

Modeling of Integrated Energy Distribution Network and Power System Security and Stability Control Based on Perception System

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In response to the problems of lagging data collection and monitoring, lack of dynamism in system models, and long fault handling and recovery time in traditional integrated energy distribution network modeling, this study constructed a perception system-based integrated energy distribution network model and power system safety and stability control method. Firstly, by deploying multiple sensors at key nodes in the distribution network, real-time monitoring of power load, thermal energy flow, and gas transmission was achieved. The collected data was then fused using the Kalman filter and data fusion algorithms (such as Bayesian fusion) to eliminate noise and redundant information, resulting in high-quality system state estimation. Then, the DreamerV2 algorithm was used to establish a dynamic model of the integrated energy distribution network, which simulated the energy flow and control strategies in the environment for long-term system optimization prediction. Finally, based on the data results after the DreamerV2 model prediction, the MILP (Mixed-integer Linear Planning) method was applied for optimization. Experimental results showed that the dynamic model had good processing capacity, high system stability. The transition response time was only 2.5 seconds, energy efficiency was about 85.5%, MTTR (Mean Time To Repair) was 1.69 hours, the average load tracking accuracy was 1.89%, the data proved the method in improving the security and stability of the power system.

Keywords: Electric Power System; Distribution Network Modeling; Deep Reinforcement Learning Algorithm; DreamerV2 Model; Data Acquisition

1. INTRODUCTION

In the contemporary power network system, the operation and management challenges of the integrated energy distribution system are significantly exacerbated [1–2] by the

integration of diversified energy types and complex and variable load types. Previous distribution network modeling methods are limited by the latency of data collection and monitoring, and rely on manual operation or periodic sampling to obtain information, which greatly hinders the system's ability to accurately assess immediate conditions [3–4]. Such delays not only weaken the system's real-time perception of emergencies such as load fluctuations and

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equipment failure, but also further threaten the stability and safe operation of the power system [5–6]. Another major problem is that most of the existing models lack the necessary dynamic characteristics. They can only capture the static snapshot of the system at a specific moment, but cannot fully display the dynamic characteristics of load change over time and the actual impact of energy scheduling strategy [7–8]. It is difficult to adapt this static perspective to the current reality of increasingly complicated energy structures and rapidly changing electricity demand, resulting in scheduling decisions that are untimely and inaccurate [9]. In terms of fault response and recovery, traditional distribution networks often rely on the preset protection mechanism and recovery process [10–11]. These strategies cannot be dynamically adjusted according to the real-time operating state, resulting in long troubleshooting time and low recovery efficiency, which seriously affects the reliability of users' power supply and the overall operation efficiency of the system [12].

To address the aforementioned issues, this study proposes a comprehensive energy distribution network modeling and power system security and stability control method based on perception system. This method deploys multiple sensors at key nodes in the distribution network to monitor real-time power load, thermal energy flow, and gas delivery. The data is transmitted to the central data processing unit using Zigbee or LoRa (Long Range) wireless communication protocols. A Kalman filter and Bayesian fusion technology can be applied to fuse the collected data, eliminate noise and redundant information, and obtain high-quality system state estimation. A Kalman filter is used in this study to smooth the time series data to enhance data reliability and introduces Bayesian fusion strategy to integrate information from different sources and improve data quality. It also uses the DreamerV2 algorithm to build a comprehensive dynamic model of an energy distribution network. The model simulates and analyzes the flow of energy in the system and the corresponding control strategy to realize the long-term optimization prediction of the future state of the system. Based on the accurate prediction results provided by the DreamerV2 model, the MILP method is further used to make optimization decisions. In this process, clear optimization objectives are set, such as cost minimization or system efficiency maximization, and a set of necessary constraints are set according to the actual situation. To solve this complex optimization problem, a high-performance mathematical solver CPLEX or Guobi is required to ensure a high-quality optimization scheme.

The core purpose of this study is to achieve an accurate estimation of the power system state and high-quality data acquisition by deploying advanced sensor networks, combined with Kalman filtering and Bayesian fusion technology. The dynamic model established by the DreamerV2 algorithm can optimize the energy flow and control strategy more effectively. This article combines MILP method to achieve multi-objective optimization scheduling. The ultimate goal is to enhance the safety and stability of the power system and reduce the time required for fault handling.

2. RELATED WORK

In the study of integrated energy distribution networks, traditional research has focused on energy coordination and optimization scheduling, as well as issues related to electricity markets and pricing mechanisms. Li proposed a scheduling model based on opportunity-constrained programming to enable integrated demand response in community integrated energy systems in uncertain environments, in order to minimize system operating costs. Among them, the IDR (Integrated Demand Response) program is used to explore the potential interaction capabilities between electric pneumatic thermal flexible loads and electric vehicles [13]. Zhang proposed an optimal alliance strategy to maximize the utility of different types of individual electricity retailers in response to the discrepancies between consumption and energy contracts in China's forward electricity market. He considered EDS (Energy Deviation Settlement) cost reduction and cooperation costs based on transaction cost theory analysis [14]. Traditional research has certain limitations, and there is still insufficient exploration of the dynamic response capability and system stability of integrated energy distribution networks.

In order to improve the response times and enhance system stability, many scholars have proposed different modeling and control strategies. Buxiang introduced switch variables and radial constraints in the distribution electronics system to address the problem of distribution network reconstruction in the Integrated Energy System (IES) with bidirectional coupling between electricity and gas. On this basis, he established a distribution network reconstruction model that takes into account the integrated energy system, which can reduce the operating costs of the integrated energy system and effectively support the voltage of the distribution electronics system and the pressure of the gas distribution subsystem [15]. Ehsan proposed using an active distribution network planning model to replace traditional distribution network planning models, providing appropriate planning solutions for active distribution networks and achieving optimal integration of distributed energy [16]. Oikonomou proposed robust planning for distributed battery energy storage systems from the perspective of distribution system operators to improve network flexibility [17]. However, these proposed solutions have difficulty handling multi-source heterogeneous data fusion and dealing with complex fault modes. In particular, when there are diverse operating scenarios and uncertain factors affecting the system, the adaptability of control strategies is poor.

In the research on modern distribution networks, although there have been many innovative achievements, there are still some significant limitations that affect the dynamic response capability and system stability of integrated energy distribution networks. Traditional research focuses mainly on energy coordination and optimal scheduling, while multi-source heterogeneous data fusion is lacking of exploration. With the rapid development of smart sensor technology and the Internet of Things, distribution networks now need to meet the challenges of processing massive real-time data, and existing models are often overwhelmed with the complexity

and real-time nature of these data, making effective decision-making difficult in a dynamic environment. There is still insufficient research on system stability and fault recovery capability. Although many scholars have achieved good results in the areas of power market optimization and pricing mechanism, the existing control strategies are still not flexible enough to deal with failure modes under diversified operation scenarios.

Another problem to be solved is the lack of an effective real-time monitoring and dynamic control mechanism. Most studies are still focused on the construction of static models and fail to fully utilize real-time data for dynamic adjustment, which undoubtedly limits the flexible responsiveness of the system. In particular, given the frequent changes in the external environment and increasing fluctuation of user demand, the adaptability of distribution network becomes critical.

3. METHOD

3.1 Data Collection and Data Preprocessing

3.1.1 Sensor Deployment and Data Collection

It is very important to choose suitable sensor types, including current sensors, temperature sensors, and gas flowmeters. A current sensor is used to monitor the power load in real time, a temperature sensor is responsible for monitoring the equipment and ambient temperature, and a gas flowmeter is used to monitor the flow of gas. The arrangement of the sensors covers the key nodes of the substation, branch lines and end users of the distribution network.

The sensor transmits the collected data to the central data processing unit in real time through the wireless communication protocol. Wireless communication is chosen for its flexibility and adaptability, especially in the distribution network environment where wiring is difficult. Wireless communication protocol utilizes Zigbee or LoRa due to low power consumption and low latency, which is suitable for short distance communication. LoRa can provide long-distance transmission, ensuring that the data can be effectively transmitted to the central processing unit. During data transmission, encryption technology is used to protect the security of data and prevent it from being attacked and lost.

3.1.2 Data Fusion and State Estimation

Data fusion and state estimation are the key links ensuring the stability and real-time capability of the system. Data fusion uses the Kalman filter algorithm to estimate the system state [18–19]. The algorithm is based on a state-space model and provides the best estimate of the system state by predicting and updating it.

In systems based on state space models, the prediction of system state depends on the previous state and the control inputs. The prediction of system state can be achieved by using state transition equations, such as formula 1:

$$x_k = F_{k-1}x_{k-1} + B_{k-1}u_{k-1} + w_{k-1} \quad (1)$$

where x_k represents the system state at the current time k , and x_{k-1} represents the state at the previous time $k - 1$. F_{k-1} is the state transition matrix, which describes the transition relationship of states from time $k - 1$ to time k . u_{k-1} is the control input, B_{k-1} is the control input matrix, representing the impact of the control input on state changes. w_{k-1} is process noise, usually assumed to follow a Gaussian distribution with zero mean and a covariance matrix of Q_{k-1} , that is, $w_{k-1} \sim \mathcal{N}(0, Q_{k-1})$.

The actual measured values can be compared with the predicted values, and the state estimation can be updated by weighted Kalman gain to reduce estimation errors. The calculation of Kalman gain is based on the covariance of measurement noise and prediction error, effectively improving the estimation accuracy, as shown in formulas 2 and 3:

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \quad (2)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H_k \hat{x}_{k|k-1}) \quad (3)$$

where K_k is the Kalman gain, H_k is the observation matrix, z_k is the measurement value, and R_k is the measurement noise covariance.

The Bayesian fusion algorithm can comprehensively analyze data from multiple sensors [20–21]. This method uses Bayes' theorem to combine the data of each sensor to form the global state estimation. Set the prior distribution of the system state, initialize based on expert knowledge, such as formula 4:

$$p(x) = \mathcal{N}(\mu_0, \Sigma_0) \quad (4)$$

Set the prior distribution of system state x as Gaussian distribution, μ_0 as initial mean, and Σ_0 as covariance matrix.

Different sensors may cause measurement errors due to noise or other factors. Therefore, the likelihood function provides a basis for adjusting the weight, as shown in Formula 5:

$$p(z|x) = \mathcal{N}(z; H_k x, R_k) \quad (5)$$

where z is the observation data, H_k is the observation model, and R_k is the observation noise covariance.

By using Bayes' theorem to update the posterior distribution of the system state, and combining the prior distribution and likelihood function, a more accurate state estimation can be obtained with formula 6:

$$p(x|z) = \frac{p(z|x)p(x)}{p(z)} \quad (6)$$

The posterior distribution can be calculated, where $p(z)$ is the marginal likelihood, which can be obtained by integrating $p(x|z)$ over x .

Finally, by integrating the posterior distributions of each sensor, a comprehensive state estimate of the system is obtained. The estimation result has high accuracy and reliability, and is suitable for subsequent dynamic model establishment and control strategy optimization, as shown in formula 7:

$$p(x|z_1, z_2, \dots, z_n) \propto \prod_{i=1}^n p(z_i|x)p(x) \quad (7)$$

Table 1 Verification of State Estimation.

Measurement Time (s)	Estimated State (kW)	Actual State (kw)	Estimation Error (kw)	RMSE (kW)
0	150	145	5	
1	155	150	5	
2	160	158	2	
3	162	160	2	
4	159	157	2	
5	155	153	2	
6	150	148	2	
7	148	145	3	
8	145	142	3	
9	140	138	2	
Average	152.4	149.6	2.80	3.03

After completing the state estimation, it is necessary to validate the estimation results. The accuracy of the estimation can be verified by comparing it with the real system state, calculating the estimation error and RMSE (Root Mean Square Error). For significant estimation errors, it is necessary to analyze the reasons and adjust the parameter settings in Kalman Filter and Bayesian fusion to improve the adaptability of the model.

The state estimation results at each second are given in Table 1, which lists the measurement time from 0 to 9 seconds, the estimated and real active power and the error of estimation. From these figures it can be observed that the error of estimation is less fluctuating with a mean error of 2.80kW and the employed state estimation approach is very accurate and robust. The per second difference between the predicted and true states evaluate the model's performance. In the first couple of seconds, the estimation error was slightly greater, but the model performance was converging. The RMSE of overall estimate is 3.03kW as shown in the last column, which further verifies the correctness of data fusion and state estimation. This demonstrates the successful application of data fusion technology for the state estimation, which means the system can really reflect the actual operation status of the distribution network in real time, and then establish foundation for power system safety and stability control.

3.2 Dynamic Model Establishment

3.2.1 Environmental Modeling

In the stage of environmental modeling, the major integrated energy distribution network is consistently described. Specifically, Kirchhoff's current and voltage laws are applied to the power generating units to develop a power flow model[22–23]. A linear system of equations with node voltages and branch currents is developed to model the output characteristics of each distributed power unit [24–25]. In particular, load curves and weather data are separately introduced to reflect the stability and volatility of output for the conventional thermal and the renewable energy (e.g., wind and solar) generation units. Modeling of load node: The load node modeling is based on time series to build a load prediction model using historical loading data. Then, by

means of seasonal and intraday variation patterns the model is established to accurately mimic real load variations over time. The load prediction model incorporates measures of economic activity and population to improve its predictive accuracy. The charge and discharge model for an energy storage system is applied to specify its dynamical properties, including charging efficiency, discharging efficiency, and energy loss.

During model building, the inputs and outputs of all components are connected together via a series of linear and nonlinear equations to form a global environmental model. By adjusting the parameters of each module, the model is guaranteed stability and applicability under the various running states. Moreover, by establishing boundary condition and operational constraints, the model can be simulated effectively under real operational conditions.

The power generation unit in Figure 1 is the core of the integrated energy distribution system. It transfers power to the power node and delivers excess power the energy storage unit. When the power demand is less than that being generated, the energy storage units take up the surplus power and discharge it as an emergency power supply during peak hours. Load nodes depend on intelligent metering systems to track and log energy consumption, providing immediate access to information on the user's electricity requirements. The smart metering system is strongly linked with the central control unit, which manages the energy scheduling within the whole distribution network. By extensively processing the information sent by the intelligent metering system, the central control center is able to modify power of the power generation unit on power output without delay, so as to make the system maintain active and safe status under different load conditions. The central control unit adaptively regulates the output of the power generation unit to the varying energy demand at the power node in order to achieve an effective resource allocation and a fast fault response.

3.2.2 Definition of Status and Action

In the process of defining states and actions, the specific composition of state space and action space is clarified. The state space S is defined as a multidimensional vector, as shown in formula 8:

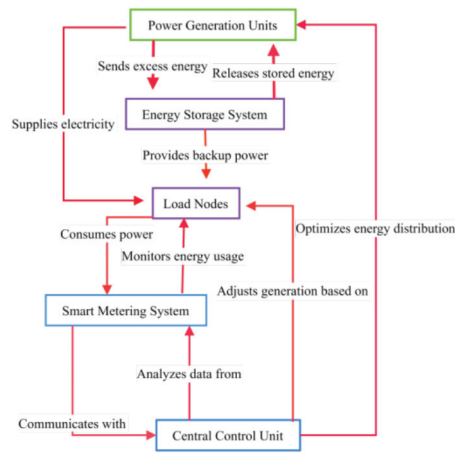


Figure 1 System architecture diagram.

$$S = \begin{bmatrix} V_1 \\ I_1 \\ P_{load} \\ Q_{load} \\ \dot{Q}_{thermal} \\ F_{gas} \end{bmatrix} \quad (8)$$

where V_1 represents voltage, I_1 represents current, P_{load} and Q_{load} represent active and reactive power of the load, $\dot{Q}_{thermal}$ represents thermal energy flow rate, and F_{gas} represents gas flow rate. These state variables are collected by real-time sensors and normalized to form a standardized state vector, as shown in formula 9:

$$S_{norm} = \frac{S - S_{min}}{S_{max} - S_{min}} \quad (9)$$

In the definition of action space A , the control capability of the system is considered, including power generation output P_{gen} , load scheduling $P_{dispatch}$, and charging and discharging decisions E_{charge} of energy storage devices. Each action is discretized, as shown in formula 10:

$$A = \begin{bmatrix} P_{gen}^{(1)} \\ P_{gen}^{(2)} \\ \vdots \\ P_{gen}^{(n)} \\ P_{dispatch}^{(1)} \\ \vdots \\ E_{charge}^{(on/off)} \end{bmatrix} \quad (10)$$

P_{gen} is divided into multiple discrete levels, represented as $P_{gen}^{(n)}$, where n represents the discrete level. Load scheduling relies on the priority of load forecasting, and the state of energy storage devices is defined as binary decision-making, with the formula 11:

$$E_{charge} = \begin{cases} 1, & \text{if charging} \\ 0, & \text{if discharging} \end{cases} \quad (11)$$

Through the systematic definition of these states and actions, a model highly consistent with the actual operating

environment has been formed, laying a solid foundation for the implementation of dynamic optimization and control strategies.

3.2.3 Strategy Optimization

The DreamerV2 algorithm, based on the reinforcement learning framework, is utilized to improve the control policy of the integrated energy delivery system [26–27]. A dynamic model is therefore constructed based on the state space in which states, actions and reward functions of the system are integrated [28–29]. The state comprises the power load, energy storage level and environment parameters, while the action contains power generation control, load shifting and energy storage control. The reward function design is based on the maximization of system efficiency and stability, which can be used to quantitatively determine the power balance, fault response time, and resource utilization [30].

When training, a model predictive control approach was taken, using historical data and real-time feedback to optimize the policy [31–32]. With the acquisition of environmental feedback and the strategy network update, the control-decision accuracy can be improved.

An offline training method is employed to store experience data in various states via a replay memory module to mine valuable information in subsequent work. By merging the iterative updates of strategy gradient and value function, the system can monotonically self-improve, enabling it to perform dynamic adjustment and real-time response. The model also employs the principle of multitask learning for the cross-training of different working conditions and fault modes so that it can be generalized and maintain high efficiency under different situations.

The change of average reward within each training round is presented in Figure 2 where the horizontal coordinate is the number of training rounds, and the range is [1,100]; i.e., in total, 100 rounds of training are performed. The y-axis denotes the expected reward and the feedback value received by the agent in every training round.

In the data section, the simulated reward data exhibit an incremental trend. The mean reward for the first 20 rounds is about 10, and then it starts to increase for the next 30 rounds,



Figure 2 Training process curve.

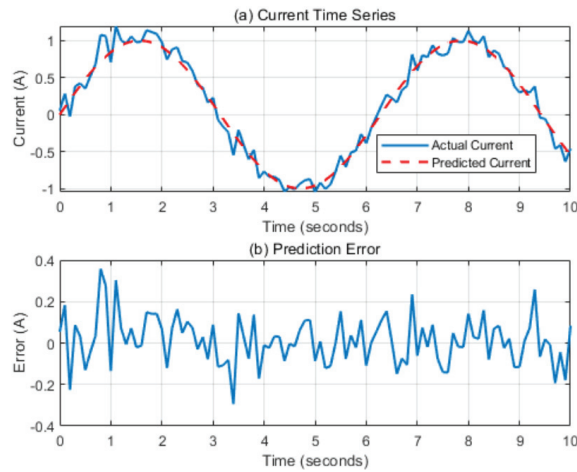


Figure 3 Data simulation and prediction.

with a mean of almost 15. The reward is further increased to 20 for the last 50 rounds. The model performance is relatively unstable at the beginning of training. As the number of training rounds increases, the agent gradually captures the environmental dynamic and is capable of producing more powerful decisions.

The upward trend of rewards indicates the enhancement of the model's capability in reinforcement learning. The increase of reward makes the model's policies more rational and efficient in dealing with all kinds of challenges in the environment and, to some extent, energy utilization and distribution can be optimized, resulting in greater protection and stability of the system. The result of this training not only corroborates the rationality of the model design, but also provides a source of confidence for future system applications.

3.2.4 Dynamic Simulation and Prediction

In the dynamic simulation and prediction stage, the trained DreamerV2 model is used to simulate the real-time operation of the integrated energy distribution network. During the simulation, the dynamic response and recovery capability of the system are analyzed by setting fault scenarios, such as the sudden failure or load fluctuation of power equipment. The

model is based on the feedback mechanism of reinforcement learning and automatically adjusts the control strategy to minimize the response time and energy loss of the system. A time series analysis method is used to fit the historical operation data so as to optimize future energy scheduling and load allocation schemes, and ensure the stability of the system under different operating conditions. Data simulation and prediction effect are shown in Figure 3.

Figure 3(a) is a timing diagram showing the change between the actual value and the predicted value of the current over the 10-s time range. The horizontal axis represents time (unit: seconds), and the vertical axis represents current (unit: amperes). The solid blue line represents the actual current whose value fluctuates in time, mainly affected by noise, and exhibits sine wave morphology with random fluctuations. The dashed red dotted line is the value of the predicted current, which shows an ideal sinusoidal waveform, not affected by noise. Figure 3(b) illustrates the prediction error as a time series, which is the error between the true current and the predicted current, and the variation range of the predicted values reflects the prediction accuracy in a certain time interval. The value of the error changes in the time series, which can be interpreted as a breakdown of the model anticipator at some instant of time and necessitating refinement and tuning of the model. This by no means

undervalues the need for real-time monitoring or suggests that prediction algorithms are infallible when faced with uncertainty.

3.3 Optimizing Scheduling and Resource Allocation

3.3.1 Objective Function Setting

When optimizing scheduling, the setting of the objective function is a key step aimed at minimizing the cost of the integrated energy distribution network. Firstly, the objective function is defined as the sum of system operating costs, including electricity purchase costs, power generation costs, energy storage costs, and environmental costs, as shown in mathematical formula 12:

$$\min Z = \sum_{t=1}^T (C_{purchase} + C_{generation} + C_{storage} + C_{emission}) \quad (12)$$

where $C_{purchase}$ represents the purchase cost of electricity during time period t , $C_{generation}$ is the generation cost, $C_{storage}$ reflects the operating cost of the energy storage system, and $C_{emission}$ covers the environmental costs caused by carbon emissions. These cost functions are the product of electricity consumption and unit costs, accurately indicating the economic viability of each form of energy.

When setting the objective function, it is necessary to use linearization technology to ensure that all the cost functions are in linear form to make the solution process efficient and feasible. During data collection stage and real-time monitoring, the market price and operation efficiency of each resource are obtained to ensure the dynamic adaptability and accuracy of the objective function. The decision variables include power purchase amount, power generation output and energy storage state. The decision variables are introduced into the objective function to form a complete mathematical model.

3.3.2 Construction of Constraints

In the construction of constraints, the power balance constraints need to be defined to ensure that the power generation during each period matches the load demand. A mathematical model is established and the relationship between supply and demand is set using formula 13:

$$\sum P_{gen} = D \quad (13)$$

where P_{gen} represents the output of each power generation unit, and D represents the load demand during the corresponding period. This constraint ensures that the system can provide stable power supply at any time.

Secondly, the capacity constraint of the generator should be considered to ensure that the output of each power generation unit does not exceed its design limit. By introducing minimum and maximum output limits for the generator, the constraint condition can be expressed with:

$$P_{min} \leq P_{gen} \leq P_{max} \quad (14)$$

This constraint effectively prevents the failure of the generator caused by overload operations, and also ensures the overall reliability of the system.

For energy storage systems, charge discharge constraints and energy storage constraints can be constructed to ensure the operational efficiency and safety of energy storage equipment. The update formula for energy storage status is as follows:

$$E_{stored}(t+1) = E_{stored}(t) + \eta_{charge} \cdot P_{charge} - \frac{P_{discharge}}{\eta_{discharge}} \quad (15)$$

where E_{stored} represents the energy storage state, and η represents the charging and discharging efficiency. This constraint ensures that energy storage devices follow the principle of energy conservation during the charging and discharging process, avoiding energy waste and equipment damage.

Set volatility constraints on renewable energy to cope with uncertainties in renewable resources such as wind and solar power. By introducing a probability model, the distribution characteristics of wind speed and light intensity are defined to adjust the expected generation of renewable energy. This constraint not only enhances the flexibility of the system, but also strengthens its ability to cope with uncertain factors.

In the final stage of safety constraint of equipment operation, the minimum and maximum operating time of the equipment is limited to avoid damage to the equipment by frequent starting and stopping. Combined with the above constraints, a complete optimization model is created to ensure the safety and stability of the system under different operating conditions.

3.3.3 Solver Selection and Model Solving

When solving the optimization model, Gurobi was chosen as the solver because of its efficient algorithm that can handle complex MILP problems. The constructed objective function and constraints can be input into Gurobi in the form of mathematical expressions to ensure the accuracy and completeness of the model. It can use the Python interface to call Gurobi's optimization functions, and set related parameters such as time limit and precision requirement to trade off the computing burden and the quality of solution.

In the process of model solution, Gurobi takes advantage of the methodology of branch and bound and the technique of pruning to effectively restrict the solution space and rapidly seek for the global solution. The branch-and-bound method converts complicated IP problems into a series of simple sub-problems by successively splitting the original problem, and the global optimum solution is approached gradually. The pruning method checks the feasibility and optimality of the current solution, and it quickly removes the search branches that do not need to be searched, so the solving speed is greatly accelerated.

As a solution, Gurobi also offered a multi-thread feature that makes full use of the multi-core resource of the computer to run in parallel, speeding up the solution procedure. After the completion of the solution, a Gurobi result analysis tool is utilized to extract the best solution and its corresponding

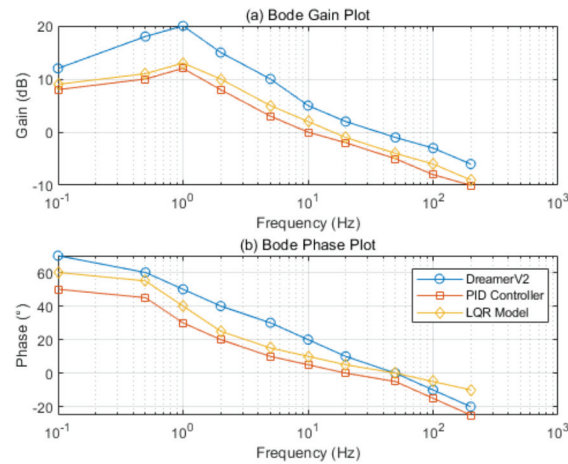


Figure 4 Bode plot.

decision variable from the solution, and the feasibility and effectiveness of the power dispatch plan is ensured.

This tool can check whether the optimal solution obtained satisfies all constraints and can be compared with actual operating parameters to ensure that the model is reliable. If any deviations are found, the model should be modified for specific problems to achieve the iterative and continuous improvement of the optimization process. This sequence of processes guarantee the highly efficient optimization and scheduling of an integrated energy delivery network within a sophisticated scenario.

3.3.4 Implementation and Feedback of Scheduling Plan

In the scheduling plan execution stage, the optimized power scheduling scheme can be uploaded to the distribution management system so that the system can execute the scheduling instructions automatically. A real-time monitoring mechanism has also been established to guarantee the validity of the scheduling plan, which continuously acquires the key parameters including power load, output of generator, and status of energy storage via sensors and data acquisition system being deployed.

The state monitoring methodology can be utilized to monitor, for instance, live data, and determine whether any operational anomalies occur in real time by comparing with the preset value in the optimization model. In anticipation of potential abnormal situations, the system has an automatic alarm system. Once the deviation exceeds the preset threshold, the operation and maintenance personnel will be alerted immediately, and be provided with detailed data of the deviation and the proposed plans for adjustment.

Furthermore, the operation and maintenance staff also regularly assess the scheduling plan and test it for effectiveness. The data for actual operations are taken for future analysis, and checked for verification of consistency between actual working condition and theoretical model. If a bad resource allocation or load shifts are shown to undermine the system stability, the operations team may also, based on real-time system information and rapid decision-making assistance tools, modify and reconfigure the power generation

and energy storage policies dynamically to counterbalance the instability and return the system to a stable and safe operational state.

All the feedback data on the execution can be recorded and fed back into the system database to update the model so as to enhance its performance. By processing the historical data and real-time feedback information, the system is able to adapt the scheduling algorithms online to strengthen the reliability of power supply and improve the efficiency of resource utilization. Through this closed-loop feedback, the scheduling scheme maintains dynamic flexibility and the scheduled results are continuously improved, resulting in a safe and stable control of the integrated energy distribution system.

4. SYSTEM SECURITY AND STABILITY ANALYSIS

4.1 System Stability Indicators

The stability of the system is the main indicator showing the performance of integrated energy delivery networks; usually, the relative stability margin and transition response time are used for assessment. The relative stability margin is employed to express the extent to which a system recovers to the steady state after being subjected to exogenous disturbances. The calculation is carried out in the system transfer function and the gain and phase margins of the system are obtained for different load and fault conditions through the bode plots in order to obtain the required stability of the system. As a general rule, the larger the relative stability margin, the more disturbance-resistant the system will be and, thus, the more stable it is.

Figure 4 is a bode plot of different control models in the integrated energy distribution network. The figure contains three models: the DreamerV2 model of this system, the traditional PID controller model, and the advanced LQR model.

In (a), the horizontal axis is frequency, and the vertical axis is gain. It is evident that the DreamerV2 model has much

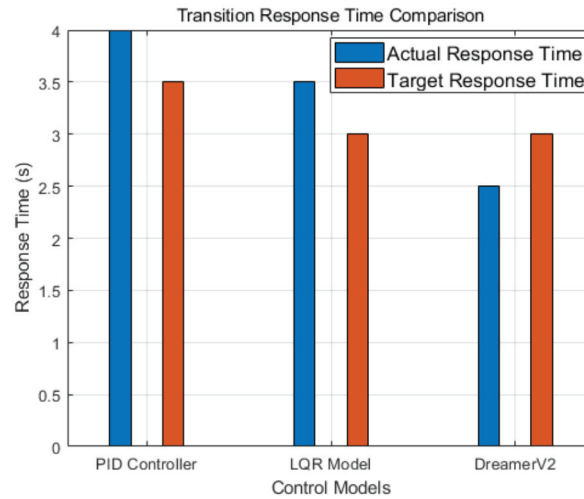


Figure 5 Comparison of Model Transition Response Time.

larger gain in the low frequency range from 0.1 Hz to 1.0 Hz than the other two models, especially at 1.0 Hz it reaches 20 dB. This large gain value indicates that DreamerV2 can offer stronger dynamic response capability under the system disturbances. At low frequencies, the PID controller has quite small gain and rapidly decays after 1.0 Hz, which means it is not good at controlling very fast changes. The gain of the LQR model is smaller than that of DreamerV2 for all the frequency intervals, which demonstrates the inadequate control ability. The x -axis for Figure 4b is frequency and the y -axis is phase. The phase of DreamerV2 stays within 70° to 40° in 0.1 Hz to 2 Hz, while with rapid decay in the frequency region the phase of PID controller is lower. This indicates that DreamerV2 has a more robust system and a quicker recovery rate after disturbances are generated. In the low-frequency range, the phase performance of the LQR model is in between the two, although its overall stability is inferior to that of DreamerV2.

As shown in Figure 4, the differences in responses between the time domain and frequency domain considering control strategies are evident, with the benefits of the DreamerV2 model in integrated energy distribution networks becoming even more apparent, verifying its applicability to dynamic, complex scenarios. Moreover, transition response time is employed to determine how long the system takes to move from the initial state to the steady state, and characterizes the dynamic feature of the system. This time can be determined by applying time-domain methods to the step response of the system. The dynamic performance can be quantified by measuring the time required for the system response to attain a steady state, and comparing it with the prespecified target time. A smaller transition response time indicates that the system can adapt to changes at a faster rate, which is essential for providing fast recovery capabilities under disturbances or load variations.

Figure 5 shows the target response times and actual response times for each of the models. The x -axis consists of three control models: the PID controller, the LQR model and the DreamerV2PID controller; the y -axis is the response time. One pair of columns shows the actual response time, the other shows the target response time. The response time

of DreamerV2 is 2.5 seconds and the target response time is 3.0 seconds; the response time of the PID controller is 4.0 seconds and the target response time is 3.5 seconds; the response time of the LQR model is 3.5 seconds and the target response time is 3.0 seconds.

The bar graph indicates that the actual response time of the DreamerV2 model appears to be in a declining trend relative to the target response time, which indicates good performance in terms of the system's fast adaptation to oscillations. The response time of the PID controller is also far beyond the desired value, demonstrating a lag in its reaction process, which could harm the system's stability. The actual response time of the LQR model is also greater than the target time but it is still better than the PID controller. Together, these two items indicate the superior performance of the DreamerV2 model in terms of dynamic response efficiency, which is quite instrumental in providing a swift tuning and improvement for the system.

The stability of the energy distribution network can accurately assessed through the quantitative calculation of these indicators. Stability indexes can be used not only to detect potentially weak points of the system, but also to serve as a guide in the design of more effective control schemes to strengthen the security and the reliability of the overall system.

4.2 Energy Coordination

When evaluating the energy coordination of the integrated energy distribution network, the energy utilization efficiency needs to be calculated with formula 16:

$$\text{Energy Efficiency} = \frac{\sum_{i=1}^n E_i^{\text{useful}}}{\sum_{j=1}^m E_j^{\text{input}}} \times 100\% \quad (16)$$

where E_i^{useful} represents the effective utilization of type i energy, while E_j^{input} represents the input of type j energy. By summarizing monitoring data of various types of energy, this formula reflects the overall efficiency of the energy

Table 2 Energy Coordination Evaluation Indicators.

Metric	Value
Energy Efficiency (%)	85.5
Energy Balance Error	0.024
Coordination Cost (\$)	1500
Total Useful Energy Output (kWh)	20000
Total Input Energy (kWh)	23400
Actual Supply (kWh)	20500
Theoretical Demand (kWh)	20500
Optimized Total Cost (\$)	12000
Baseline Total Cost (\$)	13500

conversion system and the utilization of various forms of energy.

Next, calculate the energy balance error using formula 17:

$$\text{Energy Balance Error} = \frac{|\sum_{k=1}^p S_k^{\text{actual}} - \sum_{l=1}^q D_l^{\text{theoretical}}|}{\sum_{l=1}^q D_l^{\text{theoretical}}} \quad (17)$$

where S_k^{actual} represents the actual supply of class k energy, while $D_l^{\text{theoretical}}$ represents the theoretical demand for class l . This indicator can effectively quantify the coordination between energy sources and indicate the balance of system operation by comparing actual supply and demand.

Calculate the coordination cost by formulas such as formula 18:

$$\text{Coordination Cost} = C_{\text{baseline}} - C_{\text{optimized}} \quad (18)$$

where $C_{\text{optimized}}$ is the total cost of the optimized scheduling scheme, and C_{baseline} is the total cost of the benchmark scheme. By comparing the differences between the two, the economic benefits brought by optimal scheduling can be quantified and reflect the optimization potential of resource allocation.

The above calculation methods combine various mathematical formulas to comprehensively evaluate the energy coordination capability of the system, providing a basis for optimizing energy management.

Table 2 presents the energy coordination evaluation index values of the integrated energy distribution network. This energy efficiency is high at 85.5%, which means the input energy of 23400 kWh is effectively used as energy output of 20000 kWh, the high energy efficiency of the system is also reflected in it. Second, when $eA = 0.024$, the system reliability at the energy balance error is close to the actual energy supply = 20500, which is energy actually utilized = 20000 and the estimated energy demand = 20500, and there is very good system coordination.

To the economic aspect, the coordination cost is 1500, which means the optimized scheduling plan can save 1500 compared to the scheduling plan without any coordination cost. The optimal total cost is 12,000 while the benchmark cost is 13,500, which implies a saving of 1,500 achieved by the optimization and further validates the effectiveness of the proposed scheduling optimization. Taken together, these results illustrate where the system excels in energy coordination ability, economy, and operation works to strong

support of subsequent to energy management and decision-making.

4.3 Fault Response Time

Three key indicators were used to determine the fault response time: MTTR fault detection time and recovery time ratio. MTTR records the duration of all repair events after a system failure, as calculated with formula 19:

$$MTTR = \frac{\sum_{i=1}^n T_i}{n}$$

where T_i represents the repair time for each fault, while n represents the total number of faults. This indicator shows the average response efficiency of the system after a fault occurs, and can directly reveal the response ability and processing speed of the operation and maintenance team.

The time required to detect a fault obtained by analyzing system logs and monitoring records. The operation requires going back in time from the time of the fault occurrence up to the timestamp of the moment when the system first detected the fault, and computing the difference. This time indicates the sensitivity and real-time property of the monitoring system, and the main point is to improve the sensor response and real-time data processing to identify potential anomalies as soon as possible.

The time-to-recovery ratio is a measure used to assess the ratio of the actual recovery time to the estimated or expected recovery time. In a nutshell, this metric indicates how well the system performs in fault handling in terms of its efficiency and reliability by comparing planned recovery targets against actual results. To guarantee the precision of the data, all indicators undergo statistical analysis and historical data comparison, which can improve the scientific and operational nature of evaluation.

The following fault events are summarized in Table 3: transformer fault, circuit breaker trip, sag/swell, overcurrent notification, generator failure, relay malfunction, and feeder disruption. The mean repair time for each incident varies from 1.0 to 2.2 hours, indicating the effectiveness of different types of fault treatment. The fault detection time ranges from 8 to 20 minutes, which can also be used as the monitoring response speed under different monitoring states. The recovery time ratio is a relative measure of the actual

Table 3 Fault Response Indicators.

Fault Type	Repair Time (MTTR) (hours)	Detection Time (minutes)	Recovery Time Ratio
Transformer Failure	1.5	10	0.8
Circuit Breaker Trip	2.0	15	0.9
Voltage Drop Issue	1.0	8	0.85
Overcurrent Alarm	1.8	12	1.0
Generator Malfunction	2.2	20	0.75
Relay Failure	1.7	18	0.95
Feeder Disruption	1.6	11	0.9
Average	1.69	13	0.88

Table 4 Load Tracking Accuracy Data.

Time (s)	Actual Load (kW)	Target Load (kW)	Tracking Error (kW)	Tracking Accuracy (%)
0	150	145	5	3.45
1	155	150	5	3.33
2	160	158	2	1.27
3	162	160	2	1.25
4	159	157	2	1.27
5	155	153	2	1.31
6	150	148	2	1.35
7	148	145	3	2.07
8	145	142	3	2.11
9	140	138	2	1.45
Average	152.4	149.6	2.8	1.89

recovery time and the expected recovery time, each ranging from 0.75 to 1.0.

The mean MTR time is 1.69 hours, the mean detection time is 13 minutes, and the recovery time ratio is 0.88. Based on these indicators, a quantified measurement of the power system's response capability in fault handling can be obtained, giving an indication for system optimization and reliability enhancement in future.

4.4 Load Tracking Accuracy

In order to measure the ability of a full-scale energy distribution system to respond to the variations in the load, an indicator for load-tracking precision must be defined. This assessment is initiated by closely observing the current load of the distribution network and checking how far it is from the predetermined ideal load state. The process of data collection depends on a network of high-precision sensors deployed at crucial nodes, with the objective of acquiring timely and on-target power load data.

For the computation of load tracking accuracy, the real load is obtained by integrating the historical record and real-time monitoring information, and the expected load value is assigned based on the system scheduling plan. The load tracking accuracy is calculated with this formula: load tracking accuracy = (|actual load - target load| / target load) × 100%. This percentage-based formula clearly reveals the distance between actual load and target load and measures how efficient the system is in responding.

In order to improve the precision of the data processing, the Kalman filtering algorithm is applied to smooth and

filter the actual load data during processing stage, the purpose of which is to eliminate any external interference and measurement error. This method minimizes the deleterious influence of noise on load measurement and increases the confidence in the accuracy of results obtained for load tracking. The target load value can be compared with the filtered data to obtain the result of load tracking accuracy.

Table 4 shows the data for load tracking accuracy, including actual load, target load, tracking error, and tracking accuracy. The data time ranges from 0 to 9 seconds. The tracking error is calculated in kilowatts and indicates the difference between the actual load and the target load. For example, at 0 seconds, the actual load is 150 kW, the target load is 145 kW, the tracking error is 5 kW, and the corresponding tracking accuracy is 3.45%.

With the passage of time, there is a significant change in tracking error, although for most of the time, the tracking error remains around 2 kW. The lowest tracking accuracy occurs in the third second, at 1.25%, demonstrating the system's good responsiveness to load changes.

The average tracking error is 2.8 kW and the average tracking accuracy is 1.89%, indicating that the comprehensive energy distribution network has strong tracking ability under load changes and can better meet the needs of the target load.

5. CONCLUSION

This paper proposes a method for comprehensive energy distribution network modeling and power system security and stability control based on perception. Real-time monitoring of power load, thermal energy flow, and gas transmission

is achieved by deploying multiple sensors to ensure the accuracy and timeliness of data. The use of Kalman Filter and Bayesian data fusion techniques effectively eliminates data noise and improves the accuracy of system state estimation. By utilizing the DreamerV2 algorithm to establish a dynamic model and combining it with MILP for optimization, efficient scheduling and resource coordination of the integrated energy system have been achieved. The results for load tracking accuracy show that the system has good response capability under load changes, proving the effectiveness of the proposed method in improving the safety and stability of the power system. Future research needs to further investigate the application of this method, explore more complex energy management strategies to cope with the increasing energy demand and system dynamic changes, and promote the intelligence and sustainable development of integrated energy distribution networks.

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