Engineered Science
DOI: https://dx.doi.org/10.30919/es1885

Integrated Energy Agent State Awareness Method Based on Multi-Agent Deep Learning Algorithm

Zhenlan Dou,[1] Chunyan Zhang,[1] Songcen Wang,[3] Huamin Wen,[4] Jiawei Wang[5] and Dejian Yang[2,*]

Abstract

As the global energy system accelerates its transformation to clean, low-carbon, and intelligent systems, the integrated energy system, as a key carrier supporting multi-energy synergy and complementarity, has significantly increased its operational complexity and dynamic uncertainty. Traditional centralized state awareness methods struggle to cope with the problems of nonlinear interference and incomplete information caused by multi-energy flow coupling, making it urgent to break through the limitations of local identification for a single agent. This paper proposes a comprehensive energy agent state awareness method based on a multi-agent deep learning algorithm, which enables cross-level mapping of local observations and global state inference by constructing a distributed agent network. This method utilizes dual upsampling fusion technology, combined with deep and shallow feature extraction modules. The deep feature extraction unit integrates the ShuffleNet v2 efficient network, resulting in a parameter count approximately half that of an ordinary network. It also introduces the SE (Squeeze-and-Excitation) channel attention mechanism to enhance the capture ability of key information. Experiments based on the I-BLEND dataset demonstrate that the model achieves an accuracy of 97.21% after 52 months of power data training, which is significantly better than the comparative models' accuracies of 90.10% and 93.50%. The state awareness results show that the external state prediction error of the agent effectively converges within the steady-state covariance ellipse region. The position error decreases to approximately 4 when the prediction time step is 2, and the minimum update frame rate increases to approximately 38. Multi-index joint analysis reveals that the power forecasting range spans -20 to 20, the price forecasting error fluctuates within the range of 0.05 to 0.20, the load level forecasting deviation is controlled within the range of 0 to 8, and the introduction of an uncertainty margin enables dynamic adaptation to changes in forecasting difficulty. The relative rate distribution of agents under different parameter combinations shows significant differences. For example, K1 agents aggregate in the relative rate interval of 80-100, while K3 agents have a state perception score of more than 0.8. Through principal component analysis optimization, the dimensionality of the model is reduced to 9 dimensions when the cumulative variance contribution rate reaches 85%, and the F ratio is as high as 4.70, which verifies the robustness and real-time advantages of the algorithm in multi-energy flow coupling scenarios.

Keywords: Multi-agent deep learning; Integrated energy systems; State awareness; Feature fusion; Super-resolution recognition.
Received: 02 September 2025; Revised: 05 November 2025; Accepted: 12 November 2025
Article type: Research article.

1. Introduction

With the accelerated transformation of the global energy system to clean, low-carbon, and intelligent, the operational complexity and dynamic uncertainty of the integrated energy system, as the key carrier supporting multi-energy synergy, complementarity, and efficient utilization, have significantly increased.[1,2] The traditional energy system mainly operates independently in the form of a single energy source, while the integrated energy system forms a highly correlated network structure through the coupling of multiple energy flows such as electricity, heat, cold and gas, and the equipment in each link presents strong interactivity and nonlinear response characteristics in the space-time dimension.[3] In this context, the accurate state perception of each agent in the system is not only the basic premise for realizing multi-energy flow optimal scheduling, fault warning and resilience improvement, but also the core link to promote the evolution of the energy system from "passive control" to "active intelligence".[4] However, the dynamic evolution of agent states in integrated energy systems is influenced by the interplay of multiple

1,#State Grid Shanghai Municipal Electric Power Company, Shanghai, 200122, China
2,#Northeast Electric Power University, Jilin, 132012, China

factors, encompassing not only gradual changes in their own physical properties but also random disturbances in the external environment. Moreover, the coupling correlation between multiple agents forms a complex, nonlinear feedback mechanism, which makes it difficult for single-modal data to characterize its operating state fully. Traditional state awareness methods based on fixed thresholds or single model reasoning face significant limitations.[5,6]

In recent years, deep learning technology has demonstrated strong capabilities in feature extraction and pattern recognition, particularly in handling high-dimensional and nonlinear data, offering a new technical approach for analyzing integrated energy system states.[7,8] However, existing research mostly focuses on the local state recognition of a single agent or adopts a centralized architecture to process global information in a unified manner. The former tends to overlook the synergy and cascade effects among multiple agents, while the latter suffers from computational bottlenecks and communication redundancy problems, making it challenging to meet the needs of real-time perception in large-scale integrated energy systems.[9] By constructing a distributed agent network with independent decision-making ability, the multi-agent deep learning algorithm enables each agent to not only extract features based on local observation data, but also realize the implicit fusion of global information through communication and cooperation with other agents, which enhances the ability to model the overall operation logic of the system while retaining the flexibility of local perception.[10] This method addresses the single-point dependence defect of the traditional centralized model, enabling more accurate capture of the dynamic correlation law of state changes in multi-energy flow coupling scenarios through policy interaction and information sharing among agents.[11]

The state awareness of integrated energy agents is essentially a deep mining process of physical laws and operating modes hidden in multi-source heterogeneous data.[12,13] The multi-agent deep learning algorithm can realize cross-level mapping from local observations to global state inference by designing a neural network structure tailored to the functional characteristics of different agents and incorporating a cooperation mechanism between agents.[14] In this process, the agent not only needs to process the real-time data of its own sensors, but also needs to obtain neighborhood information through interaction with other agents, and then dynamically adjust its own perception strategy and feature representation, and finally form a consistent cognition of the overall running state of the system.[15] This perception paradigm, based on multi-agent collaboration, can effectively address the problems of nonlinear interference and incomplete information caused by multi-energy flow coupling in integrated energy systems, providing a more robust solution for accurate state identification in complex scenarios.[16,17]

At present, the large-scale deployment and intelligent upgrade of integrated energy systems put forward higher requirements for state awareness technology: it must not only meet the high-precision identification requirements under the coordinated operation of multiple energy flows, but also adapt to the real-time response constraints in dynamic environments; It is necessary to solve not only the local uncertainty of a single agent, but also the problem of collaborative consistency among multiple agents. In this context, exploring a comprehensive energy agent state perception method based on a multi-agent deep learning algorithm can not only provide key data support for the optimal operation of multi-energy complementary systems, but also help promote the energy system towards autonomous perception and self-adaptation. The intelligent development of adjustment and self-organization collaboration has both important theoretical value and practical significance in improving energy utilization efficiency and ensuring the safe and stable operation of the system.

The core value of multi-agent deep learning algorithm models lies in their deep compatibility with system characteristics, rather than directly applying general complex system models. The multi energy flow coupling characteristics of integrated energy systems can easily cause distortion in the coupling modeling of general models, making it difficult to accurately perceive the system state. The model achieves adaptation through the "divide and conquer collaborative perception" architecture: it divides each sub agent based on multiple energy flows, uses deep learning modules to accurately construct nonlinear characteristic models of each energy flow, and integrates local information through communication and collaboration between agents to compensate for incomplete information and suppress coupling interference. Its core function is to break through the adaptation bottleneck of general models, build a "local global" perception system, effectively solve the problems of nonlinear interference suppression and information completion, and provide accurate support for system monitoring, early warning, and scheduling.

Multi agent technology faces key challenges in integrating energy intelligent agent state perception, such as heterogeneous perception data between agents, insufficient collaborative perception accuracy under dynamic working conditions, and difficulty in modeling complex energy network state coupling. This article innovatively proposes a multi-agent perception data fusion framework based on deep learning. Through distributed feature extraction and global collaborative decision-making mechanism, it achieves efficient integration of heterogeneous data and accurate state

[3]*China Electric Power Research Institute, Beijing, 100192, China*
[4]*School of Information Engineering, Nanchang University, Nanchang, Jiangxi, 330031, China*
[5]*Quzhou Power Supply Company, State Grid Zhejiang Electric Power Co., Ltd., Quzhou, Zhejiang, 324000, China*
[#]*State Grid Shanghai Municipal Electric Power Company and Northeast Electric Power University are co-first affiliations.*
[*]*Email:* Ydjian1015@163.com (Dejian Yang)

perception under dynamic working conditions. At the same time, a coupled adaptive modeling method is constructed to effectively solve the coupling interference problem of state perception in complex energy networks.

The core innovation of the integrated energy intelligent agent state perception method based on multi-agent deep learning algorithm lies in the construction of a novel multi-agent deep learning framework, which efficiently coordinates heterogeneous energy intelligent agents in the comprehensive energy system, accurately solves the problem of system state perception, and improves the accuracy and adaptability of perception.

2. A state-aware framework for the fusion of multi-agent systems and deep learning

2.1 Definition of integrated energy agent

In the transmission process, changes in power grid flow can have an impact on the electricity demand of gas grid compressors, leading to changes in natural gas transmission pressure; The heat dissipation of the heating network pipeline is dynamically related to the output of the heat pump powered by the power grid. In the conversion process, the combined heat and power (CHP) unit achieves electric thermal joint production, the electric refrigeration unit achieves electric cooling conversion, and the gas boiler completes gas thermal conversion, thus forming bidirectional or multi-directional conversion coupling between energy flows. In the storage process, when the power storage system performs charging and discharging operations to regulate the grid load, it indirectly affects the energy supply rhythm of the thermal or cold storage devices, and the fluctuation of storage pressure also restricts the output stability of gas power generation equipment.

This multi energy flow coupling phenomenon directly affects the state perception dimension of integrated energy intelligent agents by changing the supply-demand balance of energy, dynamically adjusting energy conversion efficiency, and interfering with state parameters of energy storage. It greatly increases the dynamic perception requirements of intelligent agents for state parameters such as energy production and consumption, pipeline pressure and temperature, and equipment operating conditions. At the same time, it also presents complex characteristics of multivariate correlation and nonlinear transmission in state changes.

The concept of an agent originated in the 1970s, began to attract attention in the late 1980s, and was widely recognized by the mid-1990s.[18] These entities typically possess autonomy, interactivity, rapid reaction, and the ability to proactively explore.[19] In view of the limitations of a single agent in dealing with complex problems, researchers propose innovatively combining multiple simple yet highly autonomous agents to build a multi-agent system, thereby enhancing the overall problem-solving ability.[20]

A multi-agent system is a complex network composed of multiple independent or semi-independent agents, which are closely connected by network communication technology.[21] These agents can quickly sense environmental changes, make independent decisions, and execute actions to achieve goals through efficient collaboration. This system complements the concept of energy agent system and has been widely used in power system fields, such as energy management, distributed optimization and frequency control. The multi-agent system can effectively integrate microgrid units, improve the utilization rate of renewable energy, reduce costs, and enhance economy and reliability.[22,23] Currently, the research primarily focuses on three areas: multi-agent game strategy, consensus

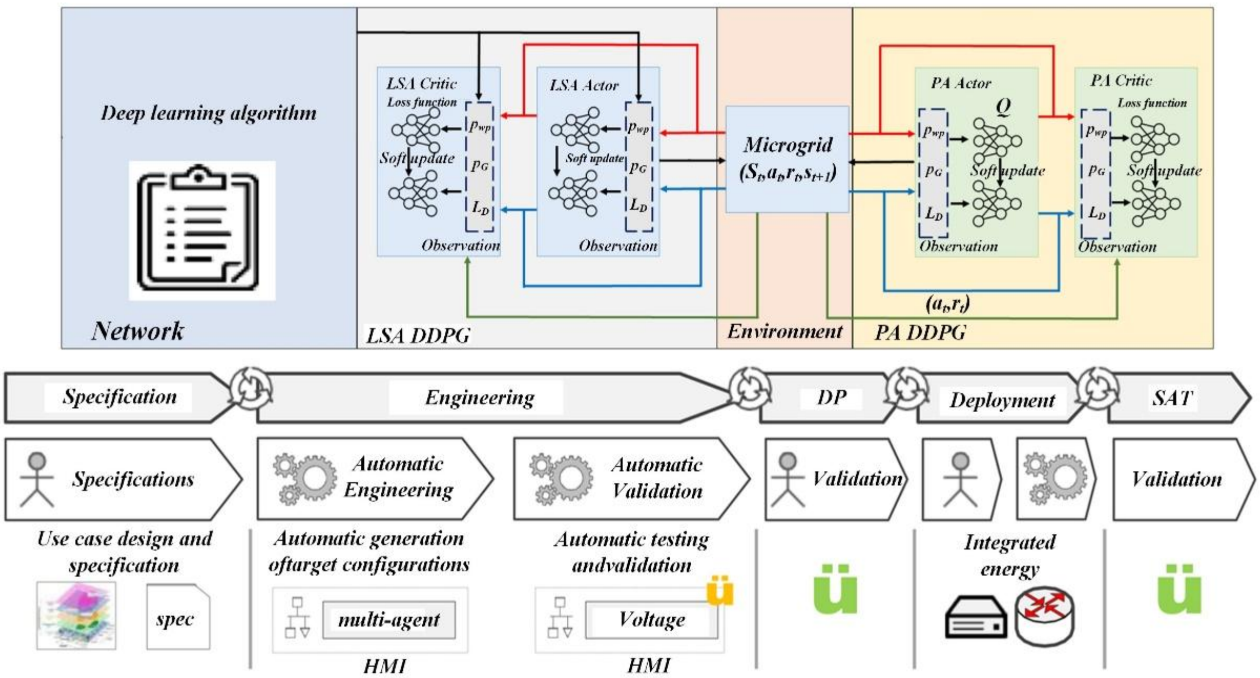

Fig. 1: Deep learning architecture.

algorithms, and reinforcement learning technology.

2.2 Theoretical core of multi-agent deep learning

Deep learning is a machine learning method that mimics the human brain, using multi-layer neural networks for learning and decision-making.[24,25] In integrated energy systems, multi-agent deep learning algorithms are an important application of deep learning, which can efficiently support intelligent agent state perception. In response to the heterogeneous, dynamic, and massive characteristics of multi-source data, distributed learning of sub agents is used to achieve parallel data processing, and then through collaborative communication fusion, traditional single algorithm information loss and redundant computing problems are solved; At the same time, relying on deep learning networks and autonomous learning capabilities, mining the correlation patterns of states in data, combining with intelligent agent interaction to optimize model parameters, reducing interference such as weather and sudden energy consumption, greatly improving the accuracy and real-time perception of device health, supply and demand balance by integrated energy intelligent agents, and providing support for efficient system scheduling and fault warning. The deep learning architecture is shown in Fig. 1. These networks are composed of multiple layers of neurons that can automatically extract complex features and patterns from big data. It is particularly suitable for processing high-dimensional and complex data such as images, audio, and text, and is more scalable and flexible than traditional machine learning techniques, reducing the need for feature engineering.[26]

Deep learning uses techniques such as gradient descent to reduce errors and improve the accuracy of prediction and classification by adjusting neural network weights and biases.[27]

Neural networks imitate human brain information processing and solve machine learning problems. Its structure is inspired by the biological nervous system and performs multi-layer computational tasks, each layer consisting of nodes that convert inputs into outputs for further processing or decision-making. Neural network mainly consists of input layer, hidden layer and output layer. The input layer receives the data, the hidden layer processes the data, and the output layer produces the result.[28] A network composed of multiple hidden layers is called a deep neural network. Each node of the input layer corresponds to a data feature, and the hidden layer contains multiple neurons that weighted to sum the output of the previous layer and transform the results. The number of neurons in the output layer varies according to the nature of the problem. For example, in the classification problem, each node may represent the prediction probability of a class. The neuron output is expressed by Eq. (1).

$$y = f(\sum_{i=1}^{n} w_i x_i + b) \tag{1}$$

y denotes neuron output; f is the activation function; w is the input weight; x is the input signal; b is the bias amount.

When building a neural network, each layer receives input and outputs, and the output is processed by an activation function.[29] Nonlinear activation functions are usually used to make the network learn complex relationships and improve the ability of the model to fit complex problems. The Sigmoid function expression is shown in Eq. (2).

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The $ReLU$ function is shown in Eq. (3):

$$ReLU(x) = max(0, x) \tag{3}$$

When constructing neural networks, the learning process relies on two key steps: forward propagation and back propagation. These two steps ensure a complete calculation flow from input to output, as well as feedback of model errors and parameter tuning.

Forward propagation is the flow path of data in a neural network, from the input layer to the output layer. The output of each layer will become the input of the next layer. Back propagation is the key link of neural network training, and the gradient of network parameters is calculated by chain rule. It is used to determine the contribution of each layer to the error and adjust the parameters accordingly to reduce the output error. The error calculation starts at the output layer and involves the difference between the predicted value and the true value. The error is measured by different loss functions, such as mean square error or cross-entropy loss. The gradient calculation is carried out continuously by the chain rule, and the purpose is to obtain the partial derivative of the loss function with respect to the weight and bias of each layer, that is, the gradient. Parameter updates utilize the calculated gradients to adjust the weights and biases of the network, usually by gradient descent or an improved version thereof.

Forward propagation and back propagation together constitute the complete framework of neural network training. Forward propagation converts input information into output results, and back propagation adjusts model parameters according to output error feedback to continuously improve network performance. This process repeats itself until the model performance meets expectations or reaches the established training cycle.

2.3 State perception theory

State awareness technology obtains target state data through detection and estimation algorithms, provides real-time observation data for the system, supports intelligent control decision-making, and ensures that the system independently responds to environmental changes. In industrial networks, it is crucial for system reliability and stability.[30]

A centralized state awareness system sends sensor data directly to a remote center for state estimation. For example, the calculation process of linear discrete-time system with N sensors is shown in Eqs. (4)-(5).

$$x(k+1) = Ax(k) + w(k) \tag{4}$$

$$y_n(k) = C_n x(k) + v_n(k), \forall n \in \mathcal{N} \tag{5}$$

In the *k-th* period, the system state vector *x(k)* and the observation vector $y_n(k)$ of the *n-th* sensor both belong to the real number set *R* with dimensions *a* and *b*, respectively. The state transition matrix is *A* and the observation matrix is C_n. *w(k)* and *v(k)* are independent white Gaussian noises with zero mean and Q_W is a perception weight parameter for heterogeneous energy intelligent agents, used to dynamically allocate perception data weights for different types of agents and solve the problem of perception bias caused by multi-source data heterogeneity; Q_V is a state aware value parameter used to quantify the contribution of intelligent agent perception results to the global state assessment of integrated energy systems, providing valuable basis for coordinated decision-making in multi-agent deep learning frameworks, and ultimately improving the accuracy and global synergy of state perception, as shown in Eq. (6).

$$Y(k) = Cx(k) + V(k) \tag{6}$$

Y(k) represents the aggregated observation value of the *k-th* period of the remote estimation center, denoted as $[y_1^T(k),\ldots, y_N^T(k)]$; *C* is the aggregate observation matrix, denoted as $[C_1^T,\ldots, C_N^T]$; *V(k)* is the aggregated observation noise, denoted as $[V_1^T(k),\ldots, V_N^T(k)]$. After the remote estimation center aggregates the observation values, the standard Kalman filtering is performed to obtain the system state estimation value $\hat{x}(k|k)$, and the steps are shown in Eqs. (7)-(11):

$$\hat{x}(k \mid k-1) = A\hat{x}(k-1 \mid k-1) \tag{7}$$

$$P(k \mid k-1) = AP(k-1 \mid k-1)A^T \tag{8}$$

$$F(k) = P(k \mid k-1)C^T(I + CP(k \mid k-1)C^T)^{-1} \tag{9}$$

$$\hat{x}(k \mid k) = \hat{x}(k \mid k-1) + F(k)(Y(k) - C\hat{x}(k \mid k-1)) \tag{10}$$

$$P(k \mid k) = P(k \mid k-1) - F(k)CP(k \mid k-1) \tag{11}$$

In the formula, $\hat{x}(k|k-1)$ represents the system state prediction value; *P(k|k-1)* is the covariance of the predicted value; *F(k)* is the Kalman filter gain; $\hat{x}(k|k)$ represents a system state estimate; *P(k|k)* is the covariance of the estimated value; *I* is the identity matrix.

In order to balance the communication load and estimation accuracy of the state awareness system, a fusion optimization idea can be adopted: first, a hybrid hierarchical architecture is built, and sensor nodes are allowed to perform local intelligent preprocessing to extract key features, and then upload them after initial fusion by regional centers, thereby reducing core network traffic; On this basis, an event-triggered transmission mechanism is adopted to start transmission only when the data changes significantly or the uncertainty is high, which greatly improves communication efficiency; At the same time, intelligent compression technology is used to screen high-value data before transmission, and finally advanced fusion algorithms are combined in the estimation center to process information from different sources, so as to make up for the accuracy loss caused by distributed architecture and achieve the performance goal of approaching the optimal estimation under limited bandwidth.

Constructing energy storage optimization scheduling as a Markov decision process model, the key lies in solving the optimal action value function that satisfies the Bellman optimal equation. This model uses deep Q-networks as a function approximation tool and introduces the target network mechanism and dual Q-learning theory, aiming to stabilize the training process and eliminate value estimation bias. The decision-making process strictly follows the constraints of energy storage dynamics, especially the evolution equation of the state of charge and its boundary conditions, and then solves the optimal charging and discharging strategy using stochastic gradient descent method within the theoretically feasible interval to ensure system safety.

3. Design of state awareness method based on multi-agent deep learning

3.1 Overall architecture of multi-agent depth awareness models

In the perception model, the integrated energy storage decision model is the key to enhancing the system's perception and decision-making capabilities. The energy storage model serves as an auxiliary decision-making unit and dynamic feedback module, generating charging and discharging strategies based on system state information. Its output provides input features for the state perception model, enhancing the ability to dynamically characterize multiple time scales and improving the accuracy of situation estimation. Meanwhile, the state perception model predicts the perception results formed by the fusion of multi-source heterogeneous data. Feedback to the energy storage model to optimize scheduling strategies to improve system economy and stability. The two construct a "perception decision collaboration" coupling mechanism through bidirectional closed-loop interaction, improving the adaptive operation level of the system in uncertain environments.

Considering the high inertia characteristics commonly present in thermal and gas systems, where the state changes often have hysteresis, slow response speed, and are significantly affected by historical states, an intelligent agent based on Recurrent Neural Networks (RNNs) is specifically configured in the algorithm. By utilizing the strong dependence modeling ability of RNNs on time-series data, the algorithm accurately captures the inertia laws of the state evolution of thermal and gas systems over time; For low inertia carriers such as electrical systems, which have fast state response speed, frequent dynamic changes, and higher real-time requirements, the algorithm deploys specialized intelligent agents with faster response times. Through optimized model structure and computational logic, the instantaneous state changes of the electrical system are quickly tracked. Finally, through the collaborative interaction of the two types of intelligent agents, comprehensive and accurate perception of the state of multiple carriers in the integrated energy system is achieved.

The overall structure of the model is shown in Fig. 2. In response to the dimensional differences and time-dependent characteristics of multi energy flow coupled data, an integrated architecture of "dual upsampling deep and shallow feature extraction feature fusion" was adopted. After inputting low-frequency power data, the dual upsampling unit first applies a dual channel interpolation strategy for processing: one channel expands the time resolution through time axis interpolation for the temporal sparsity of power data; The other channel aligns the scale differences of multi energy data such as electricity, heat, and gas through feature dimension adjustment, forming a "dual upsampling fusion data". The data is then input in parallel into shallow and deep feature extraction units. The shallow unit adopts lightweight convolution combined with short-time convolutional network (TCN), focusing on capturing the low-frequency features of smooth changes such as electric thermal load base value correlation and multi energy flow steady-state coupling; Deep level units use stacked dilated convolutions and Long Short Term Memory (LSTM) networks to mine high-frequency dynamic features such as load transients and transient responses of energy storage devices. The extracted deep and shallow features are then input into a cross scale attention fusion unit, which enhances the representation of key coupling relationships such as "electricity load fluctuation gas network peak shaving response" by calculating the correlation weights between time dimension and energy type dimension, and generates deep and shallow feature fusion data. Finally, based on the fused features, the super-resolution state perception results are output through the fully connected layer, achieving high-precision perception of the operating status of the multi energy flow coupled system.

The dual upsampling unit integrates two methods of

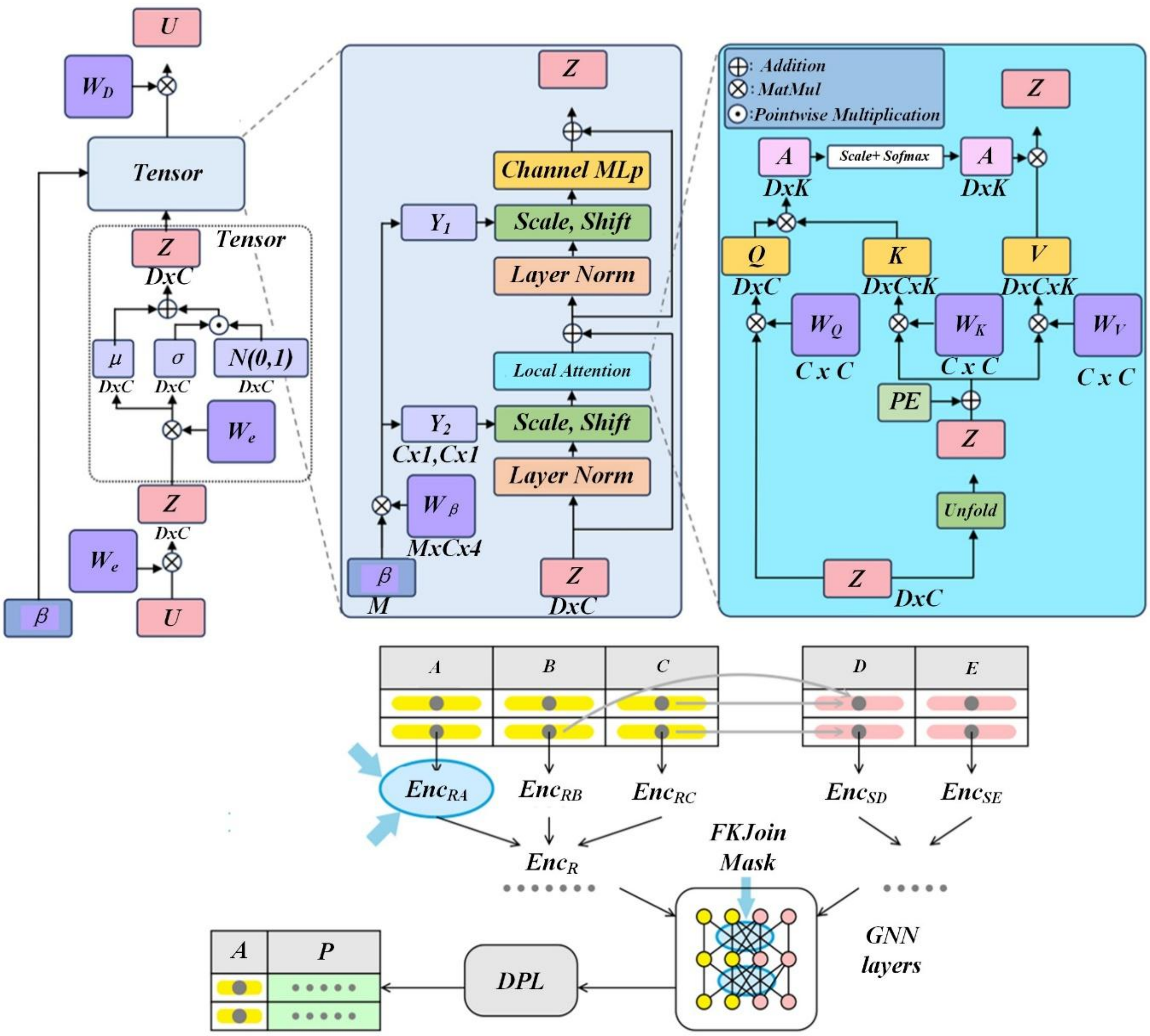

Fig. 2: Multi-agent depth perception model.

deconvolution upsampling and bicubic interpolation upsampling. Deconvolution upsampling enhances sampling accuracy with learnable parameters, whereas bicubic interpolation achieves approximate contour recovery of the data at a lower computational cost. Although the interpolation method will lose some detailed information, its reconstructed overall structure can provide effective assistance to the model. The two are spliced in the channel dimension to fully leverage their respective advantages and build a more accurate upsampled output.

In the deep feature extraction module, we employ a deep network comprising multiple convolutional layers to capture complex features in the data. Although deep networks have a strong feature representation ability, excessive parameters can easily lead to model expansion and performance degradation. To this end, we introduce ShuffleNet v2, a lightweight network structure whose parameters are approximately half those of traditional convolutional networks, effectively controlling the model's complexity while maintaining high accuracy. In addition, by embedding the SE channel attention mechanism, the network can adaptively focus on key feature channels, further enhancing feature extraction capabilities and model expression capabilities.

The shallow feature extraction module focuses on retaining key low-frequency information in the input data to prevent information loss, while reducing the number of parameters and accelerating model convergence through a small number of convolutional layers. This module can learn the intrinsic correlation between high-frequency and low-frequency components in power data and delve deeply into feature structures, thereby improving the recognition accuracy of super-resolution reconstruction.

The feature fusion module is responsible for channel superposition and the fusion of deep and shallow features, serving as the information perception path for the entire model. This module recognizes complex features while retaining key low-frequency information, effectively enhancing the model's comprehensive recognition capabilities, reducing its size, speeding up training, and further improving the accuracy of power data super-resolution tasks.

Aiming to address the challenges of limited resources in embedded devices, difficulty in deploying large-scale models, and high real-time requirements, this model simplifies the overall architecture through an efficient convolutional structure design. The deep module ensures the effective extraction and reconstruction accuracy of complex features, while the shallow module provides auxiliary support in a lightweight manner, ultimately realizing the efficient operation of the model in super-resolution tasks.

This study focuses on the state perception method of comprehensive energy systems based on multi-agent deep learning algorithms. The core implementation steps are refined as local intelligent preprocessing of sensor nodes, event triggered transmission mechanism, and multi-source information fusion algorithm of estimation center, in order to improve the real-time, accuracy, and communication efficiency of state perception. A lightweight layered preprocessing module is designed at the sensor node end, which extracts shallow features through a one-dimensional convolutional layer (with a kernel width of 5 and a step size of 1), preserves key features through mutual information filtering rules (threshold of 0.05), and stacks convolutional layers to obtain deep trend features; The event triggered transmission mechanism adopts a dual threshold criterion, which triggers transmission through data changes (relative amplitude>5%) and uncertainties (LSTM prediction error>0.1); The estimation center fusion algorithm first aligns and normalizes the feature vectors in time, and then achieves multi-source information fusion through a weighted fusion layer (dynamically assigning weights based on signal-to-noise ratio) and a deep learning enhanced fusion layer (GRU (Gated Recurrent Unit) network capturing temporal dependencies and combining Kalman filter residual correction) to improve estimation accuracy and robustness in complex environments.

3.2 Building of an agent local perception feature extraction module

In the feature extraction unit, the input data is first processed through a two-dimensional convolutional layer, and the number of channels is increased in the initial stage, and then halved. Increasing the number of channels enhances the model's expressive power to handle more complex features. Reducing the number of channels can refine the feature information and gradually restore the spatial shape of the data. In this study, the ReLU activation function is introduced to enhance the model's nonlinear fitting ability, allowing it to learn complex feature mappings and thereby improve its perceptual performance. By setting part of the output to zero, the ReLU function introduces a certain degree of sparsity, reduces the network's dependence on parameters, and mitigates the risk of overfitting. In addition, the SE channel attention mechanism assigns learnable weights to different channels, strengthens the contribution of key channels, and suppresses the influence of non-important channels, thereby reducing the interference of redundant features on the model.

As the core structure of deep feature extraction, efficient convolutional layers are built by stacking multiple convolutional layers. In this layer, the input data channel is divided equally into two parts and processed separately. The upper branch first adjusts the number of channels through 1 × 1 convolution and fuses feature information, then goes through 3 × 3 deep separable convolution (DW (DepthWise) convolution) to improve computational efficiency, and finally learns the nonlinear relationship through the ReLU activation function. The lower branch keeps the original data unchanged. After the two parts are processed, they are re-integrated, keeping the total number of channels unchanged. To further promote feature interaction and prevent information loss, a channel reorganization mechanism is introduced to enhance the learning and transmission capabilities of features by adjusting the channel arrangement order.

3.3 Decision and reward and punishment functions

The defined system state is a multidimensional vector, which aims to quantitatively characterize real-time dynamics from the entire process of system operation. Specifically, the state vector includes five core dimensions of energy production, transmission, conversion, storage, and consumption. At the level of energy production, state indicators cover the actual power generation of distributed photovoltaic power plants, real-time active power output of wind turbines, *etc*. These indicators reflect the immediate availability of uncontrollable energy. During the transmission phase, the status mainly involves physical parameters such as real-time load rate, voltage, and temperature of key power grid lines and heating network pipelines, which are used to evaluate the network's transmission capacity and safety redundancy. In the energy conversion stage, the state focuses on the operating conditions of key conversion equipment such as combined heat and power (CHP) units and power to gas (P2G) units, such as the power generation, efficiency, and start stop status of the units. In the storage phase, the core state variable is the state of charge (SOC) of various energy storage devices (such as batteries and thermal storage tanks), which directly reflects the energy buffering capacity of the system. Finally, at the consumption level, the state is manifested as the aggregated demand for electricity, heating, and cooling loads from various users (industrial, commercial, residential), which is the driving factor for the balance of supply and demand in the system. By integrating the multi-dimensional and heterogeneous real-time operational data mentioned above, the constructed state vector provides comprehensive input information for multi-agent deep learning algorithms to perceive the system's operational situation, which is a necessary prerequisite for achieving collaborative optimization and intelligent decision-making.

The agent complies with the constraints of the energy agent by controlling the stored energy, including the daily charge-discharge cycle amount and capacity limits. Every decision brings immediate and long-term benefits.

The system must ensure that the charging and discharging power of the energy storage unit remains within the allowable range and does not exceed the capacity limit throughout the entire process. The energy storage decision model based on deep learning employs a target network and a double Q-network structure to mitigate the Q-value estimation bias problem in deep reinforcement learning. The executor strategy network outputs the mean and standard deviation of a Gaussian distribution, and based on this, action sampling is carried out. The experience playback pool is used to store historical interaction data and provide training samples for updating network parameters.

4. Verification and application analysis

4.1 Experimental datasets

The state perception of integrated energy systems relies on real-time collection and in-depth analysis of multi energy flow operation data such as electricity, heat, cold, and gas. The input data processed by this model mainly includes multi-source heterogeneous data such as electrical quantities, thermal parameters, cooling parameters, and gas parameters. These data exhibit significant complex characteristics: firstly, temporal nature, manifested as high-frequency sequences sampled at the minute level, and containing periodic fluctuations such as daily, weekly, and yearly patterns as well as long-term trends; Secondly, heterogeneity refers to the significant differences in dimensionality and dynamic response speed among data from different energy flows; Thirdly, strong correlation, due to the coupling effect of energy conversion equipment (such as gas turbines and heat pumps), leads to close spatiotemporal correlations between multiple energy flow data; Fourthly, noise characteristics are introduced by random fluctuations caused by sensor errors and communication interference.

To transform raw data into a regular dataset suitable for training multi-agent deep learning models, a rigorous data preprocessing process needs to be executed. Firstly, data cleaning is carried out by using statistical methods and clustering algorithms to identify and eliminate outliers that are significantly beyond the physical range. For missing values caused by communication interruptions, linear interpolation or time series prediction methods are used to fill in the gaps based on their length. Secondly, data standardization is implemented. To eliminate dimensional differences, Z-Score or Min Max methods are usually used to normalize the data of each energy subsystem to ensure the numerical stability of model training. Finally, complete data spatiotemporal alignment, resample multi-source data to the same time granularity (15 minutes interval) using a unified timestamp, and associate measurement points with corresponding agents or network nodes based on system topology to construct spatiotemporal consistent input samples. Through the above preprocessing, the essential features of the data can be effectively extracted, laying a reliable foundation for subsequent intelligent agents to carry out collaborative state perception.

This study evaluates the super-resolution perception algorithm for power data using the I-BLEND dataset. This dataset contains power operation parameters for up to 52 months, including variables such as current, voltage, and active power, with a sampling frequency of once per minute. To enhance the modeling integrity of Integrated Energy Systems (IES), this study further integrated heating and cooling load data to more comprehensively reflect the actual operational characteristics of multi energy coupled systems. The large time span and rich types of data are helpful for in-depth analysis of the pattern characteristics and interrelationships of various energy consumption such as electricity, heat, and cold. A longer observation period facilitates the capture of periodic patterns and long-term trend changes in energy consumption behavior, providing sufficient data support for the training and validation of multi-agent deep learning models, especially in tasks involving multi energy coupling state perception and time series analysis.

4.2 Experimental results and analysis

Fig. 3 shows the state perception results of a multi-agent system. The above figure shows the external state of the intelligent agent changing over time. The blue and green lines represent predicted values, while the red and purple lines represent actual external values. The curve fluctuations reflect dynamic characteristics. The following figure shows the distribution of state space, with black dots representing prediction errors, blue circles representing steady-state covariance, and elliptical regions reflecting the degree of error aggregation, indicating the convergence of the algorithm for state estimation.

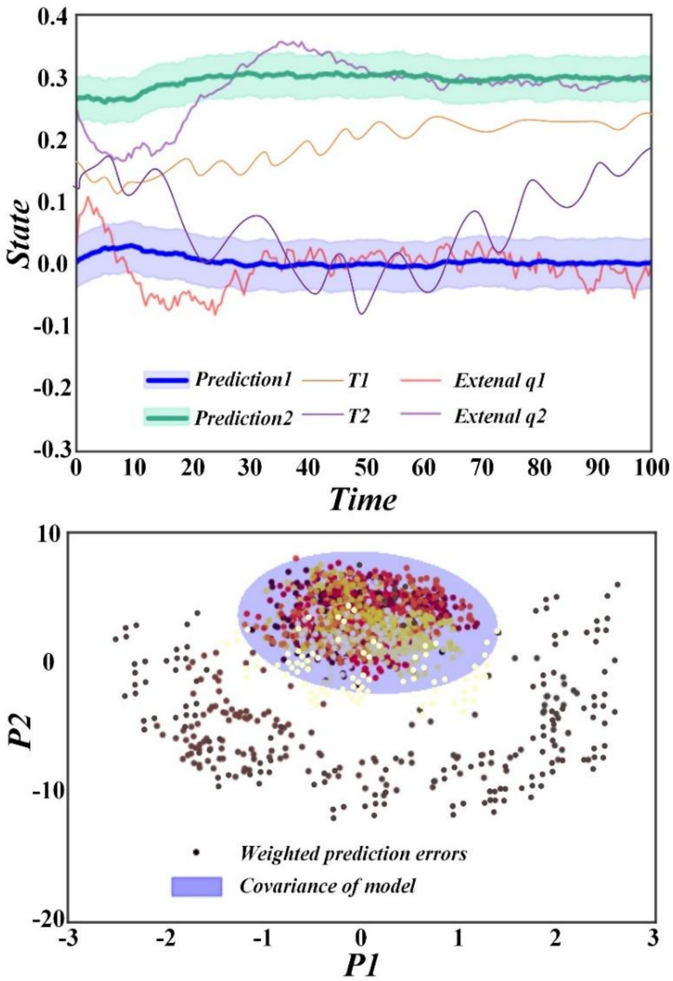

Fig. 3: Multi-agent system state awareness results.

Fig. 4 shows the relative sun-rate distribution of comprehensive energy agents based on a multi-agent deep learning algorithm with d_x and d_y as variables. The red area corresponds to K1, the blue area to K2, and the green area to K3. The data points are distributed among them. For example, the relative rate of the data points in K1 ranges from 80 to 100, reflecting the difference in agent states under various parameter combinations.

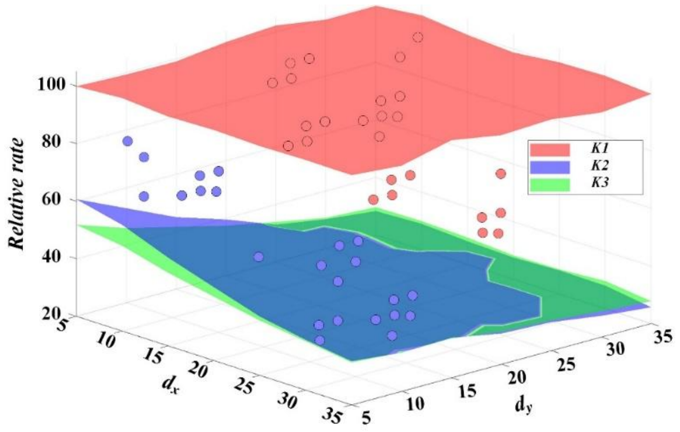

Fig. 4: Relative rate distribution of integrated energy agents under different parameters.

According to the data in Table 1, feature weighting and data compression are performed. The principal component with a cumulative variance contribution rate exceeding 85% and an eigenvalue greater than 1 is selected, and the cumulative variance contribution rate of the ninth component is 85%, so the PCA (Principal Component Analysis) dimensionality reduction optimization dimension is set at 9.

Fig. 5 illustrates the changes in power and state levels of the integrated energy system over time, under both sunny and cloudy weather conditions. The upper half shows the power consumed, the power generated on sunny days, and the power generated on cloudy days. The lower part presents the curve of state-level change under different weather conditions. In the 3rd to 5th hours, the power generation is high on sunny days and the state level is relatively stable, which reflects the system state perception under the multi-agent deep learning algorithm.

Fig. 6 illustrates the forecast performance of power forecasts (approximately -20 to 20), price (approximately 0.05 to 0.20), and load level (approximately 0 to 8) at various points in time for an integrated energy system based on multi-agent deep learning. The blue solid line represents the predicted value of the model, the green solid line represents the prediction error, and the red dashed line shows the prediction interval after introducing the uncertainty margin. Experimental data show that the model can effectively capture the dynamic changes of each index, and its prediction error fluctuates at different time points, while the uncertainty margin expands with the increase of prediction difficulty (such as around time points 4-5), which verifies the effectiveness of the method for complex energy system state awareness.

To verify the advantages of the model proposed in this paper (Model 3), we employed the cross-validation method for training and testing, and the accuracy comparison results are presented in Table 2. The analysis reveals that the accuracy rate of Model 3 reaches 97.21%, which is significantly higher than that of the comparative model. Specifically, its accuracy rate is 7.11 and 3.71 percentage points higher than that of Model 1 (90.10%) and Model 2 (93.50%), respectively, with relative improvements of 7.9% and 4.0%. This result fully demonstrates the effectiveness and superiority of the multi-agent deep learning framework and feature fusion strategy presented in this paper in enhancing the state perception accuracy of integrated energy agents.

Fig. 7 shows the frequency distribution of all points, inner points, and outer points for Distance K1-K4. For example, in Distance K1, the distribution of each point is scattered; in K2, the distribution exhibits a certain pattern. These data provide a basis for understanding the state distribution of agents and subsequent research on perception methods.

The left side of Fig. 8 is a pulse number normalized frequency histogram for different sets of data. The right side illustrates the relationship between standard deviation and the 'hits @ 1' and 'hits @ 3' indicators. As the standard deviation increases, the index values decrease to varying degrees, reflecting the performance of agent state perception under different statistical characteristics.

Table 1: Calculation results of F ratio of each dimension.

Experiment 1	Dimensionality	1	2	3	4	5	6	7
	F ratio	3.07	3.35	3.06	3.01	2.59	2.14	2.22
Experiment 2	Dimensionality	8	9	10	11	12	13	14
	F ratio	4.63	2.06	1.62	2.47	3.06	3.21	3.53
Experiment 3	Dimensionality	15	16	17	18	19	20	21
	F ratio	4.70	4.26	3.25	3.34	3.84	3.68	3.74

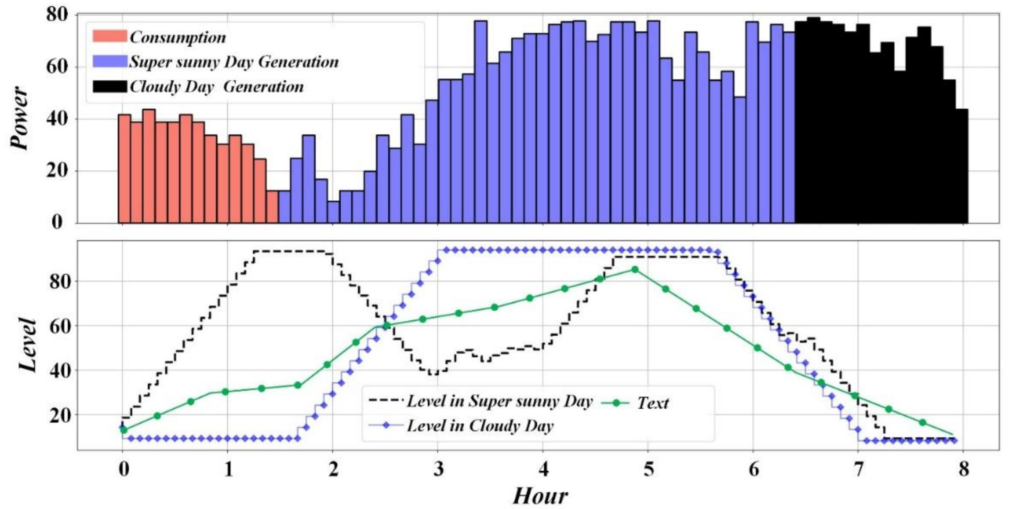

Fig. 5: Changes in power and state level of integrated energy system under different weather conditions.

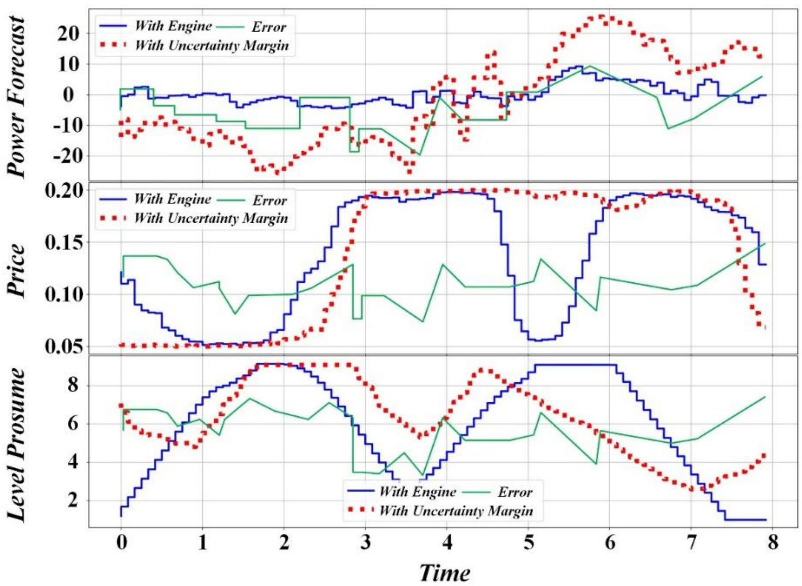

Fig. 6: Multi-index prediction and error analysis of comprehensive energy agent.

Table 2: Comparison results of Accuracy of variant algorithm.

Model Name	Model 1	Model 2	Model 3
Accuracy rate	90.10%	93.50%	97.21%

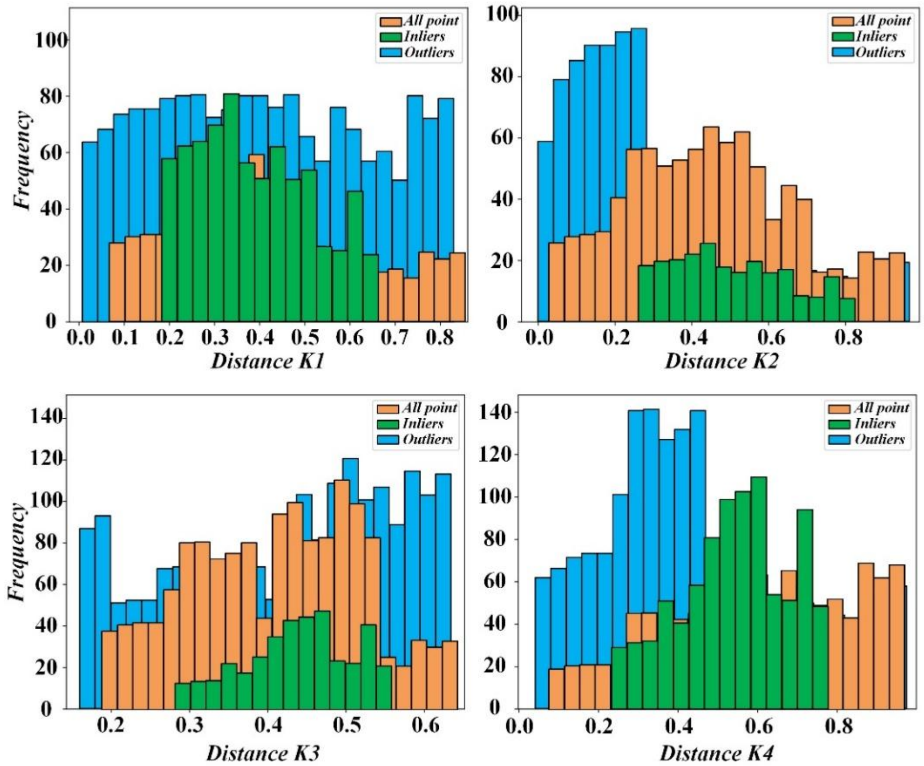

Fig. 7: Distribution of state awareness related distance of integrated energy agents under multi-agents.

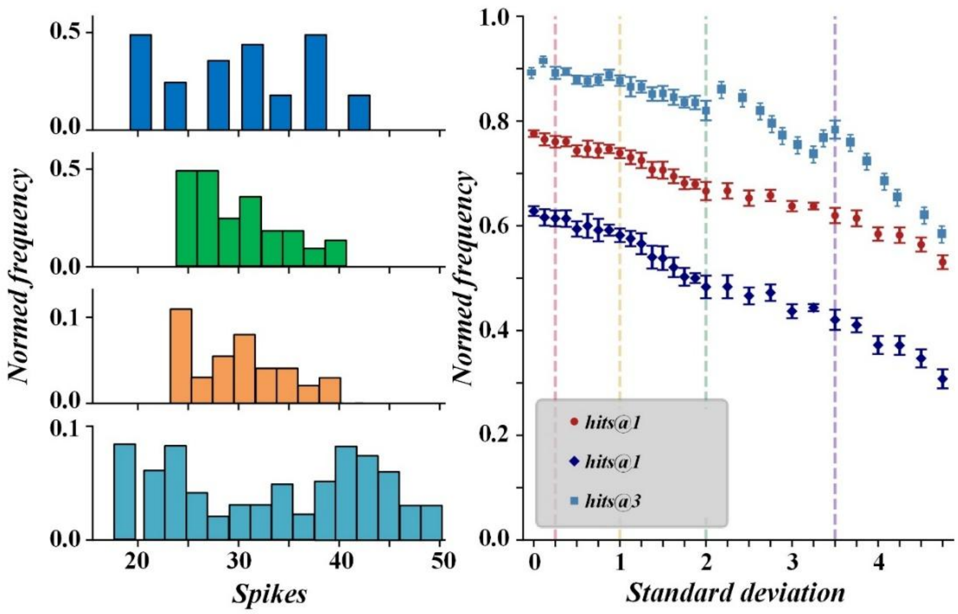

Fig. 8: Correlation analysis of state awareness of comprehensive energy agents under multi-agent deep learning.

After normalizing and fusing the test indicators using the D-S (Dempster-Shafer) evidence theory optimized by Pearson relationship coefficients, the results (Table 3) revealed significant differences in the characteristics of different agent types and verified the effectiveness of the proposed perception method. Specifically, the state confidence levels of N3 and N4 agents are highly concentrated in the V2 level (the confidence levels are 0.552 and 0.667, respectively), indicating that their operating status is excellent and stable; The confidence of N2 agents is mainly distributed in V4 and V5 levels (0.755 in total), suggesting that they are the key weak links in the system that need to be paid most attention to. This clear and differentiated confidence distribution, on the one hand, shows that the improved D-S fusion algorithm can effectively reduce uncertainty and make accurate judgments with high confidence on the status of various agents; On the other hand, it also confirms from the perspective of information fusion that the perception model proposed in this article has strong discrimination capabilities and robustness, and can provide reliable quantitative basis for differentiated monitoring and accurate operation and maintenance of integrated energy systems.

Table 3: Fusion results of improved D-S for test indicators.

Type	Status Grade				
	V1	V2	V3	V4	V5
N1	0.088	0.445	0.325	0.101	0.041
N2	0.054	0.100	0.111	0.335	0.420
N3	0.332	0.552	0.098	0.029	0.010
N4	0.040	0.667	0.212	0.069	0.040

Fig. 9 illustrates the energy efficiency situation in the experiment using a multi-agent deep learning algorithm. The figure on the left illustrates that energy efficiency changes at the minimum rate, and the WBS and NBS algorithms exhibit different performances under varying S values. The figure on the right shows that the energy efficiency changes with the number of iterations, and the convergence of energy efficiency for the WBS algorithm differs for different S values.

Fig. 10 illustrates the changes in state perception values based on three methods, including, multi-agent deep learning, across, four trend scenarios from S1 to S4. Among them, the multi-agent deep learning method (yellow) has a higher perception value in some scenarios, such as about 0.8 in S1. Compared with the limited method (purple), it has obvious advantages, reflecting its effectiveness in comprehensively perceiving the energy agent state.

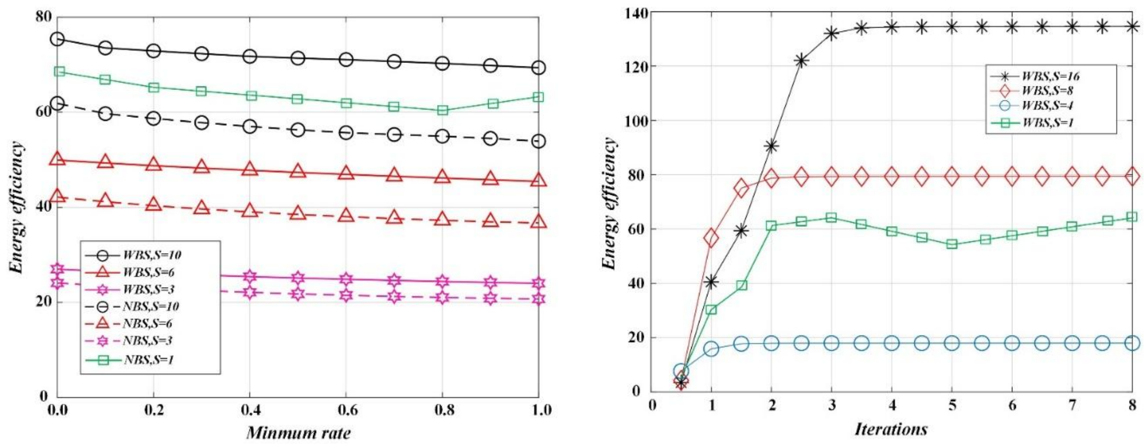

Fig. 9: Relationship between energy efficiency and related parameters under different algorithms.

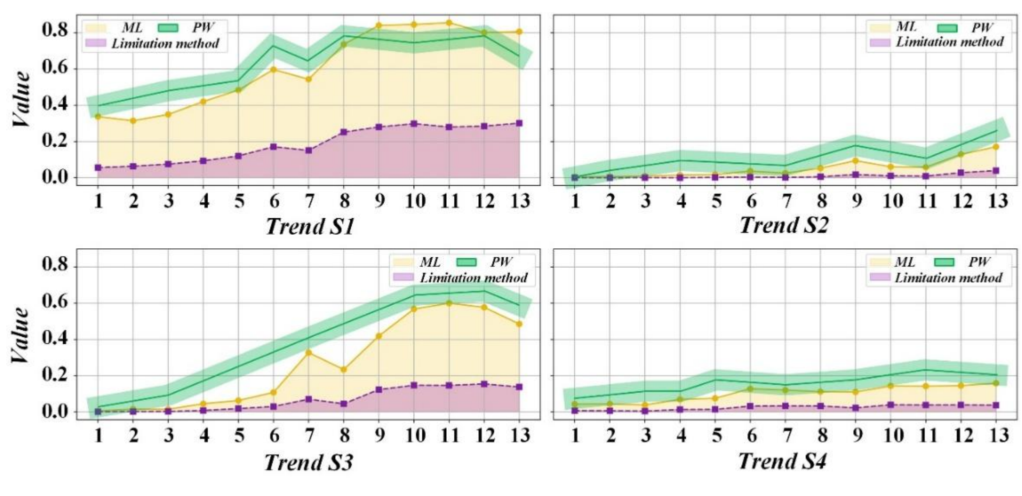

Fig. 10: Comparison of state awareness methods of integrated energy agents in different scenarios.

Fig. 11 shows the results for predicting time steps 1, 2, and 3. In terms of position error, time step 2 performs better than time steps 1 and 3, with relatively lower errors; The error between time step 1 and time step 3 is relatively high. In terms of perceptual accuracy or percentage, the performance of time step 2 and time step 3 is similar, both better than time step 1. It is seen that different prediction time steps have a significant impact on the state perception performance of integrated energy intelligent agents, especially in terms of position error and perception accuracy.

Fig. 12 illustrates the velocity variation for the three methods. Blue is the Baseline, green is the Error, and orange is the Proposed: non-signalized intersections method. There are obvious velocity fluctuations at about 200m and 700m, and the overall velocity performance of the proposed method is better, which reflects its potential in integrated energy agent state perception.

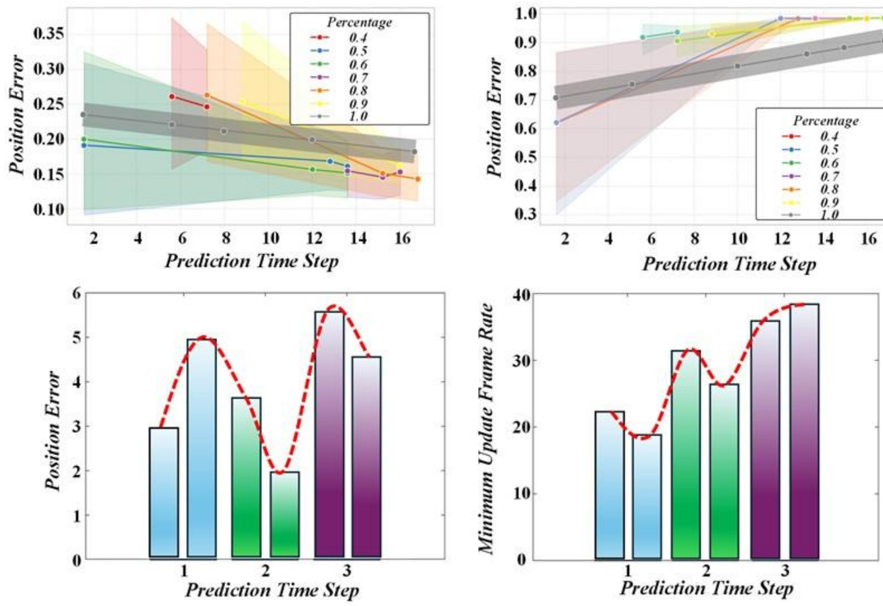

Fig. 11: Position Error and Perception Performance Percentage at Different Prediction Time Steps.

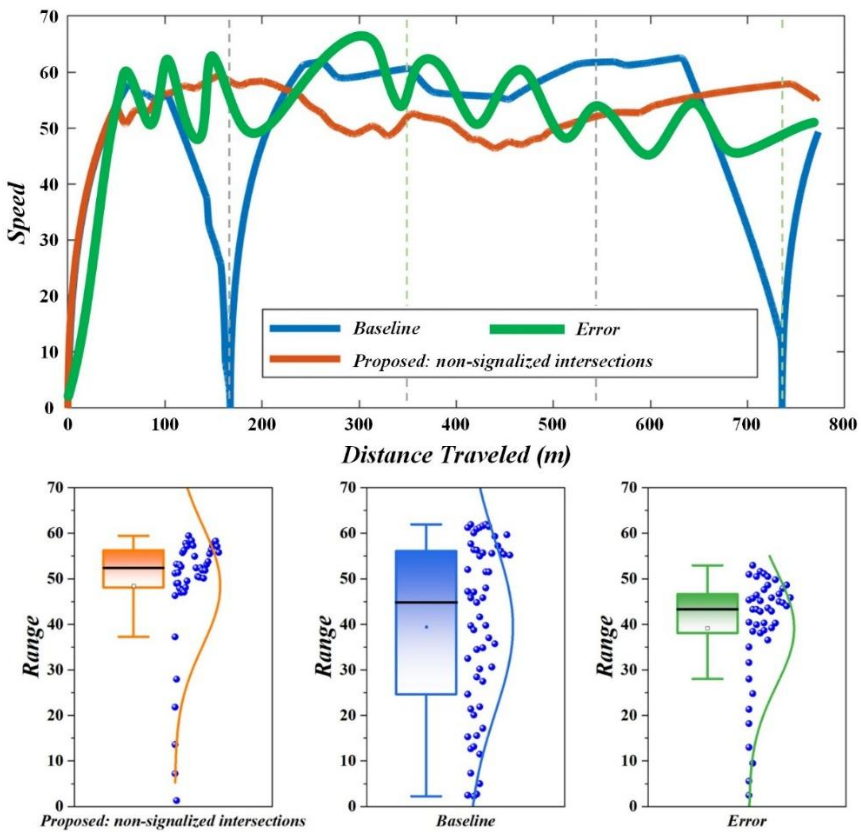

Fig. 12: Velocity-distance relationship of integrated energy agents under different methods.

5. Discussion

To verify the performance of the state perception method for integrated energy intelligent agents based on multi-agent deep learning, case studies were designed from multiple dimensions for validation. Firstly, the state perception results and parameter sensitivity of the multi-agent system were analyzed through Figs. 3 and 4, verifying the convergence and state discrimination ability of the algorithm; Secondly, by combining weather conditions and PCA feature optimization, the robustness of the method in multi energy coupling scenarios was confirmed; Furthermore, through multi indicator prediction and improved D-S evidence fusion, uncertainty quantification and accurate evaluation of agent states have been achieved; Finally, in the accuracy comparison and multi scenario testing, the proposed model achieved an optimal accuracy of 97.21%, significantly better than the comparison methods. In addition, the advantages of the method in terms of perceptual stability and practicality were comprehensively verified from the perspectives of state distribution, energy efficiency optimization, and time step size.

6. Conclusion

Aiming to address the state awareness problem caused by multi-energy flow coupling in integrated energy systems, this article proposes an intelligent agent state perception method based on multi-agent deep learning algorithm, which can achieve cross layer mapping of local observations and global collaboration through distributed intelligent agent networks. This method constructs a model architecture that includes dual upsampling units, deep and shallow feature extraction modules, and feature fusion units. By combining the ShuffleNet v2 efficient network and the SE channel attention mechanism, it reduces the number of parameters and enhances the ability to capture nonlinear features.

The proposed method was validated on the I-BLEND dataset containing 52 months of electrical operation data, and the model accuracy reached 97.21%, which was significantly better than the comparative model (90.10% and 93.50%).

In terms of dynamic prediction performance, the model effectively controls the prediction error fluctuation range of power (range about-20 to 20), price (error about 0.05 to 0.20) and load level (deviation about 0 to 8). After introducing the uncertainty margin, the model can dynamically adapt to changes in prediction difficulty, and the prediction interval is correspondingly expanded during periods of high complexity, thus enhancing its robustness.

The multi-agent collaboration mechanism shows significant advantages, and the relative rate distribution of agents under different parameter combinations shows differentiated characteristics. For example, K1 agents have data point aggregation in the relative rate range of 80-100, and K3 agents have a state perception score of more than 0.8, which reflects the algorithm's ability to identify the states of different types of agents effectively.

Through principal component analysis, the dimension reduction optimization of features is carried out. When the dimension is reduced to 9, the cumulative variance contribution rate reaches 85%, and the F ratio reaches 4.70, which verifies the efficiency and representativeness of the feature extraction module.

The study also found that the prediction time step has a key impact on performance. When the time step is 2, the position error decreases to about 4, which is better than time step 1 (about 5) and time step 3 (about 6), and the minimum update frame rate is increased to about 38 frames/second, indicating that the model achieves a good balance between accuracy and real-time performance at this time step.

This study provides effective temporal data support for multi-agent deep learning algorithms based on the I-BLEND dataset and supplementary cooling and heating load data. However, the dataset itself has limitations, and the integration of its power data with cold and hot data may not fully reflect the dynamic coupling characteristics and spatial heterogeneity of real integrated energy systems, which to some extent affects the universality of research conclusions. It is necessary for future research to further validate the performance and robustness of the model in complex real-world scenarios based on a complete real dataset covering synchronous collection of multiple energy sources such as electricity, heat, and cold. The state perception method proposed in this study achieves global accurate perception through distributed collaboration and deep feature mining. It theoretically fills the gap in collaborative perception, improves heterogeneous data processing theory, balances accuracy and real-time performance technically, and enhances robustness. In practice, it helps the system operate safely and efficiently.

Acknowledgments

The work was financially supported by Science and Technology Projects from State Grid Corporation of China, (Research and demonstration of multi-agent collaboration and interaction technology for urban regional integrated energy system to strengthen grid resilience, No.:5400-202317577A-3-2-ZN). Additionally, State Grid Shanghai Municipal Electric Power Company and Northeast Electric Power University are co-first affiliations.

Conflict of Interest

All authors declare that they have no conflict of interest.

Supporting Information

Not applicable.

CRediT Statement

Zhenlan Dou: Original draft. **Chunyan Zhang:** Data collection. **Songcen Wang:** Computer simulation. **Huamin Wen:** Formal analysis, Validation. **Jiawei Wang:** Data curation, Visualization. **Dejian Yang:** Review & editing, Supervision. All authors read and approved the final manuscript.

References

[1] L. Zhang, Q. Li, Y. Fang, Y. Yang, H. Ren, L. Fan, N. Tai, Optimization scheduling of community integrated energy system considering integrated demand response, *Journal of Building Engineering*, 2024, **98**, 111230, doi: 10.1016/j.jobe.2024.111230.

[2] B. Xu, J. Wang, Optimal energy optimization of the integrated hybrid energy system considering storage system performance, *Multiscale and Multidisciplinary Modeling, Experiments and Design*, 2024, **7**, 705-710, doi: 10.1007/s41939-023-00239-9.

[3] M. Zhu, C. Xu, S. Dong, K. Tang, C. Gu, An integrated multi-energy flow calculation method for electricity-gas-thermal integrated energy systems, *Protection and Control of Modern Power Systems*, 2021, **6**, 1-12.

[4] E. Bazdar, M. Sameti, F. Nasiri, F. Haghighat, Compressed air energy storage in integrated energy systems: a review, *Renewable and Sustainable Energy Reviews*, 2022, **167**, 112701, doi: 10.1016/j.rser.2022.112701.

[5] A. E. H. Berjawi, S. L. Walker, C. Patsios, S. H. R. Hosseini, An evaluation framework for future integrated energy systems: a whole energy systems approach, *Renewable and Sustainable Energy Reviews*, 2021, **145**, 111163, doi: 10.1016/j.rser.2021.111163.

[6] T. Upadhayay, J. Jamnani, Integrating hybrid energy storage system for power quality enhancement of grid integrated large scale wind energy system, *Smart Grids and Sustainable Energy*, 2024, **10**, 1, doi: 10.1007/s40866-024-00232-2.

[7] I. H. Ahmed, C. Brewitt, I. Carlucho, F. Christianos, M. Dunion, E. Fosong, S. Garcin, S. Guo, B. Gyevnar, T. McInroe, G. Papoudakis, A. Rahman, L. Schäfer, M. Tamborski, G. Vecchio, C. Wang, S. V. Albrecht, Deep reinforcement learning for multi-agent interaction, *AI Communications*, 2022, **35**, 357-368, doi: 10.3233/aic-220116.

[8] D. Fan, H. Shen, L. Dong, Switching-aware multi-agent deep reinforcement learning for target interception, *Applied Intelligence*, 2023, **53**, 7876-7891, doi: 10.1007/s10489-022-03821-9.

[9] H. Jiang, D. Shi, C. Xue, Y. Wang, G. Wang, Y. Zhang, Multi-agent deep reinforcement learning with type-based hierarchical group communication, *Applied Intelligence*, 2021, **51**, 5793-5808, doi: 10.1007/s10489-020-02065-9.

[10] A. Oroojlooy, D. Hajinezhad, A review of cooperative multi-agent deep reinforcement learning, *Applied Intelligence*, 2023, **53**, 13677-13722, doi: 10.1007/s10489-022-04105-y.

[11] G. Liapis, I. Vlahavas, Multi-agent system for emulating personality traits using deep reinforcement learning, *Applied Sciences*, 2024, **14**, 12068, doi: 10.3390/app142412068.

[12] Z. Lin, F. Jiang, Y. Luo, K. Liu, X. Zhang, Data-driven situation awareness of electricity-gas integrated energy system considering time series features, *Frontiers in Energy Research*, 2022, **10**, 921296, doi: 10.3389/fenrg.2022.921296.

[13] A. S. Sani, D. Yuan, G. Loukas, Z. Y. Dong, UReum: a universally composable blockchain-enabled model for secure and privacy-preserving data awareness in energy Internet, *IEEE Access*, 2024, **12**, 171396-171417.

[14] S. Gronauer, K. Diepold, Multi-agent deep reinforcement learning: a survey, *Artificial Intelligence Review*, 2022, **55**, 895-943, doi: 10.1007/s10462-021-09996-w.

[15] S. Song, H. Wei, Y. Lin, C. Wang, A. Gómez-Expósito, A holistic state estimation framework for active distribution network with battery energy storage system, *Journal of Modern Power Systems and Clean Energy*, 2022, **10**, 627-636.

[16] C. Wu, J. Peng, H. He, J. Ruan, J. Chen, C. Ma, Health-awareness energy management strategy for battery electric vehicles based on self-attention deep reinforcement learning, *Journal of Power Sources*, 2024, **623**, 235463, doi: 10.1016/j.jpowsour.2024.235463.

[17] H. Dun, Y. Zhao, Q. Shi, W. Liu, E. Huan, Energy efficiency optimization for D2D communication with statistical channel state information and QoS awareness, *KSII Transactions on Internet and Information Systems*, 2024, **18**, 3177-3197, doi: 10.3837/tiis.2024.11.005

[18] H. Ma, Intelligent planning for large-scale multi-agent systems, *AI Magazine*, 2022, **43**, 376-382, doi: 10.1002/aaai.12069.

[19] Y. Abd Alrahman, N. Piterman, Modelling and verification of reconfigurable multi-agent systems, *Autonomous Agents and Multi-Agent Systems*, 2021, **35**, 47, doi: 10.1007/s10458-021-09521-x.

[20] B. Cheng, G. Li, K. An, C. Yu, Distributed robust matrix-scaled consensus control of perturbed multi-agent systems, *Control Theory and Technology*, 2024, **22**, 623-637, doi: 10.1007/s11768-024-00203-z.

[21] Z. Al Zahra Sanai Dashti, G. Oliva, C. Seatzu, A. Gasparri, M. Franceschelli, Distributed mode computation in open multi-agent systems, *IEEE Control Systems Letters*, 2022, **6**, 3481-3486, doi: 10.1109/LCSYS.2022.3185419.

[22] Y. Shi, E. Nekouei, Secure distributed adaptive control of nonlinear multi-agent systems, *IEEE Transactions on Automation Science and Engineering*, 2024, **22**, 8937-8951, doi: 10.1109/TASE.2024.3493136.

[23] M. Köhler-Bußmeier, J. Sudeikat, Defining adaption measures for organisational multi-agent systems, *International Journal of Parallel, Emergent and Distributed Systems*, 2023, **38**, 507-521, doi: 10.1080/17445760.2023.2243005.

[24] Y. Zhu, J.-H. Pang, T. Gao, F.-B. Tian, Learning to school in dense configurations with multi-agent deep reinforcement learning, *Bioinspiration & Biomimetics*, 2023, **18**, 015003, doi: 10.1088/1748-3190/ac9fb5.

[25] Z. Xie, C. Ji, C. Qiao, W. Song, Z. Li, Y. Zhang, Y. Zhang, Mutual information oriented deep skill chaining for multi-agent reinforcement learning, *CAAI Transactions on Intelligence Technology*, 2024, **9**, 1014-1030, doi: 10.1049/cit2.12322.

[26] G. Elías Alonso, X. Jin, Skeleton-level control for multi-agent simulation through deep reinforcement learning, *Computer Animation and Virtual Worlds*, 2022, **33**, e2079, doi: 10.1002/cav.2079.

[27] M. Soltani, K. Khajavi, M. Jafari Siavoshani, A. H. Jahangir, A multi-agent adaptive deep learning framework for online intrusion detection, *Cybersecurity*, 2024, **7**, 9, doi: 10.1186/s42400-023-00199-0.

[28] Z. Luo, Z. Chen, S. Liu, J. Welsh, Multi-agent reinforcement learning with deep networks for diverse QQ-vectors, *Electronics Letters*, 2025, **61**, e70342, doi: 10.1049/ell2.70342.
[29] M. Geng, S. Pateria, B. Subagdja, A.-H. Tan, HiSOMA: a hierarchical multi-agent model integrating self-organizing neural networks with multi-agent deep reinforcement learning, *Expert Systems with Applications*, 2024, **252**, 124117, doi: 10.1016/j.eswa.2024.124117.
[30] Q. Meng, J. Wu, H. Wang, Research on new energy power system stability situation awareness based on index screening and dynamic evaluation, *Processes*, 2023, **11**, 1509, doi: 10.3390/pr11051509.