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EEDAL
Energy Efficiency in Domestic Appliances and Lighting

Forecasting spot market prices for residential prosumers based on a deep learning model

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Contents

1. Context

2023 Energy Mix

Global primary energy consumption hit a record high for the second year, driven by non-OECD countries, where **Fossil Fuels make up 84% of their energy mix and lead growth**.

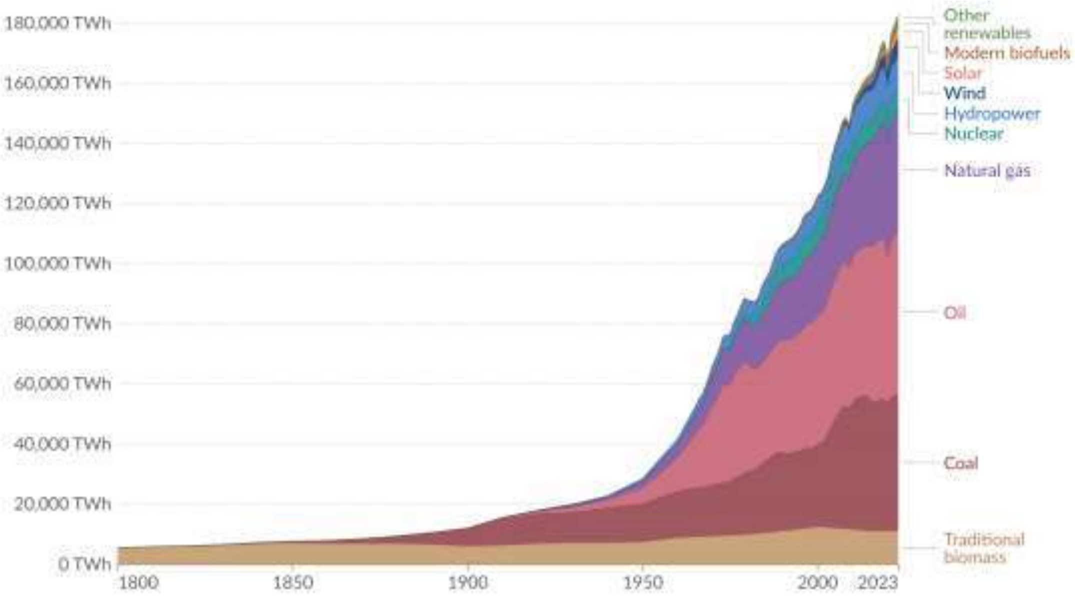


Fig. 1-1 Global primary energy consumption by source (1800-2023)*

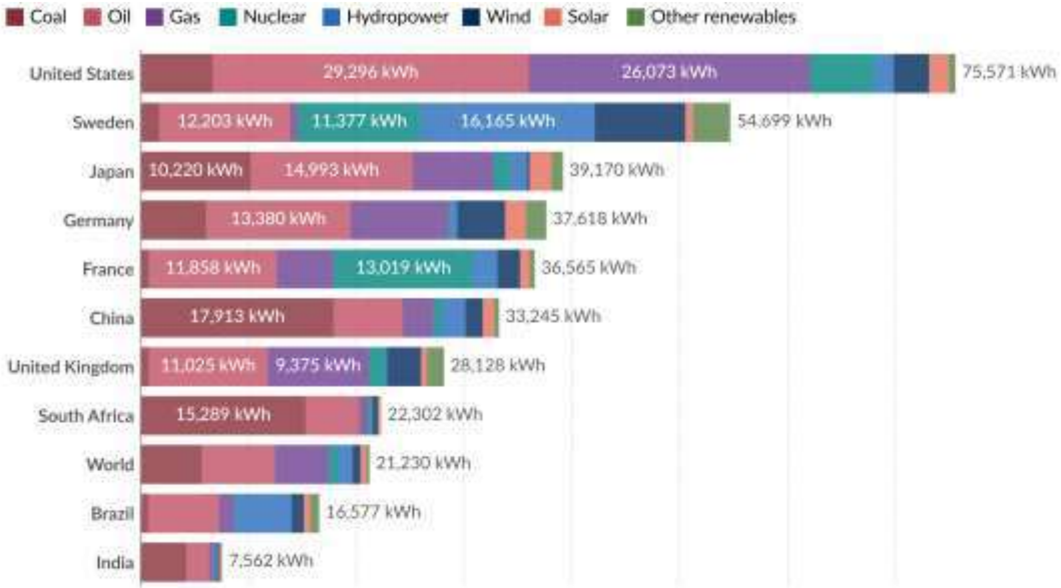


Fig. 1-2 Per capita primary energy consumption by source (2023)*

*Statistical Review of World Energy, Energy Institute 2024

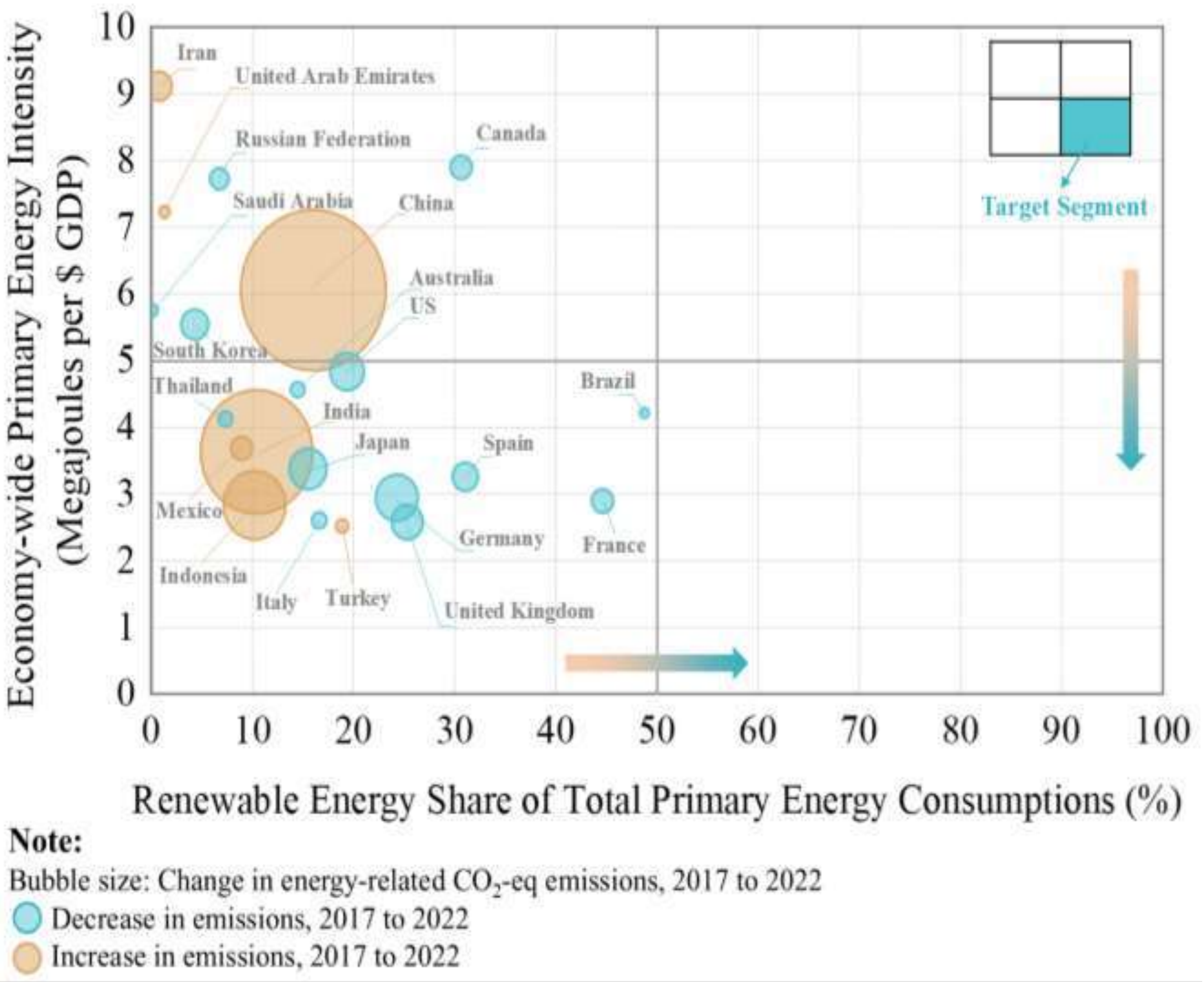


Fig. 1-3 Energy transition landscape

Global Energy Transition Targets

2030

2040

2050

- By 2030, annual global clean energy investment must reach **$4 trillion**.
- By 2040, coal and oil plants without emissions reductions will be phased out, achieving **net-zero power generation**.
- By 2050, **Renewable Energy** will dominate, with **solar** as the largest source.

1. Context

Electricity Markets are Central to Decarbonising The Power Sector

- Currently, **50% of global electricity is generated in liberalized markets**, expected to rise to 76% as China implements its power markets.
- Decarbonization efforts in the short and medium term will largely depend on these market-driven systems to reduce costs and attract investment.

- Retail market had been gradually liberalized since 2000.
- **Since April 2016, retail electricity market in Japan has been fully opened up for competition**. But regulated tariffs by GEUs are still exist in low voltage consumer for consumer protection.

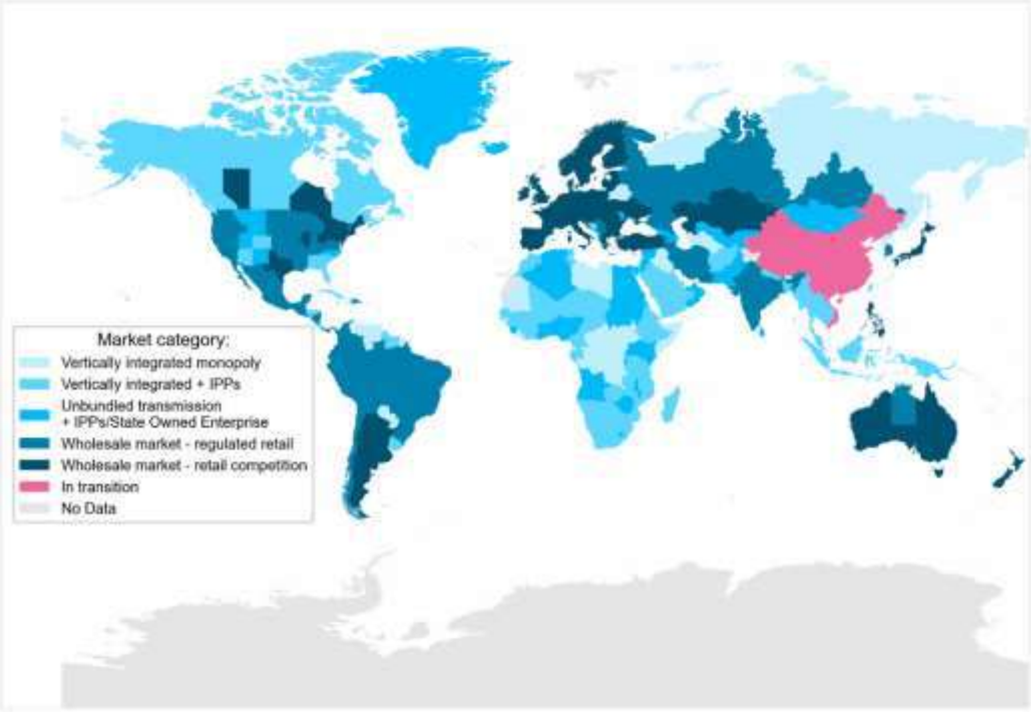


Fig. 1-4 Status of electricity markets around the world in 2022*

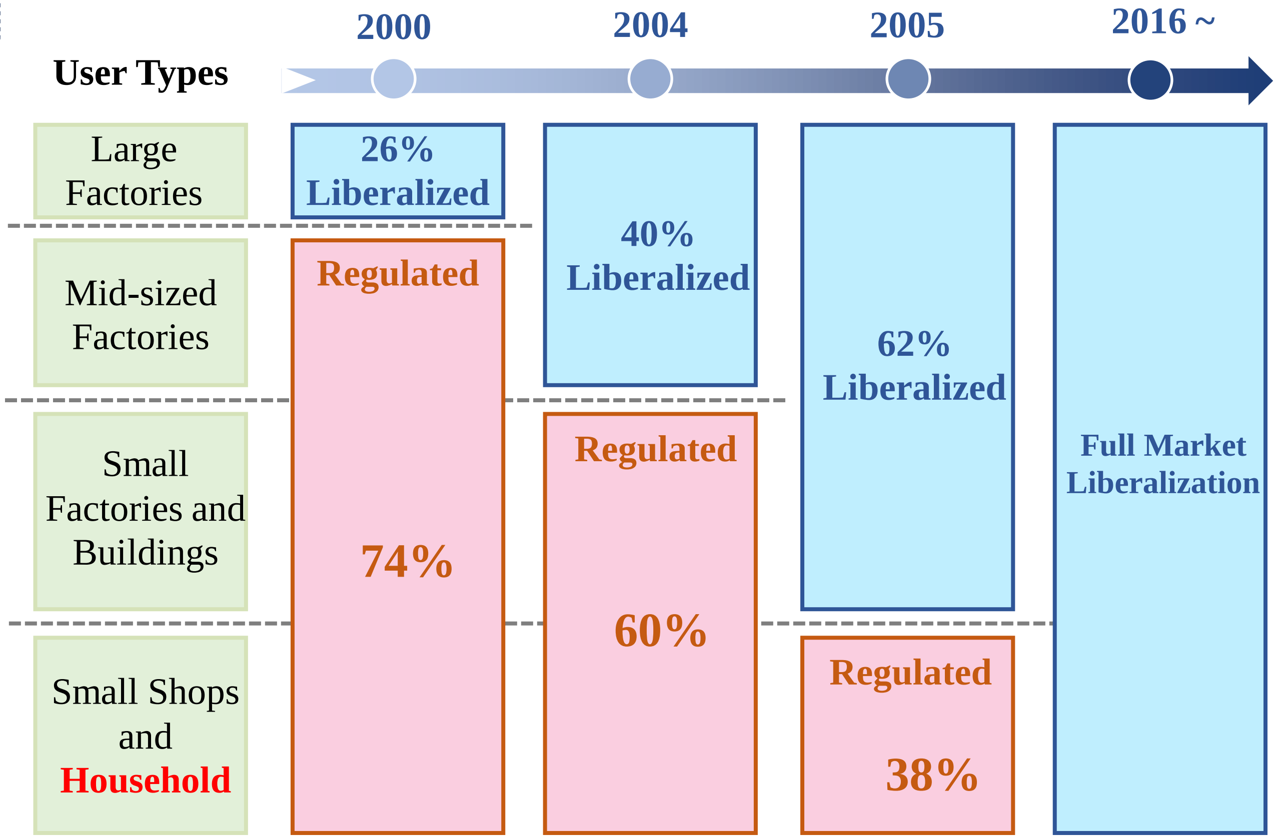


Fig. 1-5 History of electricity market development in Japan

*Steering Electricity Markets Towards a Rapid Decarbonisation, IEA 2022

Japan Electric Power Exchange (JEPX) was founded in 2003 as Japan's physical wholesale spot market for electricity. Trading volumes of electricity until 2016 were very small, representing approximately **2%** of Japan's generation supply. **This changed dramatically starting in 2016.**

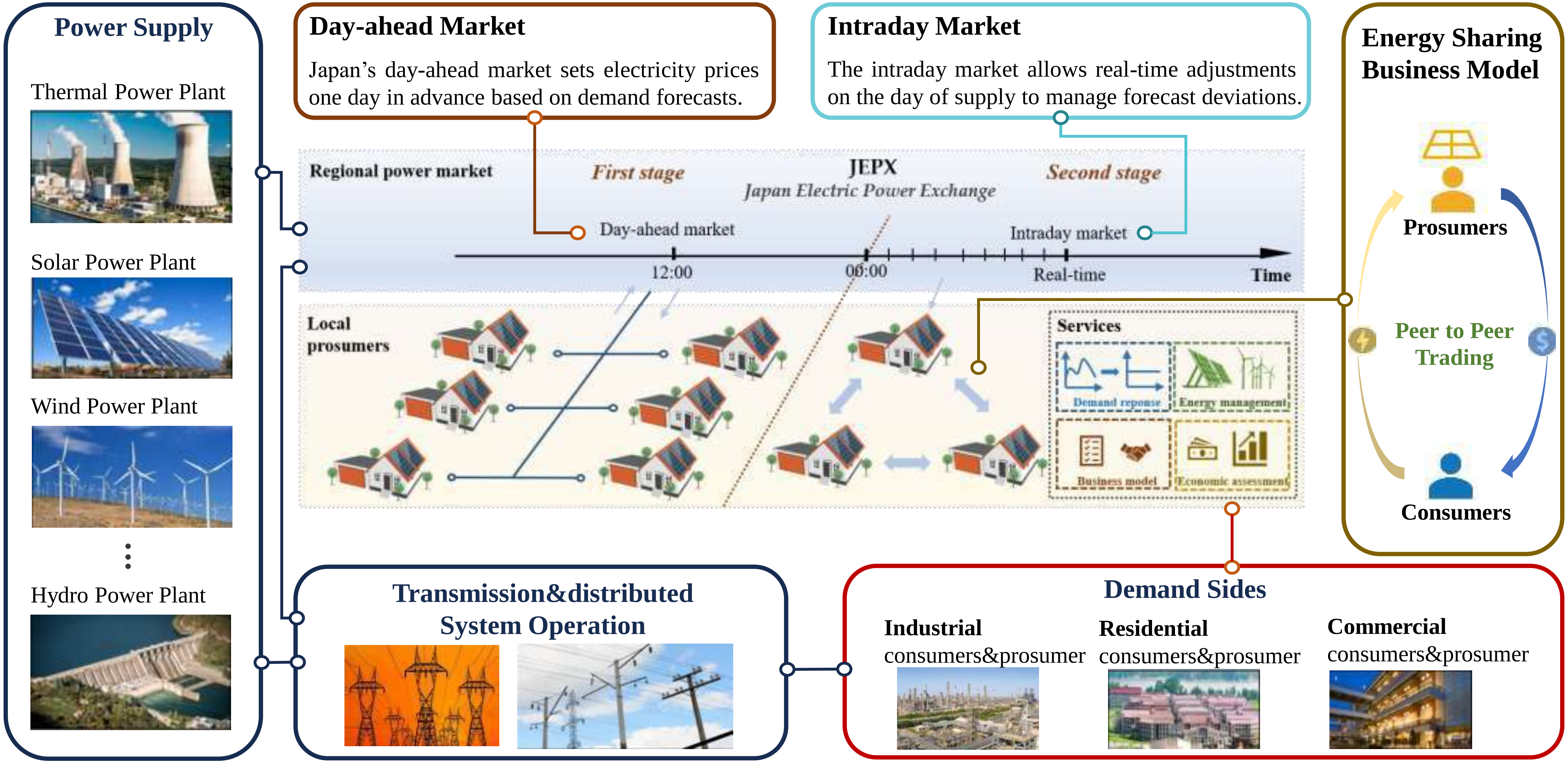


Fig. 1-6 Overview of Japan electricity trading mechanism after full liberalization

Practical significance of this study:

In practice, accurate forecasting greatly benefits electricity market participants. A company, producer, or consumer that can reasonably predict fluctuating electricity prices can **reduce trading risks and maximize profits** by adjusting bidding strategies and production or consumption schedules in the day-ahead market.

Limitations of existing methods:

- Models often lack robustness despite high accuracy.
- Many models adapt slowly to new data.
- Spatiotemporal features are not well captured.
- Long-term forecasting is not well addressed.

Comparison of the existing Forecasting Models

Comparison Criteria	LSTM	PSO-SVM	ARIMA	Random Forest
Prediction Accuracy	✓	✓	✗	✓
Convergence Speed	✗	✓	✓	✓
Spatiotemporal Feature Handling	✓	✗	✗	✗
Hyperparameter Optimization Efficiency	✗	✗	✗	✓
Robustness to Market Volatility	✗	✓	✗	✓
Long-term consideration	✘	✘	✘	✘

Contributions of this study:

- The BO-CNN-LSTM model effectively balances prediction accuracy and robustness to market fluctuations.
- The model quickly adapts to data changes while capturing complex spatiotemporal relationships.
- Fourier series theory is used to forecast long-term electricity price trends, extending beyond short-term horizons.
- SHAP provides insights into the model's decision-making, offering greater transparency in machine learning predictions.

2. Method

2. Method

The Development of Machine Learning (ML)

Initial stage		Mid-stage	Current-stage	Future outlook
1980-1990	1990-2000	2000-2010	2010-2024	2024-

1980-1990: Based on statistical methods

Predictive models initially used mainly statistics-based methods such as **time series analysis** and **regression analysis**. Although these methods are relatively simple, they still have some utility in short - and medium-term forecasting.

1990-2000: Introducing machine learning

With the improvement of computing power and the increase of data volume, machine learning methods are gradually introduced into the field of predictive models. **Artificial Neural Networks (ANN)** became a popular method to automatically learn load patterns from data.

2000-2010: Optimization of machine learning methods

Machine learning methods developed further during this period, and methods such as **Support Vector Machines (SVM)** were gradually applied to data prediction. At the same time, more optimization and improvement of the model are carried out to improve the prediction performance.

2010-2024: Rise of deep learning

With the rise of deep learning techniques, especially the application of **Recurrent Neural Networks (RNN)**, **Convolutional Neural Networks (CNN)**, and **Long and Short Term Memory Networks (LSTM)**. At the same time, this period also began to use larger data sets and more powerful computing resources.

2024-: Integrated approach and real-time

Since 2020, forecasting technology has evolved with trends in **deep learning**, **multi-source data fusion**, and **model integration**.

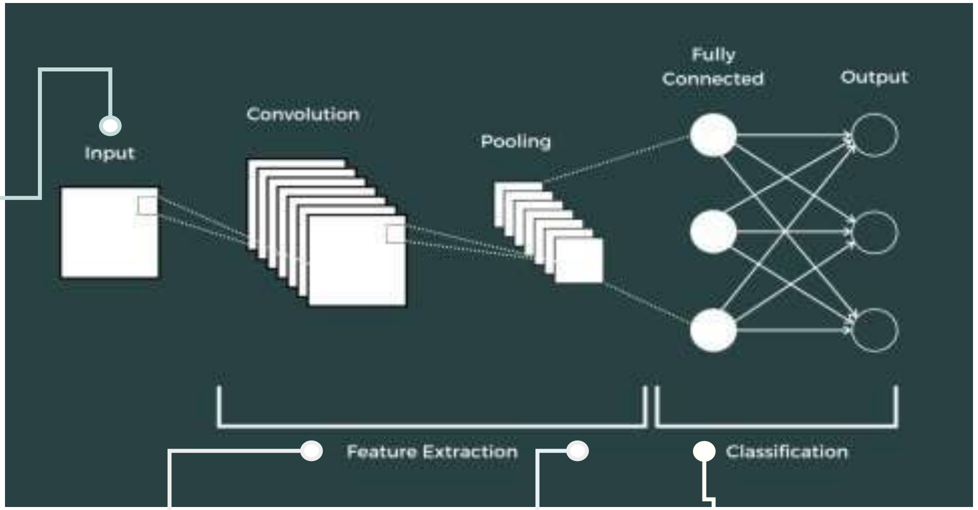
More studies focuse on **uncertainty modeling**, **real-time**, **adaptive enhancements**, and **renewable energy integration**. These advances aim to improve accuracy, adaptability, and real-time performance in energy management and power systems.

Convolutional Neural Network (CNN) is a deep learning model that automatically detects patterns in data, like images or time series. It uses layers of filters to identify features and builds them up to understand complex structures, **making it effective for recognizing sequences and trends with minimal pre-processing**.

1. Input Data

Time series data is split into small sequences (windows) as input for the CNN. Each window of size k looks like:

$$X^{(i)}=[x_{t-k+1}, x_{t-k+2}, \dots, x_t]$$



Note:
The core of convolution is a process of **feature extraction** and **information compression**, where sliding filters are applied to input data to capture local patterns.

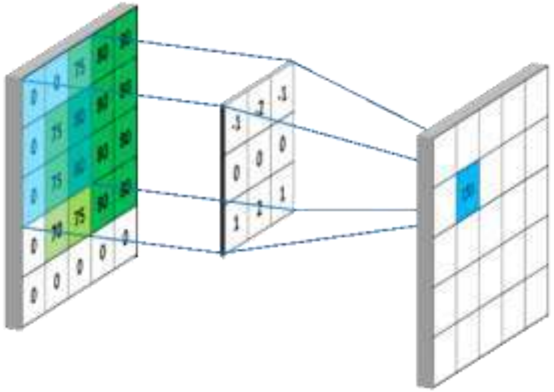


Fig. 2-2 Animated diagram of CNN in processing

2. Convolution Layer

The convolution layer extracts features from each window by applying a filter, which moves along the sequence.

$$h_t=\sigma(\sum_{j=1}^{k} w_j \cdot x_{t-j+1}+b)$$

3. Pooling Layer

The pooling layer reduces the size of the feature maps, keeping the important information.

$$p_t=\max(h_t, h_{t+1}, \dots, h_{t+m-1})$$

4. Fully Connected Layer

The fully connected layer make the final prediction.

$$\hat{y}=\sigma(\sum_{i=1}^{n} w_i' \cdot p_i+b')$$

Fig. 2-1 Framework of Convolutional Neural Network (CNN)

LSTM (Long Short-Term Memory) is a deep learning model commonly used for processing sequential data. Compared to traditional RNNs (Recurrent Neural Networks), LSTM introduces three gates (**input gate**, **forget gate**, and **output gate**, as shown in the figure below) and a **cell state**. These mechanisms enable LSTM to better capture long-term dependencies in sequences.

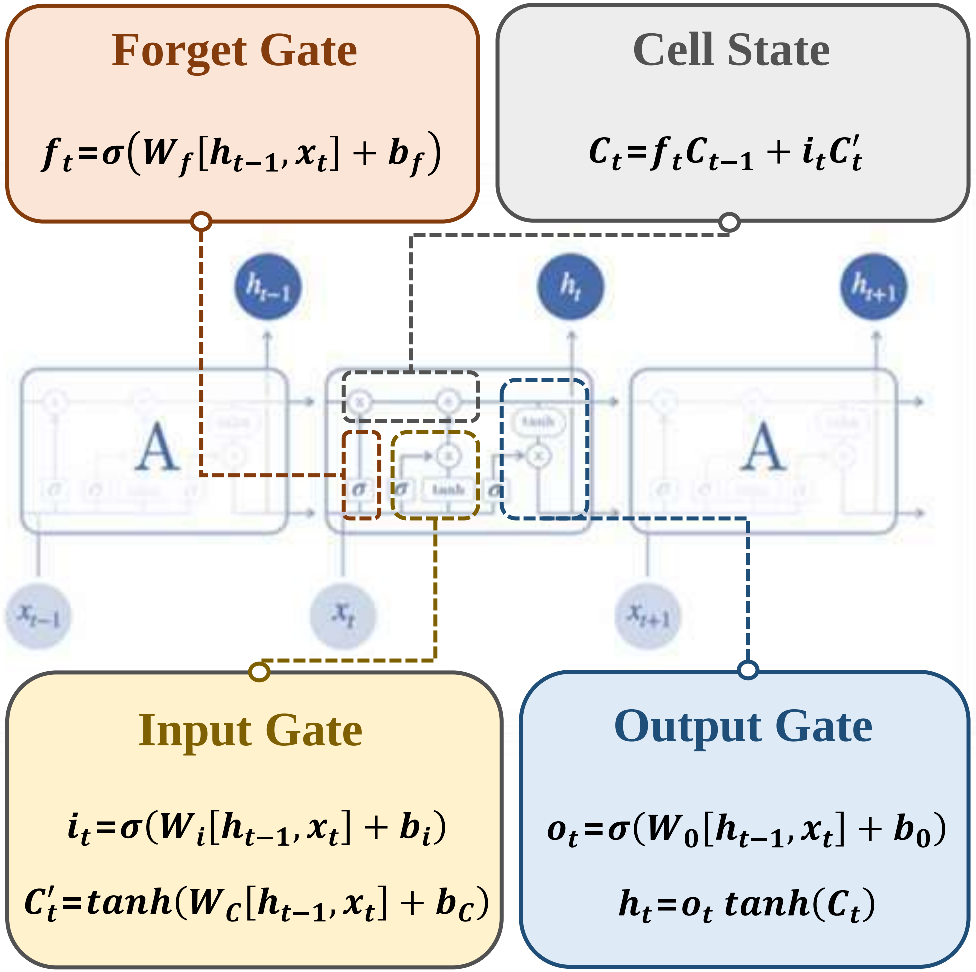


Fig. 2-3 Framework of Long Short-Term Memory (LSTM)

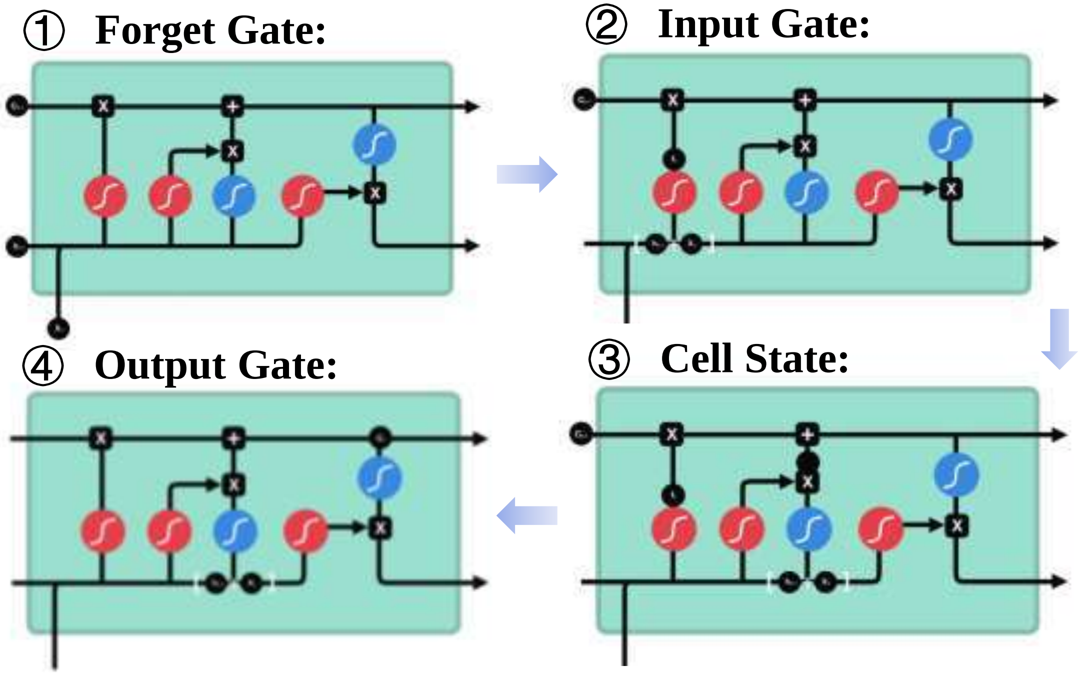


Fig. 2-4 Animated diagram of LSTM in processing

Advantages of LSTM:

- **Remembers important info longer.**
- **Filters out unnecessary data.**
- **Works great for time-based tasks.**

Bayesian Optimization Model

The **Bayesian Optimization (BO)** algorithm is less prone to getting trapped in local optima, **making it a reliable and faster method for adjusting hyperparameters in machine learning**, particularly when the cost of evaluating the objective function is high or the function is complex to handle.

Objective function:

$$f_{\Theta} = min(training\ RMSE + validation\ RMSE)$$

Table. 2-1 BO algorithm for hypeparameter tuning

BO algorithm for hyperparameter tuning.
Input: f: The objective function, Θ: Hyperparameter space, N: Number of iterations, GP: Gaussian process surrogate model, EI: Expected improvement acquisition function, ΔEI_{min}: Threshold for minimum improvement, D: Dataset.
Output: θ_{best}: The best-performing hyperparameter set.
1. Initialize: $EI_{prev} = \infty$
2. for n = 1 to N do
3. θ_n = argmax EI(Θ, GP, D)
4. $y_n = f(\theta_n)$
5. $D = D \cup \{(\theta_n, y_n)\}$
6. Update GP using D
7. $EI_{curr} = EI(\theta_n \mid GP, D)$
8. $\Delta EI = EI_{prev} - EI_{curr}$
9. if $\Delta EI \leq \Delta EI_{min}$ then
10. $\theta_{best}, y_{best} = \min\{ y_n \mid (\theta_n, y_n) \in D\}$
11. $GP_{final} = GP$
12. end if
13. $EI_{prev} = EI_{curr}$
14. end for
15. Update Θ

Three Evaluation Criteria

To evaluate the predictive performance of the proposed model, three performance metrics were selected: Root Mean Square Error (**RMSE**), Mean Absolute Percentage Error (**MAPE**), and the coefficient of determination, **R^2**. MAPE represents the average absolute prediction error across m samples. RMSE is the square root of the mean squared error for m samples. The coefficient of determination, R^2, is used to assess the accuracy of the predictions. These metrics are mathematically defined as follows:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(y_i - y_{pre}\right)^2}$$

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\frac{\left|y_i - y_{pre}\right|}{y_i} \times 100$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}\left(y_i - y_{pre}\right)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2}$$

2. Method

SHapley Additive exPlanations (SHAP)

What is SHAP?

SHAP (SHapley Additive exPlanations) is a method used to **explain machine learning model predictions**. It shows how each input feature contributes to the model's output.

Core Idea of SHAP Values:

SHAP values are based on **Shapley values from cooperative game theory**, calculating each feature's contribution across all possible combinations. It's like analyzing each feature's contribution to the overall performance.

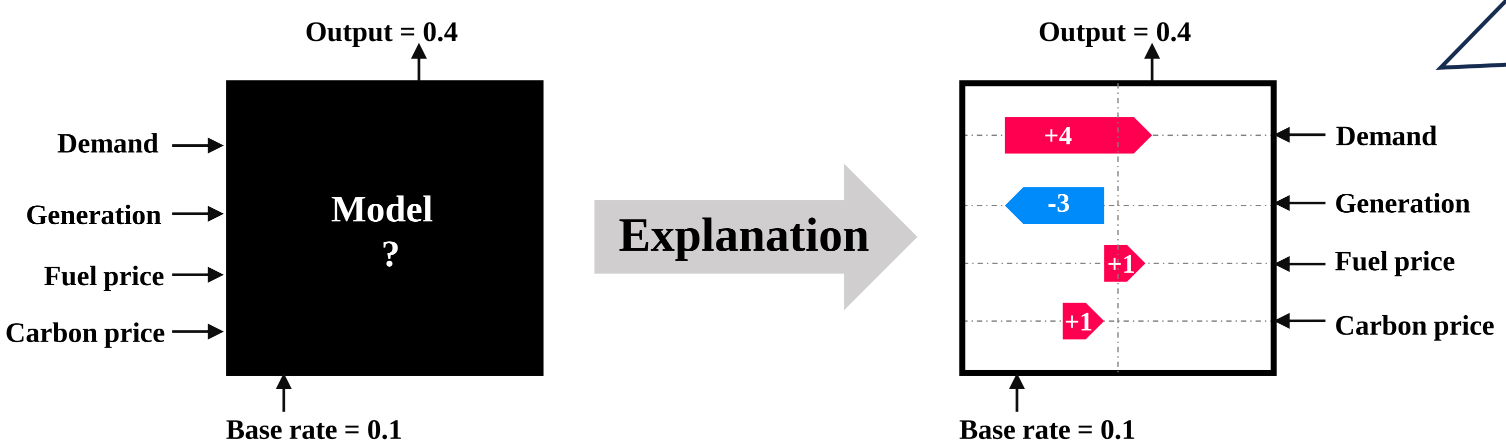


Fig. 2-5 The principle of SHAP

SHAP Main Formulas:

$$f(x) = g(x') = \phi_0 + \sum_{i=1}^{M} \phi_i x'_i$$

$$\phi_i(f, x) = \sum_{z' \subseteq x'} \underbrace{\frac{|z'|!\,(M-|z'|-1)!}{M!}}_{\text{Weighting}} \underbrace{[f_x(z') - f_x(z' \setminus i)]}_{\text{Contribution}}$$

Shapley value for feature i

Subset

Simplified data input

Advantages of SHAP:

- **Transparency**: SHAP explains black-box models, revealing why the model made a certain decision.
- **Fairness**: Every feature's contribution is averaged across all combinations, ensuring a fair calculation.

2. Method

Address Long-term and Uncertain Issues

1 **Identify Annual Price Drivers**

- Economic factors
- Supply and demand factors
- Environmental factors

10 Annual Price Drivers were chosen.

2 **Construct Data-Driven Models**

Fit future annual electricity prices using **Fourier Series**

$$P_t = a_0 + \sum_{n=1} (a_n \cos(2\pi nt/T) + b_n \sin(2\pi nt/T)) + g(X_t)$$

3 **Introduce Virtual Factors for Disturbance Simulation**

- Add virtual factors to the model to simulate policy changes and market uncertainties.
- Adjust price drivers based on disturbance coefficients

4 **Predict Hourly Data Within the Year by BO-CNN-LSTM**

5 **Introduce Virtual Factors for Disturbance Simulation**

- Combine annual trends with hourly forecasts.
- Use **Empirical Interval Prediction** to define uncertainty.

Fig. 2-6 Flowchart depicting the solution process for the long-term issues

Past (2016-2021)

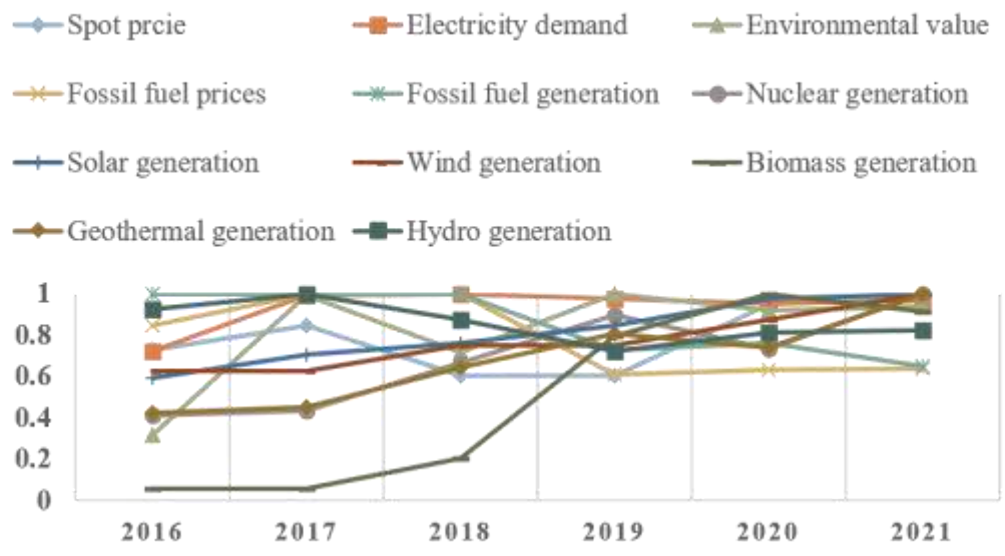


Fig. 2-7 Past annual price drivers trends. (2016-2021)

Future (~2050)

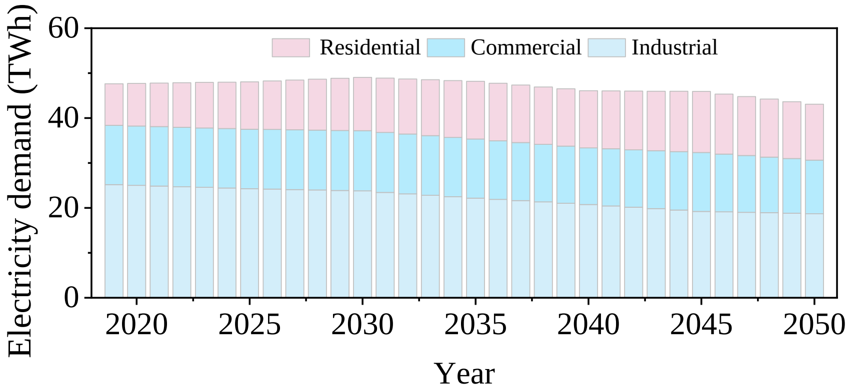


Fig. 2-8 Future annual price drivers trends. (Demand)

Overview of The Proposed Forecasting Model

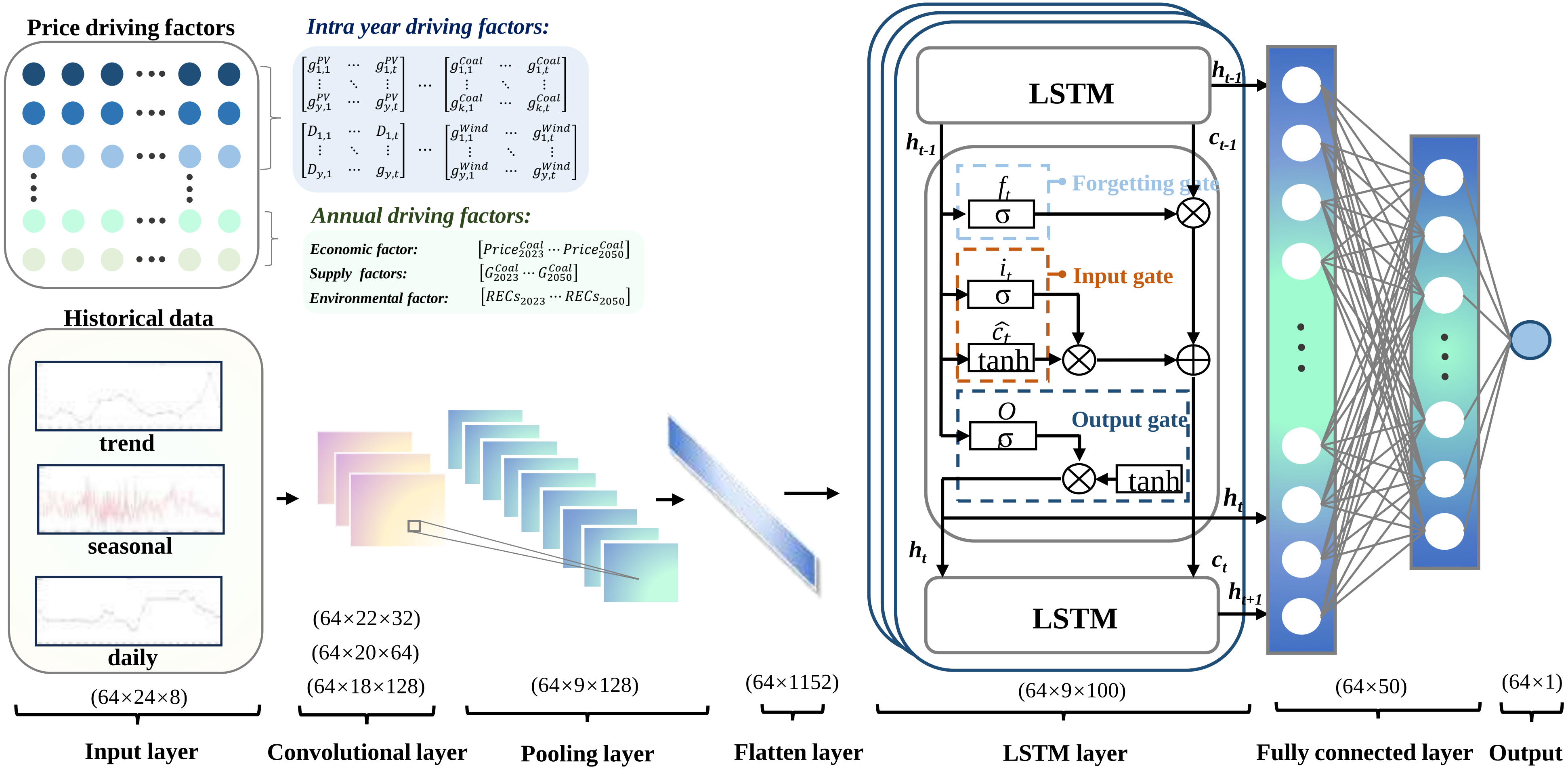


Fig. 2-9 Overview of the proposed forecasting model

Table. 2-2 Parameters settings

Parameter	Value
Learning Rate	0.001
Convolutional	3
Kernel Size	5x5
Pooling Size	3x3
LSTM Layers	3
Hidden Units	100
Batch Size	64
Epochs	300
Regularization	0.001
Initial Points	5
Iterations	30
Exploration	0.5

3. Results and discussion

Case study ⟶ JEPX Kyushu electricity spot market (2006-2022)
Price drivers ⟶ Energy prices, Polices, Generation and Demand

In Japan, **Nine electric power companies** (Except Okinawa) have provided their utility services as a regional monopoly. **JEPX was only 1.5% to total generation in 2016.** Notebly, by 2020, increased access to infrastructure aimed to lower costs for suppliers.

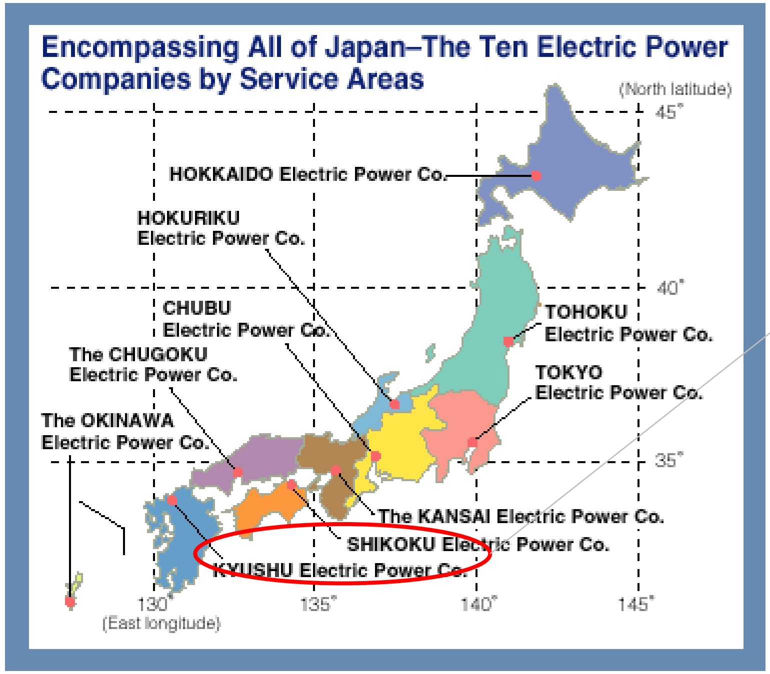


Fig. 3-1 Encompassing all of Japan-The Ten Electric Power Companies by Service Areas

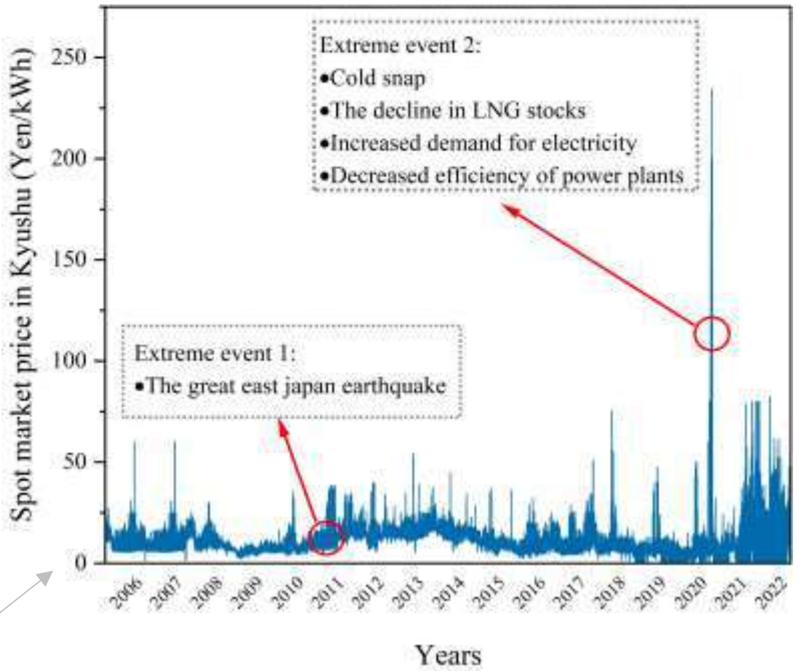


Fig. 3-2 Spot market price in Kyushu. (2006-2022)

The **2011** Fukushima nuclear disaster reshaped Japan's energy landscape. In **2021,** a severe cold snap spiked electricity demand, depleted LNG reserves, and pushed prices above **250 JPY/kWh**.

We selected **8 Intra year price driving factors** (RES generation, Demand, etc) and **10 Annual driving factors** (Fossil fuel prices, RES Introduction, etc) as features of the forecasting model.

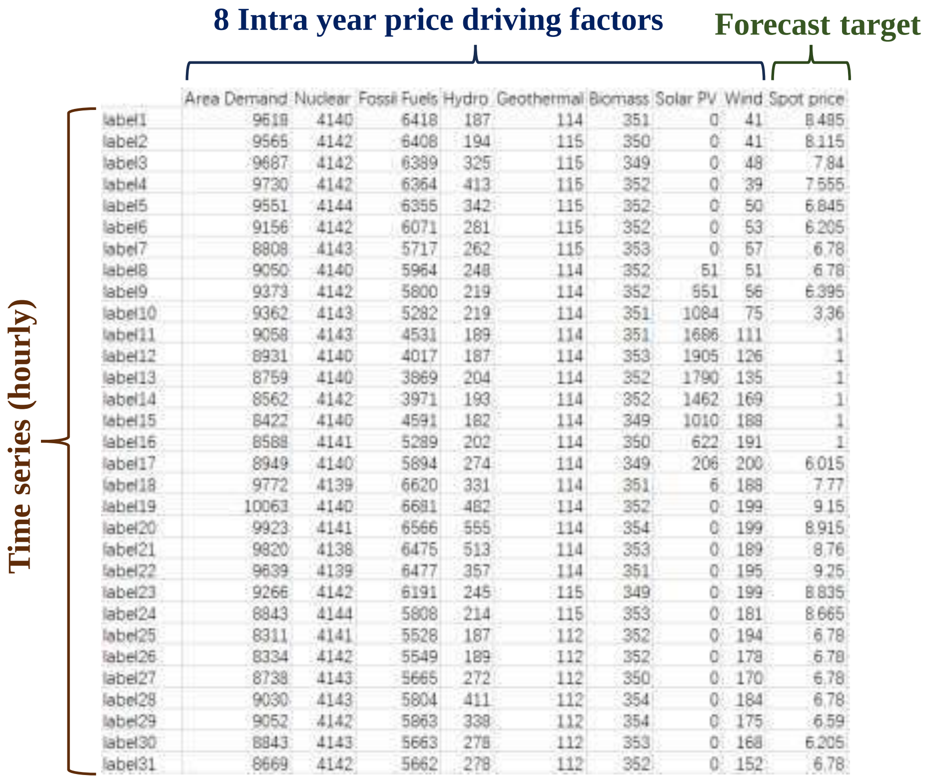
Table. 3-1 Data sourses.

Description	Reference
Historical price data	
Spot price (Kyushu 2006-2022)	JEPX, 2023
Price driving factors	
1. Intra year driving factors	
Demand	ISEP, 2024
Power generation	ISEP, 2024
2. Annual driving factors	
Supply factors	REI, 2021
Economic factors	REI, 2021
Environmental factors	NPN, 2023

3. Results and discussion

Comparison of the predictive performance of the three models.

- To validate the accuracy of our model, we compared it against two other prediction models: a single **LSTM** model and a **Particle Swarm Optimization Support Vector Machine (PSO-SVM)** model.
- The BO-CNN-LSTM model shows superior performance in both convergence speed and prediction accuracy compared to the single LSTM and PSO-SVM models.



	Area Demand	Nuclear	Fossil Fuels	Hydro	Geothermal	Biomass	Solar PV	Wind	Spot price
label1	9618	4140	6418	187	114	351	0	41	8.485
label2	9565	4142	6408	194	115	350	0	41	8.115
label3	9687	4142	6389	325	115	349	0	48	7.84
label4	9730	4142	6364	413	115	352	0	39	7.555
label5	9551	4144	6355	342	115	352	0	50	6.845
label6	9156	4142	6071	281	115	352	0	53	6.205
label7	8808	4143	5717	262	115	353	0	57	6.78
label8	9050	4140	5964	248	114	352	51	51	6.78
label9	9373	4142	5800	219	114	352	551	56	6.395
label10	9362	4143	5282	219	114	351	1084	75	3.36
label11	9058	4143	4531	189	114	351	1686	111	1
label12	8931	4140	4017	187	114	353	1905	126	1
label13	8759	4140	3869	204	114	352	1790	135	1
label14	8562	4142	3971	193	114	352	1462	169	1
label15	8422	4140	4591	182	114	349	1010	188	1
label16	8588	4141	5289	202	114	350	622	191	1
label17	8949	4140	5894	274	114	349	206	200	6.015
label18	9772	4139	6620	331	114	351	6	188	7.77
label19	10063	4140	6681	482	114	352	0	199	9.15
label20	9923	4141	6566	555	114	354	0	199	8.915
label21	9820	4138	6475	513	114	353	0	189	8.76
label22	9639	4139	6477	357	114	351	0	195	9.25
label23	9266	4142	6191	245	115	349	0	199	8.835
label24	8843	4144	5808	214	115	353	0	181	8.665
label25	8311	4141	5528	187	112	352	0	194	6.78
label26	8334	4142	5549	189	112	352	0	178	6.78
label27	8738	4143	5665	272	112	350	0	170	6.78
label28	9030	4143	5804	411	112	354	0	184	6.78
label29	9052	4142	5863	338	112	354	0	175	6.59
label30	8843	4143	5663	278	112	353	0	168	6.205
label31	8669	4142	5662	278	112	352	0	152	6.78

Fig. 3-3 The mode of data input.

Table. 3-2 Comparison of the predictive performance of the three models.

	BO-CNN-LSTM	PSO-SVM	LSTM
RMSE	7.31	10.49	13.33
MAPE	17.53%	25.17%	35.26%
R^2	0.69	0.53	0.46

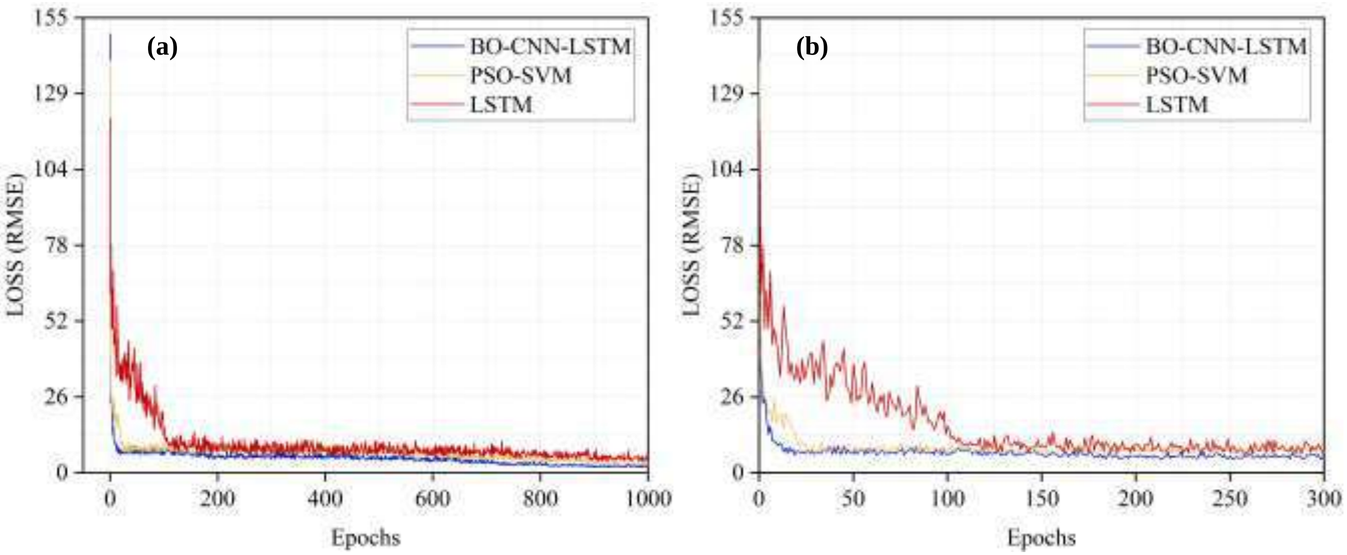


Fig. 3-4 Comparison of three model training set for different epochs. (a) 1000 epochs; (b) 300 epochs.

Summer shows the poorest model prediction performance. This is because, from a time series perspective, **it involves complex, nested two-dimensional variations**. Electricity prices in summer often display more extreme values, making it difficult for PSO-SVM and LSTM models to adapt to these fluctuations.

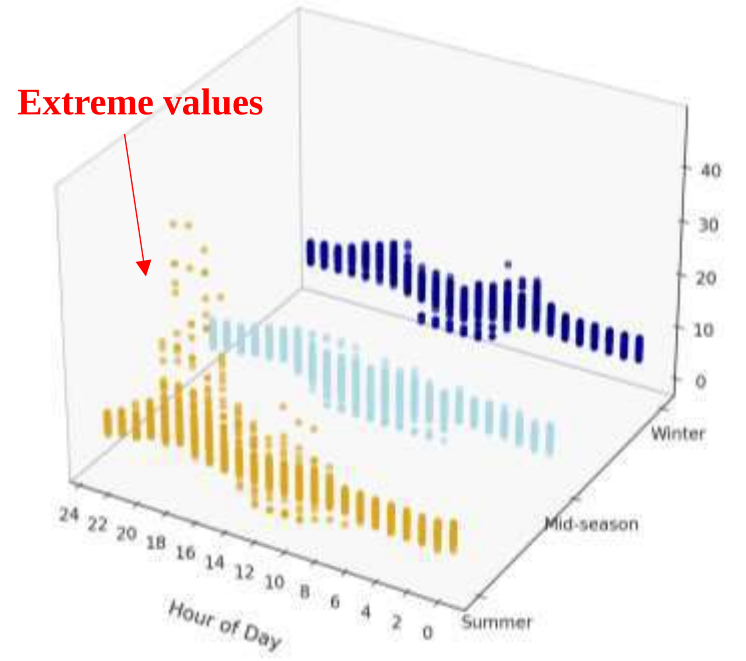


Fig. 3-5 Seasonal electricity price distribution.

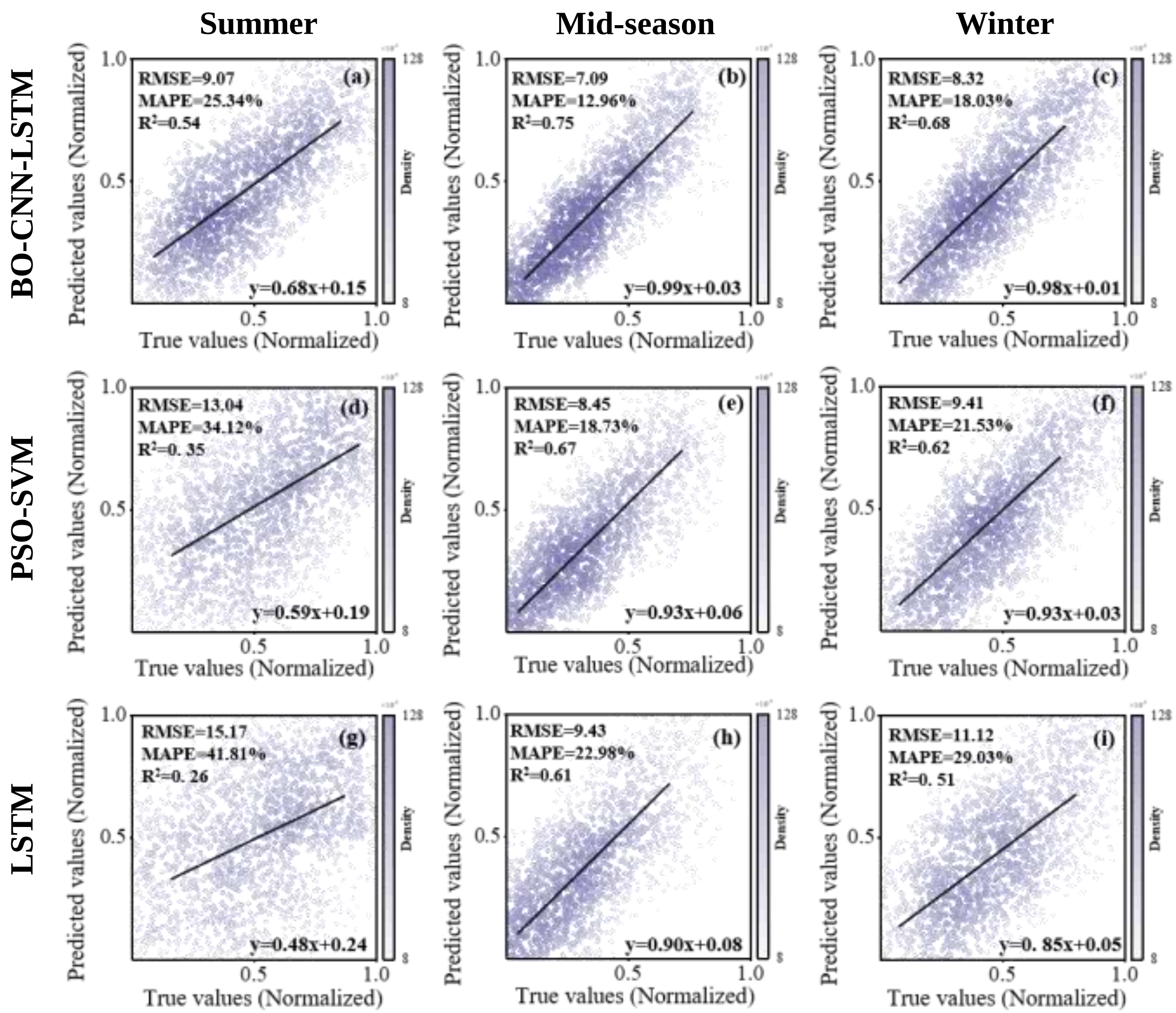


Fig. 3-6 Accuracy evaluation using different methods.

The BO-CNN-LSTM model accurately captures patterns in complex scenarios, showing strong reliability. It responds quickly to local changes, which helps handle unexpected events. **This is because CNN-LSTM has excellent memory capabilities**. While traditional LSTM models may struggle with long sequences, the CNN-LSTM uses flexible convolutional layers to adapt to different scales of data, making it more effective for complex sequences.

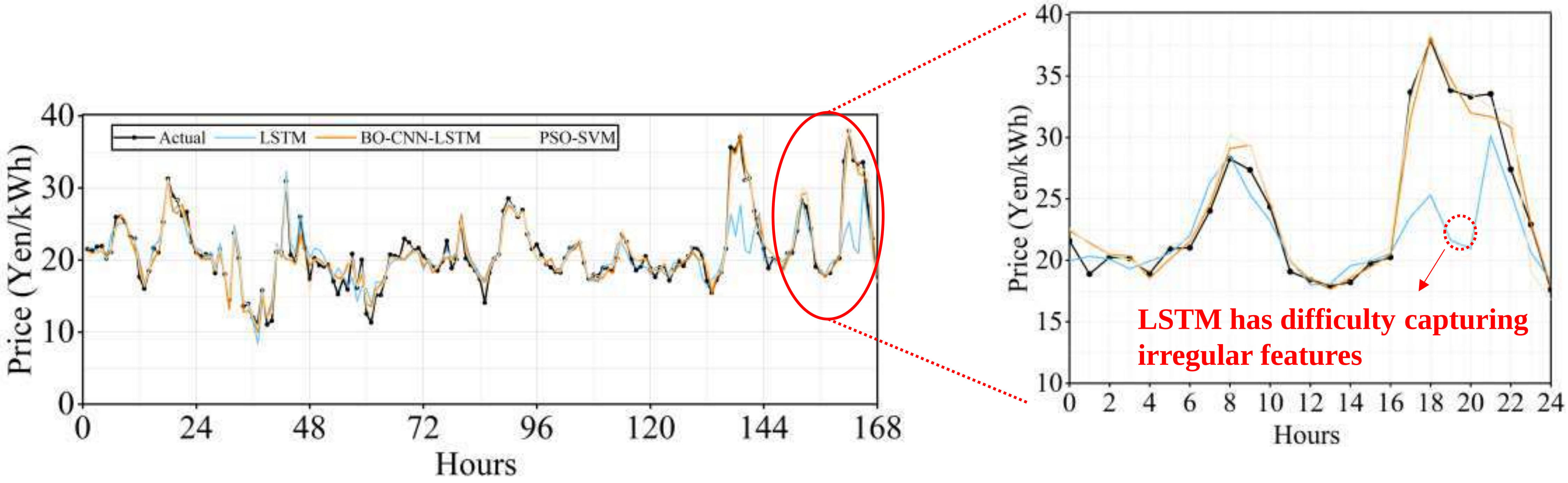


Fig. 3-7 Accuracy evaluation using different methods. (A summer week)

- **Red represents high values** and **blue low values**. Eg. fossil fuel generation are positively correlated, meaning higher fossil fuel prices push up electricity prices.
- **Fossil fuels and demand have the most significant impact on hourly price fluctuations**, indicated by their larger SHAP values.

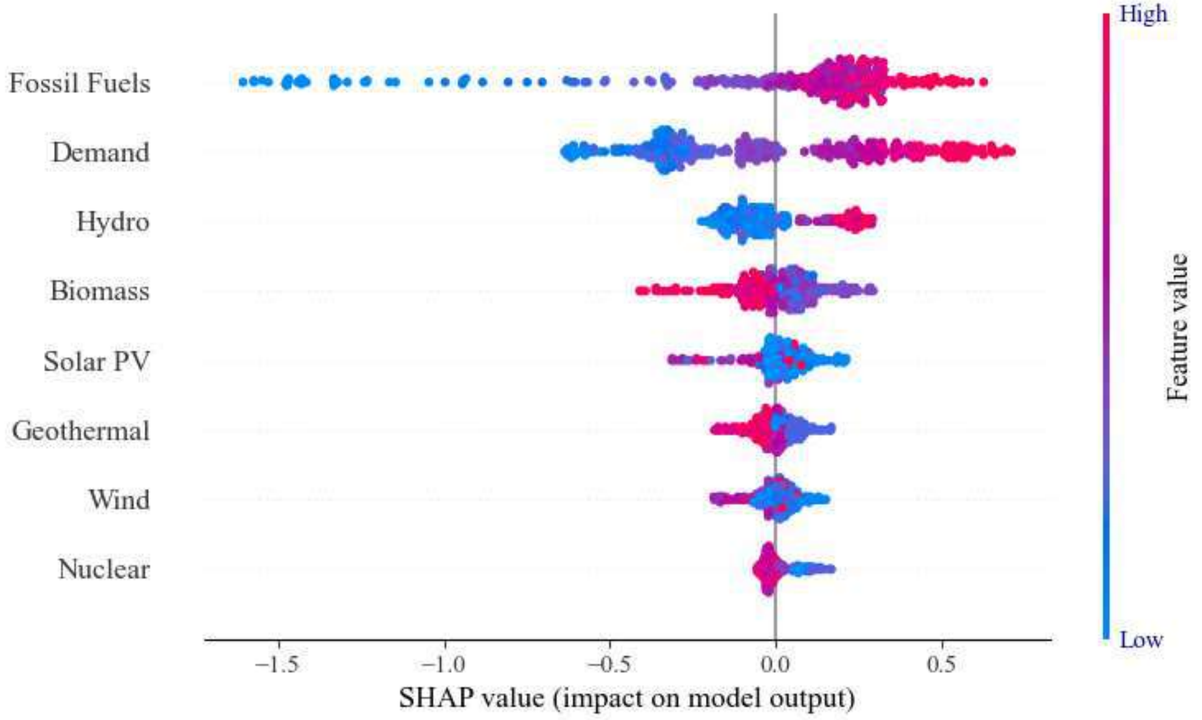


Fig. 3-8 SHAP values summary plot

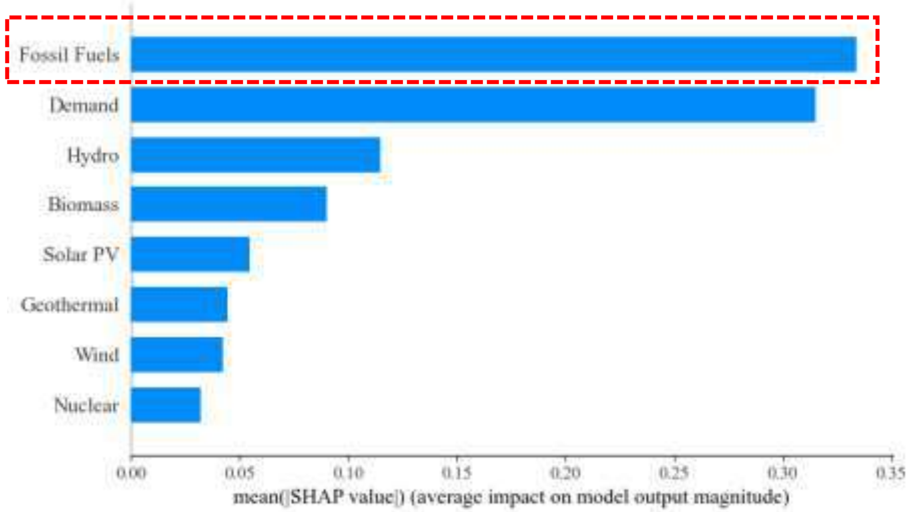


Fig. 3-9 SHAP value impact on model output

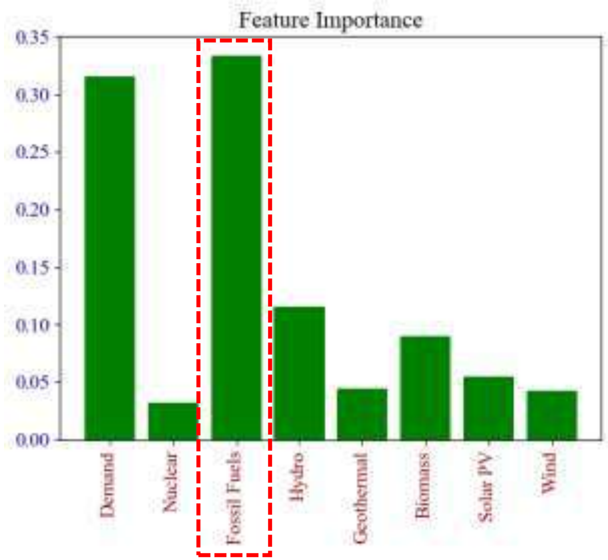


Fig. 3-10 Feature importance

Five key features were selected for pairwise dependency analysis: **Demand**, **Fossil fuels generation**, **Solar PV**, **Wind** and **Biomass**.

- There is a strong positive correlation between demand and fossil fuels power generation.
- Higher values of solar PV generation lead to a slight decrease in electricity prices. **As biomass power generation increases and thermal power decreases, the market price will significantly drop**.
- For wind power generation, an increase in wind power tends to lower electricity prices, **but rising demand can drive prices back up**.

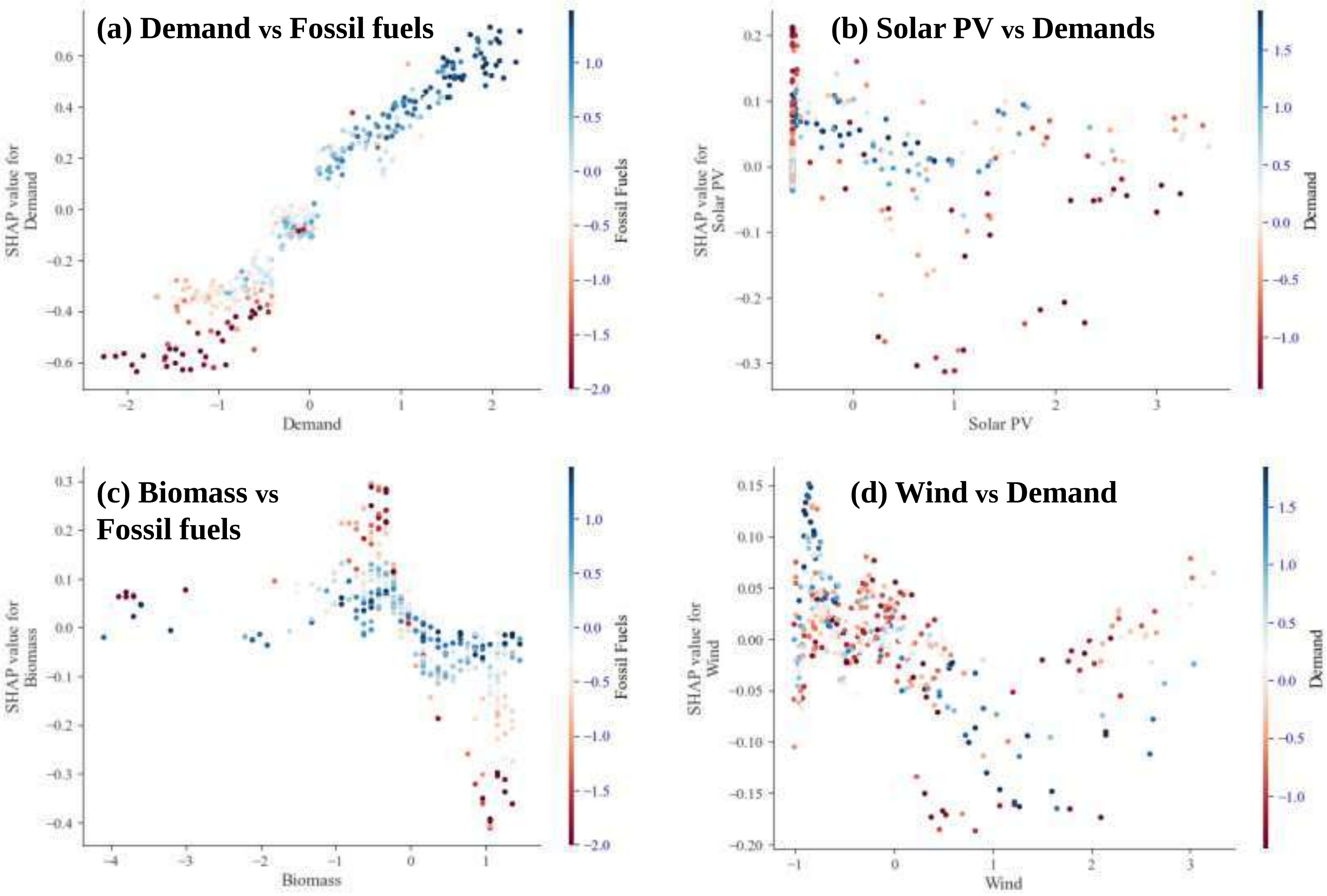


Fig. 3-11 Features dependence plot

3. Results and discussion

SHAP Features Explanation Analysis

◆ **Renewable energy** interactions also exist but are **less impactful in short-term**.

◆ The effects of thermal power generation and demand are significant throughout in the forecasting process.

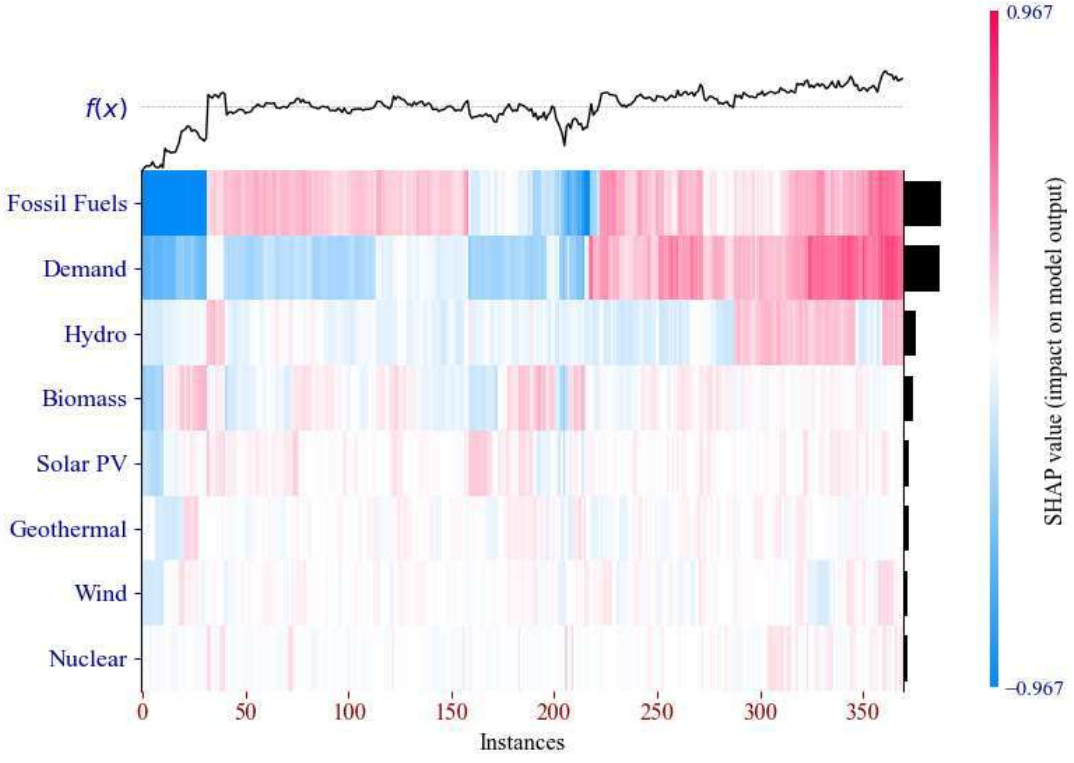


Fig. 3-12 Interaction Values Heatmap

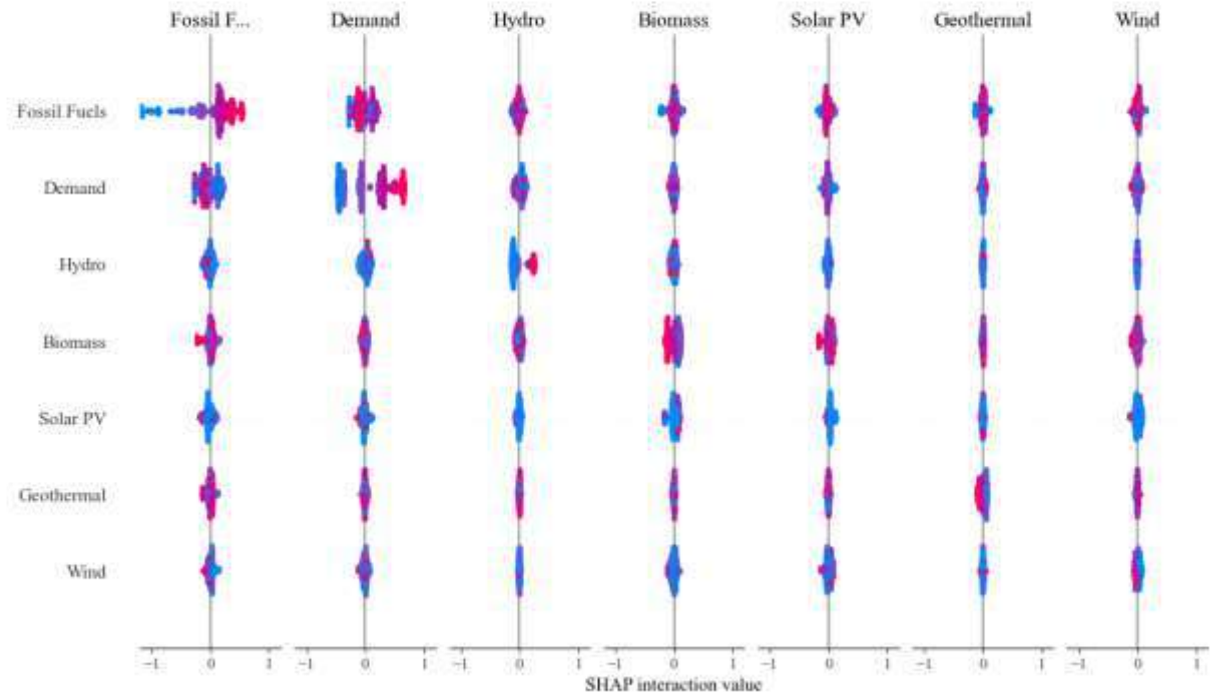


Fig. 3-13 Interaction Values

- Most annual price drivers factors show a positive correlation with annual electricity prices. **Fossil fuel prices show the highest correlation with annual electricity prices,** while electricity demand showed a negative correlation.
- **After 2030, with more renewables and fewer thermal power plants, market prices are expected to decline and stabilize**. Any price increase from renewables will be far smaller than that caused by fossil fuels.

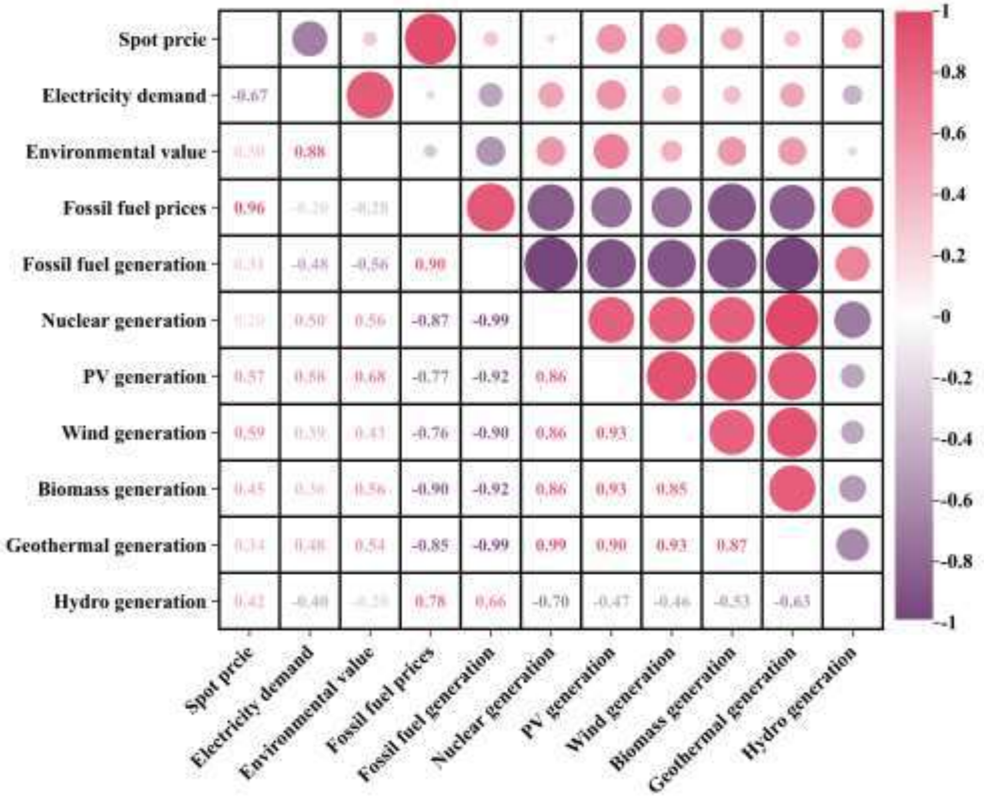


Fig. 3-14 Pearson correlation coefficients of annual electricity prices.

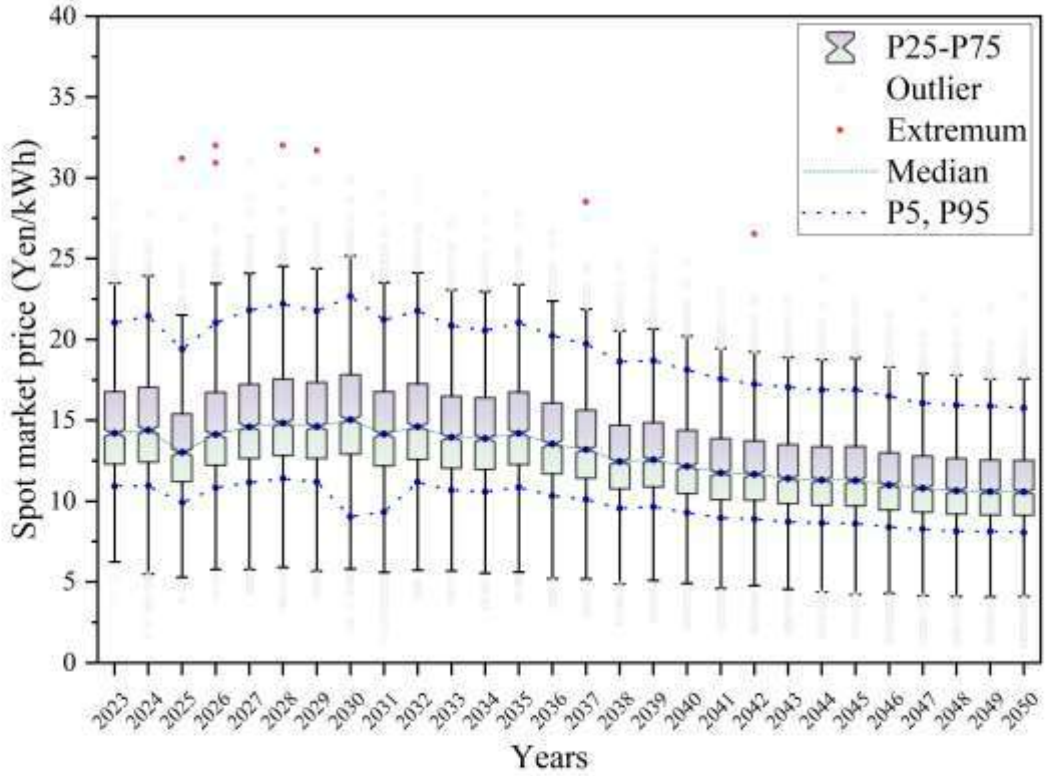


Fig. 3-15 Long-term forecasting based on a data-driven approach

4. Conclusions

4. Conclusions

In this study, we developed a BO-CNN-LSTM model and a data-driven approach to forecast the spot market electricity prices for residential prosumers in Japan, considering key energy policy impact factors. The model integrates convolutional operations within a traditional LSTM structure and leverages Bayesian optimization for efficient hyperparameter tuning, enhancing both prediction accuracy and long-term forecasting capabilities. We also focus on explaining the role of characteristic variables in machine learning model prediction. The main conclusions are as follows:

- **The BO-CNN-LSTM model demonstrates superior predictive accuracy and convergence speed compared to traditional models**. It achieves up to a 45.4% reduction in RMSE and a 50.6% decrease in MAPE over the LSTM model, and a 7.5% improvement in RMSE compared to the PSO-SVM model. The model's R^2 value is 22.6% higher than that of LSTM and 1.5% higher than PSO-SVM, indicating a closer alignment with market trends.

- SHAP values provide an interpretable breakdown of the model's predictions, **identifying key drivers demand and fossil fuel generation as major contributors to market price fluctuations**. This transparent approach to feature importance helps validate the model's outputs and offers deeper insights into market dynamics.

- **Long-term forecasts indicate significant price volatility around the year 2030**, corresponding to climate policy milestones in Japan. The energy supply structure, particularly changes driven by renewables (RES), notably influences market prices. The introduction of more RES stabilizes market fluctuations, and the forecast suggests a decline in median prices by 2050 due to the maturity of renewable technologies and energy storage, steering the market towards greater stability and alignment with decarbonization goals.

5. Limatations and prospect

- **The model heavily relies on the quality of historical data**, and its stability still requires further improvement.

- **Our study focuses on a single electricity market, which may limit its scope.** Examining interactions between multiple markets could reveal additional price-driving factors, offering an interesting area for future research.

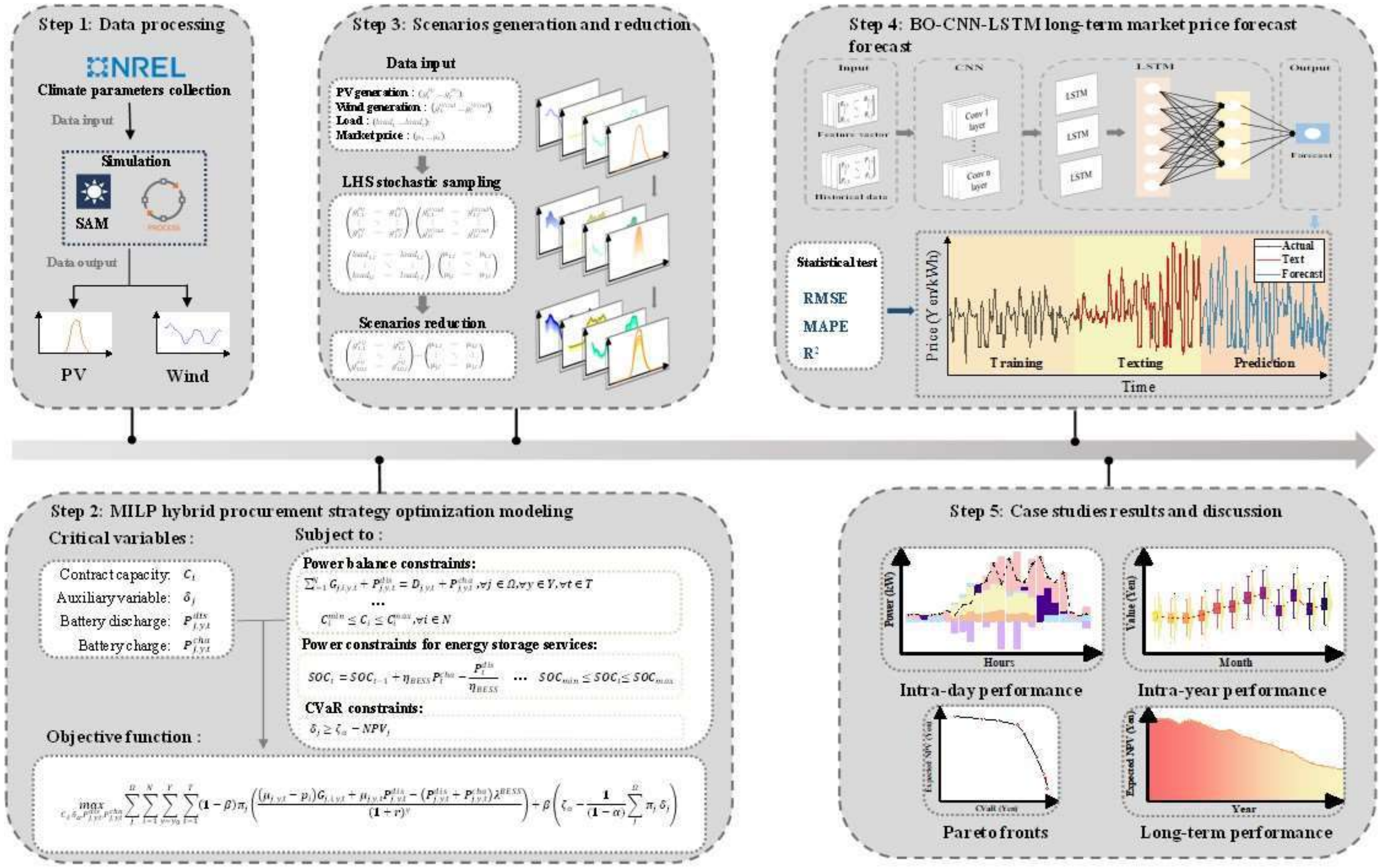
- The long-term price evolution is based on a series of scenario assumptions. While we provide a range of future price variations using a data-driven model with empirical interval prediction, **extreme events could significantly impact these results.**

Title:

Mitigating long-term financial risk for large customers via a hybrid procurement strategy considering power purchase agreements

Energy

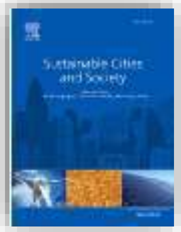
Graphical abstract



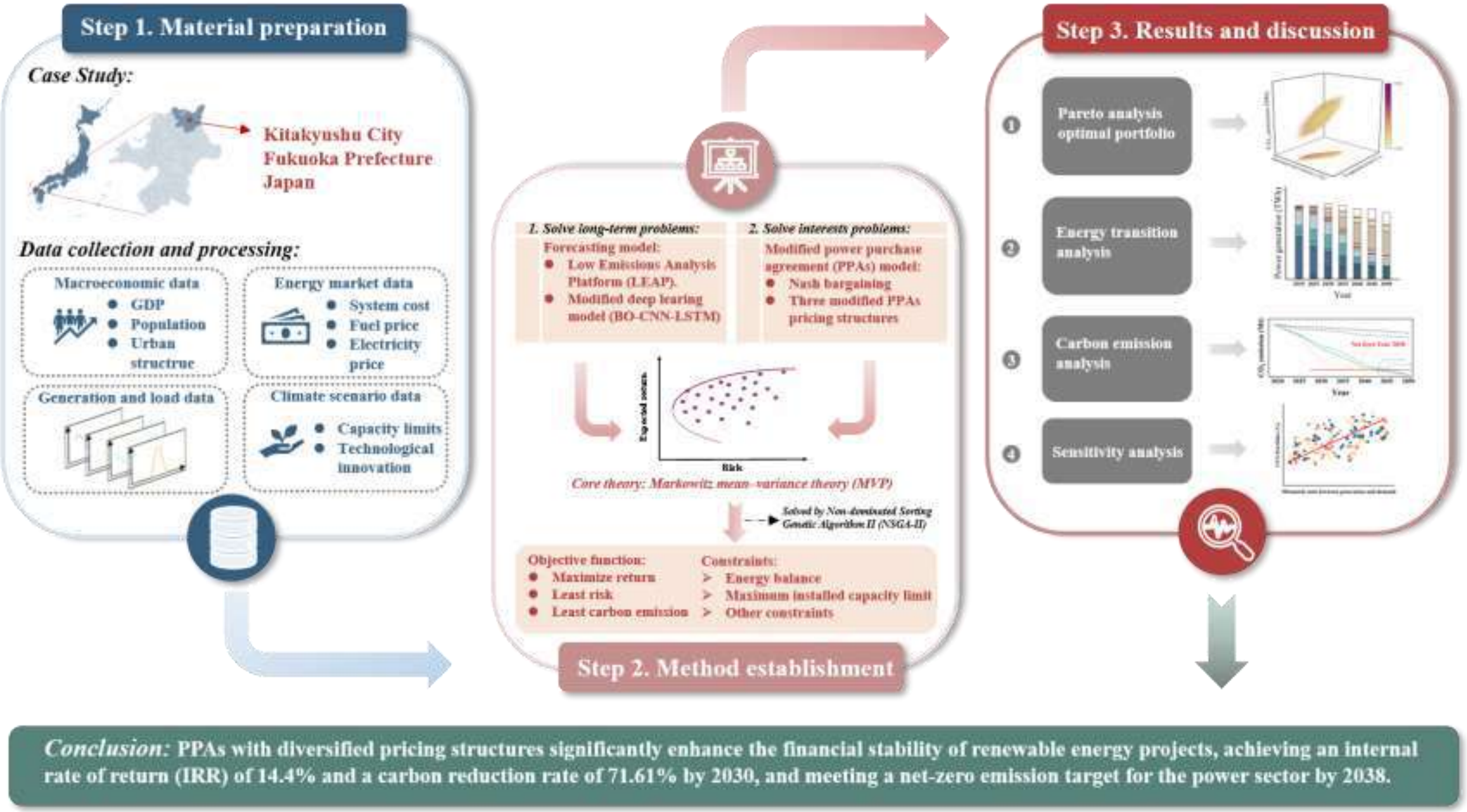
Title:

Urban-Scale Power Decarbonization Using a Modified Power Purchase Agreements Framework Based on Markowitz Mean-Variance Theory

Sustainable Cities and Society



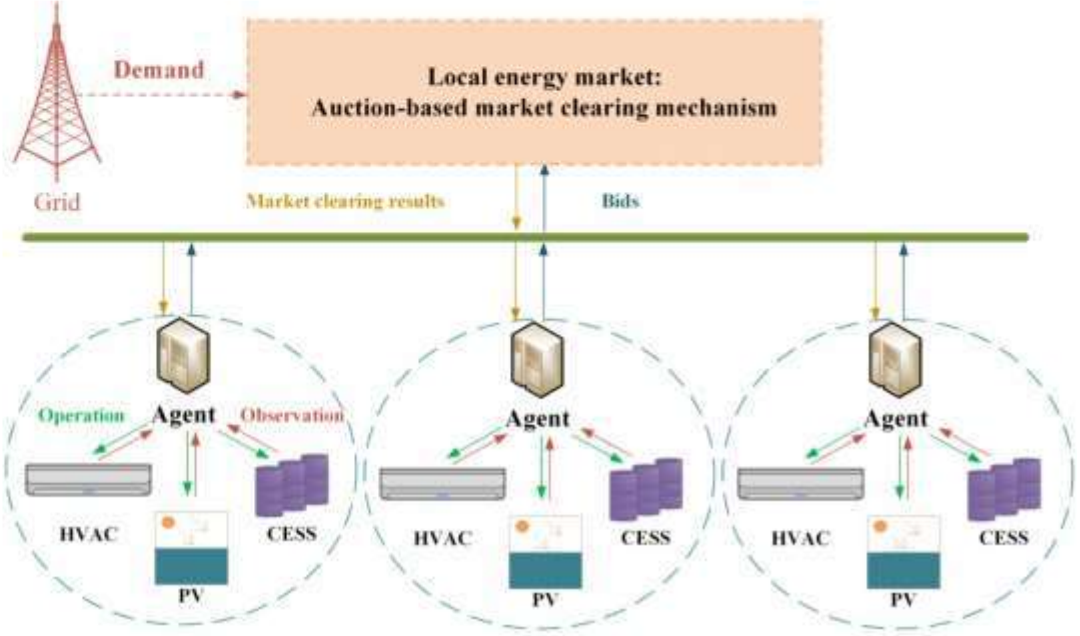
Graphical abstract



Future research directions —— Multi-agent deep reinforcement learning (MADRL)

MADRL is a method where multiple intelligent agents learn to make decisions by interacting with their environment and receiving feedback. **It's like teaching a group of robots to cooperate and optimize tasks by learning from their successes and mistakes.** In smart energy communities, MADRL helps manage energy use efficiently by allowing systems to learn and adapt over time, reducing costs and improving performance.

The framework of MADRL



MADRL used in smart energy communities

Thanks for listening !

ご清聴ありがとう
ございました。