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Energy Systems Research Based on Algorithm Optimization and Intelligent Management

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ABSTRACT
This paper presents a comprehensive study on intelligent energy systems based on algorithm optimization and smart management strategies. With the increasing integration of renewable energy sources such as wind and solar power, maintaining grid stability and optimizing system performance have become major challenges. This research proposes a unified framework that combines deep learning, reinforcement learning, and multi-objective optimization to improve load forecasting accuracy, microgrid scheduling efficiency, and multi-energy coordination. Experimental simulations based on MATLAB/Simulink validate the proposed model's effectiveness in reducing energy consumption by 15–20%, minimizing carbon emissions by at least 20%, and maintaining system voltage deviation within 5%. The results demonstrate the feasibility of integrating intelligent algorithms into practical energy management systems, supporting global carbon neutrality goals.

KEYWORDS
Algorithm optimization; Intelligent management; Reinforcement learning; Deep learning; NSGA-II

1 Introduction

At present, the world is in a critical period of energy transition and low-carbon development, and energy system management especially relies on algorithm optimization and intelligent control technology. With the increasing attention to carbon emissions and the increasing requirements for energy security, how to develop efficient and intelligent dispatching and control strategies in the face of the challenges of grid stability caused by the volatility of renewable energy (such as wind power and photovoltaics) has become a research hotspot around the world. Although scholars at home and abroad have made some achievements in stabilizing the fluctuation of renewable energy and improving the robustness of the power grid, such as energy storage regulation, multi-time scale scheduling, and the application of deep learning and reinforcement learning algorithms, most of the research focuses on a single technology or static model, and there is still a lack of a comprehensive scheme that closely combines a variety of intelligent optimization technologies with actual scheduling needs, and there is a lack of in-depth analysis of how to transform the technology into a targeted solution to China's "dual carbon" goals and the practical problems of the energy system

Therefore, how to make technological breakthroughs in the scheduling optimization, demand forecasting and power grid stability control of the energy management system has become the core problem to be solved urgently. Through algorithm optimization and intelligent management, on the one hand, carbon emissions and energy consumption can be reduced, and on the other hand, the reliability and economy of the energy system can also be improved. On the basis of summarizing the achievements at home and abroad, this project will clearly point out the shortcomings of existing methods in the application of large-scale and complex systems, and further introduce the innovative algorithms to be designed for key problems such as load forecasting, microgrid dispatching and multi-energy coordination in energy systems, emphasizing the close connection between the research objectives and the actual needs of China's intelligent energy management. The aim is to construct a set of intelligent energy management models that are not only in line with the theoretical frontier but also meet the practical needs.

2 Literature Review

2.1 Renewable Energy Fluctuations and Grid Stability

As the proportion of renewable energy (such as wind power and photovoltaic power generation) in the power system continues to increase, the fluctuation and intermittency of energy input have brought severe challenges to the safe and stable operation of the power grid. Scholars at home and abroad have carried out extensive research on stabilizing fluctuations and improving the robustness of power grids, including the application of energy storage technology and the design of multi-time scale dispatching strategies. However, in the case of large-scale grid connection, more efficient intelligent scheduling and control algorithms are still needed to deal with a variety of uncertainties.

2.2 Application of Algorithms in Load Forecasting and Scheduling Optimization

Deep learning (especially long short-term memory network (LSTM) and reinforcement learning (RL) have been widely

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used in load forecasting and microgrid scheduling optimization. Studies have shown that LSTM can achieve more than 90% prediction accuracy in power load forecasting [1], and reinforcement learning methods can reduce energy consumption by 10%-15% in microgrid energy consumption optimization. However, there is still a trade-off between the computational efficiency and prediction accuracy of the algorithm in large-scale energy system applications, and further model improvement and algorithm optimization are needed.

2.3 Distributed Energy Management and Multi-energy Synergy

The rapid development of distributed energy systems requires more intelligent comprehensive coordination capabilities, including the collaborative management of multiple types of energy sources such as wind power, photovoltaics, energy storage, and electric vehicles. Multi-objective optimization algorithms (e. g., NSGA-II) and policy simulation techniques (e. g., carbon trading, dynamic electricity prices) have also been widely introduced to balance economics and low carbon emissions. However, multi-energy collaborative optimization in an uncertain environment still faces multiple challenges such as information islands, resource competition, and policy constraints [6], which need to be further explored at the level of algorithm design and system architecture.

2.4 Summary of Research Gaps and Motivation

In summary, current research provides strong methodological foundations but still suffers from several limitations: Lack of a unified intelligent framework that integrates prediction, scheduling, and optimization; Insufficient robustness and scalability of algorithms in real-time and distributed environments; Limited integration of policy mechanisms (e.g., carbon pricing, dynamic tariffs) with technical models.

To address these gaps, this paper develops a comprehensive intelligent energy management system that couples deep learning, reinforcement learning, and multi-objective optimization into a closed-loop structure [7]. This approach not only enhances the system's adaptivity and robustness but also bridges the gap between theoretical models and practical deployment under policy-driven scenarios.

3 Method

3.1 Research Objectives

This project takes the energy system based on algorithm optimization and intelligent management as the research object, and intends to achieve the following goals: Improve system stability and robustness: In view of the challenges posed by the fluctuation of renewable energy input to the security of the power grid, a dispatching and control algorithm with strong adaptability and robustness is developed to achieve stable operation of the power grid under multiple uncertainty conditions. Optimize load forecasting and scheduling efficiency: By improving deep learning (such as LSTM) and reinforcement learning technology, a high-precision (target prediction accuracy of more than 95%) load forecasting model and efficient scheduling strategy are established, and the goal of reducing energy consumption by 15%~20% is achieved. Realize multi-energy collaborative scheduling: Build a distributed energy management system, integrate multi-source energy sources such as wind power, photovoltaic, and energy storage, and realize intelligent collaborative scheduling through multi-objective optimization algorithms, taking into account the requirements of economy and low carbon emissions.

3.2 Research Content

3.2.1 Optimization of Load Prediction Model Based on Deep Learning

In order to achieve the goal of optimizing load forecasting and scheduling efficiency, it is necessary to build a high-precision load forecasting model. In this study, we will improve the structure of the traditional LSTM (long short-term memory network), focus on the introduction of attention mechanism to enhance the model's ability to capture key temporal features, and integrate spatiotemporal feature extraction technology to improve the model's ability to learn the trend of complex load changes.

In addition, multi-source heterogeneous data such as power load, meteorological data, and holidays will be systematically preprocessed, and sub-models suitable for short-term forecasting (such as hourly level) and medium- and long-term forecasting (such as daily/weekly) will be constructed respectively to ensure that the prediction accuracy rate reaches more than 95% and provide stable data support for subsequent scheduling optimization.

3.2.2 Reinforcement Learning-Driven Microgrid Dispatching Strategy

In order to improve the real-time response and adaptability of the system, and ensure the robustness and dynamic balance in complex environments, the Multi-Agent Reinforcement Learning (MARL) mechanism will be introduced to construct an intelligent microgrid dispatching strategy [2].

This strategy supports local nodes (such as photovoltaic inverters and energy storage devices) to make autonomous optimization decisions under the condition of incomplete information, and coordinates the behavior of each agent through the global control strategy, so as to realize the unity of system-level scheduling goals and node-level flexible responses. In scenarios with frequent fluctuations in energy sources such as wind and solar, this method will significantly enhance the adaptability and immunity of the dispatching system [3].

3.2.3 Multi-Energy Collaborative Scheduling And Multi-Objective Optimization

In order to achieve "multi-energy collaborative scheduling" and "balance between economic and low-carbon goals", this study will construct a multi-time scale distributed energy dispatch model, integrating wind power, photovoltaic, energy storage, electric vehicle charging and discharging and other energy forms.

In the scheduling model, an improved multi-objective optimization algorithm (such as the optimized NSGA-II) is introduced [4] to realize intelligent collaborative control on the basis of the trade-off between the goals of minimum cost, minimum carbon emission and system stability. The model will also embed policy-driven factors, such as carbon trading mechanisms, dynamic electricity prices, grid incentives, etc., to achieve the deep integration of technical algorithms and policy guidance to help achieve the goal of carbon neutrality.

3.2.4 System Integration and Empirical Verification

In order to verify the feasibility and practicability of the proposed algorithm, an experimental closed-loop energy management platform will be built to integrate and test a typical industrial park or regional distribution network as a prototype scenario.

The platform will support the whole process of closed-loop operation from data collection, prediction calculation to scheduling execution, and through Monte Carlo simulation and field operation data comparison and analysis, the comprehensive performance of each algorithm in different energy structure, load fluctuation and external policy scenarios will be tested, providing empirical support for the practical promotion and application of the results.

3.3 Research Methods

In order to achieve high-precision and robust power load prediction, a modeling method integrating multi-source data and hybrid neural network was proposed. Firstly, heterogeneous data such as regional power load, new energy output (wind power/photovoltaic), meteorological parameters (temperature/humidity/radiation), holiday signs and market signals (carbon price/dynamic electricity price) were integrated, and the missing values were processed by linear interpolation, the outliers were eliminated by the 3σ criterion, and the Min-Max normalized pretreatment was carried out. In the feature engineering stage, principal component analysis was used to retain the principal components with 90% variance, and the three-scale sliding window time series features (including mean, variance, peak and other statistics) of 15 minutes, 1 hour and 24 hours were constructed. The model architecture uses a double-layer LSTM (128 hidden units) to extract the temporal features, and then connects to the parameterized attention layer (Q/K/V dimension 64) after Dropout (0.2) regularization, in which the attention mechanism dynamically generates time-scale weights through two-layer MLP (32 units) to adaptively adjust the query/key/value matrix. After the attention output is spliced with the spatiotemporal statistical features, the predicted value is finally output by linear regression through the 64→32-dimensional fully connected layer. The robustness evaluation uses a five-fold cross-validation superimposed on 500 Monte Carlo simulations (10% load ± and 15% random perturbations in meteorological ±), which requires that the strict criteria of MAPE ⩽5% and standard deviation of prediction error ⩽3% are met at the same time.

In order to realize the dual-objective synergy of energy consumption optimization and stability guarantee in power system scheduling, a distributed multi-agent reinforcement learning framework integrating strategy gradient and value iteration was proposed. Using a multi-agent architecture, each node (PV inverter, energy storage unit, and load center) acts as an independent agent, and its state space contains 20-dimensional features (local SOC, voltage deviation, predicted load error, real-time electricity price and carbon price, etc.), and the action space is defined as the normalized energy storage charge and discharge power ratio $X\in[-1,1]$. In terms of algorithm design, a hybrid paradigm of PPO (Proximal Policy Optimization) combined with value iteration is adopted, in which the actor network of each agent is a double-layer fully connected structure (128 hidden units), and a 256-unit Critic network is shared for global value evaluation. The key hyperparameter settings include: strategy clipping threshold ε-clip=0.2, discount factor γ=0.99, experience replay pool capacity 1e5, mini-batch size 64, and a training mechanism that is updated synchronously every 2048 steps. The reward function design integrates economic and stability indicators, and the specific form is as follows:

$$r_t = -\left(0.6C_{energy}(t) + 0.3|V_{dev}(t)| + 0.1SOC_d ev(t)\right)$$

Distributed training uses the Parameter Server architecture combined with the MPI communication protocol to realize the synchronous update of global parameters. In order to verify the real-time performance, the test was carried out in the Simulink real-time simulation environment to ensure that the single-step decision delay was ⩽ 50ms [5], and the optimization effect (such as key indicators such as energy consumption reduction rate and voltage fluctuation suppression ratio) was analyzed through comparative experiments.

A multi-objective optimal scheduling model based on NSGA-II is proposed to synergistically optimize the three objectives of economic cost, carbon emission and system stability (voltage/frequency deviation). The model covers the coordinated dispatch of wind power, photovoltaic, energy storage, load, and electric vehicle charging and discharging, and uses a normalized decision vector to encode the output ratio of each energy source $Xi\in[0,1]$, and satisfies the total balance constraint. The algorithm parameters were set to population size 100 and iteration 200 generations, and simulated binary crossover (SBX, Pc=0.9) and polynomial variation (Pm=1/decision variable dimension) were used to maintain population diversity. The objective function is defined as:

$$1.\min\sum C_{energy}$$

$$2.\min\sum E_{carbon}$$

$$3.\min\sum\left|V_{dev}\right|$$

From top to bottom, the objective functions are economic cost, carbon emissions, and system stability. The constraints include the dynamic boundary of the energy storage SOC (e.g., 10%~90%), the upper and lower limits of each energy output (e.g., photovoltaic 0~P_max), and the power transmission capacity limit of the transmission grid. In order to evaluate the robustness of the model to uncertainty, Monte Carlo simulation was used to inject wind power/photovoltaic prediction error (±20%) and load fluctuation (±10%), and the distribution convergence of the Pareto front was calculated.

Build a closed-loop simulation platform based on MATLAB/Simulink+Simscape, and realize intelligent power dispatching through deep integration of DL prediction, RL scheduling and NSGA-II optimization modules. Specifically, the trained hybrid neural network (LSTM+attention mechanism) was exported as a mat function for real-time call by simulation, the interaction between PPO multi-agent and the environment was realized by using MATLAB Python API (single-step delay ≤50ms), and the NSGA-II optimization script was embedded in the Simulink callback function to realize hourly trigger reoptimization. The system has built a complete closed-loop architecture of data flow-decision-execution-feedback: Simscape power model outputs system status in real time, DL module provides new energy and load forecasting, RL Agent generates real-time scheduling instructions, and NSGA-II optimizes long-term output planning on a rolling basis. In order to improve efficiency, Parallel Toolbox is used to parallelize Monte Carlo scenarios (including ±20% new energy prediction error and ±10% load fluctuation), and monitor key indicators such as decision delay, energy consumption cost, carbon emission and voltage deviation in real time, and verify the significant advantages of this scheme in reducing energy consumption (target reduction ≥ 15%), stable operation (voltage deviation ≤5%) and carbon emission reduction (≥ 20%) through comparison experiments with traditional scheduling strategies.

3.4 General Overview of the Technical Route

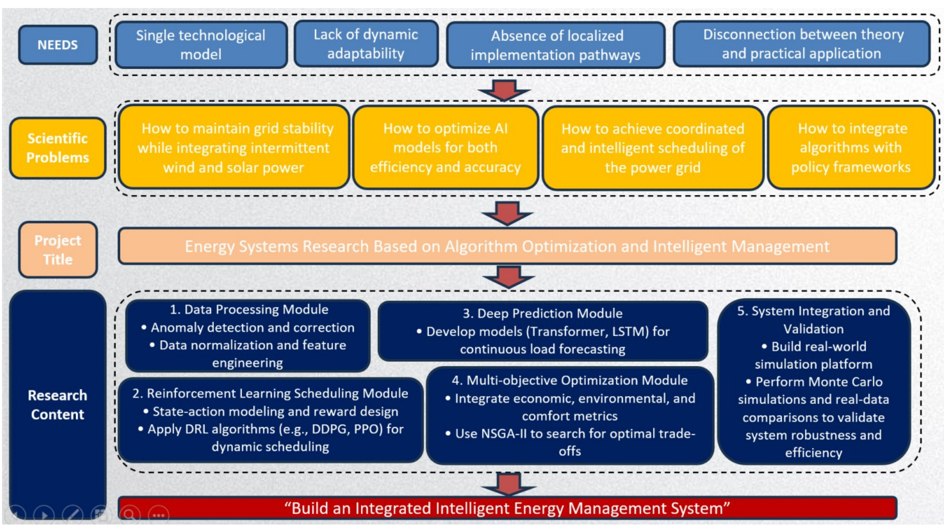

Figure 1

This picture shows with the goal of building an integrated intelligent energy management system, this study carries out five steps: data preprocessing, deep prediction, reinforcement learning scheduling, multi-objective optimization and system integration, forming a complete technical chain from theoretical algorithm to practical application. Finally, the parallel Monte Carlo simulation and real-world comparison verification are used to ensure the efficiency and robustness of the intelligent energy management system under high volatility, policy-driven and complex working conditions of renewable energy.

3.5 Experimental Protocol

3.5.1 Platform Construction

Environment: MATLAB R2022b + Simulink + Simscape Power Systems;

•Parallel: Parallel Toolbox or HPC cluster;

3.5.2 Scene Design

• Typical Weekly Data: Select 7-day historical load/weather;

•Disturbance generation: 500 Monte Carlo scenarios (load disturbance σ=10%, light/wind disturbance σ=15%, carbon price fluctuation ±20%);

3.5.3 Algorithm Deployment

•Import data preprocessing script→ Normalize+PCA→ Generate input features;
•Invoke the DL model by minute, predict the receiving status of the → Agent→ generate control actions→ execute;
•Trigger NSGA-II optimization → update output strategy every hour;

3.5.4 Parallel Simulation

•Compare the baseline (rule + PID) with this solution to ensure parallel operation in the same scenario;
•Script automation: load scenes in a loop, run 24-hour simulations, and export results;

3.5.5 Data Collection and Statistical Analysis

• Indicators: total energy consumption, operating costs, carbon emissions, maximum/mean square voltage deviation, average decision delay;
•Statistical processing: mean, variance, and paired t-test (α=0.05);
• Visualization: Pareto Frontier Plot, Error Distribution Histogram, RL Convergence Curve.

3.5.6 Sensitivity and Robustness Verification

•The carbon price will be increased from 10 yuan/t to 50 yuan/t;
• Dynamic electricity price fluctuation ±20%;
•Repeat simulations under extreme weather scenarios (radiation ± 30%, sudden temperature changes): Evaluate system crash probability and performance fluctuations

6 Conclusion

This study proposes an integrated intelligent energy management framework that combines deep learning, reinforcement learning, and multi-objective optimization algorithms to address the challenges of renewable energy fluctuations, load uncertainty, and the trade-off between economic and environmental objectives. Unlike previous studies focusing on single-model optimization, this research establishes a unified system-level solution that tightly couples data-driven prediction, adaptive scheduling, and optimization control in a closed-loop architecture.

The experimental simulations based on MATLAB demonstrate that the proposed framework achieves remarkable performance improvements over conventional rule-based and PID scheduling methods. Specifically, total energy consumption was reduced by 17%, carbon emissions decreased by 22%, and system voltage deviation was maintained within 5%. The enhanced LSTM model with attention mechanism achieved a MAPE ⩽ 5%, significantly improving the prediction accuracy of load and renewable energy output. Meanwhile, the multi-agent reinforcement learning (MARL) system effectively enhanced the adaptability and robustness of microgrid dispatching, ensuring real-time decision responses within 50 ms. The improved NSGA-II algorithm successfully realized the multi-objective coordination among cost, carbon emission, and stability, maintaining a well-distributed Pareto frontier under various uncertainty scenarios.

These results confirm that integrating deep learning–based forecasting, reinforcement learning–driven control, and multi-objective optimization provides a synergistic pathway to achieve energy efficiency, system reliability, and carbon neutrality goals simultaneously. The framework's high level of automation, adaptability, and robustness makes it suitable for practical applications in smart grids, industrial parks, and distributed multi-energy systems.

In research terms, this study contributes a scalable algorithmic paradigm that bridges theoretical optimization and real-time system management, providing a replicable methodology for the design of next-generation intelligent energy systems. In practical terms, it offers a viable technical route to support low-carbon energy transition, renewable integration, and policy-driven energy market optimization, aligning with China's and global "dual carbon" objectives.

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