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A review of deep learning methods for multi-energy load joint forecasting in integrated energy systems

Wuyou Xiao¹, Yibo Ding^{1,2}, Zhao Xu^{1,2,3*}

¹Department of Electrical Engineering, The Hong Kong Polytechnic University, Hong Kong, China

²Research Institute for Smart Energy, The Hong Kong Polytechnic University, Hong Kong, China

³Shenzhen Research Institute, The Hong Kong Polytechnic University, Shenzhen, 518129, China

*E-mail: eezhaoxu@polyu.edu.hk

Abstract. To accommodate the large-scale integration of renewable energy, and enhance the utilization efficiency of multiple energy types, such as electricity, gas, cooling, and heat, the Integrated Energy System (IES) has emerged in recent years. The forecasting of multiple loads, is a key challenge in guiding the operational strategies of IES, and the development of deep learning (DL) technology, with its advantages in efficiency and accuracy, provides an effective solution. This review first explains the uniqueness and challenges of IES multi-load forecasting, which involves predicting load time series while accounting for the temporal characteristics of each load and their interdependencies. It then summarizes traditional forecasting methods and analyses the advantages of DL-based methods, focusing on key aspects of the capability of dealing with load time series characteristics, load coupling, multi-task learning, and privacy protection. Finally, future challenges and trends in DL for IES multi-load forecasting are discussed.

1. Introduction

With the continuous growth of global energy demand and the rapid development of renewable energy, the introduction of renewable energy such as photovoltaic, wind energy, and hydrogen energy provides clean and sustainable energy options, the energy transition creates opportunities for low-carbon development but also poses challenges to traditional energy system operations and balance because of the volatility and instability of renewable energy[1][2]. Under the traditional energy system, due to the lack of effective integration, the utilization rate of electricity, heat and other energy is low, which leads to the loss of overall economic benefits. The utilization of renewable energy is restricted if electric power networks and district heat networks are not optimally coordinated[3]. Meanwhile, the uncertainty of wind and solar is prone to cause the risk of both power shortage and part-load operating [4]. IESs are an effective way to adapt to the penetration of renewable energy and improve energy efficiency [5][6]. By coordinating the supply and demand of various energy, it improves energy utilization efficiency and promotes the development of energy systems in a more interconnected and complementary direction.

The core of IES operation is to maintain the balance of energy supply and demand, among which accurate load forecasting is one of the most critical cornerstones [7]. However, in IES, the interdependency among heterogeneous energy systems is becoming more and more prominent[8],



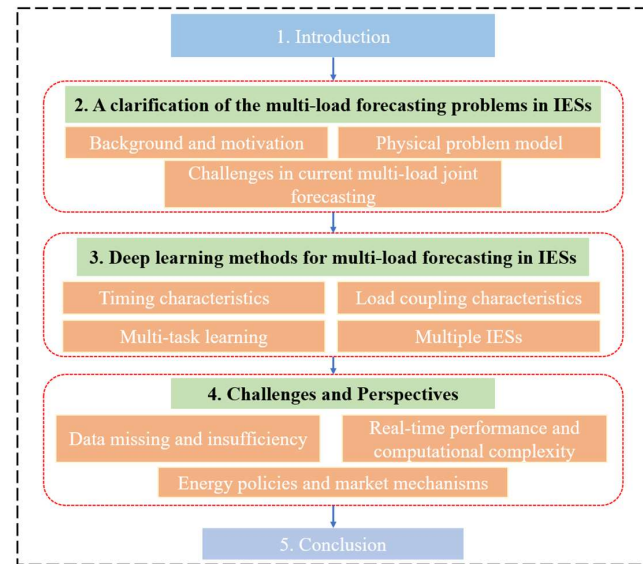


Figure 1. The structure of this review.

due to its inherent multi-energy coupling characteristics, the prediction problem of IES is very complex and difficult. If unresolved, this issue will severely impact the stable operation of IES, leading to economic losses and energy waste.

In recent years, with the rapid advancement of AI, data-driven load forecasting has gained attention for its accuracy, scalability, and ability to handle complex, nonlinear relationships. Traditional methods, while effective in specific cases, struggle with the complex coupling of multiple loads in IES. In contrast, DL excels in multi-energy load forecasting due to its strong nonlinear feature extraction and high-dimensional spatiotemporal data processing capabilities.

Figure 1 outlines the review structure. Chapter 2 covers the background, physical problem model, and challenges in multi-load joint forecasting. Chapter 3 introduces DL methods for IES forecasting, focusing on timing characteristics, load coupling, multi-task learning, and multiple IESs. Chapter 4 addresses key challenges: data insufficiency, real-time performance, computational complexity, and energy policies. Chapter 5 provides the conclusion.

2. A clarification of the multi-load forecasting problems in IESs

2.1 Background and motivation of multi-load forecasting in IES

The IES integrates power, gas, and thermal systems for multi-energy complementarity, coordinated supply, and efficient utilization via energy conversion and storage [7]. It encompasses energy production, conversion equipment (e.g., Combined Heat and Power (CHP), Combined Cooling, Heating and Power (CCHP), Power to Gas (P2G)), transmission and distribution networks, energy users, and storage systems [9]. Accurate multi-load forecasting in IES is vital for optimal operation, cost reduction, and integrating renewable energy [12]. However, it faces challenges like high data dimensionality, complex spatiotemporal correlations, and nonlinear relationships between energy loads, worsened by renewable energy volatility. [10][11].

2.2 IES multi-load forecasting physical problem model

This forecasting problem is essentially a multivariate time series forecasting problem that considers the dynamic coupling and randomness between variables.

1) Objective Function

The load forecasting problem can be formulated as a regression problem, where the goal is to minimize the error between the actual load value and the predicted load value. The actual load at time t can be expressed as:

$$\mathbf{L}(t) = [L_e(t), L_h(t), L_c(t)] \quad (1)$$

where $L_e(t)$ is the power load, $L_h(t)$ is the heat load, and $L_c(t)$ is the cooling load.

The predicted load at time t can be expressed as:

$$\hat{\mathbf{L}}(t) = [\hat{L}_e(t), \hat{L}_h(t), \hat{L}_c(t)] \quad (2)$$

where $\hat{L}_e(t)$, $\hat{L}_h(t)$, $\hat{L}_c(t)$ are the predicted electricity, heat, and cooling loads.

The goal is to find a model that minimizes the sum of the errors of all loads:

$$\min_{\theta} \mathcal{L} = \frac{1}{T} \sum_{t=1}^T \frac{1}{N} \sum_{i=1}^N \ell(L_i(t), \hat{L}_i(t; \theta)) \quad (3)$$

where T is the time steps for prediction, and N is the load types, and ℓ is the loss function used to measure the prediction error. θ are the parameters of the model, which are optimized during minimization.

2) Input

The model input at time t can be expressed as follows:

$$\mathbf{X}(t) = [\mathbf{L}(t-n:t-1), \mathbf{W}(t)] \quad (4)$$

where $\mathbf{L}(t-n:t-1)$ represents the historical load within the past n time steps, $\mathbf{W}(t)$ represents the other factors such as temperature, humidity, wind speed and typical days.

3) Load Forecasting Model

The relationship between input features and predicted values can be modeled by a mapping φ that captures the relationship between load and other influencing factors.

$$\hat{\mathbf{L}}(t) = \varphi(\mathbf{X}(t)) \quad (5)$$

The mapping φ is parameterized by a set of trainable parameters θ , which are optimized during model training to minimize the prediction error.

2.3 Challenges in current multi-load joint forecasting

Multi-load forecasting in IES is faced with unique challenges due to the diverse characteristics of different loads and the complex coupling between them in both time and space. Electricity load is affected by economic activities and user behavior, while heat and cooling loads are more sensitive to seasonal changes and weather conditions [13]. Additionally, the system's multi-energy coupling, where energy is converted between forms, creates intricate interdependencies between loads, requiring accurate modeling of these relationships to improve forecasting accuracy.

Traditional forecasting methods, such as ARMA[14], ARIMA[15], and SARIMA[16], are widely used due to their simplicity but face limitations in multi-load forecasting. These methods assume linear relationships and rely heavily on historical values, making them inadequate for capturing the nonlinear and dynamic characteristics of IES loads. For example, linear regression models are static and fail to adapt to changing conditions, reducing forecast accuracy over time [17]. While machine learning models, such as SVMs and ensemble methods, offer improvements in capturing

nonlinear and multi-dimensional patterns [18][19][20], which still struggle to fully account for the complex coupling relationships between different energy forms in IESs.

Table 1. Representative DL methods applications in IES load forecasting.

Ref.	Lead times	Input variables	Feature engineering	Models	Augmentation strategies	Target variables
[26]	Short-term	Electric, cooling and heat loads	MIC	BiLSTM	MTL	Electricity, heat, cooling loads
[27]	Ultra-short term and short-term	Electricity, cooling, and heat loads, weather data	–	LSTM, Encoder-Decoder, GBDT	Logarithmic transformation	Electricity, heat, cooling loads
[31]	Short-term	Electricity, cooling, and heat loads, weather data, calendar information	CNN, pixel reconstruction	BiLSTM	MTL	Electricity, heat, cooling loads
[13]	Short-term	Electricity, gas, cooling, heat loads, weather data	CNN, PCC	GRU, Transfer Learning	MMD	Electricity, gas, cooling, heat loads
[34]	Short-term	Electricity, cooling, and heat loads, weather data, calendar information	CNN, ICA, PCC	BiGRU, Attention	MTL, GWO	Electricity, heat, cooling loads
[35]	Short-term	Electricity, cooling, and heat loads, weather data	CNN, PCC	BiGRU, Attention	Multi-task loss weight	Electricity, heat, cooling loads
[36]	Short-term	Electricity, cooling, and heat loads, weather data, calendar information	GRA, PCC	Transformer, Multi-head attention	–	Electricity, heat, cooling loads
[37]	Short-term, mid-term	Electricity, cooling, and heat loads, weather data, calendar information	reversible instance normalization, MIC	DTformer (Transformer-based)	–	Electricity, heat, cooling loads
[38]	Short-term	Electricity, cooling, and heat loads, weather data	PCC, GRA, seasonal-trend loss,	Bayesian Multiple-Decoder Transformer	–	Electricity, heat, cooling loads
[41]	Short-term	Electricity, cooling, and heat loads, weather data, calendar information	–	ComNN	Geometric loss function	Electricity, heat, cooling loads

^a MIC(Maximum Information Coefficient), CNN(Convolutional Neural Networks), PCC(Pearson Correlation Coefficient)

ICA (Influencing Factors Correlation Analysis), GWO(Improved Gray Wolf Algorithm), GRA(Grey Relational Analysis)

3. DL methods for multi-load forecasting in IESs

3.1 Advantages of DL in IES Multi-energy Forecasting

DL methods provide notable advantages over traditional approaches in IES multi-energy forecasting. They excel at handling complex nonlinear relationships and can automatically extract features from multi-source data, enabling unified modeling[21]. Furthermore, DL is highly effective for real-time predictions and managing the volatility of renewable energy. These advantages make DL widely used in multi-energy forecasting. Table 1 summarizes key references that showcase representative applications of DL methods in IES load forecasting.

3.2 DL multi-load forecasting method considering timing characteristics

Considering the time series and periodic characteristics of load data in IESs, DL models such as LSTM and GRU, which are well-suited for processing temporal features, have been widely used in various studies to model both long-term and short-term dependencies within load profiles[22]. Reference [23] identifies typical load days, extracts dynamic similar day features, and builds an LSTM-based multi-feature IES load forecasting model, which predicts load using the

characteristics and meteorological data of adjacent and similar days. Reference [24] adds multiple layers of LSTM units to build a model, and realizes short-term prediction of multiple loads based on deep LSTM. Reference [25] considers the different time scales of different loads in the system and proposes a multi-stage LSTM model based on the interpolation method for load forecasting on multiple time scales. Reference [26] uses bidirectional LSTM (BiLSTM) to process time series bidirectionally, accounting for seasonal load characteristics and predicting the coupled load of multi-energy systems. Reference [27] proposes an LSTM-based encoder-decoder (LSTMED) model to capture high-dimensional time dynamics of historical load series. Reference [28] considers the dynamic coupling characteristics of loads, extracts deep features of multi-energy loads through deep belief network (DBN), and uses GRU to predict time series from these features.

Compared with traditional recurrent neural networks (RNN) and LSTM, the temporal convolutional network (TCN) can ensure the causality of time series data through extended causal convolution and has good time series processing capabilities. Reference [29] introduces participation factors to represent different load proportions and proposes a method combining multi-task learning (MTL) with temporal convolutional networks (TCN) for multi-load prediction. Reference [30] proposes a QTCN framework based on TCN, combining attention mechanism and quantile regression for probabilistic multi-energy load forecasting.

3.3 DL multi-load forecasting method considering load coupling characteristics

Considering the coupling between loads in the IES, reference [31], based on BiLSTM, draws on the distribution pattern of static image pixels, reconstructs irregular multi-energy load data into a 3D pixel matrix, retains its spatiotemporal correlation. Reference [32], based on the LSTM model, uses CNN to extract the spatial coupling features of data, and adopts the Auto-Regression (AR) model to capture the autocorrelation features of loads in an ultra-short time range. Reference [33] builds a CNN-LSTM-BiLSTM short-term power load prediction model, and assigns weights to the extracted features through the attention module. Reference [13] uses CNN-GRU to extract the coupling characteristics between different loads and the correlation between meteorological variables. Reference [34][35] adds attention mechanism in the forecasting model based on CNN-BiGRU, and constructed a multi-task learning model to improve prediction accuracy.

In recent years, models based on attention mechanisms, such as Transformer, have gradually become important in load forecasting due to their powerful ability to capture global dependencies and dynamic associations. Reference [36] proposes MultiDeT based on Transformer to solve the problem of difficult parallel training of neural networks. It uses a unified encoder and multiple task-specific decoders to achieve joint forecasting of loads; Reference [37] proposes a DTformer model by optimizing transformer terminal attention mechanism and use a time window attention module (TWA) to capture long-term dependencies and reduce computational complexity; Reference [38] integrates a Bayesian neural network into the attention mechanism within a Bayesian Transformer framework to generate load probability distributions, assigning trainable weights to subtasks to quantify uncertainty. Reference [39] proposes a coupling auxiliary transformer (CAFormer) model based on Transformer model, which extracts the temporal features of each sequence and maps them into a coupling space. A coupling auxiliary sequence is constructed in the coupling space to capture the interdependence between the original sequences.

3.4 DL multi-load forecasting method considering multi-task learning (MTL)

The idea of MTL is to simultaneously train several related tasks with shared information, so that the hope is to improve the generalization performance of each task by the assistance of other tasks[40]. Reference [36] proposes a MultiDeT method, which uses multiple decoders to handle

each sub-task separately and jointly trains multiple tasks through an end-to-end training approach. Reference [38] introduces a multi-task balancing method, where trainable weights are assigned to different sub-tasks to quantify uncertainty. Reference [41] proposes a complex neural network (ComNN) with a geometric loss function (GLF) to balance multi-task training and prevent domination by tasks with large losses. The GLF is extended to a geometric quantile loss function to capture uncertainty in load prediction. Reference [42] proposes a neural network Gaussian process (NNGP) method for multi-task learning with small-sample data, reducing computational complexity and sharing information across different loads.

3.5 DL multi-load forecasting method of multiple IESs

For multi-load forecasting across multiple IESs, centralized forecasting methods require the collection of raw data from multiple IESs, which poses a risk of data privacy leakage. Reference [43], from the perspective of privacy protection, proposes a Spatial-Temporal Adaptive Personalized Federated Learning Approach. This approach achieves privacy protection by sharing local model weights through a decentralized framework. It captures the complex dynamic dependencies between different energy load demands using a spatial-temporal transformer with a self-attention mechanism. Reference [44] proposes another federated learning-based model to address privacy protection issues. This model uses a distributed approach to train the forecasting model within the federated learning framework and considers false data injection attacks.

4. Challenges and Perspectives

4.1 Data missing and insufficiency

IES load forecasting with DL typically requires extensive historical data, which may be unavailable in newly built systems or during disasters. Reference [42] employs a neural network Gaussian process model to enhance prediction on small datasets, bypassing matrix operations and compensating for the lack of large-scale historical data in IES. Transfer learning holds significant potential in IES load forecasting, as it transfers knowledge from a well-established source domain to a target domain with limited data. Reference [13] proposes a CNN-GRU-based multi-energy load forecasting model using transfer learning, fine-tuning it during training to enhance accuracy.

4.2 Real-time performance and computational complexity

For large IESs, load forecasting requires rapid response to system changes to achieve timely system energy dispatch and optimization, therefore real-time prediction is very important. However, DL methods often use more complex models, which have higher computational costs. Therefore, how to reduce the computational complexity of the model and improve the real-time prediction capability of the model while ensuring the prediction accuracy is a significant challenge.

4.3 Energy policies and market mechanisms

Changes in energy policies and market mechanisms are also one of the major challenges for IES multi load forecasting. Carbon emission policies, renewable energy subsidy policies, market electricity price fluctuations, etc. will directly or indirectly affect users' energy consumption behavior, thereby affecting the system load. If the impact of policies and market mechanisms is ignored during forecasting, the model's forecasting effect may deviate from the actual situation.

5. Conclusion

In summary, with the rapid development of IES, efficient and accurate multi-energy forecasting became important and challenging. This review offers a comprehensive overview of DL methods

for IES multi-energy forecasting, detailing the problem's background, motivation, modeling, and key challenges. It also examines various DL forecasting methods, analyzing their applicability, advantages, and limitations based on factors like time series and coupling characteristics. Moreover, this review also proposes possible future development trends and challenges for the multi-energy forecasting problem in IES, and provides some directions worth exploring.

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