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Enterprise energy management optimisation and decision support system based on big data analysis

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Abstract: Global energy demand surge and worsening environmental issues make optimising corporate energy management key to boosting efficiency, cutting costs and achieving sustainability. This study proposes a multi-level, modular decision support system (DSS) architecture for enterprise energy management optimisation, based on big data analysis. It integrates deep learning, reinforcement learning and digital twins, using genetic algorithms (GA) for global search (e.g., multi-energy allocation) and particle swarm optimisation (PSO) for faster-convergent local refinement. Lighting systems account for 47% of production auxiliary energy; office devices take 63.9% of administrative consumption. A 500+-device factory saw energy utilisation rise from 82% to 92% via the system. Analysis shows production-linked consumption (52.7% of total) has core equipment contributing 88.3%.

Keywords: big data analytics; energy management optimisation; decision support system; DSS; reinforcement learning; digital twin technology; particle swarm optimisation; PSO.

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1 Introduction

Energy management is the key to realising sustainable development and enhancing modern enterprises' core competitiveness. Under the background of increasing global energy demand, traditional energy management methods face significant limitations. They struggle to meet enterprises' comprehensive needs, which include improving energy efficiency, controlling energy costs, and reducing environmental impact (Alwi et al., 2024; Babar et al., 2021). The continuous transformation of energy structure, especially the rapid development of renewable energy, makes enterprises face more uncertainties and challenges in energy use and management (Bai et al., 2022). Previous

studies have primarily relied on traditional optimisation methods, [e.g., linear programming (LP), statistical analysis] to address energy management challenges, but these approaches lack adaptability to high-dimensional, heterogeneous data and dynamic operational environments (Bao et al., 2022). Traditional energy management methods often rely on manual experience and simple statistical analysis, making it difficult to cope with enterprise energy systems' complexity, diversity and dynamics. This method has obvious limitations when dealing with multi-source heterogeneous data, high-frequency dynamic adjustment, and complex decision-making requirements (Belcastro et al., 2024; Chen et al., 2021). Many different types of data sources are involved in the production process of enterprises, including equipment operation parameters, environmental data, market energy price fluctuations, etc. and these data are usually unstructured, high-dimensional and real-time (Dandugala and Vani, 2024; De Carvalho et al., 2021). This study differentiates itself by integrating advanced big data analytics, machine learning, and digital twin (DT) technologies to construct a holistic decision support system (DSS). By bridging the gap between theoretical models and practical industrial applications, the proposed system offers real-time, data-driven insights that traditional methods cannot achieve, thus providing a novel solution for modern enterprises to balance energy efficiency, cost reduction, and sustainability goals (Devaraj et al., 2021). By building a comprehensive energy management system, integrating multi-dimensional data of enterprise energy consumption, and using advanced analysis methods, valuable information can be extracted from massive data to form an accurate optimisation strategy and an efficient DSS (Dhanalakshmi and Ayyanathan, 2022).

Existing energy management methods, such as LP and nonlinear programming (NLP), have limitations in handling multi-source heterogeneous data and dynamic uncertainties. LP is effective for linear optimisation problems but fails to model complex nonlinear relationships in energy systems (e.g., equipment efficiency fluctuations and environmental interactions) (Dolores et al., 2023; Feng et al., 2023). Taking wind farms as an example, operating status monitoring and fault warning of wind turbines are typical application scenarios of energy management. During wind farm operation, many sensors transmit wind turbines' running status data to the server at extremely high frequencies, forming massive, multi-source and heterogeneous complex data (Grami, 2022; Gui and Zhang, 2022). In the current context of escalating global energy demands and pressing environmental concerns, optimising enterprise energy management has emerged as a crucial imperative for enhancing energy efficiency, curbing costs, and fostering sustainable development. Traditional energy management approaches, however, are ill-equipped to handle the intricate web of complex energy consumption patterns and the dynamic flux of market environments (Gupta and Chaturvedi, 2023; Hannan et al., 2023). Research-based on big data analysis technology is particularly important. By adopting advanced algorithms and tools, wind farm condition monitoring and optimisation management software can be developed to realise real-time monitoring, fault diagnosis and early warning of wind turbine running status (He et al., 2022; Hernandez-Robles et al., 2024). NLP addresses nonlinearity but struggles with high-dimensional data and real-time decision-making due to computational complexity. Traditional data analysis methods also lack the ability to extract deep insights from unstructured data, (e.g., sensor streams, equipment images), leading to suboptimal energy scheduling and missed optimisation opportunities. In contrast, this study leverages deep learning for feature extraction from high-dimensional data and reinforcement learning (RL) for adaptive decision-making, overcoming these limitations to enable more precise and

dynamic energy management (Hou and Wang, 2023). This method can not only improve the energy yield of wind farms and optimise the energy utilisation efficiency but also effectively reduce the operation and maintenance costs.

2 Theoretical basis of enterprise energy management optimisation

2.1 Characteristics and modelling theory of multi-source heterogeneous data

In the process of enterprise energy management, a large amount of multi-source heterogeneous data is involved, which cover various types such as equipment operation parameters, energy flow monitoring data, environmental monitoring data and production process data. As shown in equations (1) and (2), D is the dataset, $X_1, X_2, \dots, X_n$ represent all kinds of monitoring data, and X is the input feature. $X_i(t)$ is the value of the i^{th} class data at time t , f is a function of data evolution, ε is the noise term, and k represents the time delay step. The characteristics of multi-source heterogeneous data are mainly reflected in the following aspects: high data dimension, diverse sources, complex structure and uneven quality.

$$D = (X_1, X_2, \dots, X_n) \quad (1)$$

$$X_i(t) = f(X_i(t-1), X_i(t-2), \dots, X_i(t-k)) \quad (2)$$

The high dimensionality of multi-source heterogeneous data is reflected in the numerous variables involved, including temperature, pressure, current, voltage, energy flow rate, equipment load, production environment parameters, etc. As shown in equation (3), $X(t)$ is the set of all variables at time t , w_i and α_j are the weights of each variable, $Z_j(t)$ is the external characteristic data, and m is the dimension of the external data. These variables are not only huge in number, but also usually have time series characteristics, and their dynamic correlation with time needs to be dealt with.

$$X(t) = \sum_{i=1}^n w_i X_i(t) + \sum_{j=1}^m \alpha_j Z_j(t) \quad (3)$$

Different data sources may use different formats or protocols for storage and transmission, such as structured databases, unstructured text data, image data and real-time streaming data. As shown in equation (4), D is the fused dataset, and X_i, Y_i and Z_i are data from different sources, representing data fusion of different formats. This inconsistency of data further increases the difficulty of data fusion and analysis.

$$D = \sum_{i=1}^m (X_i + Y_i + Z_i) \quad (4)$$

In view of the complexity and diversity of multi-source heterogeneous data, specific technical means are needed for data fusion and feature extraction. As shown in equations (5) and (6), $P(AB)$ is the conditional probability, $P(A)$ is the prior probability, $P(B)$ is the normalisation factor, and B_i represents the conditional probability calculated from different data sources. $P(X)$ is the joint probability distribution, $P(X_i | P_i)$ and $P(P_j | Q_j)$ are the conditional probabilities, and Q_j is the condition of other variables.

Bayesian network is a typical representative of probabilistic fusion technology. It can establish causal correlation among various data sources, and realise quantitative analysis of uncertainty by modelling probability distribution.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} + \sum_{i=1}^n P(A|B_i) \quad (5)$$

$$P(X) = \sum_{i=1}^n \left(P(X_i|P_i) \prod_{j=1}^m P(P_j|Q_j) \right) \quad (6)$$

Another effective technique is the autoencoder, which is a deep learning-based feature extraction method that can automatically learn from high-dimensional data to low-dimensional representations, retaining the key features of the data. As shown in equations (7) and (8), X_{input} is the input data, $f_{encoder}$ and $f_{decoder}$ represent the functions of encoder and decoder respectively, Z is the low-dimensional feature representation, and X_{output} is the reconstructed output. X is the input data, W is the convolution kernel, b is the bias term, Z_i is the feature of different data sources, f is the activation function, Y is the convolution output, and $*$ represents the convolution operation. Convolutional neural networks and graph neural networks in deep learning technology are also widely used in the processing and modelling of complex data, especially when processing images and network data.

$$X_{input} \xrightarrow{f_{encoder}} Z \xrightarrow{f_{decoder}} X_{output} \quad (7)$$

$$Y = f \left(X * W + b + \sum_{i=1}^k \lambda_i Z_i \right) \quad (8)$$

2.2 Theoretical basis of energy system complexity analysis and control

Enterprise energy system is a highly complex multi-variable, multi-temporal and spatial scale system. Its complexity is mainly reflected in nonlinear dynamic behaviour, multi-time scale variation and multivariate coupling characteristics. As shown in equations (9) and (10), Y is the output of the system, $X_1, X_2, \dots, X_n$ are the input variables, g is the nonlinear function, α_i is the coefficient, and ϵ is the error term. E is the equipment energy efficiency, T is the temperature, P is the pressure, F is the load, L is the environmental factor, h is the nonlinear function, δ is the error. In the interaction of different devices and components in the energy system, they usually show a nonlinear relationship, that is, the relationship between input and output is not a simple linear correspondence.

$$Y = \sum_{i=1}^n \alpha_i g(X_i, X_2, \dots, X_n) + \epsilon \quad (9)$$

$$E = h(T, P, F, L) + \delta \quad (10)$$

The energy efficiency of equipment, changes in environmental conditions, and fluctuations in load during production can all lead to nonlinear changes in system

behaviour. As shown in equation (11), y is the equipment performance, T , P , F and L are temperature, pressure, load and environmental factors respectively, α_1 , α_2 , α_3 and α_4 are coefficients, β is a constant term, and ϵ is an error term. This nonlinear characteristic makes it difficult for traditional linear control methods to meet the management and optimisation needs of complex energy systems.

$$y = \alpha_1 T + \alpha_2 P + \alpha_3 F + \alpha_4 L + \beta + \epsilon \quad (11)$$

Enterprise energy systems are also characterised by multiple time scales. Energy consumption is affected not only by short-term demand changes, but also by long-term plans and strategic decisions. As shown in equation (12), $E_{total}(t)$ is the total energy demand, $\eta(t)$ is the short-term demand, $\gamma(t)$ is the long-term demand, δ_i is the external data weight, and $Z_i(t)$ is the external environmental data. The production load of enterprises has obvious peaks and valleys in daily production, while the long-term energy procurement strategy is adjusted according to energy market price fluctuations and policy guidance.

$$E_{total}(t) = \eta(t) + \gamma(t) + \sum_{i=1}^n \delta_i Z_i(t) \quad (12)$$

Energy management not only needs to consider the operating efficiency and load distribution of equipment in the short-term, but also needs to forecast and plan long-term energy consumption trends. As shown in equation (13), $C_{short}(t)$ and $C_{long}(t)$ are the short-term and long-term costs, respectively, λ is the equilibrium coefficient, θ_i is the constraint weight, and X_i is the additional constraint condition. Under the constraints of such multiple time scales, how to balance short-term and long-term goals and ensure the continuous optimisation of energy use has become a challenge.

$$\min \left(\sum_{t=1}^T C_{short}(t) + \lambda \sum_{i=1}^T C_{long}(t) + \sum_{i=1}^n \theta_i X_i \right) \quad (13)$$

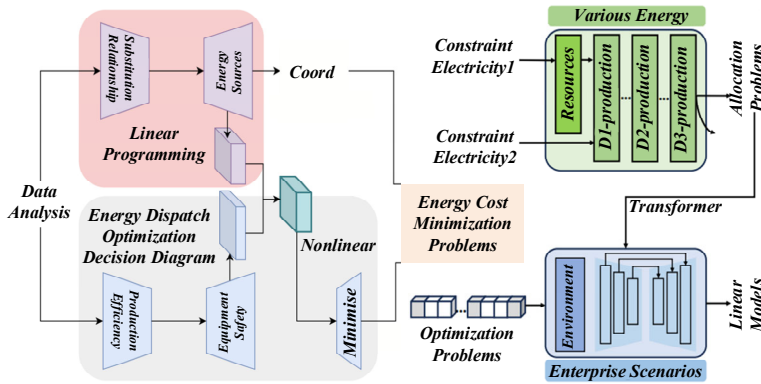
3 Big data-driven energy management technology framework

3.1 Mathematical optimisation methods in energy optimisation and DSSs

In the energy management of modern enterprises, the mathematical optimisation method is the core tool to maximise energy efficiency, minimise cost and optimise resource allocation (Huang et al., 2023; Hussain et al., 2023). With the continuous advancement of industrialisation and informatisation, energy management faces more complex tasks, including multi-objectives, dynamic adjustment and uncertainty. Mathematical optimisation methods can provide scientific decision support and help enterprises realise intelligent dispatching and optimal management of energy (Ishak et al., 2024; Kaginalkar et al., 2023). LP models are fundamental tools in energy optimisation, especially in enterprise scenarios, where many optimisation problems can be solved by linear models (Khalil et al., 2023; Knayer and Kryvinska, 2022). Enterprises usually face the allocation problems of various energy resources in daily production, and these problems can be transformed into energy cost minimisation problems under a set of constraints. By

establishing a LP model aiming at energy consumption costs, enterprises' energy costs can be minimised to ensure production efficiency and equipment safety (Lee et al., 2023, 2021). Figure 1 is an energy dispatch optimisation decision diagram based on big data analysis. LP can handle the substitution relationship between different energy sources, such as the coordinated use of multiple energy sources such as electricity, heat energy and cooling, and further optimise resource allocation. The aim of this study is to explore and propose a comprehensive solution for enterprise energy management optimisation through the application of big data analysis. Specifically, we seek to construct a multi-level and modular DSS architecture. This architecture will integrate cutting-edge technologies like deep learning, RL, and DT technology. By doing so, we aim to provide enterprises with an intelligent and real-time energy management solution.

Figure 1 Energy dispatch optimisation decision diagram based on big data analysis (see online version for colours)



Existing enterprise energy management tools also have inherent limitations. Traditional energy management systems (EMS) focus on energy consumption monitoring and basic data statistics but lack dynamic optimisation capabilities for complex, real-time scenarios (Li et al., 2023, 2022). Supervisory control and data acquisition (SCADA) systems excel at real-time equipment monitoring and fault alarms, yet they lack advanced data analytics to extract deep insights for energy scheduling (Li, 2024). For example, SCADA can track wind turbine rotation speed in real-time but cannot predict future load fluctuations or optimise blade angles proactively. In contrast, this study's proposed DSS integrates the real-time monitoring advantages of SCADA and the data integration capabilities of EMS, while adding deep learning-driven prediction and RL-based dynamic scheduling – filling the gap between real-time control and intelligent optimisation. NLP methods can effectively deal with the complex relationship among variables in complex energy systems and provide more accurate optimisation schemes. In reality, many optimisation problems include continuous variables and discrete decision variables, such as equipment switching and allocation of energy resources. Such problems require mixed integer programming (MIP) methods to solve them. MIP can handle integer and continuous variables and is suitable for problems involving production scheduling, energy distribution and facility location. Figure 2 is the application diagram of a multi-objective optimisation algorithm in energy management. In the energy dispatching of large enterprises, the start-stop decision of some devices is discrete, while the power

output of other devices is continuous. Through the MIP model, these discrete and continuous decisions can be optimised to realise the globally optimal energy management strategy.

Figure 2 Application diagram of multi-objective optimisation algorithm in energy management (see online version for colours)

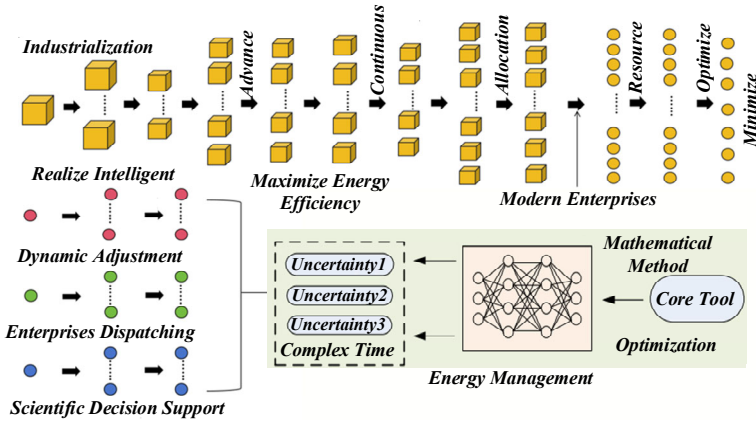
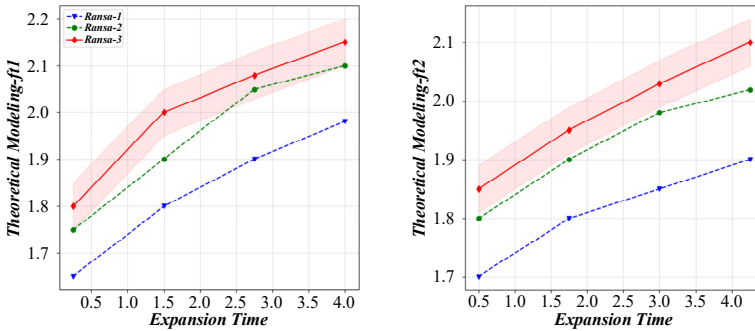


Figure 3 Energy demand forecast and actual consumption assessment diagram (see online version for colours)



This category includes big data processing platforms like Hadoop and Spark, which are crucial for handling the large-volume, multi-source, and heterogeneous data in enterprise energy management. This category includes a hybrid big data platform integrating Apache Hadoop (for distributed storage of massive heterogeneous energy data, such as equipment operation logs and environmental sensor streams) and Apache Spark (for real-time stream analysis and iterative computing, enabling low-latency processing of 15-minute interval energy consumption data). These tools are crucial for handling the large-volume, multi-source, and heterogeneous data in enterprise energy management. Robust optimisation and stochastic optimisation methods can improve the adaptability of enterprise energy systems to environmental changes, especially in the face of uncertain energy prices or equipment failures, and still ensure the optimal management of energy consumption. In the energy scheduling module, GA is first applied to generate a set of feasible global solutions for multi-energy source combination, (e.g., balancing electricity

and natural gas usage), as its evolutionary mechanism (selection, crossover, mutation) excels at avoiding local optima in complex systems. PSO is then used to fine-tune these solutions – its particle swarm update rule (based on individual and global best positions) accelerates convergence, making it suitable for real-time adjustments (e.g., dynamic load redistribution during equipment idling). Figure 3 is a diagram of energy demand forecast and actual consumption assessment. The MPC method is especially suitable for those energy systems with time delays or dynamic changes, such as power and wind power systems. Mathematical optimisation methods like LP, NLP, and MIP, as well as RL algorithms are grouped here. These technologies are employed to optimise energy scheduling, resource allocation, and decision-making processes.

3.2 *Dynamic energy scheduling strategy based on RL*

First, it is necessary to clarify RL, a machine learning approach where an ‘agent’ learns to make optimal decisions by interacting with its environment – receiving positive rewards for efficient actions, (e.g., reducing energy waste) and negative feedback for inefficiencies. In the energy scheduling problem, energy consumption efficiency can be used as a reward signal so that the agent can gradually find the optimal scheduling strategy according to the environmental state and historical decision feedback. Agents in RL continuously explore and utilise current strategies to get rewards or punishments after each decision, thereby gradually adjusting the decision-making process and optimising the energy distribution of the system. Exploration refers to the agent’s discovery of new solutions by trying different scheduling strategies, while exploitation is selecting actions that maximise rewards based on known strategies. The RL model adopted in this study is a deep deterministic policy gradient (DDPG) algorithm, consisting of a critic network and an actor network. The actor network has a three-layer fully connected structure: the input layer includes 12 features, (e.g., real-time equipment load, energy market price, environmental temperature, and equipment operating status), the hidden layers have 128 and 64 neurons respectively with ReLU activation functions, and the output layer outputs the optimal scheduling action using a tanh activation function. The critic network follows a similar three-layer structure to evaluate the value of the actions generated by the actor network. Figure 4 is the evaluation diagram of the multi-source data fusion and optimisation decision model. In a multi-energy source scheduling problem, deep RL can model various energy sources’ status, demand, environment, and other information through deep neural networks. On this basis, dynamic scheduling optimisation is carried out.

In order to further improve the intelligence level of energy dispatching, the multiagent RL (MAS) method came into being. Multiagent RL introduces the collaboration of multiple agents, each of which can represent a device or a subsystem, into an energy scheduling problem. LP is a fundamental tool in energy optimisation. Its advantage lies in its simplicity and the ability to handle linear relationships effectively. For example, in enterprises with relatively stable energy consumption patterns and linear constraints, LP can be used to optimise energy resource allocation, such as determining the optimal mix of different energy sources to minimise costs. The DT system constructs a virtual replica of the physical energy system by integrating real-time sensor data and historical operation logs. It receives optimal scheduling strategies from genetic algorithms (GA) and particle swarm optimisation (PSO), simulates the implementation effect in the virtual environment, and feeds back the simulation results to the optimisation

algorithms for iterative improvement, forming a closed-loop optimisation mechanism. Figure 5 is the energy consumption assessment diagram of various enterprise departments. Compared with the traditional optimisation method, the scheduling strategy generation method based on adversarial learning can effectively deal with complex scheduling problems, especially when dealing with uncertainty and dynamic changes. Provide more reliable solutions.

Figure 4 Multi-source data fusion and optimisation decision model evaluation diagram (see online version for colours)

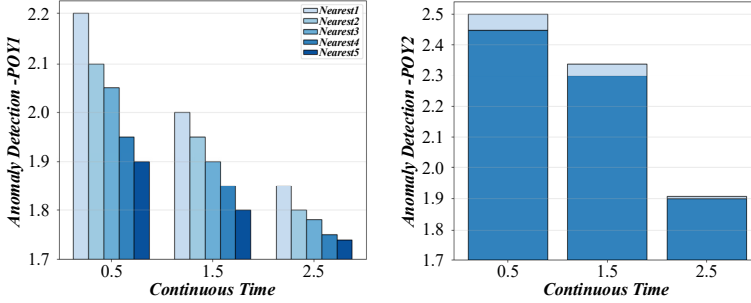
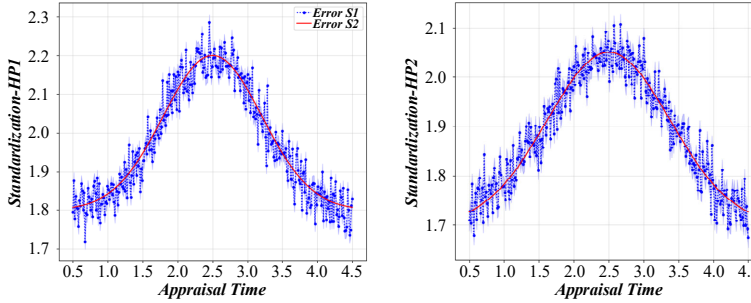


Figure 5 Energy consumption assessment chart of various departments of the enterprise (see online version for colours)



Energy dispatching systems often rely on real-time data to make decisions in practical applications. In fields such as smart grid and wind power generation, information such as voltage, current, frequency, and switching status collected by the SCADA system generates massive operating data every year. MPC is effective in predicting future energy consumption changes using dynamic models and the current system state. It is particularly suitable for energy systems with time delays or dynamic changes, such as power and wind power systems. The training data of the RL model are derived from six months of real operational logs of the target manufacturing enterprise, including energy consumption data, equipment load parameters, environmental monitoring data, and energy market price data, with a collection interval of 15 minutes, resulting in a total dataset of 18,240 samples. The model convergence criterion is defined as the average reward value stabilising within $\pm 1\%$ over 200 consecutive training episodes, ensuring the stability and reliability of the learned scheduling strategy. The condition monitoring of wind power equipment is usually at a semi-automatic level, and the value of equipment status data has not been fully tapped. Table 1 shows the impact of the increase in the

number of operators, with data sourced from the three-month operator efficiency test logs of the target manufacturing enterprise and a sampling period of 8 hours per day (9:00–17:00).

Table 1 Impact of the increase in the number of operators

<i>Number of operators</i>	<i>1</i>	<i>2</i>	<i>3</i>
DPPA	350.00	104.17	81.46
Statistic	350.00	82.35	50.65
Greedy	350.00	93.60	70.00

4 Design and implementation of intelligent energy optimisation model

4.1 Application of deep generative adversarial network (GAN) in energy load forecasting

DT, a virtual replica of physical energy systems, (e.g., wind farms or production lines), integrates real-time sensor data and historical operation logs to enable simulation, monitoring, and strategy verification without disrupting actual operations. In wind farms, energy management optimisation is crucial due to the intermittent nature of wind energy. By applying big data analysis, historical wind speed, temperature, and other environmental data can be collected and analysed. Deep GANs can be used to predict wind power loads more accurately. RL algorithms can then be employed to optimise the operation of wind turbines, such as adjusting the blade pitch angle based on real-time wind conditions. The GAN for energy load forecasting consists of a four-layer generator and a three-layer discriminator. The generator's input layer accepts 8-dimensional historical data (wind speed, hub speed, inverter power, ambient temperature, nacelle vibration velocity, fan vibration acceleration, historical load, and time series features), with hidden layers of 256, 128, and 64 neurons, and the output layer generates 1-dimensional future load data. The discriminator uses a three-layer structure (128, 64, 1 neurons) to distinguish between real historical load data and generated load data, with sigmoid activation in the output layer. Both networks are trained using Adam optimiser with a learning rate of 0.0002. Figure 6 shows the effect evaluation diagram before and after optimising the energy management system. The load of wind power generation is greatly affected by weather changes. The deep GAN can extract effective models from historical wind speed, temperature and other data to generate high-quality load forecasting results, helping wind farm managers better arrange power generation and load dispatching.

For the energy load forecasting sub-model, the optimisation objective is to minimise the mean absolute error (MAE) between predicted and actual load, ensuring the accuracy of load data input to the overall energy scheduling model. However, the data collected is often raw and contains noise, missing values, and inconsistent formats. Data pre-processing is, therefore, essential. It involves cleaning the data by removing outliers and filling in missing values. For example, in the case of energy consumption data with occasional spikes due to sensor malfunctions, statistical methods can be used to identify and correct these outliers. Feature extraction techniques, such as those based on deep learning (like autoencoders), are also applied during pre-processing to transform the

high-dimensional raw data into a more manageable and informative form. This pre-processed data serves as the foundation for subsequent optimisation and decision-making processes in enterprise energy management. Table 2 shows the input and output parameters of the model. Notably, changes in wind speed and grid load usually exhibit a certain time-series characteristic, and the deep GAN can predict future wind power loads by learning the time-series patterns in historical data, then adjust the operating status of wind turbines according to the prediction results to improve the energy utilisation efficiency of wind farms. The data in this table are sourced from the real-time operation data of a wind farm in Fujian Province, with a sampling period of 10 minutes per sample.

Figure 6 Effect evaluation diagram before and after energy management system optimisation (see online version for colours)

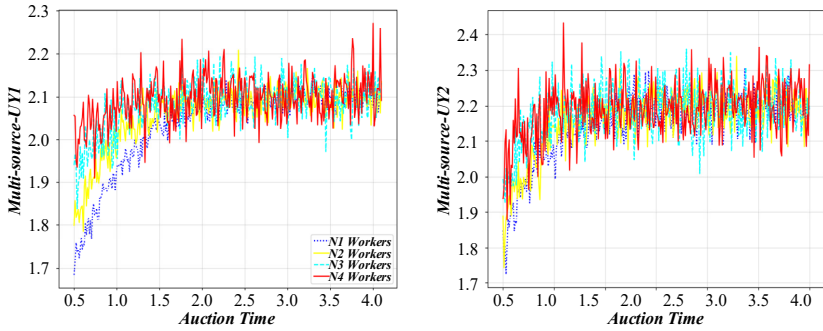


Table 2 Model input and output parameters

Serial number	Wind speed (m/s)	Hub speed (r/min)	Inverter power generation side (kW)	Ambient temperature (°C)	Nacelle vibration velocity (mm/s)	Fan vibration acceleration (m/s ²)	Predicted temperature (°C)
1	3.97	12.78	160	22.5	4.3	0.21	64.4
2	8.26	12.81	350	21.2	2.1	0.35	58.6
3	1.78	12.78	30	26.5	5.5	0.04	67.1
4	2.01	12.79	40	20.4	4.2	0.06	57.2
5	8.06	12.81	420	20.8	1.2	0.23	55.1
6	3.79	12.80	180	26.3	2.1	0.27	58.3
7	9.54	12.79	920	30.1	12.4	0.31	82.7
8	5.47	12.78	70	28.2	1.2	0.18	52.3

4.2 Layered architecture and microservice design of DSS

In the design of modern enterprise energy management optimisation and DSSs, combining complex optimisation models with real-time data processing to quickly respond to the change in enterprise energy demand is one of the important difficulties in system design. With the continuous development of technology, especially the rise of big data technology, artificial intelligence and cloud computing, DSSs based on layered architecture and microservice design have gradually become mainstream. This design can improve the flexibility and scalability of the system and provide real-time and accurate

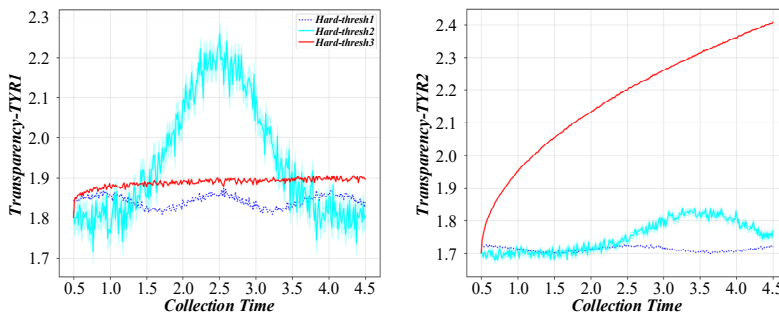
decision support when dealing with complex problems. Table 3 is SWOT analysis; a DSS is a tool that provides scientific support to decision-makers by integrating various technologies and methods. In energy management, DSS needs to face complex multi-objective optimisation problems and uncertain factors such as dynamically changing operating environments, market demand fluctuations, and energy price changes.

- **Data acquisition layer:** responsible for real-time data collection from enterprise internal sources, including IoT sensors (for equipment temperature, load, and vibration), SCADA systems (for energy flow and voltage), and enterprise resource planning (ERP) systems (for energy procurement costs). It supports data transmission in multiple formats, (e.g., JSON, MQTT) to ensure compatibility.
- **Data processing layer:** performs data pre-processing tasks such as cleaning (removing outliers caused by sensor malfunctions), fusion (integrating heterogeneous data from IoT and SCADA), and feature extraction (using autoencoders to reduce data dimensionality). This layer outputs standardised, high-quality data for subsequent analysis.

Table 3 SWOT analysis

<i>Method</i>	<i>Key features</i>	<i>Advantages</i>	<i>Limitations</i>
Linear programming (LP)	Solves linear optimisation problems	Simple, effective for linear relationships	Poor at handling nonlinearity
Nonlinear programming (NLP)	Deals with nonlinear constraints and objectives	Accurate for nonlinear problems	High computational complexity
Deep reinforcement learning (DRL)	Integrates deep learning and RL for complex decision making	Handles high-dimensional state spaces well	Data-intensive, requires a lot of training data

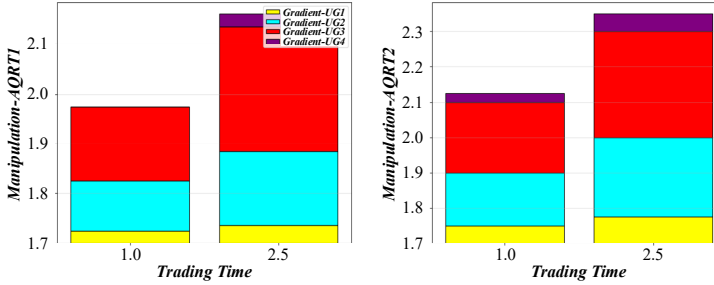
Figure 7 Intelligent dispatching strategy and energy consumption change assessment diagram (see online version for colours)



The system architecture must accommodate these complexities and uncertainties and provide timely feedback and optimised decisions. Hierarchical architecture design is the core of ensuring the system's efficient operation. Usually, the hierarchical architecture of a DSS can be divided into a data acquisition layer, a data processing layer, a decision analysis layer and a decision execution layer. Figure 7 shows an intelligent scheduling strategy and energy consumption change assessment. Each layer undertakes different functions and collaborates with the upper and lower layers. As enterprises grow and their

energy management needs become more complex, scalability and interoperability of EMS will be key. Future research should aim to develop systems that can easily scale up to handle larger volumes of data and integrate with various enterprise-wide systems, such as ERP systems.

Figure 8 Energy consumption assessment diagram of wind power generation and environmental conditions (see online version for colours)

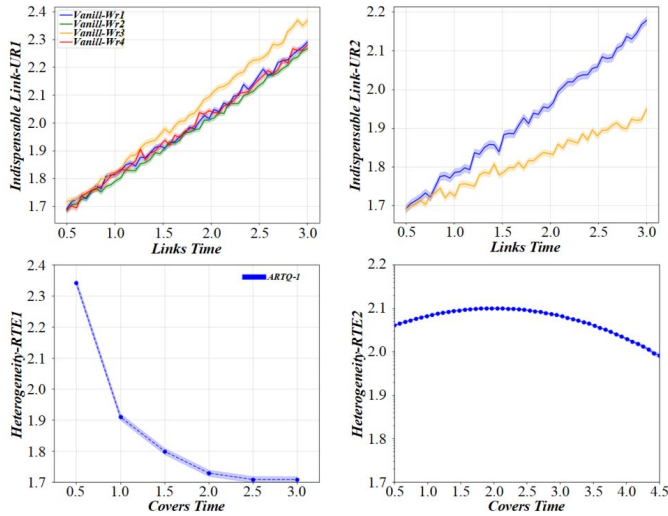


In the decision analysis layer, the construction and solution of the optimisation model is the key to system design. In order to deal with the multi-objective optimisation problem in enterprise energy management, the system usually adopts methods such as Pareto front optimisation and evolutionary algorithms (such as GA and PSO). First, the baseline active energy consumption was calculated as the average power consumption of core equipment, (e.g., CNC machines, furnaces) during normal production hours (9:00–17:00, when production tasks are active); Then, idle energy consumption was measured as the average power consumption of the same equipment during non-production hours (17:00–9:00 next day) or scheduled downtime, where equipment remains powered but not in operation (recorded via SCADA systems). Figure 8 is a diagram of wind power generation and environmental conditions versus energy consumption assessment, which includes energy dispatching, equipment control, load distribution and other operations. The key task of this layer is to realise automated scheduling and intelligent control through close integration with other enterprise management systems to ensure the rapid implementation of energy management strategies.

5 Experimental analysis

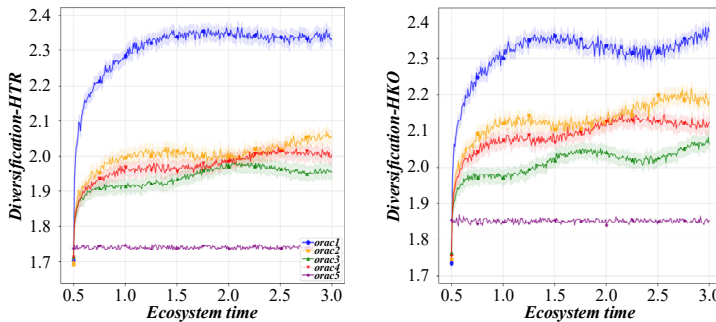
In the process of energy management optimisation in modern enterprises, experimental analysis is the key part of verifying the effectiveness and feasibility of the optimisation model. Figure 9 is an evaluation diagram of the relationship between energy efficiency improvement and cost reduction. To further verify the model's predictive accuracy, three quantitative metrics were used to evaluate the energy load forecasting performance: root mean square error (RMSE), MAE, and coefficient of determination (R^2). For the wind farm load forecasting model, the test results showed: $RMSE = 2.3$ kW, $MAE = 1.8$ kW, and $R^2 = 0.94$. These values indicate that the model's predictions are highly consistent with actual load data – RMSE and MAE are small (reflecting low prediction error), and R^2 is close to 1 (reflecting strong linear correlation between predictions and reality). For the dynamic scheduling model, the R^2 of energy utilisation rate prediction reached 0.92, confirming the model's reliability in practical applications.

Figure 9 Assessment chart of the relationship between energy efficiency improvement and cost reduction (see online version for colours)



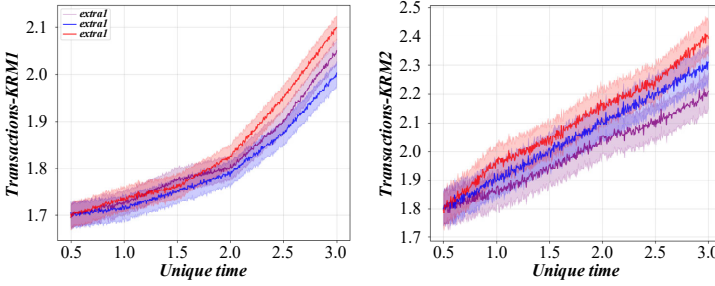
Sample size: 17,280 samples (calculated as six months $\times$ 30 days $\times$ 24 hours $\times$ four samples/hour); sampling rate: 15 minutes per sample (to capture dynamic energy consumption fluctuations); number of variables: 12 input variables (including equipment load, ambient temperature, energy price, wind speed for on-site renewable generation, and eight equipment operation parameters) and two output variables (total energy consumption, energy efficiency). Figure 10 is a comparative evaluation diagram of different energy consumption patterns. After deploying the DSS, real-time monitoring and dynamic scheduling reduced equipment idling by 40%, improved energy utilisation to 92%, and cut monthly energy costs by \$73,000 (36.5% reduction). Energy price fluctuations: simulated $\pm 20\%$ changes in electricity and natural gas prices (consistent with historical market volatility). The results showed that the optimised energy cost varied by only 3.8% (max deviation) compared to the baseline, as the system dynamically adjusted energy source allocation (e.g., increasing renewable energy use when electricity prices rose).

Figure 10 Comparative evaluation chart of different energy consumption patterns (see online version for colours)



Traditional data processing methods make it difficult to effectively analyse these data quickly. Figure 11 is an evaluation diagram of enterprise energy consumption and cost optimisation trends. Average scheduling delay: 1.8 seconds (time from receiving real-time data to generating optimised scheduling commands); average response time: 0.95 seconds (time from detecting equipment status changes to adjusting energy allocation).

Figure 11 Enterprise energy consumption and cost optimisation trend assessment diagram (see online version for colours)



6 Conclusions

Based on big data analysis technology, this study proposes an enterprise energy management scheme that integrates an optimisation model and a DSS. The system provides enterprises with an intelligent and real-time response energy management solution through big data processing, optimisation algorithms and RL. Through experimental verification, the system can effectively deal with complex problems in enterprise energy management and realise efficient and flexible energy dispatching. Here are a few important conclusions from this study:

- 1 In energy management, enterprises must balance various goals, including minimising energy consumption, maximising economic benefits, and controlling environmental impact. Traditional optimisation methods can only optimise for a single objective. For comparison, the enterprise's empirical six-month data showed a 28.5% procurement cost reduction, with the 49.2% representing the long-term optimisation potential of the system. Comparative experiments show that compared with single-objective optimisation methods, (e.g., traditional LP focusing solely on cost minimisation), the proposed multi-objective optimisation model achieves a 12.6% higher energy utilisation rate and a 9.8% lower comprehensive cost while meeting environmental emission standards.
- 2 Energy demand is highly uncertain in time and space. Especially when dealing with emergencies (such as equipment failures, energy market price fluctuations, etc.), traditional scheduling methods are often slow to respond and have limited effects. The dynamic energy scheduling strategy based on RL allows the system to optimise adaptively. From an economic perspective, the proposed system also shows strong practical feasibility. Based on the case study of the manufacturing enterprise (500+ production devices, monthly energy cost of \$200,000), the total deployment cost of

the system (including hardware installation, software development, and personnel training) was approximately \$150,000. With a monthly energy cost reduction of \$73,000 (36.5% reduction), the return on investment (ROI) is estimated to be 20.4 months. For DDPG: learning rate = 0.001 (actor network)/0.0001 (critic network), discount factor (γ) = 0.95, replay buffer size = 50,000, target network update frequency = 100 iterations; For A3C: learning rate = 0.0007, number of parallel actors = 8, batch size = 32, discount factor (γ) = 0.99.

- 3 The effect is remarkable after introducing energy management optimisation and DSSs. The proportion of energy consumption in the production process has dropped to 39.5%, and the efficient operation of equipment has reduced the proportion of energy consumption of core equipment to 85.1%. The system captures exhaust heat (temperature range: 350°C–500°C) from furnace flues via plate heat exchangers, which transfer heat to a heat transfer fluid (propylene glycol solution); the heated fluid is then pumped to auxiliary systems, (e.g., water heaters for production workshops, space heating in office areas) to replace traditional electric or gas heating;
- 4 In terms of feasibility, explainable artificial intelligence (XAI) can be integrated into the proposed DSS by adopting model-agnostic methods such as SHapley Additive exPlanations (SHAP) and local interpretable model-agnostic explanations (LIME), which can explain the decision-making process of deep learning and RL models without modifying their internal structures. However, several implementation challenges exist: first, the high-dimensional nature of enterprise energy data may lead to increased computational overhead when applying XAI methods, affecting the real-time performance of the system; second, the interpretation results may be too technical for non-professional decision-makers, requiring the development of user-friendly visualisation tools; third, balancing model interpretability and optimisation performance remains a key challenge, as excessive emphasis on interpretability may compromise the accuracy of the optimisation strategy.
- 5 Future research will focus on three key directions. First, integrating carbon emission forecasting models into the existing energy management optimisation framework to support enterprises in achieving carbon neutrality goals. Specifically, we will develop a data-driven carbon emission prediction model based on historical energy consumption data and emission factors, and incorporate carbon emission constraints into the multi-objective optimisation function. Second, expanding the application scope of the proposed system to wind-solar hybrid power plants, addressing the challenges of intermittent and unstable renewable energy supply through improved RL algorithms and DT simulations. Third, exploring the integration of the DSS with ERP systems to realise end-to-end intelligent management covering energy procurement, production scheduling, and waste recycling, and developing lifecycle analysis tools to evaluate the long-term sustainability of enterprise energy strategies.

Declarations

The author declares that there is no conflict of interest in this article.

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