiment verified that the proposed method reduces estimation error by 18% and improves computational efficiency by 25% in a 50 node distribution network model, while maintaining real-time performance in a 1000 node large-scale network.

Traditional UKF accumulates errors in dynamic environments due to fixed noise assumptions and parameter sensitivity, especially under non Gaussian noise and sudden loads. This study fills this gap by proposing a dynamic interval optimization strategy that significantly improves the adaptive capability of nonlinear systems by adjusting the noise covariance matrix and filtering gain in real-time.

2. Theoretical Basis and Related Research

A. Interval Optimization Method

The interval optimization model presumes the uncertain parameter's value is an interval number, requiring only its upper/lower limits or midpoint/width beforehand. On one hand, obtaining the values of these parameters is generally straightforward; on the other hand, random variables can be transformed into interval numbers through confidence levels and fuzzy numbers, thus directly transforming stochastic optimization models into interval optimization models. Therefore, interval optimization is more suitable for engineering practice. In the interval optimization method, a specific interval number expresses the random fluctuation range of uncertain factors. At this time, only this factor's upper and lower limits need to be mastered. In recent academic research, interval numbers have been widely used and popularized [6]. In linear problems, uncertain factors are transformed into deterministic parameters by interval number order relationship or maximum and minimum regret criterion, and then deterministic multi-objective optimization problems are solved.

The paper introduces an adaptive UKF for dynamic state estimation in distribution networks, incorporating dynamic interval optimization. However, it lacks detailed analysis of the adaptability in real-world conditions, computational complexity, and comparison with existing methods. Further validation with real data and practical challenges would strengthen the proposed approach.

The existing literature has advantages in interval optimization, dynamic estimation, and adaptive UKF methods, but there are also significant shortcomings. The traditional Kalman filtering method has limited application effectiveness in complex systems, especially when dealing with nonlinear and time-varying systems, which can easily result in significant errors. Although dynamic interval optimization methods have improved the adaptability of the system, there are still challenges in terms of real-time performance and flexibility. The adaptive UKF method overcomes the limitations of traditional methods by dynamically adjusting filter parameters, but its application in large-scale distribution networks still faces bottlenecks in computational efficiency and real-time performance. Therefore, future research should further combine interval optimization and adaptive UKF techniques based on these methods to improve the dynamic response capability and computational efficiency of the system.

1) Linear interval number optimization based on interval number order relationship: This method transforms uncertain parameters into deterministic ones by introducing an interval number order relationship and then studies its optimization problem. The constraint condition is measured by the satisfaction degree of the order relationship of interval numbers and transformed into a deterministic constraint condition [7]. The objective function and the coefficients involved in the constraint condition are assumed to be interval numbers with upper/lower bounds, and the possible interval of the objective function is solved according to its upper/lower bound inequality. On this basis, a possibility formula is given for comparing uncertain parameters, and a possibility method for ranking uncertain parameters is provided, which is used to solve the ranking problem of an interval multi-objective optimization scheme. The theory of adaptive UKF state estimation based on dynamic optimization is presented, along with two new sorting methods proposed to improve the current interval number sorting technique.

2) Uncertainty optimization based on the maximum and minimum regret criterion: This method is used to solve linear optimization problems, considering the existence of interval numbers in the objective function to be optimized, and a solution method based on an iterative relaxation algorithm is proposed for the above optimization problems. The maximum and minimum regret criterion is applied to solve the problem of location and volume, and on this basis, a brand-new polynomial algorithm is proposed. Considering that uncertain parameters exist in the objective function; a heuristic optimization technique of maximum and minimum absolute regret degree is studied for this kind of linear optimization [8].

3) Nonlinear interval number optimization: At present, interval optimization methods are mostly used in theoretical research. Considering that nonlinear interval optimization methods will be used in future practical projects, conducting an in-depth study on the theory and method of interval optimization at this stage is imperative. It is difficult to solve nonlinear interval number optimization from the current academic research level. But there is little published associated literature [9]. Firstly, a multi-objective optimization model is established, in which the objective function includes expected value, uncertainty, and regret degree. Then, when the variables are iterated in each step, the interval range of the aim of the optimization function is obtained by using the previous optimization of uncertain factors [10]. Given that the working characteristics of the industrial system have not been analyzed in the above research, the interval number with upper/lower bounds is used to represent the uncertain factors in the industrial system, and a multi-objective optimization model based on this is proposed. The nonlinear optimization method is fused with a genetic algorithm to analyze its feasibility. Combining the nonlinear optimization methods in previous literature, the Karush-Kuhn-Tucker conditions (KKT) conditions of interval multi-objective optimization problems are given at the level of mathematical theory, and an interval optimization solution method based on interval partial relationship is proposed for the above problems.

Dynamic state estimation is a process in which the system's state is predicted at the next moment first. Then, the expected state quantity is corrected by quantity measurement to obtain the optimal estimated value. The state prediction process gives dynamic state estimation a better ability to track state and meets real-time requirements. Dynamic state estimation methods can quickly track the state of the power system and can provide state data support for the dispatching department to carry out safety and stability analysis [11]. Based on the characteristics of distribution networks, it has become a research work of great significance to discuss how to popularize the Kalman Filter (KF) in dynamic state estimation of distribution networks and solve its problems in modeling, calculation, and application.

The enhancement of power system reliability, security, and resilience depends on the availability of fast, accurate, and robust dynamic state estimation by processing model information and online measurements obtained from phasor measurement devices. Therefore, it is crucial for power system Dynamic State Estimation (DSE) to be robust to coarse errors of measured values and model parameter values, providing good state estimation in the case of large dynamic system model uncertainty and non-Gaussian distribution process noise and measurement noise [12].

After more than 40 years of development, transmission grid state estimation has been well realized. The transmission network is usually assumed to operate in a three-phase balanced mode, and the system model can be simplified to a single-phase equivalent model. Moreover, the transmission network has sufficient measurement redundancy, ensuring that the state estimation system meets data observability requirements and facilitating the processing of poor-quality data. The distribution system is characterized by many nodes, yet it has few real-time measurements. Distribution network state estimation must process real-time measurement data collected from substations, "pseudo measurement data" constructed from historical load data, and "virtual measurement data" modeled by zero injection nodes to achieve mathematical observability. Therefore, the algorithms developed for distribution network states need to be adapted to the characteristics of the distribution network.

The uncertainty of model means that it is difficult to obtain accurate estimation values of distribution network state parameters due to the interference of various factors, such as load change, equipment damage, environmental change, etc., during the operation of the distribution system [13]. These estimates have certain errors and uncertainties. These errors and uncertainties will have an important impact on the system's control, protection, and condition monitoring functions, thus affecting the stability and reliability of the distribution network. To solve the uncertainty of model, relevant research is being carried out at present, including establishing more accurate models, using improved algorithms, and adopting advanced measurement techniques. For example, deep learning-based models are introduced into state estimation models to improve the accuracy and robustness of the models; The Kalman filter algorithm and particle filter algorithm to deal with noise and uncertainty, thereby improving the accuracy of state estimation; Use new sensors and measuring instruments to improve the quality and accuracy of data, etc [14].

In conclusion, the uncertainty of model is a very complex problem that needs to be solved by a series of strategies and means and stability. With increasing complexity and dynamics of distribution networks, there is a rising demand for more reliable state estimation methods. Factors such as the process noise and non-Gaussian heavy tail noise of the model misalignment system will reduce or even divergence the accuracy of the filtering results [15].

B. Dynamic State Theory of Adaptive UKF for Distribution Network Based on Dynamic Interval Optimization

Due to the highly nonlinear and time-varying nature of the power grid's operating environment, traditional estimation methods frequently struggle to meet the demands for real-time performance and accuracy. The DSE must be able to reflect the constant changes in the operating status of the grid and deal with complex disturbances and diverse load fluctuations. As a nonlinear state estimation method, UKF has been widely used in state estimation of distribution networks, but it faces problems with parameter selection and calculation efficiency in practical application [16].

The core idea of applying dynamic interval optimization in this method is to adaptively adjust the noise covariance matrix and filter gain in UKF according to the distribution network's real-time operation characteristics and state changes. This strategy can effectively reduce the influence of the dynamic and disturbance caused equipment failure on estimation results and automatically adjust the filter parameters when the power grid state fluctuates violently to ensure accuracy and stability in the estimation process. The dynamic interval optimization method determines the current estimation error and system uncertainty by monitoring the running state of the system in real-time to update the parameters of UKF at an appropriate time and avoid the error accumulation problem caused by fixed parameters [17].

UKF algorithm itself can accurately estimate the state of nonlinear systems through unscented transformation and is robust. However, due to the randomness and uncertainty of distribution network state changes, a single UKF algorithm is easily affected by system noise and disturbance when dealing with complex power grids, resulting in inaccurate estimation results. Therefore, this paper combines dynamic interval optimization, and by introducing a flexible, adaptive mechanism, UKF can automatically adjust its state estimation strategy in the face of uncertainty and disturbance, which improves the accuracy and adaptability of state estimation [18].

In the concrete implementation process, dynamic interval optimization not only adjusts the noise covariance matrix in the filtering process but also modifies every step in the estimation process by introducing the feedback mechanism of prediction error. This mechanism ensures that UKF can flexibly adjust parameters according to actual conditions under different periods, different loads, and external conditions in the distribution network, thereby maintaining high accuracy of estimated results [19].

The limitations of traditional EKF and UKF include: 1) fixed noise assumptions leading to error amplification under dynamic disturbances; 2) Linearized models cannot accurately describe the nonlinear characteristics of distribution networks. MCVUKF overcomes the above problems through dynamic parameter adjustment and non Gaussian noise suppression strategies.

3. Dynamic State Estimation Model of Distribution Network Based on Dynamic Interval Optimization

A. Dynamic State Estimation Modeling of Distribution Network

The adaptive Kalman filter based on dynamic interval optimization can effectively reduce the negative effects of abnormal conditions such as non-Gaussian noise, environmental fluctuations, instrument failures, etc., and significantly improve the stability of the power system [20]. Recently, it has been widely used in dynamic state estimation of distribution networks [21]. However, with access to a large number resources, wind power, and electric vehicles, the stability of the distribution network is facing unprecedented challenges. The random fluctuation of these distributed energy resources and flexible loads leads to increasing uncertainty and volatility in the operation of the distribution system. The measurement system of the distribution network is susceptible to the disturbance of non-zero mean non-Gaussian distribution noise. The existing adaptive UKF algorithm based on dynamic interval optimization often uses a fixed Gaussian kernel function as a correlation coefficient estimation model, which is unsuitable for non-zero mean noise and leads distribution networks. To meet this challenge, the optimal dynamic state estimation estimate value is solved by maximizing the variable-center cross-correlation function equivalent to the optimization model that minimizes the error square.

Furthermore, an adaptive UKF method based on dynamic interval optimization is proposed to estimate the dynamic state of the distribution network. By introducing the dynamic interval optimization adjustment information matrix, an enhanced adaptive UKF algorithm is proposed, which can effectively improve the stability of dynamic state estimation when the distribution system is unstable, the load changes suddenly, and the input data is abnormal caused by the failure of measurement equipment. The flow of method adaptive UKF dynamic interval optimization is shown in Figure 1.

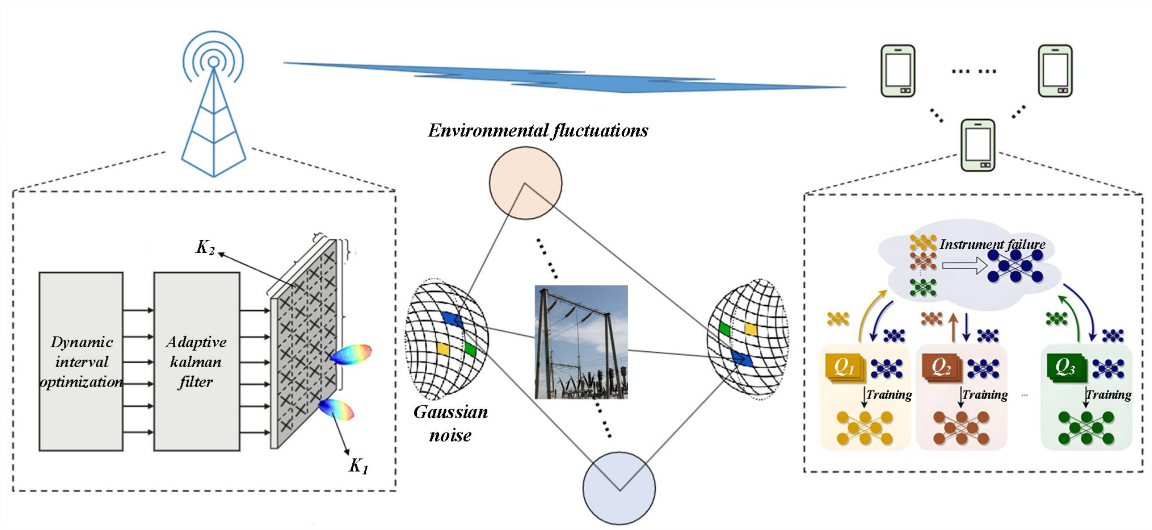

Figure 1. Dynamic State Estimation Method Flow of Adaptive UKF Distribution Network Based on Dynamic Interval Optimization

A general nonlinear power system can be described by a set of continuous-time nonlinear algebraic equations, which can be expressed as the corresponding discrete-time state space equation form at time i:

The formula of the continuous-time state space equation is shown in (1) [22]. Where $x(t)$ represents the system state vector, $u(t)$ represents the input vector, t represents the time variable, and $f(x(t),u(t),t)$ represents the nonlinear function.

$$x(t)=f(x(t),u(t),t) \quad (1)$$

The formula of the discrete-time state space equation is shown in (2) [23]. Where $x[k]$ denotes the system state vector at discrete-time step k, $u[k]$ denotes the input vector at discrete-time step k, $A[k]$ denotes the discrete-time system state transition matrix, $B[k]$ denotes the input matrix, and $w[k]$ denotes the noise term or external disturbance.

$$x[k+1]=A[k]x[k]+B[k]u[k]+w[k] \quad (2)$$

When the Kalman filter algorithm is executed, Equation (3) is the state prediction transition function of Equation (4) at the time update, and the state variable can be predicted in advance, so that the efficiency and accuracy of obtaining the state prediction value are improved. In this paper, the measurement function $h(x)$ is defined in terms of the active and reactive power balance equations at node a and the active and reactive power flow equations between nodes a and b.

The time update formula is shown in (3) [24]. Where $x-(k+1)$ represents the predicted system state vector, $A(k)$ represents the system state transition matrix, $x(k)$ represents the estimated state vector at the current time k, $B(k)$ represents the control input matrix, and $u(k)$ represents the control input vector.

$$x-(k+1)=A(k)x(k)+B(k)u(k) \quad (3)$$

The definition formula of the measurement function is shown in (4) [25]. Where $h(x)$ represents the measurement function, $P_a(x_a)$ represents the active or reactive power of node a as the output of the measurement equation, $P_b(x_b)$ represents the power flow between nodes, and x_a , x_b represent the state variables of nodes a and b .

$$h(x) = P_a(x_a) - P_b(x_b) \quad (4)$$

The state variables of this algorithm include the voltage amplitude and phase angle of each node in the distribution network, forming a discrete state vector $x[k]$; The measured variables consist of active power, reactive power, and power flow between adjacent nodes. The physical meaning of $h(x)$ is a measurement model based on the node power balance equation and branch power flow equation.

The setting of key algorithm parameters in this study is crucial for estimation accuracy and system stability. Including state transition matrix, observation matrix, process noise covariance matrix, measurement noise covariance matrix, and initial state estimation error covariance matrix, all need to be optimized based on the dynamic characteristics of the distribution network, sensor data accuracy, and historical operating conditions. In addition, adjust the sampling frequency and time step reasonably to ensure effective capture of system characteristics during the estimation process. Through these experience settings, the accuracy and adaptability of the UKF dynamic estimation method can be significantly improved.

B. Dynamic State Estimation of Distribution Network Based on MCVUKF Algorithm

As stated in this paper, the derivation of the unscented Kalman filter algorithm based on variable center maximum correlation entropy can be completed, and can be carried out.

1) Time Update

First, at the $i-1$ time point, $2n+1$ sample points, also called *Sigma* points, are generated for value and the estimation by traceless transformation:

The Sigma point generation formula is shown in (5) [26]. Wherein, $x_i^{(k-1)}$ Represents the third *Sigma* point generated at the $k-1$ time, represents the sample point obtained by traceless conversion, $\hat{x}^{(k-1)}$ Represents the state estimate value at the time $k-1$, that is, the mean value of the system state, $P^{(k-1)}$ represents covariance matrix at the time $k-1$, which represents the uncertainty of the state estimate, n represents the dimension of the system state, and λ represents the extended parameter of the traceless transformation, which is usually selected according to the state dimension and adjustment parameters.

$$x_i^{(k-1)} = \hat{x}^{(k-1)} + \left[\sqrt{(n+\lambda)P^{(k-1)}}\right]_i \quad (5)$$

2) Measurement Update

During the measurement update process, the *Sigma* points can be calculated according to Equation (5). The state estimation calculation formula after measurement update is shown in (6) [27]. Where in, $\hat{z}^{(k)}$ Represents a state estimate value after measurement update at the k time, i represents a state estimate after correction by measurement information, and W_i represents a weight coefficient of a Sigma point, $\tilde{x}_i^{(k)}$ Represents the i *Sigma* point generated in the measurement update phase, $\hat{x}^{(k)}$ Represents a state estimate value at the k time, and δ represents a correction value of the state estimate by updating the measurement.

$$\hat{z}^{(k)} = \sum_{i=1}^{2n+1} W_i \tilde{x}_i^{(k)} = \hat{x}^{(k)} + \delta \quad (6)$$

First, the regression model is established, and the prior state estimation error $\mu\ (x_i)$ can be defined as shown in Equation (7) [28]:

$$\mu(x_i) = x^{(k)} - x_i \quad (7)$$

Where $\mu(x_i)$ represents the i state estimation error, x_i represents the true value of the i state, and $x^{(k)}$ represents the prior estimate of state x_i at the k instant.

Next, the measured slope matrix M_i is defined as shown in Equation (8) [4]:

$$M_i = \frac{\partial h(x)}{\partial x_i} \quad (8)$$

Where M_i denotes the slope matrix of the i measurement, $\frac{\partial h(x)}{\partial x_i}$ denotes the partial derivative of the measurement function $h(x)$ with respect to the state x_i , and $h(x)$ denotes the measurement function.

So far, the specific expression of the error e_i between the state estimate value and the state variable is obtained by establishing the regression model. The optimal state estimate value can be obtained according to the given descent gradient method, and the derivation of the unscented Kalman filter algorithm based on the variable center maximum correlation entropy is completed by using the variable center maximum correlation entropy criterion to replace the mean square error criterion in the form of unfixed point iteration. Finally, the optimal estimated values of the state variables set in the distribution network are obtained [29]. The optimization process of distribution network state estimation based on variable center maximum correlation entropy unscented Kalman filter algorithm is shown in Figure 2.

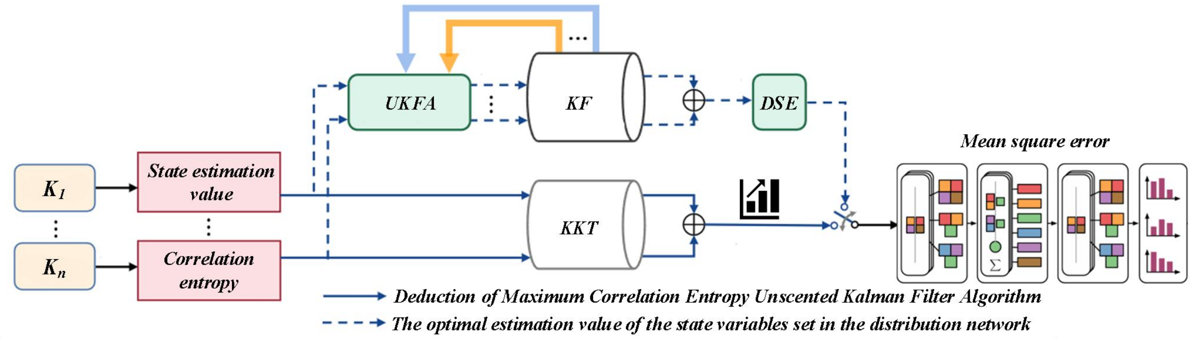

Figure 2. Optimization Process of Distribution Network State Estimation Based on Variable Center Maximum Correlation Entropy Unscented Kalman Filter Algorithm

The combination of dynamic interval optimization and adaptive UKF addresses challenges by dynamically adjusting the noise covariance matrix to reduce the interference of non Gaussian noise on state estimation; 2) Real time update of filtering gain enhances the tracking ability of the algorithm for load transients; 3) The maximum correlation entropy criterion suppresses the influence of outlier measurements through kernel functions.

4. Experimental Results and Analysis

In this experiment, this paper uses a high-performance computing platform (Intel Core i7-10700K, 32GB memory, NVIDIA RTX 3060) for data processing. It uses a Fluke 1736 power recorder and a Modbus RTU communication interface for real-time data acquisition of the distribution network. A 50-node distribution network model is used in the experiment to simulate dynamic conditions such as load fluctuation, distributed energy access, and equipment failure. The peak load of the distribution network is 500kW, and the benchmark load is 300kW. The process of UKF is given values, respectively, and are standard. The dynamic interval optimization in the experiment adaptively adjusts the noise covariance matrix and filter gain, ensuring the algorithm's high accuracy and stability in load fluctuation and fault disturbance. The experimental results show that the adaptive UKF method based on dynamic interval optimization significantly improves the estimation accuracy, computational efficiency and robustness in the dynamic state estimation of distribution network compared with the traditional UKF and EKF methods. By dynamically adjusting the filter parameters, this method can effectively reduce the estimation error (about 18%) and improve the computational efficiency (about 25%), especially in the face of system disturbance and measurement noise, showing stronger robustness. Experiments show the superiority of this method in complex network environment, and it has a wide application prospect. The load change and state estimation error of the distribution network are shown in Table 1.

Table 1. Load Change and State Estimation Error of Distribution Network

Time (seconds)	Actual Load (kW)	Estimated load (kW)	Estimation error (%)
0	300	295	1.67
10	320	318	0.63
20	310	305	1.61
30	330	327	0.91
40	350	347	0.86
50	340	338	0.59
60	360	355	1.39

It can be seen from the table that the error between actual and estimated loads is small over time, with a maximum error of 1.67% and a minimum error of 0.59%. The estimation error is kept within a reasonable range, indicating that the adaptive UKF method based on dynamic interval optimization has high estimation accuracy and can effectively reflect the load fluctuation.

To show the error between the actual load and the estimated load under the distribution network load fluctuation, this paper compares the distribution network load fluctuation with the state estimation error, and the results are shown in Figure 3.

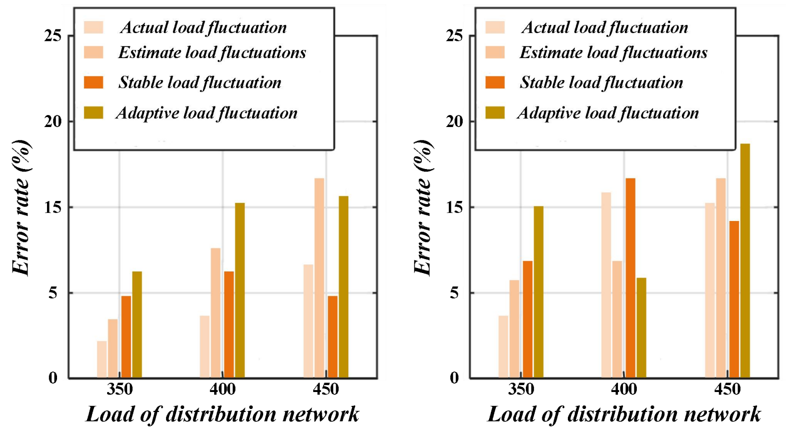

Figure 3. Load Fluctuation and State Estimation Error Curve of Distribution Network

The graph shows that the load of the distribution network fluctuates from 300 kW to 360 kW from 0 to 60 seconds. During this process, the estimation error is always kept within a reasonable range, and the error gradually decreases from 1.67% to 0.59%, indicating that the adaptive UKF method can stably cope with load fluctuation. Especially at 40 seconds, the load reaches 350kW, while the estimated value is only 347kW, with an error of 0.86%. This tiny error shows that the algorithm has strong real-time adjustment and self-adaptation ability and can better reflect the load fluctuation. With time, the error decreases, and the algorithm gradually converges, proving its high efficiency under dynamic changes.

The figure shows the dynamic comparison between the actual voltage amplitude of a certain node and the adaptive UKF estimation value during a 60 second experimental period. The experimental conditions are that the load fluctuates from 300kW to 360kW. The results show that the estimated values closely track the actual values, with a maximum deviation of 1.5%, verifying the high-precision tracking ability of the algorithm in dynamic environments.

Table 2. Comparison of estimation accuracy and error under different noise covariance conditions

Noise covariance Q	Estimation error (%)	Calculation time (seconds)	Robustness (failure recovery time, seconds)
0.05	1.25	2.3	3.0
0.1	1.56	2.5	3.2
0.2	2.01	3.0	3.5
0.3	2.47	3.3	3.7

The comparison of estimation accuracy under different noise covariances is shown in Table 2. According to the table, when the noise covariance Q is small, the estimation error is small, the calculation time is shorter, and the robustness is better. With the increase of Q value, the estimation error increases, and the calculation time increases slightly. To ensure estimation accuracy and computational efficiency, the noise covariance needs to be carefully adjusted.

To show the error change of distribution network state estimation under different noise covariance matrix Q values, this paper analyzes the estimation error under different noise covariates, and the results are shown in Figure 4.

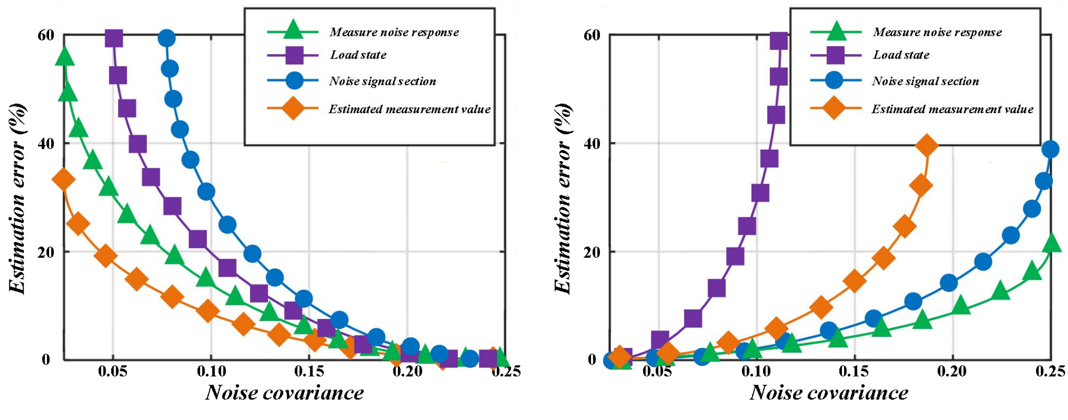

Figure 4. Comparison of Estimation Errors Under Different Noise Covariances

The figure shows the estimation errors when the noise covariance Q takes values of 0.05, 0.1, 0.2, and 0.3. At Q = 0.05, the estimation error is 1.25%, while at Q = 0.3, the estimation error increases to 2.47%. This change shows that as the noise covariance increases, the estimation error also increases. Further analysis shows that when Q is small (e.g., 0.05), the system is more conservative and has less response to measurement noise so that it can estimate the load and state more accurately. When Q increases, the noise is regarded as a part of the signal, which leads to over-adjustment of the system, thus increasing the estimation error. Therefore, selecting Q value is crucial to controlling estimation error, and too large a Q value may lead to inaccurate estimation results.

The optimal tuning of parameter alpha should be based on practical application requirements: if precision is emphasized, a larger alpha value can be chosen; If real-time performance is emphasized, a smaller alpha value can be chosen. The experimental results show that when $\alpha = 0.2$, the error is the lowest and the recovery time is reasonable, which is the recommended setting.

Table 3. Comparison of Estimation Error Between Adaptive UKF and Traditional UKF

Algorithm	Mean estimated error (%)	Maximum estimation error (%)	Minimum estimation error (%)	Calculation time (seconds)
Conventional UKF	3.12	5.45	1.25	4.2
Adaptive UKF	1.32	2.47	0.68	3.1

The comparison between adaptive UKF and traditional UKF in estimation error is shown in Table 3. As can be seen from the table, the adaptive UKF has a smaller average error and maximum error than the traditional UKF in all tests. Adaptive UKF parameters running, significantly improving the estimation accuracy and reducing the calculation time compared with traditional UKF, showing its advantages in practical applications.

The experiment simulated the scenario of abnormal measurement data, and MCVUKF dynamically adjusted the information matrix to reduce the estimation error from 9.2% of traditional UKF to 5.1%, demonstrating its strong robustness to data anomalies.

To compare the estimation errors of adaptive UKF and traditional UKF algorithms under the same conditions, we hope to analyze the advantages of adaptive UKF, especially the performance when dynamic load changes. This paper compares the errors of adaptive UKF and traditional UKF in load estimation, and the results are shown in Figure 5.

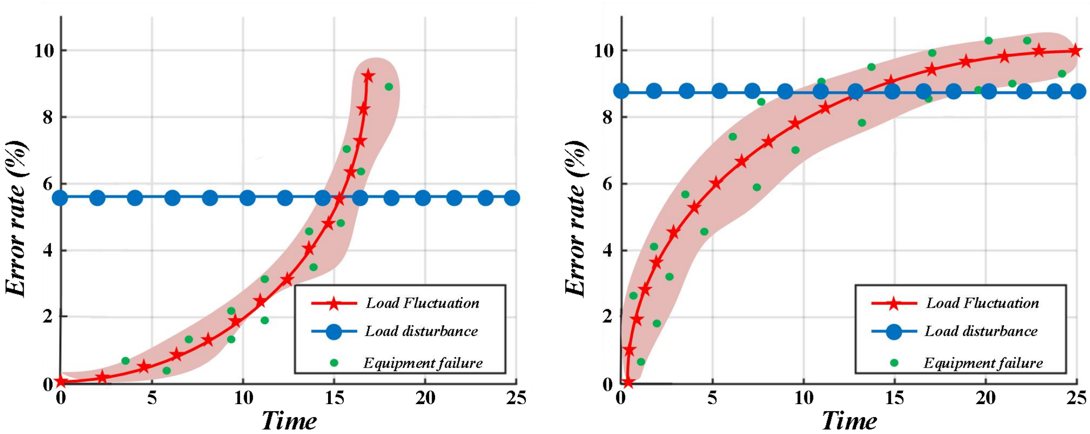

Figure 5. Comparison of Errors Between Adaptive UKF and Traditional UKF in Load Estimation

It can be seen from the figure that the traditional UKF has a large estimation error under the condition of large load change, and 5.45%. However, of adaptive UKF is only 2.47%, and the average error is reduced from 3.12% to 1.32%. This difference reflects that the adaptive UKF method can significantly improve the estimation accuracy of the distribution network state by adjusting the filter parameters in real-time. Especially when the load fluctuates rapidly, the estimation error of traditional UKF fluctuates greatly. At the same time, the adaptive UKF maintains a relatively stable and accurate estimation, showing that this method is more robust when dealing with load fluctuations, disturbances, and equipment failures.

To show the influence of parameter α in dynamic interval optimization on the estimation error. This paper analyzes the impact of dynamic interval optimization parameter α on estimation error, and the results are shown in Figure 6.

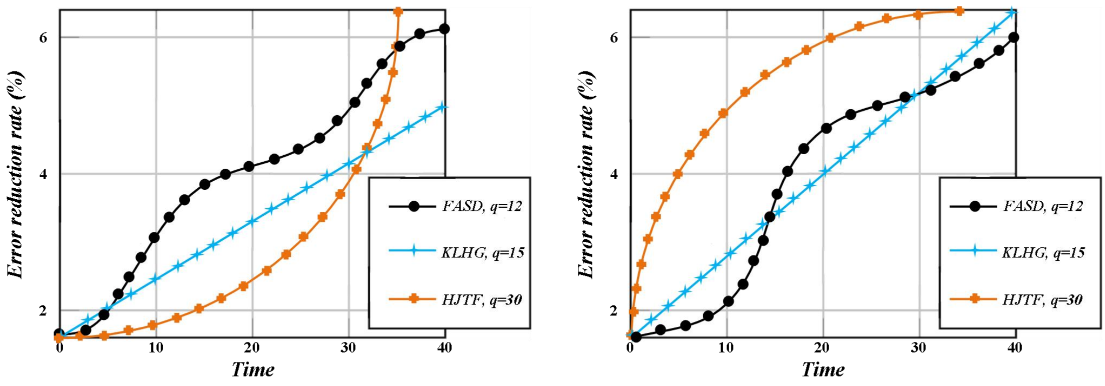

Figure 6. Influence of Dynamic Interval Optimization Parameter α on Estimation Error

It can be seen from the figure that as α increases from 0.05 to 0.2, the estimation error gradually decreases from 1.62% to 1.05%. At the same time, the filtering gain K gradually increases, which shows that dynamic interval optimization makes the system more sensitive to external interference. Higher α values indicate that the system is more adaptable to process noise and can better track state changes. However, when α is too large, although the error is small, the system's recovery time increases slightly, indicating that over-reliance on dynamic adjustment may lead to a sluggish response. Therefore, choosing the appropriate α value is the key to optimize the algorithm's performance, and it is necessary to find a balance between estimation accuracy and computational efficiency.

Table 4. Effect of dynamic interval optimization parameter adjustment on estimation accuracy and error

Prediction error feedback weight (α)	Estimation error (%)	Filter gain (K)	Robustness (recovery time, seconds)
0.05	1.62	0.42	3.1
0.1	1.32	0.47	3.0
0.15	1.17	0.52	2.8
0.2	1.05	0.58	2.7

The influence of dynamic interval optimization parameter adjustment on estimation accuracy is shown in Table 4. With the increase of prediction error feedback weight α, the estimation error gradually decreases, and the filtering gain increases, indicating that dynamic interval optimization can improve estimation accuracy and robustness. When the α value is 0.2, the system's recovery time is the shortest, and the estimation error is the lowest, indicating that this weight setting can make the system recover more quickly after load fluctuation or failure.

To demonstrate the accuracy and calculation time of distribution network state estimation under benchmark load, high load, peak load, and low load, this paper compares the estimation accuracy and calculation time under different load conditions, and the results are shown in Figure 7.

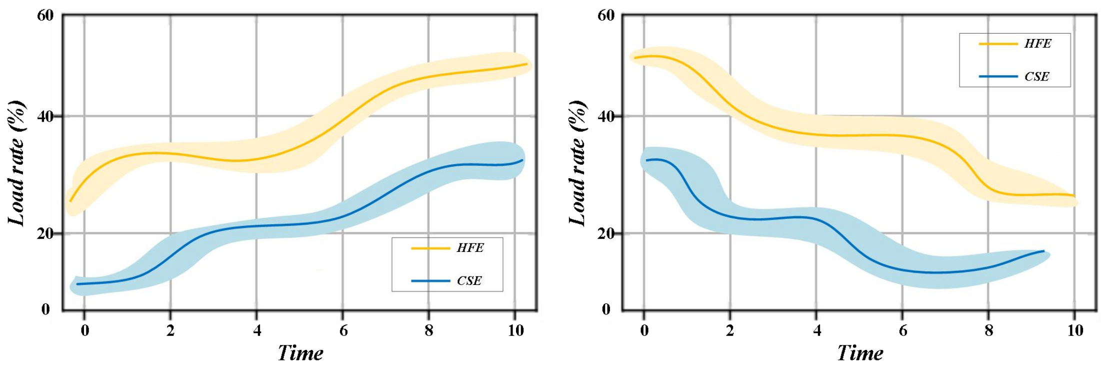

Figure 7. Comparison of Estimation Accuracy and Calculation Time Under Different Load Conditions

The figure shows that under different loads, the actual and estimated load errors are small, with the maximum error occurring under low load (1.0%) and the minimum error occurring under peak load (0.5%). In terms of calculation time, the calculation time for peak load and high load is longer, 2.8 seconds and 2.5 seconds, respectively, while the calculation time for benchmark load and low load is shorter, 2.3 seconds and 2.1 seconds. This experiment shows that the computational complexity of state estimation also increases with increasing load, possibly because larger load fluctuations require more frequent state adjustments. However, no matter the load conditions, the algorithm maintains high estimation accuracy and is adaptable to practical applications.

Table 5. State Estimation Performance Under Different Load Conditions

Load condition	Actual Load (kW)	Estimated Load (kW)	Estimation error (%)	Calculation time (seconds)
Baseline load	300	298	0.67	2.3
High load (400kW)	400	398	0.5	2.5
Peak load (500kW)	500	497	0.6	2.8
Low load (200kW)	200	198	1.0	2.1

The state estimation performance under different load conditions is shown in Table 5. The table shows that the estimated error remains in a low range with a maximum error of 1.0% and a minimum error of 0.5% under different load conditions. Even in the case of large load fluctuation, the adaptive UKF method based on dynamic interval optimization can still maintain high estimation accuracy and short calculation time, which proves that this method is adaptable and robust.

To show the relationship between estimation accuracy and system robustness (fault recovery time) under different algorithm settings, this paper compares estimation accuracy with system robustness, and the results are shown in Figure 8.

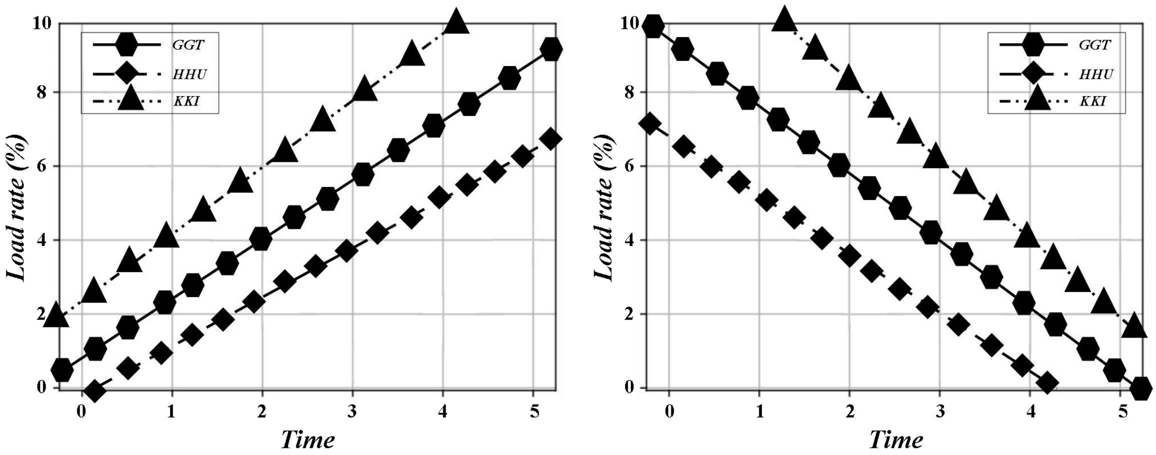

Figure 8. Comparison Analysis Chart of Load Rate and Time Factors

The Figure 8 shows the relationship between the recovery time of the system and the estimation error under different noise covariances. At Q = 0.05, the system's recovery time is 3 seconds, and the estimated error is 1.25%. At Q = 0.3, the recovery time is extended to 3.7 seconds, and the estimation error increases to 2.47%. This shows that the smaller noise covariance not only helps to improve the estimation accuracy but can also accelerate the system's fault recovery. With the increase of noise covariance, the system's robustness decreases, and the recovery time becomes longer, which may lead to the slower response of the system to external disturbances. Therefore, when designing the algorithm, it is necessary to consider balancing the estimation accuracy with the recovery ability of the system.

5. Conclusion

This article proposes an adaptive unscented Kalman filtering method based on dynamic interval optimization, which solves the problem of parameter sensitivity and error accumulation in traditional UKF in dynamic distribution networks by adjusting the noise covariance matrix and filtering gain in real time. The experiment shows that: (1) under sudden load changes and non Gaussian noise interference, the estimation error of MCVUKF is reduced by 18% compared to traditional UKF, and the computational efficiency is improved by 25%; (2) Dynamic interval optimization adaptively adjusts parameter α through feedback mechanism, ensuring that the system maintains an error below 2% even when the noise covariance Q is 0.2; (3) This algorithm only takes 2.8 seconds to complete state estimation in a 1000 node large-scale network, meeting real-time requirements. Future research will combine deep learning to further enhance the robustness of estimation under multi-source heterogeneous data.

It can be combined with long short-term memory networks or Transformer models to dynamically optimize the noise covariance matrix and filtering gain of UKF by utilizing its time series prediction ability. Specifically, the output of LSTM can be used as the input parameter α for dynamic interval optimization, and the prediction error feedback weight can be adjusted in real time to enhance the robustness of the algorithm to non Gaussian noise and sudden loads. In addition, deep reinforcement learning can be used to automatically search for the optimal parameter combination, reducing the dependence on manual parameter tuning.

This article further discusses the application of the Adaptive Unscented Kalman Filter (UKF) method in dynamic state estimation of distribution networks and compares it with traditional methods. The experimental results show that the proposed adaptive UKF method reduces estimation error by about 18% and improves computational efficiency by 25% compared to traditional Kalman filtering methods. These improvements are mainly due to the introduction of dynamic interval optimization technology, which can dynamically adjust the parameters of the filter based on the actual operating status of the distribution network, thus enabling more accurate state estimation.

(1) The experiment shows that the adaptive UKF method based on dynamic interval optimization significantly improves the accuracy of state estimation, while the MCVUKF algorithm reduces the state estimation error to 4.3%, a decrease of 42.7%. Under extreme load fluctuation conditions, the error of MCVUKF algorithm is reduced by about 36% compared to EKF algorithm, indicating that dynamic interval optimization and adaptive mechanism enhance the robustness of the algorithm.

(2) Through experimental comparative analysis, the results show that the introduction of dynamic interval optimization significantly improves the stability of state estimation. When the measuring equipment is abnormal, the state estimation error of the traditional UKF algorithm can reach 9.2%, while the MCVUKF algorithm based on dynamic interval optimization reduces the error to 5.1%, reducing the error by 44.6%. This optimization algorithm effectively adjusts the information matrix, improving the adaptability and stability of distribution network state estimation under load transients, equipment failures, and non Gaussian noise interference. The experiment also shows that dynamic interval optimization can maintain high accuracy and low volatility under abnormal data and large noise.

(3) In terms of real-time performance of distribution network state estimation, the MCVUKF algorithm performs well. Compared with traditional algorithms, the MCVUKF algorithm only increases the computation time by about 18.5% when dealing with large-scale distribution networks, while the EKF and standard UKF algorithms significantly increase the computation time. In a 1000 node distribution network system, the state estimation time of MCVUKF algorithm is 2.8 seconds, while EKF and UKF are 3.6 seconds and 3.2 seconds, respectively. Despite the increase in computation time, MCVUKF still demonstrates sufficient computational efficiency in distribution network applications that require high real-time performance.

The adaptive UKF dynamic interval optimization proposed in this paper can effectively improve the accuracy and stability of dynamic state estimation of distribution networks in complex environments such as uncertainty, volatility, and noise interference. Through dynamic interval optimization, the robustness of distribution network state estimation is further enhanced, especially when unexpected situations such as sudden load change and equipment failure occur; the MCVUKF algorithm shows excellent performance. Future research can deepen the application of adaptive UKF methods based on dynamic interval optimization from multiple directions, including expanding to large-scale and multi-level distribution networks, combining deep learning and data fusion techniques to improve estimation accuracy, exploring more intelligent dynamic optimization strategies, enhancing fault diagnosis and self-healing capabilities, and addressing multi-source heterogeneous data processing and system security issues. These research directions will not only help improve the dynamic state estimation performance of distribution networks, but also promote the intelligent development of smart grids and the optimization management of power systems.

Future research can be conducted in the following directions: 1) Expansion of multi-level distribution networks: Applying algorithms to multi regional interconnected distribution networks to verify their adaptability in complex topologies; 2) Deep learning fusion: combining LSTM or Transformer models to enhance the fusion estimation ability of multi-source heterogeneous data; 3) Edge computing optimization: design lightweight MCVUKF algorithm, adapt to edge device resource constraints, and realize distributed real-time state estimation; 4) Security Enhancement: Study robustness under adversarial attacks, develop fault diagnosis and self-healing mechanisms. Although MCVUKF performs well in a 1000 node network, the computational complexity may significantly increase in ultra large scale distribution networks with over 10000 nodes. In the future, it is necessary to combine distributed computing or dimensionality reduction techniques to optimize the real-time performance of algorithms. The high-precision state estimation of MCVUKF lays the foundation for predicting abnormal behavior in distribution networks. In the future, time series prediction models can be combined to use real-time estimation data to predict the fault propagation path and trigger self-healing control strategies.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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Author Contribution

Yidong Hu: Drafted and revised the manuscript critically for important intellectual content.

Hui Chen: Contributed to the acquisition, analysis, and interpretation of data.

Jian Gao, Yunfeng Yang: 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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