A Comparative Analysis of Time Series Forecasting Methods for Short-Term Electricity Demand Prediction

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***Abstract*—Energy demand is exploding worldwide. Accordingly, there is a growing interest in methods for maximizing energy use efficiency. Electricity demand forecasting is a technique of predicting future electricity demand based on past electricity usage data. This makes it possible to effectively manage energy usage. In particular, short-term electricity demand forecasting is essential for the optimal operation of the power system and the economic operation of the electricity market. In this paper, we compare short-term electricity demand prediction accuracy using forecasting models based on artificial intelligence. In addition, we perform electricity demand prediction for the summer period with large fluctuations.**

Keywords—Electricity demand prediction, Sequence to Sequence (Seq2Seq), LSTM, GRU, Time series forecasting

I. INTRODUCTION

Electricity is one of the most critical energy resources. It is a real-time energy resource that is produced and consumed simultaneously and cannot be stored. Therefore, electricity must be managed to keep demand and production in balance. This makes it possible to effectively adjust and optimize for balance between demand and production.

Accurate short-term demand forecasts have become important with the introduction of electricity markets, in which many generators bid for power supply. Power plants can plan and adjust electricity production according to short-term forecasted demand. This makes it possible to maximize energy efficiency. Thus, accurate short-term electricity demand prediction is essential for ensuring power system stability and efficient operation [1][2].

Recently, an electricity demand prediction model based on deep learning has been proposed [3]-[11]. The most commonly used models are LSTM(Long Short-Term Memory) [11] and GRU(Gate Recurrent Unit) [12]. LSTM and GRU are models designed to solve the long-term dependency problem of RNNs, showing high accuracy in short-term electricity demand prediction [5]-[7]. Seq2Seq(Sequence to Sequence) [13] is a deep learning technique that has been widely applied in machine translation. Seq2Seq consists of an encoder that converts a sequence into a fixed-length vector and a decoder that converts a vector back into a sequence and shows good performance in time series prediction [8]-[10].

In this paper, we compare the prediction accuracy of LSTM, GRU, and Seq2Seq which show good performance in time series prediction for comparison of short-term power demand prediction performance. In addition, we perform electricity demand prediction for the summer period with large fluctuations in electricity demand and compare the prediction results.

II. METHODOLOGY

A. LSTM(Long Short Term Memory)

LSTM[11] is an RNN series model with a recursive structure in which the previous output data enters the input data with the following sequential data. LSTM is known to show effective performance in processing sequential data such as time series data because of its structure.

Figure 1 shows the structure of LSTM. LSTM overcomes the long-term dependency problem of RNNs by using forget gate f_t, input gates i_t and $\tilde{C}$, and output gates O_t and h_t. The forget gate deletes unnecessary information from past data through the sigmoid layer. Here, the forget gate has an output value between 0 and 1. If the output value is 1, the value is kept intact, whereas if the output value is 0, the value is deleted. The input gate decides which data to update through the sigmoid layer. Then, new candidate data for learning are added through the tanh layer. Finally, the output gate decides the output value h_t through the sigmoid layer and the tanh layer.

B. GRU(Gate Recurrent Unit)

GRU[12] is a lightweight model of LSTM that reduces the amount of computation. LSTM has become a model that good performs on data with long sequences. However, it requires a lot of computation because of the relatively complex structure. GRU reduces the amount of update computation of the hidden state while maintaining a solution to the long-term dependence problem of LSTM.

Figure 2 shows the structure of GRU. The GRU is composed of r_t as the reset gate and z_t as the update gate. The reset gate removes some of the past information through the current input data x_t, and h_{t-1} received from the previous cell. The update

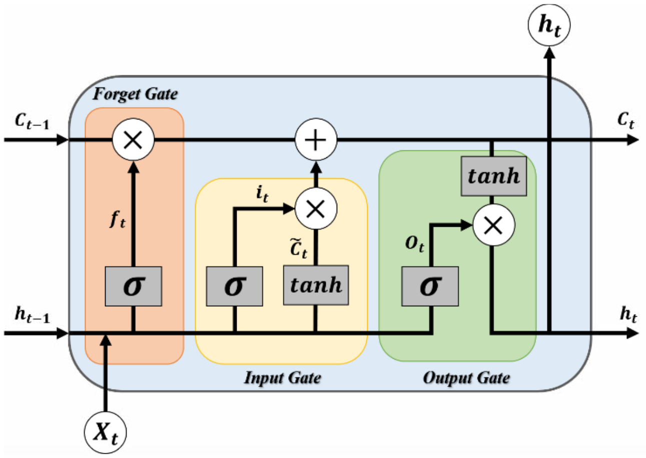


Fig. 1. LSTM basic structure

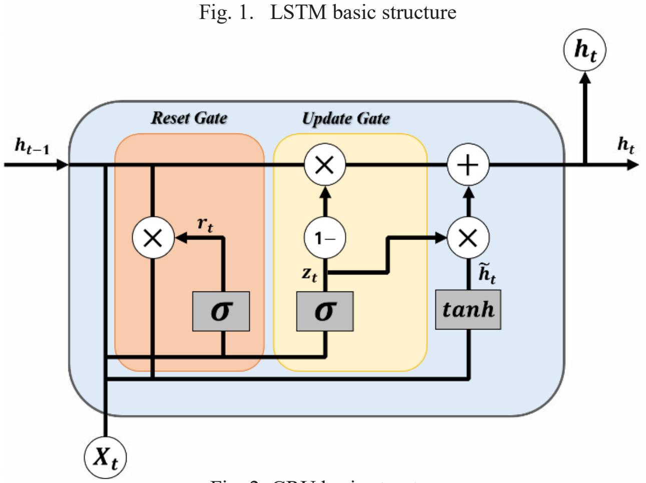


Fig. 2. GRU basic structure

gate performs both the forget gate and input gate operations of LSTM. It deletes some of the past information and determines the weight of how much to apply the current information. Then, calculate the data information candidate at the current point by multiplying the result of the reset gate without using the hidden layer information. Finally, the current h_t is calculated by combining the update gate result and the candidate calculation value.

C. Seq2Seq(Sequence-to-Sequence)

Seq2seq [13] is a model that receives a sequence with a fixed length and outputs a sequence with a length appropriate to the input sequence by using an LSTM(or GRU)-based model. Seq2Seq is primarily used in natural language processing applications such as language translation and text summarization. Also, It is used for time-series data such as stock prices, weather, and demand forecasts.

Figure 3 shows the structure of Seq2Seq. The main idea of the Seq2Seq model is that it is divided into an encoder part and a decoder part. The encoder sequentially receives the input sequence as input. Then, it summarizes and compresses the sequence information and converts it into a context vector of fixed size. The decoder uses the context vector extracted from the encoder as an initial value, and sequentially generates an output sequence. The output sequence ends when the decoder

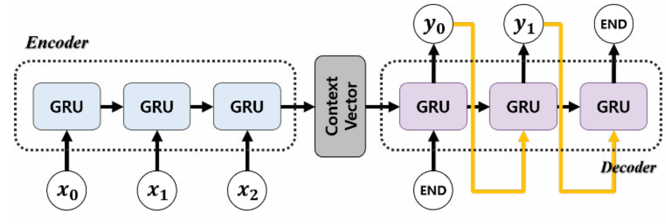


Fig. 3. Seq2Seq basic structure

generates an end-of-sequence token or reaches a maximum length.

III. Experimental Results

A. Dataset

We utilized electricity demand data provided by Korea Power Exchange(KPX) to predict short-term electricity demand. The collected data is measured every 5 minutes from January 1, 2019 to July 31, 2021. We reconstructed the data at 1-hour intervals for hourly predictions. Furthermore, we used the data for training and validation by separating the data from January 1, 2019 to June 30, 2021 into Train (70%), Validation (20%), and Test (10%). And, data from July 1, 2021 to July 31 was used for forecasting the summer interval.

We normalized the data using the MinMaxScaler function provided by scikit-learn to ensure that the data input to the model is in the [0, 1] range. In addition, a sliding window method was applied to configure a series of sets. For example, if you want to predict electricity demand from the current time point t to the future time point m (t +1, t +2,…,t + m), data from the past time point n (t, t-1,…,t-n) is used as an input to the model. Here, we set n = 9 and m = 3.

B. Experimental Setup

Our experiments are implemented utilizing the Python-based Tensorflow framework. And, it was performed on a Windows 10 system with Intel Core I9-12900 processor, 24GB RAM, and Nvidia GeForce RTX 3090 GPU. Our initial learning rate is set to 0.01 with a batch size of 64. The optimizer used Adam (Adaptive Moment Estimation), and the loss function used MSE (Mean Squared Error). We trained the model for 32 epochs. And then, Evaluated the performance of the model using MAPE (mean absolute percentage error) and RMSE (Root Mean Square Error), which are widely used evaluation metrics for time series forecasting.

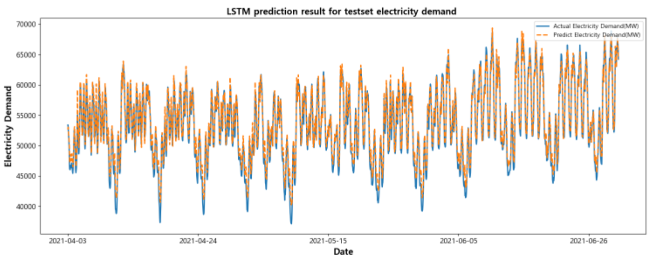
C. Results

Table 1 shows the evaluation results of LSTM, GRU, and Seq2Seq. Fig. 4 shows the hourly electricity demand prediction result for the test data, and Fig. 5 shows the hourly electricity demand prediction result for the summer period.

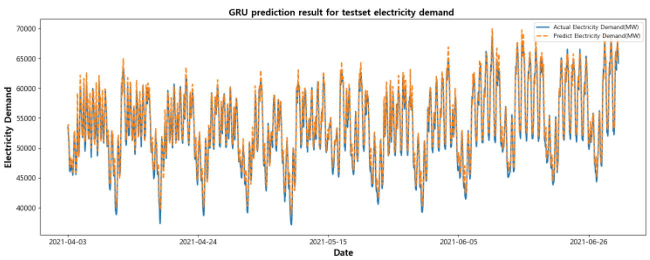
In Table 1, the overall performance of Seq2Seq on the test data was improved by 30% over LSTM and 20% over GRU. In Fig. 4, LSTM and GRU do not capture well curves that rise or fall rapidly, although the deviation between predicted values and measured values for the entire interval is not significant. In particular, this fact is clearly shown in the summer period with large fluctuations in the electricity demand (Fig5). As a result, Table 1, Fig. 4, and 5 show that Seq2Seq outperforms other models in predicting power demand and can be effectively utilized.

TABLE I. Evaluation results for each model

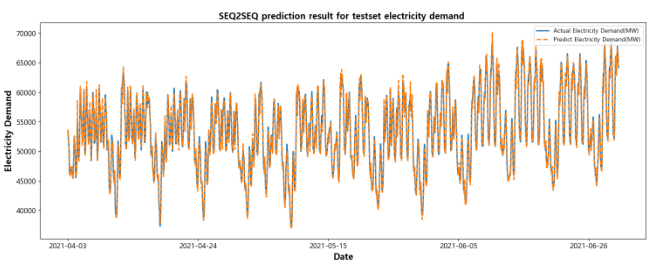
Metrics	*LSTM*	*GRU*	*Seq2Seq*
MAPE	0.020865	0.01896	0.013817
RMSE	1337.434	1221.214	934.6803



(a) Prediction result of LSTM (unit of hour)



(b) Prediction result of GRU (unit of hour)



(c) Prediction result of Seq2Seq (unit of hour)

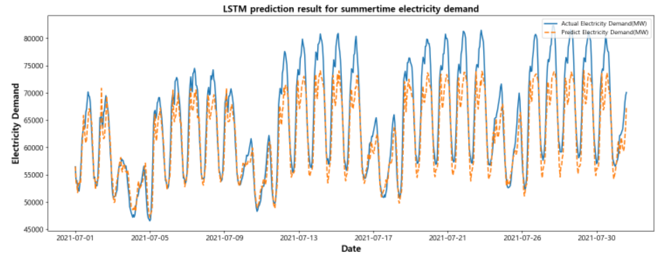
Fig. 4. Electricity demand results of LSTM, GRU, and Seq2seq

IV. Conclusion and Future Work

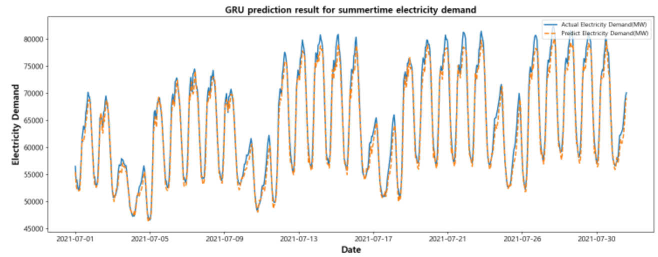
We compared and analyzed LSTM, GRU, and Seq2Seq prediction models to predict domestic short-term electricity demand. The data for the study are electricity demand data provided by the Korea Power Exchange and were reconstructed into hourly data.

We evaluated each model using a dataset from January 1, 2019 to June 30, 2021, and performed electricity demand forecasts for the summer period using the dataset from July 1 to July 31, 2021. As a result, Seq2Seq shows about 30% better prediction performance than LSTM and GRU. In particular, it provides much better performance for the summer period with large fluctuations in the electricity demand.

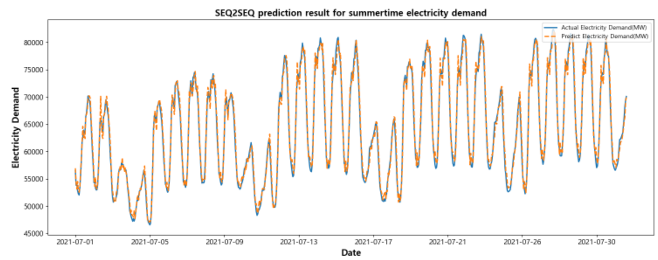
In our future work, we will conduct an extended study by considering various external variables and applying the attention technique to improve the performance of electricity demand prediction compared to existing models.



(a) Prediction result of LSTM for the summer period



(b) Prediction result of GRU for the summer period



(c) Prediction result of Seq2Seq for the summer period

Fig. 5. Electricity demand results of LSTM, GRU, and Seq2seq for the summer period

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