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Deep Learning Techniques for Wind Speed Forecasting at Palembang Airport

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Abstract

The Sultan Mahmud Badaruddin (SMB) II Palembang Meteorological Station is a technical implementation unit (UPT) of the Meteorology, Climatology, and Geophysics Agency (BMKG) that plays a role in disseminating actual weather information, particularly at SMB II Palembang Airport. Various weather parameters are observed, one of which is wind speed. During the take-off and landing processes, wind speed is a crucial parameter used by airport personnel, including pilots and air traffic controllers (ATC). This study focuses on analyzing and evaluating three deep learning methods using the architectures of LSTM (Long Short Term Memory), GRU (Gated Recurrent Unit), and BiLSTM (Bidirectional Long Short Term Memory). Time series data such as air pressure, rainfall, humidity, and temperature are used as predictors. The data is sourced from the AWOS (Automatic Weather Observation System) device. After processing the data using deep learning methods with the architectures above, an analysis will be conducted to determine which architecture model is the most accurate based on the lowest loss error rate in forecasting wind speed at SMB II Palembang Airport. The results show that the GRU deep learning architecture has the lowest loss value compared to the LSTM and BiLSTM architectures so that it can produce better wind speed forecasts in the next 12 hours and 24 hours, with RMSE of 1.62 and 1.77, respectively.

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Keywords

Deep learning, Wind Speed, LSTM, GRU, BiLSTM

Introduction

There are many traditional methods for forecasting wind speed, including observing the movement of leaves, twigs, and tree branches using mechanical devices such as cup counters, windmills, flags, and windsocks. Along with technological advances, several forecasting methods exist, such as linear and non-linear regression, time series (autoregression and moving average), and artificial neural network methods. The method approach adapts to the complexity level, data variations, and the time required to produce an accurate forecasting model.

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The wind is a crucial weather element. Wind is the movement of air masses triggered by a difference in air pressure due to temperature differences on the earth's surface, expressed in direction and speed. Wind direction is expressed in degrees, while speed is expressed in international units. It often uses a table/scale better known as the "Beaufort Scale / Beaufort Scale" with the unit "knots". (1 knots=0.5 m/s or 1.8 – 1.9 km/h) (Zakir, 2013).

This study is based on several relevant studies on predicting money time series data using the neural network method. The aspects considered in selecting previous research included the research object, methods, and fundamental theories used. The best modeling in predicting wind speed is to use the Recurrent Neural Network (RNN) algorithm using the Long short-term memory (LSTM) architecture, which has an RMSE value of 0.06281251, 30 neurons, 800 epochs, and a validation split of 0.1 (Panggabean et al., 2021).

The method used by LSTM with data from twelve hours in advance to predict the next two and three hours used statistical analysis of Pearson, MAE, and RMSE correlation statistics (Özen et al., 2022.). The results are not good enough to predict wind power plants. Other features such as air pressure, relative humidity, and the wind turbine are required.

LSTM is a type of RNN developed to overcome vanishing gradients in RNNs (Kristian et al., 2018). It has been modified by adding cell memory to store information for extended periods. The advantage of LSTM is the existence of block memory that determines which value to choose as the relevant output for the given input (Wiranda et al., 2019), as shown in Figure 1.

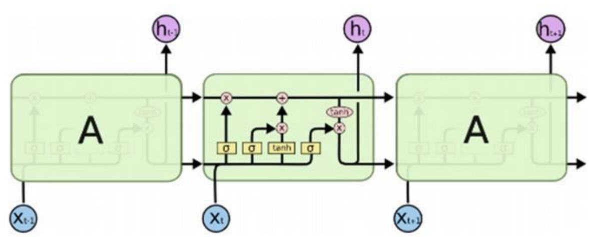

Figure 1. LSTM

Conversely, GRU is one of the RNN models that can recognize the attachment pattern of data in a separate time series data at an observation time. GRU is a network that has a loop connection equipped with a feature to control the flow of information from and to the GRU cell in the form of reset gates and update gates, which play a role in recognizing patterns of attachment between data that are relatively far apart in the sequence (Yaya Heryadi et al., 2021). GRU has capabilities commensurate with LSTM, but GRU is better for more accurate datasets (Al Hamoud et al., 2022), as shown in Figure 2.

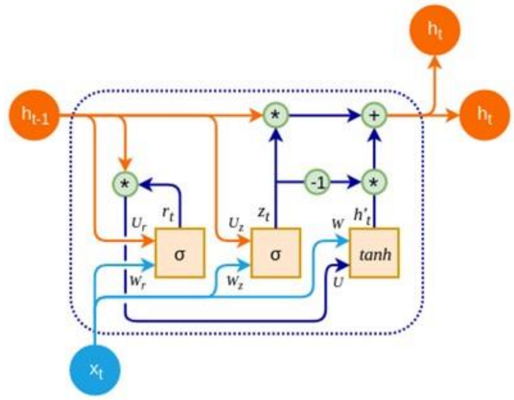

Figure 2. GRU

Furthermore, BiLSTM is another variation of LSTM that can capture information from time series data, as shown in Figure 3. It can read two-way information, namely, data from the beginning of the data to the end of the data sequence and from the end to the beginning of the data sequence. So, it is expected to produce a more comprehensive information pattern on the dataset.

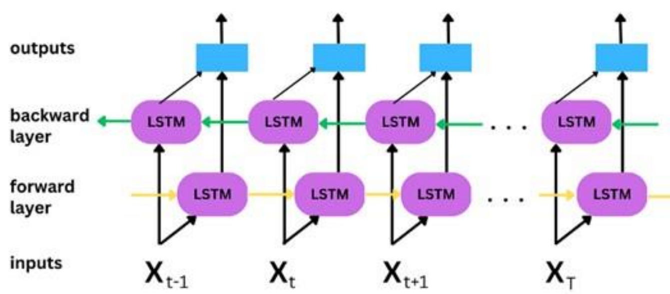

Figure 3. BiLSTM

The research uses three deep learning architectures to assess their accuracy and efficiency in forecasting wind velocity. The methods used in this research are GRU, BiLSTM, and LSTM. The selection of these three (3) architectures is based on their ability to store long-term memory in processing time series data and the size of the data.

Methodology

This research consists of data collection, preprocessing, data sharing, normalization, training of LSTM, GRU, and BiLSTM models, denormalization, and analysis and evaluation of each model, as shown in Figure 4.

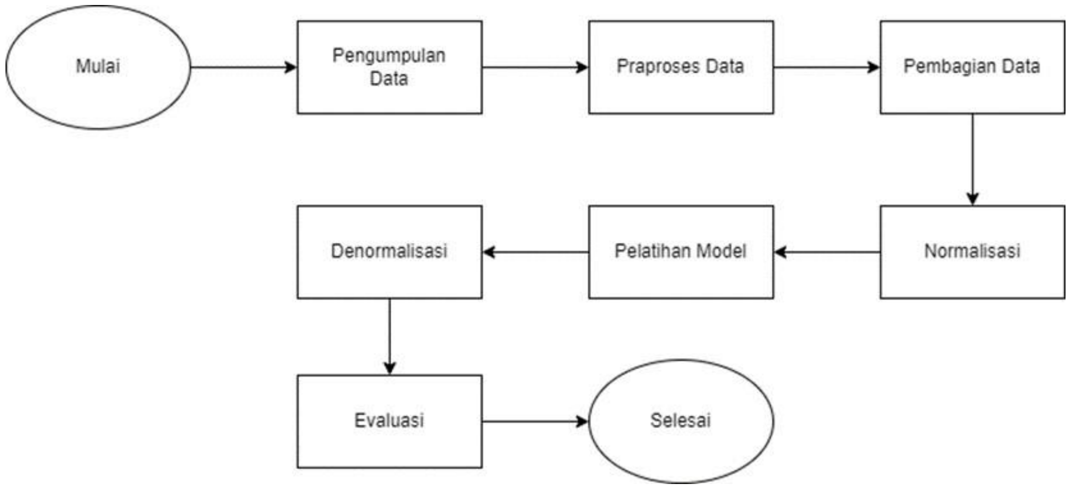

Figure 4. Research Flowchart

Data Collection

The research submitted a data request permit to the Sultan Mahmud Badaruddin II Meteorological Station in Palembang. The data used are weather parameters in the form of data on the time series of pressure, humidity, wind speed, temperature, and rainfall for two years from 2022 to 2023 in 1-hour sampling for 24 hours. An example of the dataset used for modeling can be seen in Table 1.

Table 1. Sample Research Dataset

Date and Time	Wind Speed	Temperature	Air Pressure	Rainfall	RH
2022-01-01 00:00:00	4.0	24.22	1009.49	0.0	98.0
2022-01-01 01:00:00	4.0	24.22	1009.77	0.0	96.8
2022-01-01 02:00:00	5.0	26.33	1010.10	0.0	88.6
2022-01-01 03:00:00	6.0	27.06	1010.37	0.0	83.7
2022-01-01 04:00:00	5.0	27.72	1010.52	0.0	81.9

Preprocessing Data

After obtaining the raw data, the process of checking, cleaning, and preparing the data in CSV form is carried out so that the Python programming language can process it. Then, the data was divided into predictor and target data so that the data processing process ran well. Deep learning in practice requires the stages of data distribution in the form of data training and data testing. However, there are no standard rules for dividing the dataset. In this study, a ratio of 90:10 was used.

The next stage is the data normalization process. This process adjusts the dataset scale from 0 to 1. It is hoped that this process can improve learning performance and increase accuracy.

Evaluation

Each model has different characteristics and computational processes. Therefore, an evaluation analysis was carried out for each model to obtain information on error rates based on loss values and loss validation from each deep learning model on the results of wind speed forecasts. Before evaluating the model, the stage passed is the denormalization process. That is the process of returning the normalization value to the actual value.

This study uses Mean Absolute Error (MAE) to see the accuracy based on the loss value in the modeling process and also the Root Mean Square Error (RSME) as an evaluation instrument for the model that has been generated so that it can be analyzed more deeply information about the errors generated by the model against the actual data.

Results and Discussion

This study forecasts the actual wind speed for the next 12 hours (t+12) and the next 24 hours (t+24) at SMBII Palembang airport using five (5) weather parameters such as temperature, rh, rainfall, air pressure, and wind speed for 24 hours by comparing 3 (three) deep learning architectures, namely LSTM, GRU, and BiLSTM based on the difference between the forecast value of wind speed and the actual value of wind speed of the three architectures for each step of time. This stage uses the initiation of deep learning parameter setting values, as shown in Table 2.

Table 2. Default Setting Parameter Deep Learning

Hyperparameter	Value
Number of hidden layer	2
Dropout rate	0.2
Optimizer	Adam
Activation Function	ReLu
Batch size	30
Epoch Max	100

First, the result for LSTM with t after 12 hours is shown in Table 3 and Figure 5.

Table 3. Selection of the number of hidden layer nodes LSTM (t+12)

LAYER1	LAYER2	loss	value loss	RMSE	epoch
25	25	0.0896	0.0924	1.6944	22
50	25	0.0887	0.0908	1.6685	29
75	25	0.0894	0.0903	1.672	16
100	25	0.1015	0.1507	2.5816	3
25	50	0.0917	0.1019	1.8387	16
25	75	0.0899	0.0899	1.787	21
25	100	0.0897	0.099	1.801	19

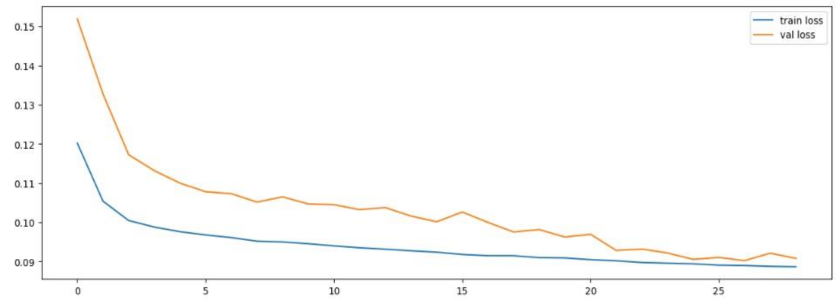

Figure 5. The best LSTM model (t+12) plots

Table 3 and Figure 5 show the evaluation results of the LSTM model (t+12) above, which has an epoch range between 3 and 29. The smallest RSME value of 1.66 uses 50 nodes in the first layer and 25 in the second layer with an epoch of 29. The highest RSME value is 2.58 using 100 nodes in the first layer and 25 in the second layer in epoch 3. Based on the analysis and evaluation results above, the LSTM model with the best RSME score for the next 12 hours is forecast based on the lowest RSME value of 50 nodes for the first layer and 25 for the second layer at epoch 29.

Secondly, the result for GRU with t after 12 hours is shown in Table 4 and Figure 6.

Table 4. Selection of the number of hidden layer nodes GRU (t+12)

LAYER1	LAYER2	loss	value loss	RMSE	epoch
25	25	0.0928	0.0994	1.7864	18
50	25	0.0935	0.0981	1.7743	18
75	25	0.0905	0.0874	1.6232	25
100	25	0.0939	0.1007	1.8231	12
25	50	0.0907	0.0967	1.7542	23
25	75	0.0898	0.0959	1.7659	28
25	100	0.0882	0.0932	1.7098	24

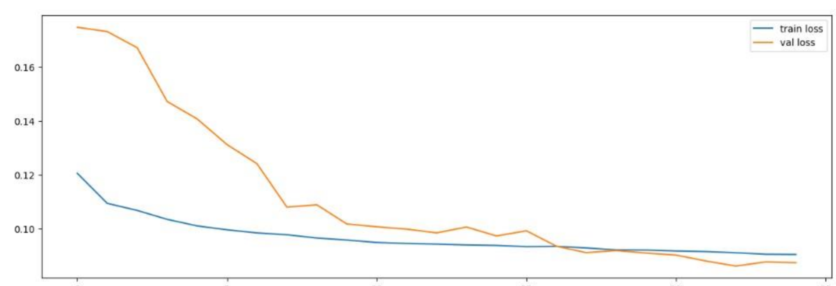

Figure 6. The best GRU model (t+12) plots

Based on Table 4 and Figure 6 above, the study for the GRU architecture (t+12) has an epoch range between 12 to 28, with the lowest RSME value of 1.62 at epoch 25 using 75 nodes in the first layer and 25 nodes in the second layer. For the highest RSME value of 1.82 in epoch 12, 100 nodes in the first and 25 nodes in the second layers are used. Based on the analysis and evaluation above, the best GRU model with the lowest RSME value in the next 12 hours is 1.62 at epoch 25, using 75 nodes in the first layer and 25 nodes in the second layer.

Thirdly, the result for BiLSTM with t after 12 hours is shown in Table 5 and Figure 7.

Table 5. Selection of the number of hidden layer nodes BiLSTM (t+12)

LAYER1	LAYER2	loss	value loss	RMSE	epoch
25	25	0.0884	0.095	1.7442	12
50	25	0.0899	0.0925	1.7116	7
75	25	0.0915	0.0968	1.7598	6
100	25	0.0892	0.0959	1.7544	8
25	50	0.0886	0.0914	1.6886	11
25	75	0.0865	0.09	1.6608	7
25	100	0.0875	0.0884	1.6399	13

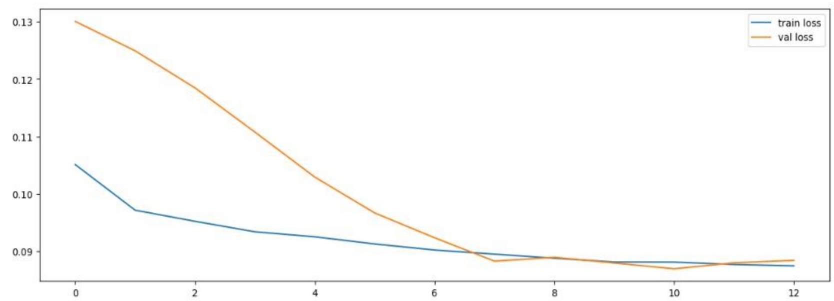

Figure 7. The best BiLSTM model (t+12) plots

Table 5 and Figure 7 above exhibit the BiLSTM architecture model's tuning for the next 12 hours forecast using an epoch range of 6 to 13. Using 25 nodes in the first layer and 100 nodes in the second layer with an epoch of 13, the lowest RSME score of 1.63 With 25 in the second layer in epoch 6 and 75 nodes in the first layer, the most excellent RSME score of 1,759 is obtained. With 25 nodes in the first layer and 100 nodes in the second, 1.63, the best BiLSTM model for (t+12), based on the study above and assessment, has the lowest RSME value.

Fourthly, the result for LSTM with t after 24 hours is shown in Table 6 and Figure 8.

Table 6. Selection of the number of hidden layer nodes LSTM (t+24)

LAYER1	LAYER2	loss	value loss	RMSE	epoch
25	25	0.0961	0.1109	1.9494	17
50	25	0.1022	0.1383	2.3739	3
75	25	0.1026	0.1396	2.3905	3
100	25	0.0926	0.0985	1.7728	25
25	50	0.0927	0.1014	1.8119	19
25	75	0.0939	0.1051	1.8686	12

25	100	0.0899	0.1005	1.8122	33

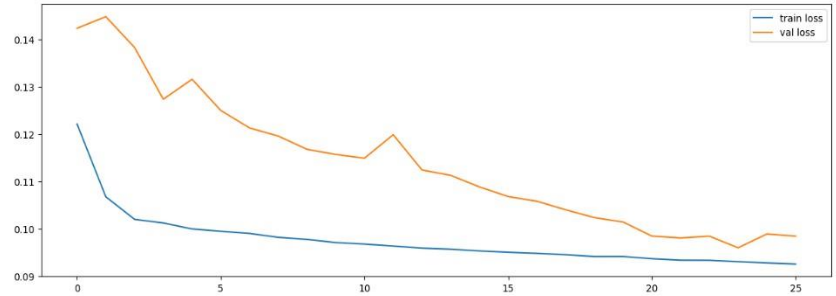

Figure 8. The best LSTM model (t+24) plots

Using 100 nodes in the first layer and 25 nodes in the second layer at epoch 25, Table 6 and Figure 8 indicate the LSTM architecture model training for the next 24 hours wind speed forecast utilizes epochs in the range of 3 to 33 with the lowest RSME value of 1.77. At epoch 3 of 2.39, with 75 nodes in the first layer and 25 in the second, the most excellent RSME value is thus at Based on the preceding analysis and assessment, employing 100 nodes in the first layer and 25 nodes in the second layer at epoch 25, the best LSTM model for the next 24 hours predicted with the lowest RSME value of 1.77.

Fifthly, the result for GRU with t after 24 hours is shown in Table 7 and Figure 9.

Table 7. Selection of the number of hidden layer nodes GRU (t+24)

LAYER1	LAYER2	loss	value loss	RMSE	epoch
25	25	0.0939	0.1023	1.8298	18
50	25	0.094	0.0989	1.78	24
75	25	0.0945	0.1037	1.855	16
100	25	0.095	0.0983	1.7707	20
25	50	0.0938	0.1078	1.9143	14
25	75	0.0914	0.1002	1.7994	27
25	100	0.0912	0.1024	1.8373	23

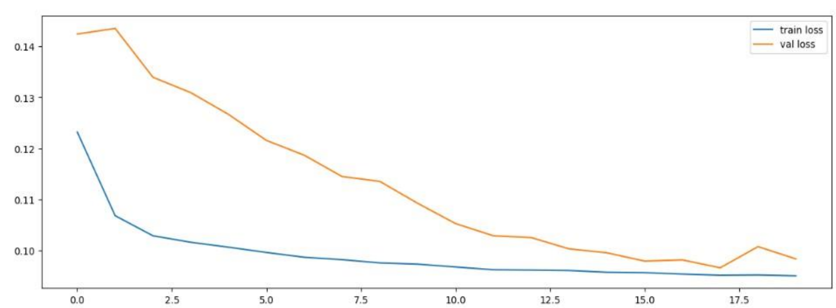

Figure 9. The best GRU model (t+24) plots

In Table 7 and Figure 9 above, the GRU model training process for the next 24 hours forecast has an epoch range of 14 to 24 with the lowest RSME value of 1.77 in epoch 20 using 100 nodes in the first layer and 25 nodes in the second layer. Then, the highest value is 1.91 in epoch 14, with 25 nodes in the first layer and 50 in the second layer. Based on the analysis and evaluation of the table above, the best GRU model for the next 24 hours forecast has the lowest RSME value of 1.77 at epoch 20, using 100 nodes in the first layer and 25 nodes in the second layer.

Table 8 and Figure 10 show the last result for BiLSTM with t after 24 hours.

Table 8. Selection of the number of hidden layer nodes BiLSTM (t+24)

LAYER1	LAYER2	loss	value loss	RMSE	epoch
25	25	0.0919	0.1009	1.8051	13
50	25	0.091	0.1047	1.8763	16
75	25	0.0907	0.0993	1.7946	17
100	25	0.0914	0.1016	1.8244	15
25	50	0.0908	0.0976	1.8244	13
25	75	0.0904	0.1023	1.8369	14
25	100	0.0901	0.1011	1.8293	12

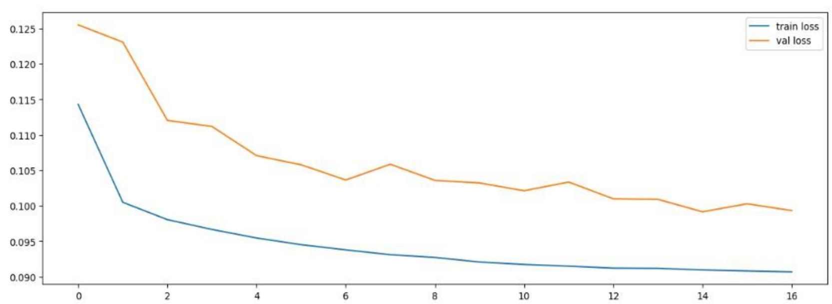

Figure 10. the best BiLSTM model (t+24) plots

According to Table 8 and Figure 10, the BiLSTM model training procedure for the following 24 hours will consist of epochs 12 to 17, with the lowest RSME value of 1.79 in epoch 17, employing 75 nodes in the first layer and 25 nodes in the second layer. The maximum value is 1.87 in epoch 16, with 50 nodes in the first and 25 in the second layers. Based on the analysis and assessment of the table above, the best BiLSTM model for the next 24 hours is expected to have the lowest RSME value of 1.79 in epoch 17, with 75 nodes in the first layer and 25 nodes in the second layer.

Comparison of LSTM, GRU, and BiLSTM model evaluation data

Figure 11 compares loss and time steps for 12 and 24 hours in each LSTM, GRU, and BiLSTM.

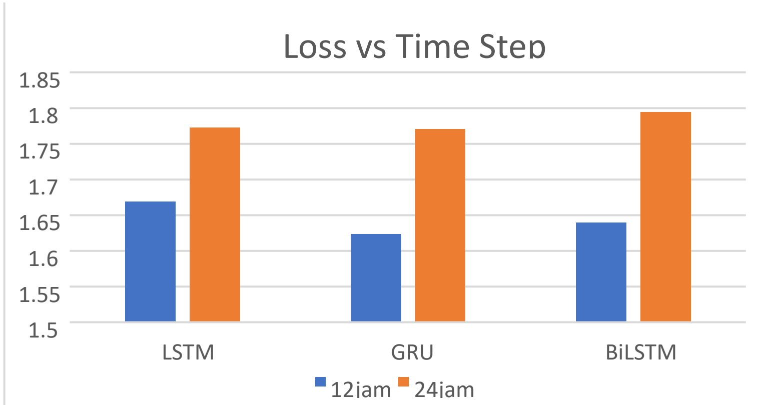

Figure 11. Comparison of 3 deep learning architectures

Figure 11 above shows the best RMSE score in the next 12 and 24 hours. Based on images from each deep learning architecture used. The best score obtained for the next 12-hour step is the GRU architecture with an RMSE value of 1.62, and the best score in the following 24-hour step is the GRU architecture with an RMSE value of 1.77. Based on this study, GRU produces the best value at the time step of the next 12 hours and the next 24 hours compared to the LSTM and BiLSTM architectures at the same time step on the number of datasets for two years with features of five and at one coordinate point.

Conclusions

The experiment was conducted, and the results were collected and compared between three (3) deep learning algorithms: LSTM, GRU, and BiLSTM. The results show that the GRU deep learning architecture has the lowest loss value compared to the LSTM and BiLSTM architectures so that it can produce better wind speed forecasts in the next 12 hours and 24 hours, with RMSE of 1.62 and 1.77, respectively. In this study, GRU scored slightly better at a closer time step. From this study, it can be concluded that GRU has good capabilities when processing smaller datasets.

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