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LOAD POWER PREDICTION IN SMART SOLAR MICROGRID BASED GATED RECURRENT UNIT

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ABSTRACT

Accurate load power prediction plays a critical role in smart solar microgrids by enabling efficient energy management and optimal power flow control. This paper proposes a load power forecasting approach based on the Gated Recurrent Unit (GRU) neural network to address the nonlinear and time-dependent characteristics of microgrid load profiles. The proposed GRU model is optimized using a grid search strategy to systematically determine key hyperparameters, thereby enhancing prediction accuracy and model stability. Historical load and operational data from a smart solar microgrid are utilized for model training and validation. To demonstrate the effectiveness of the proposed approach, the GRU model is compared with a traditional Recurrent Neural Network (RNN). Experimental results indicate that the GRU-based model consistently outperforms the RNN in terms of evaluation metrics, including loss, mean absolute error (MAE), and mean absolute percentage error (MAPE). The findings confirm that the optimized GRU model provides an effective and reliable tool for load power prediction, supporting intelligent control and energy management in smart solar microgrid systems.

Keywords: Load power prediction, gated recurrent unit, smart solar microgrid, recurrent neural network.

1. INTRODUCTION

The increasing penetration of renewable energy sources has significantly transformed traditional power systems into intelligent and decentralized energy networks, commonly referred to as smart microgrids. Among various renewable resources, solar energy has been widely adopted due to its environmental benefits, scalability, and declining installation costs. However, the intermittent and stochastic nature of solar generation, combined with dynamic load demand, poses substantial challenges to the stable operation and efficient energy management of smart solar microgrids. In this context, accurate load power prediction becomes a critical component for ensuring system reliability, optimizing energy dispatch, and enhancing overall energy efficiency. Load power forecasting plays a vital role in multiple operational tasks of smart solar microgrids, including unit commitment, energy storage scheduling, demand-side management, and real-time power flow control [1], [2]. Inaccurate load predictions may lead to inefficient utilization of renewable energy, increased dependency on backup generators, excessive energy storage cycling, or even system instability. Therefore, developing robust and accurate load forecasting models is essential for supporting intelligent control strategies and improving decision-making in smart microgrid environments.

Traditional statistical methods such as autoregressive integrated moving average (ARIMA), linear regression, and exponential smoothing were commonly used for load prediction [3]-[5]. Singh and Garg demonstrated ARIMA and seasonal ARIMA's strengths and limitations in short-term hourly prediction in PV system [3]. Mohammed et al. utilized seasonal ARIMA to forecast daily and monthly solar power in South Korea, which acquired consideration of accuracy and reliability compared to Monte Carlo method [5]. Although these approaches are computationally efficient and easy to implement, they often struggle to capture the nonlinear and time-varying characteristics of load demand in complex energy systems. With the rapid growth of data availability and computational capabilities, artificial intelligence-based techniques have been increasingly explored for load forecasting applications. Artificial Neural Networks (ANNs) have been widely deployed for load prediction in various power system applications due to their ability to model nonlinear relationships between input features and load demand [6]-[11]. Hafidh et al. employed ANN to predict the solar irradiance for short-term PV power generation, which utilized aforementioned meteorological data, to provide stable forecast in near future state [12]. Emre and Fatih proposed ANNs to predict electrical load in Afyon Kocatepe University, which included residential, laboratories, education, research, and hospital buildings [13]. The experimental outcomes proved well performances ANN model with season, timing data, and power consumption as input features. Daniel and Joel developed a novel method-based ANN structures to predict solar power in individuals and small business [14]. The tuning ANN model decreased MAE about 5.37% and RMSE about 6.83%, which minimized loss, environment impact, and cost in consumer power prediction [14]. The ANNs were developed to deliver efficient services in planning, cheduling, pricing, and customer satisfaction in Dubai [15]. The results proved higher accuracy and better stability of ANN compared to multiple linear regression (MLR), ARIMA, and random forests (RF), with almost 91.02% accuracy [15]. Phuong et al. deployed ANN structure to predict the grid power, which improved operations of energy management system in smart solar microgrid [10]. ANN-based models have demonstrated improved prediction performance compared to traditional statistical approaches, particularly under nonlinear operating conditions. However, conventional ANNs typically rely on shallow architectures and feedforward structures, which limit their capability to effectively learn temporal dependencies in time-series data. Moreover, when dealing with large-scale datasets or long-term temporal sequences, ANN models often suffer from issues such as overfitting, poor generalization, and inefficient training performance.

Deep learning algorithms have been introduced to load forecasting tasks, leveraging their hierarchical representation learning and powerful sequence modeling capabilities. Recurrent Neural Networks (RNNs) are specifically designed to handle sequential data by incorporating feedback connections, allowing information to persist across time steps. RNNs have been applied to short-term and medium-term load forecasting problems with promising results [16]-[23]. Park et al. utilized RNN techniques to predict the power generation of target locations based on sample sites, which significantly improved estimated accuracy compared to other traditional techniques [24]. However, conventional RNNs are known to suffer from vanishing and exploding gradient problems when processing long sequences, which degrades their learning effectiveness and limits their practical performance in long-horizon forecasting scenarios. Long Short-Term Memory (LSTM) networks were developed as an extension of RNNs to overcome these challenges by introducing memory cells and gating mechanisms [25], [20], [26], [23], [27]. LSTM models have shown strong capability in capturing long-term temporal dependencies and have been successfully applied to various load forecasting and energy prediction problems. Khanh et al. employed LSTM structure to predict load power in smart solar microgrid, which acquired outstanding accuracy compared to traditional RNN model [17]. Thao et al. employed LSTM structure to predict solar power in solar plant, which acuiquied outsanding performances compared to RNN structures [20]. Despite their effectiveness, LSTM networks involve relatively complex architectures with a large number of parameters, leading to higher computational cost and longer training times, which may not be ideal for real-time or resource-constrained microgrid applications.

Gated Recurrent Unit (GRU) networks, as a simplified variant of LSTM, have recently gained increasing attention in time-series prediction tasks [21], [28], [29]. GRU models employ reset and update gates to control information flow, enabling them to capture temporal dependencies while maintaining a more compact structure [30]. Yeh et al. deployey GRU structure in predicting load power in smart solar grid, which proved to acquire higher performance compared to traditional RNN model [21]. A combined GRU and sequence to sequence auto-encoder (AE) was proposed to extract internal correlation of input data for shor-term solar prediction, which outperformed other traditional techniques in 24h, 48h, and 15 days forecast [31]. Compared with LSTM, GRU networks require fewer parameters and offer faster convergence while achieving comparable or even superior prediction accuracy in many applications. These advantages make GRU a suitable candidate for load power prediction in smart solar microgrids, where both accuracy and computational efficiency are essential.

In smart solar microgrid environments, load demand exhibits strong temporal correlations influenced by various factors such as user behavior, operational schedules, and environmental conditions. Additionally, load patterns may vary significantly across different times of day, making 24-hour ahead load forecasting particularly challenging. Although deep learning-based approaches have been explored in existing literature, there remains a need for efficient and well-optimized models that can deliver high prediction accuracy while maintaining low computational complexity. In this study, a GRU-based deep learning model is proposed for 24-hour ahead load power prediction in a smart solar microgrid. To further enhance model performance, a grid search optimization strategy is employed to systematically tune critical hyperparameters, including the number of hidden units, window size, and GRU cells. This optimization process aims to improve prediction accuracy, model stability, and generalization capability. The proposed approach is evaluated using historical load and operational data collected from a smart solar microgrid system. To validate the effectiveness of the proposed model, comparative experiments are conducted against a traditional RNN-based forecasting approach. Performance is assessed using widely adopted evaluation metrics, including loss, mean absolute error (MAE), and mean absolute percentage error (MAPE). The results demonstrate that the optimized GRU model consistently outperforms the RNN model, particularly in capturing temporal variations and reducing forecasting errors. The main contributions of this paper can be summarized as follows: (1) a GRU-based deep learning framework is developed for accurate 24-hour ahead load power prediction in smart solar microgrids; (2) a grid search method is integrated to optimize the GRU architecture and hyperparameters; and (3) comprehensive experimental results confirm the superiority of the proposed approach over conventional RNN models. The proposed method provides an effective and reliable solution for intelligent energy management and power flow control in smart solar microgrid systems.

2. METHODOLOGIES

2.1. Data collecting operation in smart solar microgrid

The data utilized in this study were collected from a real-world smart solar microgrid system deployed in Taiwan. The microgrid integrates renewable energy generation, local loads, and intelligent monitoring infrastructure to support efficient energy management and operational control. To ensure the reliability and practical relevance of the proposed load power prediction model, historical operational data were continuously recorded over a one-year period in Taiwan, as presented in Fig. 1. An advanced metering infrastructure (AMI) was employed as the core data acquisition platform in the smart solar microgrid. The AMI system enables high-resolution monitoring of electrical parameters and provides reliable, real-time data communication between field devices and the central data server. As illustrated in Fig. 1, the AMI collects hourly measurements from the smart solar microgrid and transmits them to the data management layer for further processing and analysis. Four key electrical parameters were recorded at an hourly sampling rate: load power, load voltage, load current, and power factor. These parameters comprehensively reflect the operational characteristics and load behavior of the microgrid. Load power serves as the target variable for prediction, while load voltage, current, and power factors are considered influential features that capture system operating conditions and user consumption patterns. The hourly data resolution is suitable for short-term load forecasting and supports practical applications such as energy dispatch planning, storage scheduling, and power flow optimization.

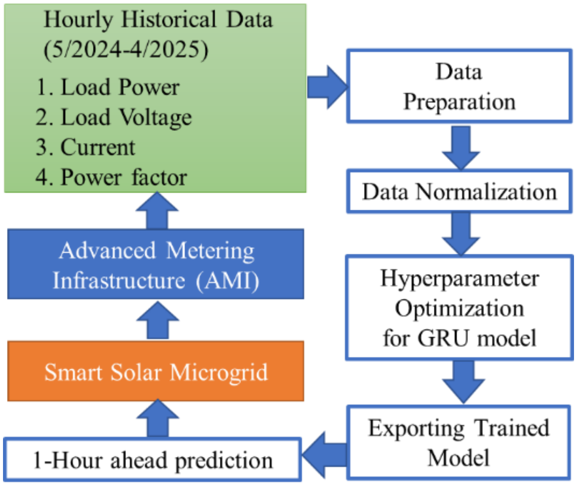

Fig. 1. The data collecting process in smart solar microgrid in Taiwan

A data preprocessing stage was implemented prior to model training to enhance data quality and improve prediction performance. First, the collected dataset was examined to identify and eliminate outliers that significantly deviated from normal operating ranges. These outliers were removed to prevent distortion of the learning process and to ensure stable model convergence. To address differences in scale among the input variables and to accelerate the training process, min–max normalization was applied to all features. This normalization technique transforms each variable into a unified range between 0 and 1, as computed in Eq. (1), where X_i is the original data at time i, X_{max} and X_{min} are the maximum and minimum values of corresponding feature. Min–max normalization helps prevent features with larger numerical ranges from dominating the learning process and improves numerical stability during GRU training.

$$X_{nor} = \frac{X_{min} - X_i}{X_{min} - X_{max}} \qquad (1)$$

2.2. Gated Recurrent Unit Introduction

Based on the preprocessed and normalized dataset, a GRU-based forecasting framework was developed to predict the load power one hour ahead. The GRU network leverages its gating mechanism to effectively capture temporal dependencies in the hourly load data while maintaining a relatively simple architecture. The gated recurrent unit is a type of recurrent neural network designed to effectively model sequential data while alleviating the vanishing gradient problem commonly observed in traditional RNNs [32], [33]. Owing to its relatively simple structure and strong capability in capturing temporal dependencies, GRU has been widely applied in time-series forecasting tasks, including load power prediction in smart energy systems. Compared with LSTM networks, GRU employs a reduced number of gating mechanisms, resulting in fewer parameters and faster training convergence while maintaining comparable predictive performance, as presented in Fig. 2. In this study, a GRU-based forecasting framework is developed to predict one-hour-ahead load power using preprocessed and normalized hourly data collected from a smart solar microgrid. The GRU architecture consists of two main gates with update and reset gates. These gates regulate the flow of historical information and determine how much past information should be retained or forgotten at each time step. The update gate z_t controls the degree to which the previous hidden state is preserved and is computed as in Eq. (2). The reset gate r_t determines how much past information should be discarded when computing the candidate hidden state, as expressed in Eq. (3). The candidate hidden state $\tilde{h}_t$ is computed as in Eq. (4). Finally, the hidden state h_t at time step t is updated by combining the previous hidden state and the candidate hidden state, as in Eq. (5), where x_t denotes the input vector at time t, h_{t-1} is the previous hidden state, $\sigma(.)$ represents the sigmoid activation function, and $\otimes$ denotes element-wise multiplication. By dynamically controlling information flow through its gating mechanism, the GRU model effectively captures short-term and long-term temporal patterns in load power data. This capability makes GRU particularly suitable for one-hour-ahead load power prediction in smart solar microgrids, providing accurate and computationally efficient forecasting to support intelligent energy management and power flow control.

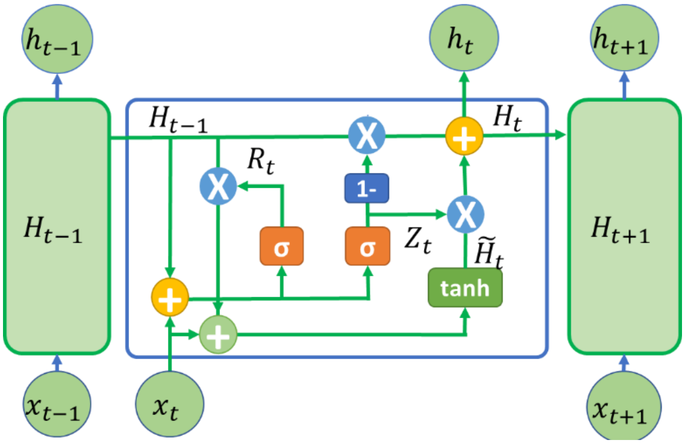

Fig. 2. The GRU structure with resetting and updating gate mechanism.

$$z_t = \sigma(W_{z,h}.h_{t-1} + W_{z,x}x_t + b_z \qquad (2)$$

$$r_t = \sigma(W_{r,h}.h_{t-1} + W_{r,x}x_t + b_r) \qquad (3)$$

$$\tilde{h}_t = tanh\ (W_{h,r}[r_t \otimes h_{t-1} + x_t] + b_c) \qquad (4)$$

$$h_t = (1 - z_t) \otimes h_{t-1} + z_t \otimes \tilde{h}_t \qquad (5)$$

The performance of the proposed GRU-based load power prediction model is evaluated using widely adopted error metrics, including mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). In this study, MSE is employed as the loss function during the training process to penalize large prediction errors and enhance model convergence, as computed in Eq. (6). MAE measures the average magnitude of absolute errors, providing a clear interpretation of prediction accuracy in the original data scale, as expressed in Eq. (7). MAPE evaluates the relative prediction error in percentage terms, allowing performance comparison under varying load conditions, as presented in Eq. (8), where Y_t and $\hat{Y}_t$ are the actual and predicted data of target load power. Together, these evaluation benchmarks provide a comprehensive and reliable assessment of the prediction accuracy and robustness of the GRU model in smart solar microgrid applications.

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\left(Y_t - \hat{Y}_t\right)^2 \tag{6}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|Y_t - \hat{Y}_t\right| \tag{7}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \tag{8}$$

3. SIMULATION OUTCOMES

3.1. Hyperparameter optimization for GRU structure with grid search technique

To achieve optimal prediction performance, the structure of the GRU model is systematically optimized using a grid search technique. Hyperparameter optimization is a critical step in deep learning-based time-series forecasting, as model performance is highly sensitive to architectural configurations and input sequence length [34]. In this study, three key hyperparameters are considered in the grid search process, input window size, number of GRU layers, and number of GRU cells per layer. These parameters directly influence the model's capability to capture temporal dependencies, learning complexity, and generalization performance in smart solar microgrid load prediction. The input window size determines the length of historical data used to predict future load power. To investigate the impact of temporal context, three window sizes with 24, 36, and 48 are evaluated, corresponding to different historical horizons of hourly load data. The depth of the GRU network is varied by configuring two and three GRU layers. Increasing the number of layers enhances the model's representational capacity and enables hierarchical feature extraction from sequential data. However, deeper architectures may also lead to overfitting and longer training times, particularly when the available dataset is limited. To further explore model complexity, the number of GRU cells in each layer is set to 32 and 64, allowing assessment of the impact of hidden unit size on prediction accuracy. The collected and preprocessed dataset is divided into training, validation, and testing sets with a ratio of 80:10:10. The experimental results of the grid search are summarized in Table 1. Different GRU configurations exhibit varying prediction performance across evaluation metrics. Models with insufficient temporal context or excessive architectural complexity tend to show higher prediction errors. Among all tested configurations, the GRU model with a window size of 36, two GRU layers, and 64 GRU cells achieves the best overall performance, yielding the lowest training and validation loss, MAE, and MAPE with 0.00429, 0.00079, 0.0274, 0.0090, 9.29%, and 7.50%, respectively. This configuration demonstrates superior capability in capturing temporal dependencies while maintaining stable generalization performance. Therefore, the GRU architecture with 36 window sizes, two GRU layers, and 64 GRU cells is selected as the optimal structure. This optimized GRU model is subsequently deployed for load power prediction in the smart solar microgrid, providing accurate and reliable forecasting to support intelligent energy management and power flow control.

Table 1. The hyperparameter fine-tuning outcomes for GRU structure with various evaluating benchmarks

Window Size	GRU Layers	GRU Cells	Loss	Val_Loss	MAE	Val_MAE	MAPE	Val_MAPE
24	2	32	0.00467	0.00128	0.0301	0.0220	12.10	12.48
24	2	64	0.00430	0.00090	0.0285	0.0109	9.62	8.56
24	3	32	0.00442	0.00094	0.0284	0.0143	9.05	9.36
24	3	64	0.00436	0.00097	0.0282	0.0141	10.01	10.15
36	2	32	0.00471	0.00091	0.0288	0.0108	12.35	8.72
36	2	64	0.00429	0.00079	0.0274	0.0090	9.29	7.50
36	3	32	0.00486	0.00095	0.0323	0.0130	13.11	9.90
36	3	64	0.00457	0.00095	0.0310	0.0144	9.67	10.07
48	2	32	0.00474	0.00094	0.0300	0.0120	11.65	9.09
48	2	64	0.00467	0.00095	0.0299	0.0129	11.60	9.35
48	3	32	0.00473	0.00089	0.0301	0.0102	11.87	8.52
48	3	64	0.00435	0.00090	0.0278	0.0127	10.48	8.87

3.2. Comparative outcomes

To further validate the effectiveness of the proposed approach, the optimized GRU model is comparatively analyzed against a traditional RNN using the same dataset and experimental settings. Both models are trained and evaluated under identical conditions to ensure a fair comparison, including the same data preprocessing procedures, and identical evaluation benchmarks. The comparative results are summarized in Table 2, which presents the training and validation performance of both models in terms of loss, MAE, and MAPE. GRU models consistently achieve lower error values than the RNN across all evaluation metrics. Specifically, the GRU attains a training loss of 0.00178 and a validation loss of 0.00090, which are substantially lower than those of the RNN model, recorded at 0.00410 and 0.00159, respectively. The reduced loss values indicate that the GRU model converges more effectively during training and exhibits better generalization capability on unseen data. This improvement can be attributed to the gating mechanism of the GRU, which efficiently controls information flow and mitigates the vanishing gradient problem commonly encountered in conventional RNNs. In terms of MAE, the GRU model also demonstrates superior performance. The GRU achieves a MAE of 0.025 and a validation MAE of 0.012, compared to 0.028 and 0.020 obtained by the RNN model. These results indicate that the GRU provides more accurate load power predictions and maintains higher stability during validation. Furthermore, the relative error evaluation using MAPE highlights the robustness of the GRU under varying load conditions. The GRU model records a MAPE of 6.267% and a validation MAPE of 8.610%, which are significantly lower than the corresponding values of 9.090% and 11.436% achieved by the RNN. To quantitatively assess the performance gains, the percentage improvements of the GRU model over the RNN are calculated and compared with the RNN structure, the GRU achieves notable improvements of 56.52% in training loss and 43.17% in validation loss. Similarly, improvements of 11.85% in MAE and 40.87% in validation MAE are observed, demonstrating enhanced prediction accuracy and consistency. In addition, the GRU model reduces MAPE by 31.06% during training and 24.71% during validation, confirming its effectiveness in minimizing relative forecasting errors.

These comparative outcomes clearly demonstrate the advantages of the GRU model for load power prediction in smart solar microgrids. By leveraging its simplified yet powerful gating structure, the GRU effectively captures temporal dependencies in load demand while maintaining computational efficiency and strong generalization performance. The superior accuracy and robustness of the GRU model make it a reliable forecasting tool for smart energy management systems, supporting informed decision-making, optimized power flow control, and improved operational efficiency in smart solar microgrid applications.

Table 2. The comparison between proposed GRU and RNN model in predicting load power

AI MODEL	Loss	Val_Loss	MAE	Val MAE	MAPE	Val MAPE
GRU	0.00178	0.00090	0.025	0.012	6.267	8.610
RNN	0.00410	0.00159	0.028	0.020	9.090	11.436
Improvement (%)						
RNN	56.52	43.17	11.85	40.87	31.06	24.71

4. CONCLUSION

This research presented an effective deep learning–based methodology for load power prediction in smart solar microgrid systems using a GRU model, which was developed and optimized through a grid search strategy to identify the most suitable hyperparameter configuration. Historical operational data collected from a real smart solar microgrid were utilized to train and validate the proposed model. Experimental results demonstrated that the optimized GRU model achieved superior performance and effectiveness in minimizing relative forecasting errors compared with a traditional RNN, with notable improvements of 56.52% in training loss, 43.17% in validation loss, 11.85% in MAE, 40.87% in validation MAE, 31.06% in training MAPE, and 24.71% in validation MAPE. The comparative analysis confirmed that the GRU's gating mechanism enables more effective learning of temporal dependencies while maintaining a relatively simple and computationally efficient architecture. The findings indicate that the proposed GRU-based approach provides a reliable and high-accuracy solution for short-term load power prediction in smart solar microgrids. The developed methodology can support advanced energy management systems by improving forecasting accuracy and operational decision-making. Future work will focus on extending the model to multi-step forecasting and integrating additional contextual features to further enhance prediction performance.

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