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# Multi-task learning load time series situational prediction based on gated recurrent neural networks considering spatial correlations

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Accurate load forecasting plays a crucial role in the effective planning, operation, and management of modern power systems. In this study, a novel approach to load time series situational prediction is proposed, which integrates spatial correlations of heterogeneous load resources through the application of Random Matrix Theory (RMT) with a Multi-Task Learning (MTL) framework based on Gated Recurrent Units (GRU). RMT is utilized to capture the complex, high-dimensional statistical relationships among various load profiles, enabling a deeper understanding of the underlying data patterns that traditional methods may overlook. The GRU-based MTL framework is employed to exploit these spatiotemporal correlations, allowing for the sharing of essential features across multiple tasks, which in turn enhances the accuracy and robustness of load predictions. This approach was validated using real-world data, demonstrating notable improvements in prediction accuracy when compared to single-task learning models. The results indicate that this method effectively captures complex relationships within the data, leading to more accurate load forecasting. This enhanced predictive capability is expected to contribute significantly to improving demand-side management, reducing the risks of grid overloading, and supporting the integration of renewable energy sources, thereby fostering the overall sustainability and resilience of power systems.

## KEYWORDS

random matrix theory, multi-task learning, gated recurrent neural networks, situational prediction, spatial correlations

## 1 Introduction

Accurate load forecasting plays a pivotal role in the reliable and economical operation of power systems (Feinberg and Genethliou, 2005). With the continuous advancement of modern power systems, load forecasting has become a critical component for effective planning, operation, and management (Xu et al., 2023). It directly influences the reliability and efficiency of power systems by optimizing resource allocation and preventing supply-demand imbalances that could lead to outages or waste (Singh et al., 2012). In the context of the “dual carbon” strategy and the rapid development of renewable energy, precise load forecasting can effectively address energy volatility, support smart grid construction, and

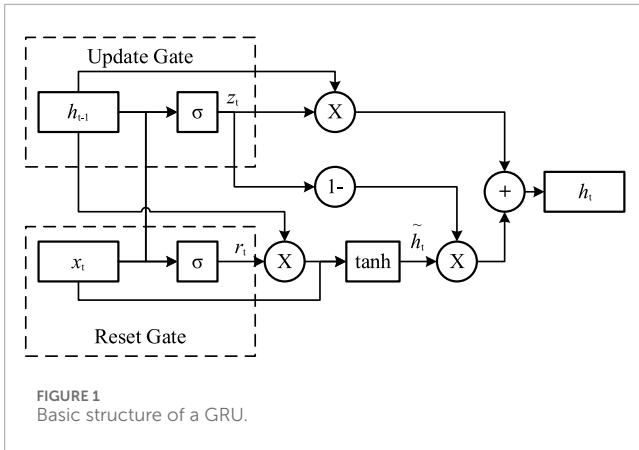


FIGURE 1 Basic structure of a GRU.

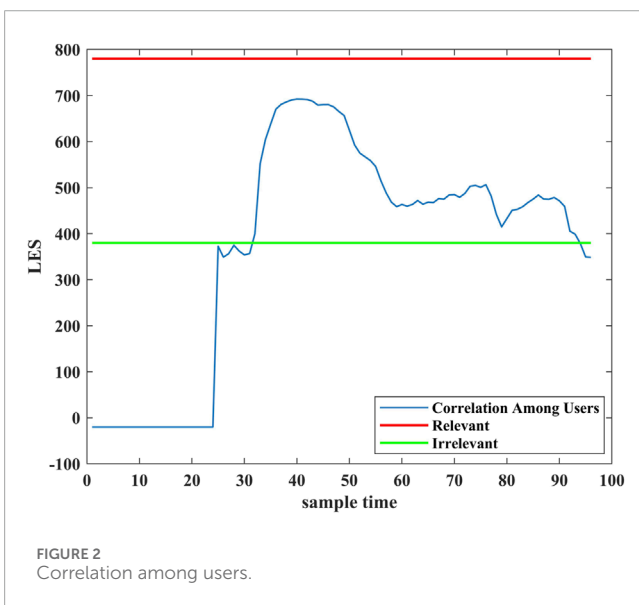


FIGURE 2 Correlation among users.

TABLE 1 Parameters.

Parameters	Value
Batch Size	16
Sequence Length	96
Learning Rate	0.001
Epochs	500

enhance system stability and operational efficiency (Li et al., 2023; Cheng et al., 2020). Thus, enhancing the accuracy and real-time performance of load forecasting holds significant strategic and practical value (Alfares and Nazeeruddin, 2002).

Traditional load forecasting methods can be broadly categorized into four major types based on their chronological development and methodological novelty: classical forecasting methods, traditional forecasting methods, modern forecasting methods, and neural network forecasting methods.

Classical methods, such as single consumption method, elasticity coefficient method, *per capita* electricity index conversion method, electricity consumption density method, and statistical analysis method, are characterized by simple mathematical principles and coarse accuracy. These methods are the earliest approaches used in electricity forecasting and are often limited by their inability to capture complex patterns and dynamic changes in load data.

Traditional methods, including trend extrapolation (Vlahović and Vujošević, 1987), regression analysis (Samuel et al., 2017), and time series methods (Sheshadri, 2020), offer more sophisticated mathematical models. These methods use various indicators to measure the model's fit with historical data and include comprehensive parameter estimation and error checking algorithms. They provide a better understanding of the relationship between different factors affecting electricity consumption and enable more reliable predictions.

Modern methods, such as grey prediction (Li and Qi, 2024), bionic algorithms (Wu et al., 2024), wavelet analysis (Zhao and Lin, 2024), combined forecasting (Xing et al., 2024), fuzzy mathematics (Li et al., 2024), and support vector machines (Chen et al., 2024), offer more diversified approaches. These methods integrate multiple data sources and advanced computational techniques to improve prediction accuracy and robustness. They are more capable of handling the non-linear and non-stationary characteristics of load data.

Neural network methods, primarily including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Probabilistic Neural Networks (PNN), have shown great potential in load forecasting due to their ability to capture long-term dependencies and complex temporal patterns. In studies (Zheng et al., 2020; Lu et al., 2019), LSTM was employed for short-term load forecasting, leading to improved prediction accuracy. The effectiveness of using GRU as the base model for load forecasting is validated in works (Wang et al., 2019; Gao et al., 2019; Yao et al., 2020). Ge et al. (2021) integrates Siamese networks, Grey Wolf Optimization, and LSTM for load forecasting, striking a balance between accuracy and algorithmic efficiency.

These methods often achieve superior results compared to traditional approaches but suffer from issues related to interpretability and flexibility. Additionally, they face challenges in incorporating static factors such as policies and international relations, which can lead to significant prediction errors.

Recent studies have demonstrated the effectiveness of Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) in short-term load forecasting, largely due to their capabilities in capturing long-term dependencies and effectively managing sequential data. These models have been particularly successful in scenarios where the load patterns exhibit temporal continuity, allowing them to predict future values based on past trends. However, despite their advantages, these existing techniques face several critical limitations. Firstly, while LSTM and GRU models are adept at handling temporal sequences, they often fall short in fully exploiting the high-dimensional statistical information that is inherently present within user data. This information is crucial in complex and dynamic environments where the load data is influenced by a multitude of factors, such as varying user behaviors, external environmental conditions, and interactions

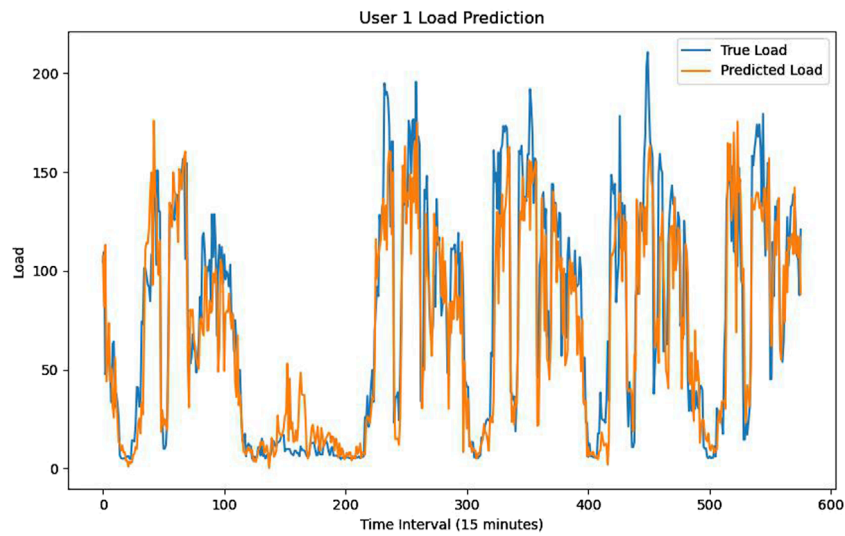


FIGURE 3  
User1 prediction result based on GRU-MTL.

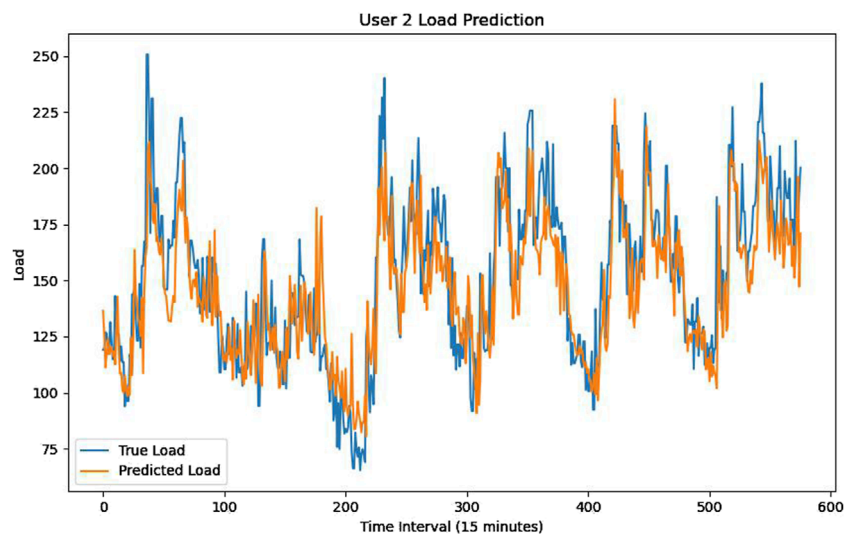


FIGURE 4  
User2 prediction result based on GRU-MTL.

among different user groups. The inability to capture and utilize this high-dimensional information can lead to suboptimal predictions, particularly when the data exhibits significant variability and complexity. Moreover, traditional LSTM and GRU models typically focus on single-task learning, where each task is treated in isolation. This approach fails to leverage the potential benefits of multi-task learning, where spatiotemporal correlations among users can be harnessed to improve prediction accuracy. These correlations are particularly important in power systems, where the consumption patterns of different users are often interdependent and influenced by shared external factors. By not considering these spatiotemporal dependencies, existing methods may miss out on valuable contextual information that could enhance the overall predictive performance.

This paper presents a novel approach that integrates Random Matrix Theory (RMT) for spatial correlation analysis with a Gated Recurrent Unit (GRU)-based multi-task learning framework, specifically designed to address the challenges of high-dimensional, real-time power data. This combination allows for the effective capture of complex spatial and temporal relationships within the data, leveraging these correlations across tasks to significantly enhance prediction accuracy and robustness compared to traditional methods. The main contributions of this paper are as follows: (1) We introduce a method for analyzing the spatial correlations of heterogeneous load resources based on RMT, which is particularly well-suited for handling the high-dimensional, large-scale, and real-time nature of power big data. Without

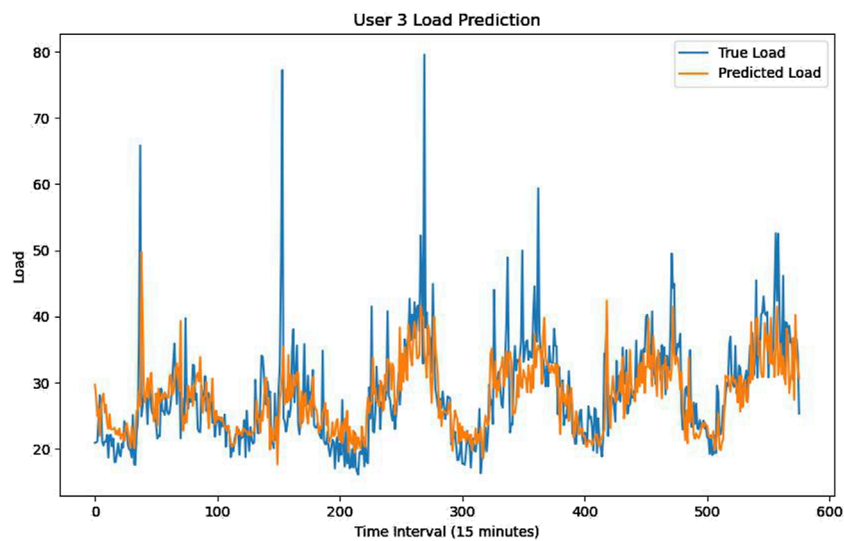


FIGURE 5  
User3 prediction result based on GRU-MTL.

TABLE 2 Comparison.

Method	GRU-MTL MSE	Individual GRU MSE
User 1	0.0189	0.0164
User 2	<b>0.0134</b>	0.0136
User 3	<b>0.0086</b>	0.0091

These bold values (0.0134 and 0.0086) represent lower mean squared errors (MSE), demonstrating better performance and more accurate predictions for User 2 and User 3 when using the GRU-MTL approach.

requiring complex physical modeling, RMT leverages advanced statistical analysis techniques to extract key features and uncover intrinsic relationships within the data. This allows for a deeper understanding of the interactions between users and enables more accurate and robust load forecasting. (2) Building on the spatial correlations identified by RMT, we propose a GRU-MTL approach that effectively leverages these correlations to enhance load forecasting. The integration of spatiotemporal correlations across tasks is crucial, as it allows the model to capture shared patterns that are otherwise missed when tasks are treated independently. By utilizing multi-task learning, the model can share relevant information across tasks, leading to improved prediction accuracy for each task and stronger generalization across different load profiles, outperforming traditional single-task methods. (3) We demonstrate the effectiveness of our proposed method through several simulations, showing significant improvements in prediction accuracy and computational efficiency.

In the following sections, we will detail the theoretical framework of our approach, describe the methodology used, and present the results of our simulations. The rest of the paper is organized as follows: [Section 2](#) presents the proposed methodology;

[Section 3](#) provides the experimental results and analysis; [Section 4](#) concludes the paper and suggests future research directions.

## 2 Methodology

### 2.1 Spatial correlation analysis based on random matrix theory

Random Matrix Theory (RMT) (Lytova and Pastur, 2009; Götze et al., 2017; Benaych-Georges, 2015) is a significant branch of modern statistics that addresses high-dimensional data analysis through the study of the limiting spectral distribution (LSD) of large matrices. In power systems, the uncertainty of user load behavior contributes to the randomness in measurement data. RMT provides effective tools to analyze such complex data structures, particularly in uncovering coupling relationships among users and between users and their environment. RMT is particularly effective in distinguishing meaningful correlations from noise in high-dimensional datasets typical of power systems. By analyzing the eigenvalue distribution, RMT uncovers significant correlations that reveal underlying dependencies among users—dependencies that are often obscured in traditional analyses. These correlations are crucial in power systems, where user behaviors are interconnected and influenced by common external factors such as regional weather conditions or grid dynamics (Wu et al., 2023; Zhang et al., 2023). The capability of RMT to handle and interpret high-dimensional data makes it well-suited for power system applications. By integrating RMT, the proposed model capitalizes on these spatial correlations, thereby enhancing the accuracy and robustness of load forecasts in complex data environments.

Using the Ring Law and Marcenko–Pastur Law from RMT, we can study the spectral distribution of high-dimensional data to reveal hidden statistical patterns. This paper employs Linear Eigenvalue Statistics (LES) to analyze the spatial correlations



of heterogeneous load resources. By constructing coupling analysis matrices that include primary user data and augmented environmental data, combined with random noise for high-dimensional data expansion, we can effectively identify and quantify the relationships among different load resources.

Linear eigenvalue statistics (LES) extract and evaluate features of high-dimensional space data by setting a fixed detection function. The general expression of LES is shown in Equation 1:

$$LES_{\varphi} = \sum_{i=1}^N \varphi(\lambda_i) \tag{1}$$

where  $\lambda_i$  are the eigenvalues of the random matrix. According to the law of large numbers, the LES converges in probability to Equation 2:

$$\lim_{N \rightarrow \infty} \frac{LES_{\varphi}}{N} = \int \varphi(\lambda) \rho(\lambda) d\lambda \tag{2}$$

where  $\rho(\lambda)$  is the probability density function of the eigenvalues of the random matrix. Observing Equation 1, the key to designing LES indicators lies in selecting appropriate detection functions  $\varphi(\cdot)$ . Common detection functions include the mean spectral radius, Chebyshev polynomial, determinant, likelihood function, etc., with their specific calculation formulas provided in Equations 3–8.

$$\varphi_{MSR}(\lambda) = \sum_{i=1}^N \frac{|\lambda_i|}{N} \tag{3}$$

$$\varphi_{T_2}(\lambda) = \sum_{i=1}^N 2\lambda_i^2 - 1 \tag{4}$$

$$\varphi_{T_3}(\lambda) = \sum_{i=1}^N 4\lambda_i^3 - 3\lambda_i \tag{5}$$

$$\varphi_{T_4}(\lambda) = \sum_{i=1}^N 8\lambda_i^4 - 8\lambda_i^2 + 1 \tag{6}$$

$$\varphi_{DET}(\lambda) = \sum_{i=1}^N \ln(\lambda_i) \tag{7}$$

$$\varphi_{LRF}(\lambda) = \sum_{i=1}^N \lambda_i - \ln(\lambda_i) - 1 \tag{8}$$

Compared to traditional low-dimensional indicators such as Pearson correlation coefficient and Spearman correlation coefficient, LES indicators have better robustness for non-continuous data and data with outliers. Although a standardized cleaning method suitable for grid data has been designed in the previous text, this method cannot directly remove abnormal data values in the sampling, thus requiring the coupling calculation indicators to have good robustness. Additionally, LES indicators can directly handle high-dimensional matrix inputs, allowing them to capture nonlinear correlations in the data more accurately compared to low-dimensional indicators.

First, certain power users in the grid are selected as the main measurement objects for this coupling analysis, using their operational data as the basic components of the coupling analysis matrix. Then, a grid measurement is added as an augmented part, combining it with the main measurements to form the coupling analysis matrix, serving as the data source for subsequent analysis. Note that in the coupling analysis, unlike the first part's selection of measurements to be cleaned, the main objects of

coupling analysis, i.e., the basic part of the coupling analysis matrix, can include multi-dimensional measurements. In other words, it can be single photovoltaic user data, a multi-dimensional measurement matrix composed of all photovoltaic users in the grid, or even data from all distributed power users. However, to ensure the accuracy of subsequent coupling analysis under general conditions, the augmented part can only contain one-dimensional measurements or measurements of similar physical meaning, such as using only ambient temperature or both maximum and minimum temperatures simultaneously. Considering these differences, during data cleaning, the augmented part measurements can be considered the main object to simplify the data normalization operations during subsequent coupling analysis.

Assuming the basic part of the coupling analysis matrix contains  $m$  measurements and the augmented part contains  $n$  measurements, when the number of normalized measurement samples is  $T$ , the dimension of the basic part data is  $T \times m$ , referred to as the basic measurement matrix  $X$ . Similarly, the dimension of the augmented part data is  $T \times n$ , referred to as the augmented measurement matrix  $Y$ .

Based on the previously mentioned measurement selection principles for the coupling analysis matrix, under general conditions, the number of basic measurements is greater than the number of augmented measurements, i.e.,  $m > n$ . To improve the accuracy of the coupling analysis, the dimensions of the augmented measurement matrix are expanded. First, the augmented measurement matrix is dimensionally expanded as shown in Equation 9:

$$Y' = [Y, Y_1, \dots, Y_k] \tag{9}$$

where the dimension of  $Y'$  is  $T \times k \cdot n$ , and  $k = \lfloor m/n \rfloor$ , representing the floor operator. To prevent repeated data from interfering with subsequent coupling analysis, random noise is introduced into  $Y'$  as shown in Equation 10:

$$Y'' = Y' + \epsilon \tag{10}$$

where  $Y''$  is the extended augmented matrix;  $\epsilon$  is a white noise matrix with dimensions  $T \times k \cdot n$ , and the noise distribution is standard normal;  $\sigma$  is the noise amplitude, which directly affects the coupling analysis results. If the noise amplitude is too small, the repeated data used for dimension expansion in the augmented measurement will still affect the coupling analysis, whereas excessive noise will distort the measurements in the extended augmented matrix, turning them into abnormal measurements.

To quantitatively evaluate and better select the amplitude of white noise, the signal-to-noise ratio of the extended augmented matrix is defined as shown in Equation 11:

$$SNR = \frac{\text{trace}(Y)}{\text{trace}(\epsilon)} \tag{11}$$

where the trace represents the sum of the diagonal elements of a matrix. Additionally, to ensure the accuracy and consistency of the coupling analysis, the signal-to-noise ratio should remain consistent throughout the entire coupling analysis process.

Combining the basic measurement matrix and the extended augmented matrix, a coupling analysis matrix is constructed as the data source for the analysis, as shown in Equation 12:

$$Z = [X, Y''] \tag{12}$$

As a comparison, a reference matrix for the coupling analysis is constructed using the basic measurement matrix and a white noise matrix to mitigate the interference caused by white noise to some extent, as shown in Equation 13:

$$Z' = [X, \epsilon] \quad (13)$$

## 2.2 Multi-task learning with gated recurrent units

Gated Recurrent Unit (GRU) networks are optimized versions of Long Short-Term Memory (LSTM) networks, simplifying the internal structure to improve real-time performance and reduce overfitting. GRUs merge the input gate and forget gate into a single update gate, streamlining the process while maintaining comparable prediction accuracy. The basic structure of a GRU is shown in Figure 1.

In this study, we develop a multi-task learning (MTL) framework using GRUs to leverage the spatiotemporal correlations among users and external factors. The MTL framework shares underlying features and external factors among different tasks, uncovering hidden relationships and improving the generalization performance of the predictive model.

The simplified expressions for the core modules, the update gate, and the reset gate are as follows, as shown in Equations 14, 15:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad (14)$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \quad (15)$$

In these equations,  $z_t$  represents the output signal of the update gate,  $r_t$  represents the output signal of the reset gate,  $x_t$  is the input at the current time step,  $h_{t-1}$  is the output of the hidden layer at the previous time step,  $W_z$  is the weight matrix for the update gate,  $W_r$  is the weight matrix for the reset gate, and  $\sigma$  is the Sigmoid function.

The update gate controls the extent to which historical state information is retained in the current state. The larger the output  $z_t$  of the update gate, the more historical information is retained in the hidden layer. The reset gate controls the extent to which historical state information is retained in the current candidate hidden layer. The larger the value of  $r_t$ , the more historical information is retained in the current candidate hidden layer.

Based on the outputs of the update gate and the reset gate, the subsequent candidate hidden layer output and the hidden layer output are as follows, as shown in Equations 16, 17:

$$\tilde{h}_t = \tanh(W_{\tilde{h}} \cdot [r_t * h_{t-1}, x_t]) \quad (16)$$

$$h_t = (1 - z_t) * \tilde{h}_t + z_t * h_{t-1} \quad (17)$$

In these equations,  $\tilde{h}_t$  is the current candidate hidden layer output, and  $W_{\tilde{h}}$  is the weight matrix for the candidate hidden layer.

## 3 Case study

This case study validates the proposed GRU-MTL method using real load data from a specific region in southern China. The data

was collected at 15-min intervals over a 6-day period. The load time series exhibits spiky behavior due to daily electricity consumption patterns, with significant peaks during high-demand periods and valleys during low-demand periods. The process involves several key steps, including spatial correlation analysis, determining the joint analysis load, and performing load predictions using both GRU-MTL and individual GRUs. The results are compared using Mean Squared Error (MSE) as the evaluation metric.

### 3.1 Spatial correlation analysis

Firstly, the correlations among users were analyzed using RMT. The correlation analysis is illustrated in Figure 2, where higher Linear Eigenvalue Statistic (LES) values indicate stronger correlations among users.

In Figure 2, the blue line represents the LES values over different sample times. The green line indicates the threshold above which the correlation is considered relevant, while the red line indicates the values that are highly relevant. The LES values begin to rise significantly after the 30th sample time, peaking around the 50th to 70th sample time, which indicates a period of high correlation among the users. This information is crucial for identifying the time windows where the joint analysis of loads is most meaningful.

### 3.2 Load prediction based on GRU-MTL

Load forecasting was carried out using both the proposed GRU-MTL and individual GRUs. The computing environment consisted of an Intel(R) Core(TM) i7-8550U CPU @ 1.80 GHz 1.99 GHz with 16 GB of memory. The programming environment utilized Python 3.9 and PyTorch 2.1. The set of parameters for training the GRU-MTL neural network is provided in Table 1.

The results of load forecasting using the proposed GRU-MTL method and individual GRU models are presented below. Figures 3–5 illustrate the load prediction results for three different users using the GRU-MTL method. The GRU-MTL method captures the overall trends and patterns of the load data effectively, demonstrating its ability to leverage shared information across multiple tasks to improve prediction accuracy.

The Mean Squared Error (MSE) are used as the evaluation metrics to compare the performance of the GRU-MTL method and individual GRU models. Table 2 summarizes the prediction accuracy of both methods.

The table reveals that the GRU-MTL method achieves lower MSE values for Users two and three compared to the individual GRU models. Specifically, for User 2, the GRU-MTL method attains an MSE of 0.0134, which is slightly better than the individual GRU model's MSE of 0.0136. For User 3, the GRU-MTL method achieves an MSE of 0.0086, which is lower than the individual GRU model's MSE of 0.0091. This reduction in error underscores the advantage of the multi-task learning framework in effectively capturing spatiotemporal correlations between tasks, which are often underutilized in single-task learning models. Unlike single-task learning, where each task is modeled in isolation, the GRU-MTL method leverages an information-sharing layer that enables the model to fully utilize the shared information across related

tasks. This shared learning process allows the model to better understand and exploit the underlying correlations, leading to significant improvements in prediction accuracy. As a result, the GRU-MTL method outperforms traditional single-task models, particularly in environments where the interrelated nature of tasks can be harnessed to enhance overall predictive performance.

In summary, the GRU-MTL method significantly outperforms the individual GRU models in terms of prediction accuracy and error metrics. The ability to incorporate spatial correlations and share information across multiple tasks enhances the model's predictive performance, making it a robust approach for load time series situational prediction.

## 4 Conclusion

This paper presented a novel approach for load time series situational prediction by integrating spatial correlation analysis based on Random Matrix Theory (RMT) with a Multi-Task Learning (MTL) framework using Gated Recurrent Units (GRUs). The proposed method was validated using real load data from a specific region, and the results demonstrated significant improvements in prediction accuracy compared to traditional individual GRU models. The study utilized RMT to analyze the spatial correlations among heterogeneous load resources, enabling the identification of significant relationships and improving the accuracy of load predictions. By developing a GRU-MTL framework that leverages spatiotemporal correlations and shares information across multiple tasks, the model's ability to predict load time series was significantly enhanced. Experiments showed that the GRU-MTL method outperforms individual GRU models in terms of MSE and prediction accuracy, highlighting its effectiveness in capturing complex dependencies and improving the robustness of load forecasting models.

The adoption of GRU-based multi-task learning for load forecasting, with a focus on spatiotemporal user correlations, represents a promising direction for the future of power system management. This approach leverages the strength of GRUs in handling sequential data and capturing long-term dependencies, while multi-task learning facilitates the simultaneous learning of multiple related tasks, enhancing overall prediction accuracy and generalization. By explicitly considering the spatiotemporal correlations of users, this method can provide more nuanced and precise load forecasts. This is particularly crucial in modern power systems, where consumption patterns are influenced by a multitude of temporal and spatial factors. Accurate load forecasting enabled by this advanced methodology can significantly improve demand-side management, reduce grid overloading risks, and support the integration of renewable energy sources, thus contributing to the sustainability and resilience of power systems.

## References

Alfares, H. K., and Nazeeruddin, M. (2002). Electric load forecasting: literature survey and classification of methods. *Int. J. Syst. Sci.* 33 (1), 23–34. doi:10.1080/00207720110067421

## Data availability statement

The original contributions presented in the study are included in the article/[Supplementary Material](#), further inquiries can be directed to the corresponding author.

## Author contributions

MH: Writing—original draft. QA: Writing—review and editing.

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## Conflict of interest

Author MH was employed by Shenzhen Power Supply Company, China Southern Power Grid.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fenrg.2024.1476613/full#supplementary-material>

Benaych-Georges, F. (2015). Exponential bounds for the support convergence in the single ring theorem. *J. Funct. Analysis* 268 (11), 3492–3507. doi:10.1016/j.jfa.2015.03.005

- Chen, Y., Xiao, C., Yang, S., Yang, Y., and Wang, W. (2024). Research on long-term power load grey combination forecasting based on fuzzy support vector machine. *Comput. Electr. Eng.* 116, 109205. doi:10.1016/j.compeleceng.2024.109205
- Cheng, L. F., Liu, G. Y., Huang, H. Q., Wang, X. G., Chen, Y., Zhang, J., et al. (2020). Equilibrium analysis of general N-population multi-strategy games for generation-side long-term bidding: an evolutionary game perspective. *J. Clean. Prod.* 276, 124123. Article ID 124123. doi:10.1016/j.jclepro.2020.124123
- Feinberg, E. A., and Genethliou, D. (2005). "Load forecasting," in *Applied mathematics for restructured electric power systems: Optimization, control, and computational intelligence*, 269–285.
- Gao, X., Li, X. B., Zhao, B., Ji, W., Jing, X., and He, Y. (2019). Short-term electricity load forecasting model based on EMD-GRU with feature selection. *Energies* 12 (6), 1140. doi:10.3390/en12061140
- Ge, L., Zhao, K., Sun, Y., Wang, Y., and Niu, F. (2021). Short-term load forecasting of distribution network based on twin network and long short-term memory network combination. *Automation Electr. Power Syst.* 45 (23), 41–50. doi:10.7500/AEPS20210522003
- Götze, F., Naumov, A., and Tikhomirov, A. (2017). Distribution of linear statistics of singular values of the product of random matrices. *Bernoulli* 23 (4B), 3067–3113. doi:10.3150/16-bej837
- Li, C., and Qi, Q. (2024). A novel hybrid grey system forecasting model based on seasonal fluctuation characteristics for electricity consumption in primary industry. *Energy* 287, 129585. doi:10.1016/j.energy.2023.129585
- Li, G., Hu, X., Chen, S., Chang, K., Li, P., and Wang, Y. (2024). Holiday peak load forecasting using grammatical evolution-based fuzzy regression approach. *Int. J. Comput. Commun. and Control* 19 (4). doi:10.15837/ijccc.2024.4.6611
- Li, K., Ye, N., Li, S., Wang, H., and Zhang, C. (2023). Distributed collaborative operation strategies in multi-agent integrated energy system considering integrated demand response based on game theory. *Energy* 273, 127137. doi:10.1016/j.energy.2023.127137
- Lu, J., Zhang, Q., Yang, Z., Tu, M., Lu, J., and Peng, H. (2019). Short-term load forecasting method based on CNN-LSTM hybrid neural network model. *Automation Electr. Power Syst.* 43 (8), 131–137. doi:10.7500/AEPS20181012004
- Lytova, A., and Pastur, L. (2009). Central limit theorem for linear eigenvalue statistics of random matrices with independent entries. *Ann. Probab.* 37 (5), 1778–1840. doi:10.1214/09-aop452
- Samuel, I. A., Emmanuel, A., Odigwe, I. A., and Felly-Njoku, F. C. (2017). A comparative study of regression analysis and artificial neural network methods for medium-term load forecasting. *Indian J. Sci. Technol.* 10 (10), 1–7. doi:10.17485/ijst/2017/v10i10/86243
- Sheshadri, G. S. (2020). "Electrical load forecasting using time series analysis," in *2020 IEEE Bangalore humanitarian technology conference (B-htc)* (IEEE), 1–6.
- Singh, A. K., Ibraheem, K. S., Muazzam, M., and Chaturvedi, D. (2012). "Load forecasting techniques and methodologies: a review," in *2012 2nd international conference on power, control and embedded systems* (IEEE), 1–10.
- Vlahović, V. M., and Vujošević, I. M. (1987). Long-term forecasting: a critical review of direct-trend extrapolation methods. *Int. J. Electr. Power and Energy Syst.* 9 (1), 2–8. doi:10.1016/0142-0615(87)90019-6
- Wang, Z., Zhao, B., Ji, W., Gao, X., and Li, X. (2019). Short-term load forecasting method based on GRU-NN model. *Automation Electr. Power Syst.* 43 (5), 53–58. doi:10.7500/AEPS20180620003
- Wu, C., Hong, H., Tseng, C. L., Wen, F., Wu, Q., and Shahnia, F. (2023). Economic dispatch of CAES in an integrated energy system with cooling, heating, and electricity supplies. *Energy Convers. Econ.* 4 (1), 61–72. doi:10.1049/enc2.12077
- Wu, H., Gao, X., Heng, J., Wang, X., and Lü, X. (2024). Bionic fusion perspective: audiovisual-motivated integration network for solar irradiance prediction. *Energy Convers. Manag.* 314, 118726. doi:10.1016/j.enconman.2024.118726
- Xing, Q., Huang, X., Wang, J., and Wang, S. (2024). A novel multivariate combined power load forecasting system based on feature selection and multi-objective intelligent optimization. *Expert Syst. Appl.* 244, 122970. doi:10.1016/j.eswa.2023.122970
- Xu, H., Chen, Y., Wang, H., Wang, H., Meng, Y., and Gu, Q. (2023). A V2G-oriented reinforcement learning framework and empirical study for heterogeneous electric vehicle charging management. *Sustain. Cities Soc.* 89, 104345. doi:10.1016/j.scs.2022.104345
- Yao, C., Yang, C., and Liu, Z. (2020). Load forecasting method based on CNN-GRU hybrid neural network. *Power Syst. Technol.* 44 (9), 3416–3424. doi:10.13335/j.1000-3673.pst.2019.2058
- Zhang, Y., Li, J., Ji, X., Ye, P., Yu, D., and Zhang, B. (2023). Optimal dispatching of electric-heat-hydrogen integrated energy system based on Stackelberg game. *Energy Convers. Econ.* 4 (4), 267–275. doi:10.1049/enc2.12094
- Zhao, Z., and Lin, W. (2024). Short-term electric load forecasting based on empirical wavelet transform and temporal convolutional network. *IET Generation, Transm. and Distribution* 18 (8), 1672–1683. doi:10.1049/gtd2.13151
- Zheng, R., Zhang, S., Xiao, X., and Wang, Y. (2020). Short-term load forecasting of multi-layer long short-term memory neural network considering temperature fuzzification. *Electr. Power Autom. Equip.* 40 (10), 181–186. doi:10.16081/j.epae.202008016