SDU ENERGY INFORMATICS

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Collected Experiment Report: SimpleNN - DeepNN .

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Introduction

This is an automated report for the Experiment with neural networks on traffic volume dataset; the following models have been analyzed:

- SimpleNN
- DeepNN

Experiment description:

Experiment with neural networks on traffic volume dataset

Model setup

The models have been used for the following forecast purposes:

- one_step
- multistep
- recursive

The models have been optimized using the following hyperparameters:

- optimizer: ['adam', 'sgd']
- epochs: [100, 200]
- batch_size: [32, 64]
- scaler: [None, StandardScaler(), MinMaxScaler(), RobustScaler(), PowerTransformer()]

And with the following search algorithms:

- grid
- random

The used performance measure is the neg_mean_absolute_error measure.

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Dataset setup

The baseline dataset used for these forecasts is the 'Metro Interstate Traffic Volume with hourly features and holiday markings.' dataset: *'Metro Interstate Traffic Volume with hourly features and holiday markings.'.*

The test size used for the forecasts is 0.2.

- Dataset 1
  - name: univariate_lagged
  - dataset_type: univariate
  - prediction_type: one_step
  - components: ['one_step_target', 'lagged_target']

- Dataset 2
  - name: univariate_temporal
  - dataset_type: univariate
  - prediction_type: one_step
  - components: ['one_step_target', 'temporal_features']

- Dataset 3
  - name: multivariate_lagged
  - dataset_type: multivariate
  - prediction_type: one_step
  - components: ['one_step_target', 'lagged_target', 'feature_columns']

- Dataset 4
  - name: multivariate_lagged_temporal
  - dataset_type: multivariate
  - prediction_type: one_step
  - components: ['one_step_target', 'temporal_features', 'feature_columns', 'lagged_target']

- Dataset 5

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- name: univariate_lagged_multistep
- dataset_type: univariate
- prediction_type: multistep
- components: ['multistep_target', 'lagged_target']

○ Dataset 6

- name: multivariate_lagged_temporal_multistep
- dataset_type: multivariate
- prediction_type: multistep
- components: ['multistep_target', 'temporal_features', 'feature_columns', 'lagged_target']

Results

For the models; SimpleNN, DeepNN, the following models and datasets yielded the best results.

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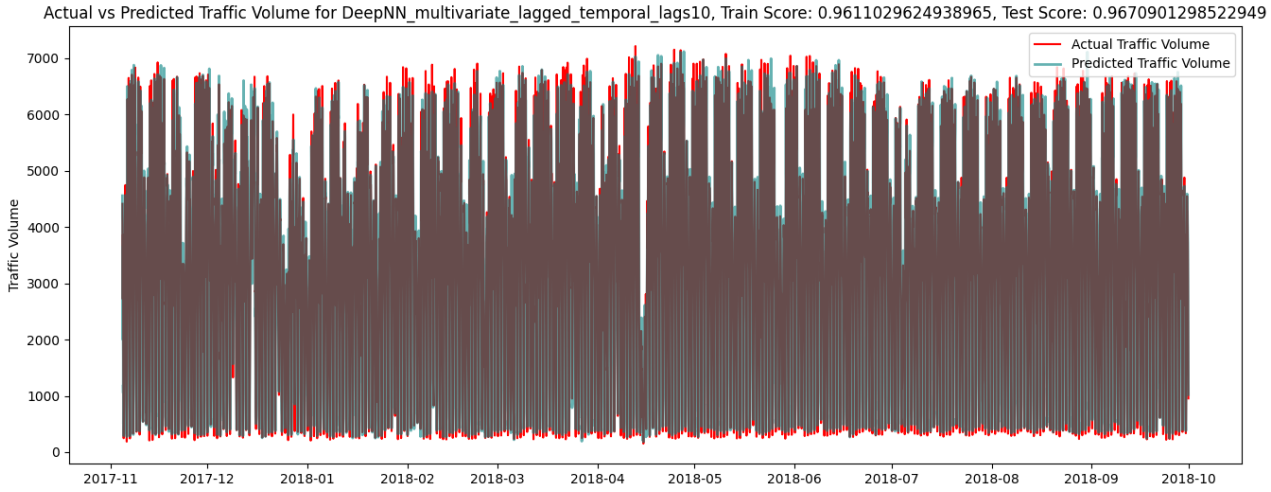
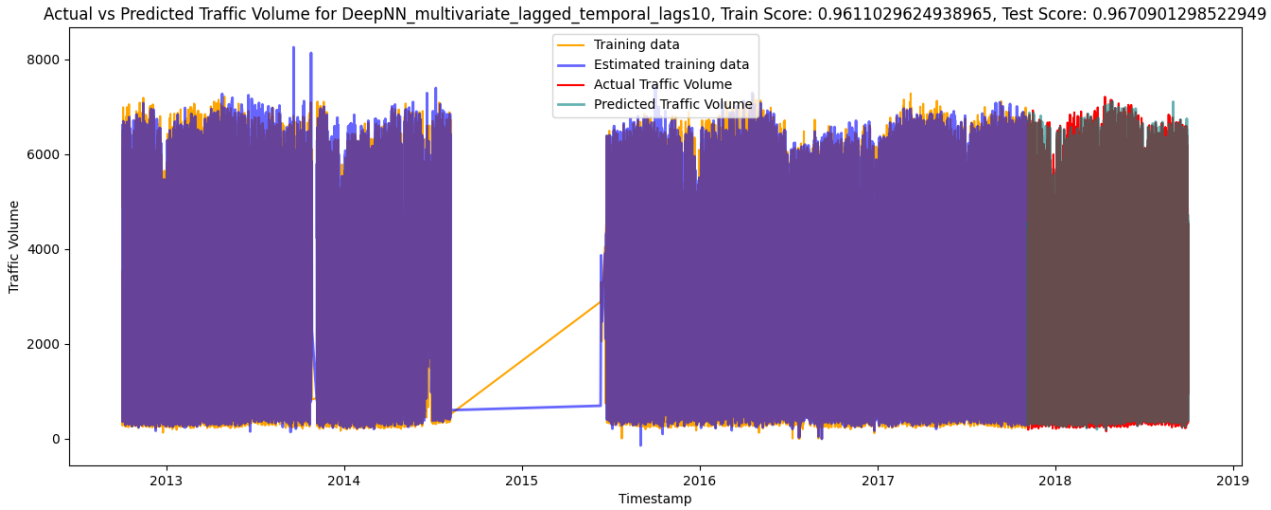
The best model for one_step forecasting.

The best model for one_step forecasting is the DeepNN model.
The model has been trained on the multivariate_lagged_temporal_lags10 dataset.

The best score for the one_step forecasting is 0.9670901298522949.

Best DeepNN forecast over time





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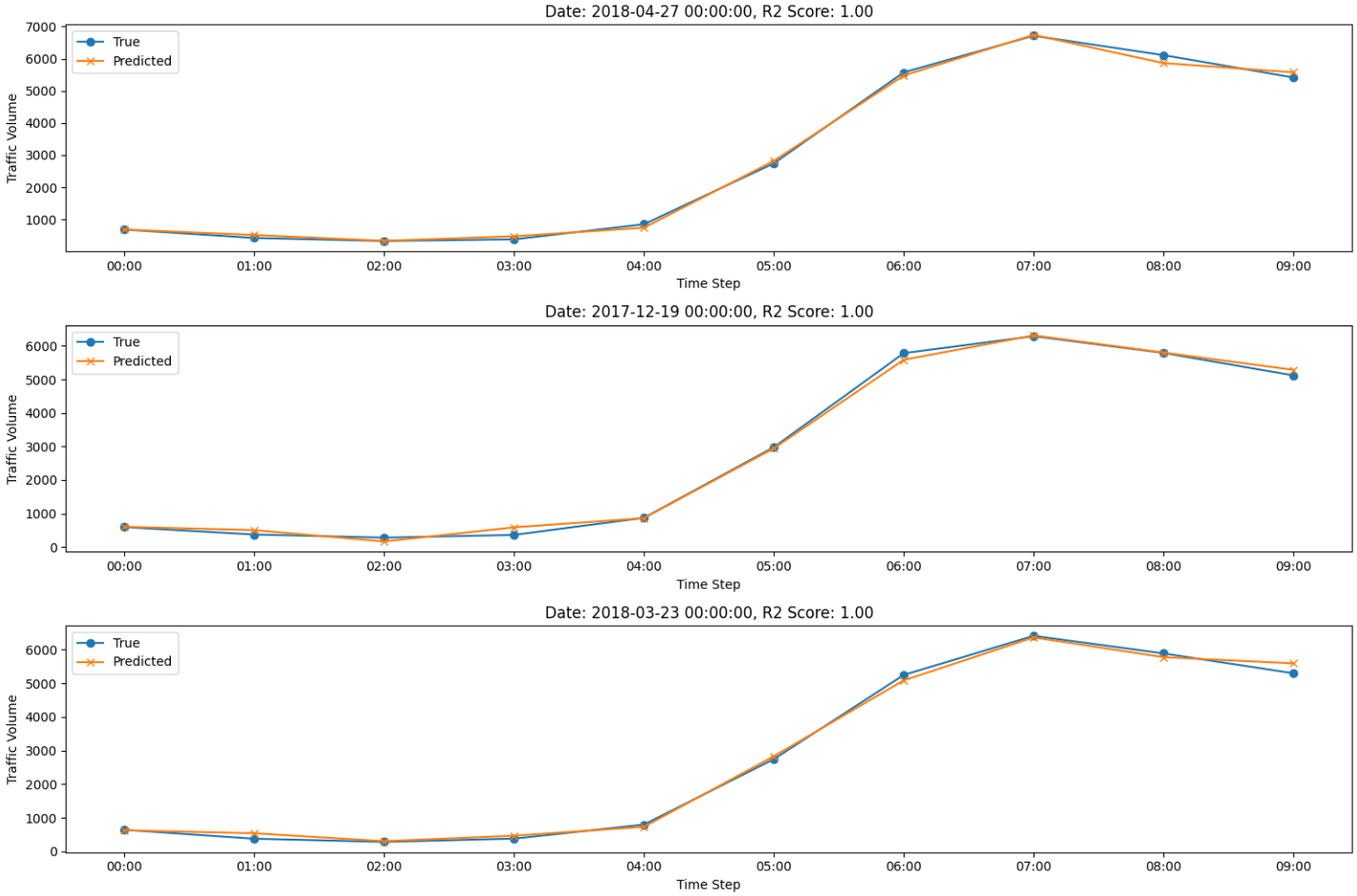
The best model for multistep forecasting.

The best model for multistep forecasting is the DeepNN model.
The model has been trained on the multivariate_lagged_temporal_multistep_lags10_steps10 dataset.

The best score for the multistep forecasting is 0.8332775235176086.

Best predicted days for DeepNN.



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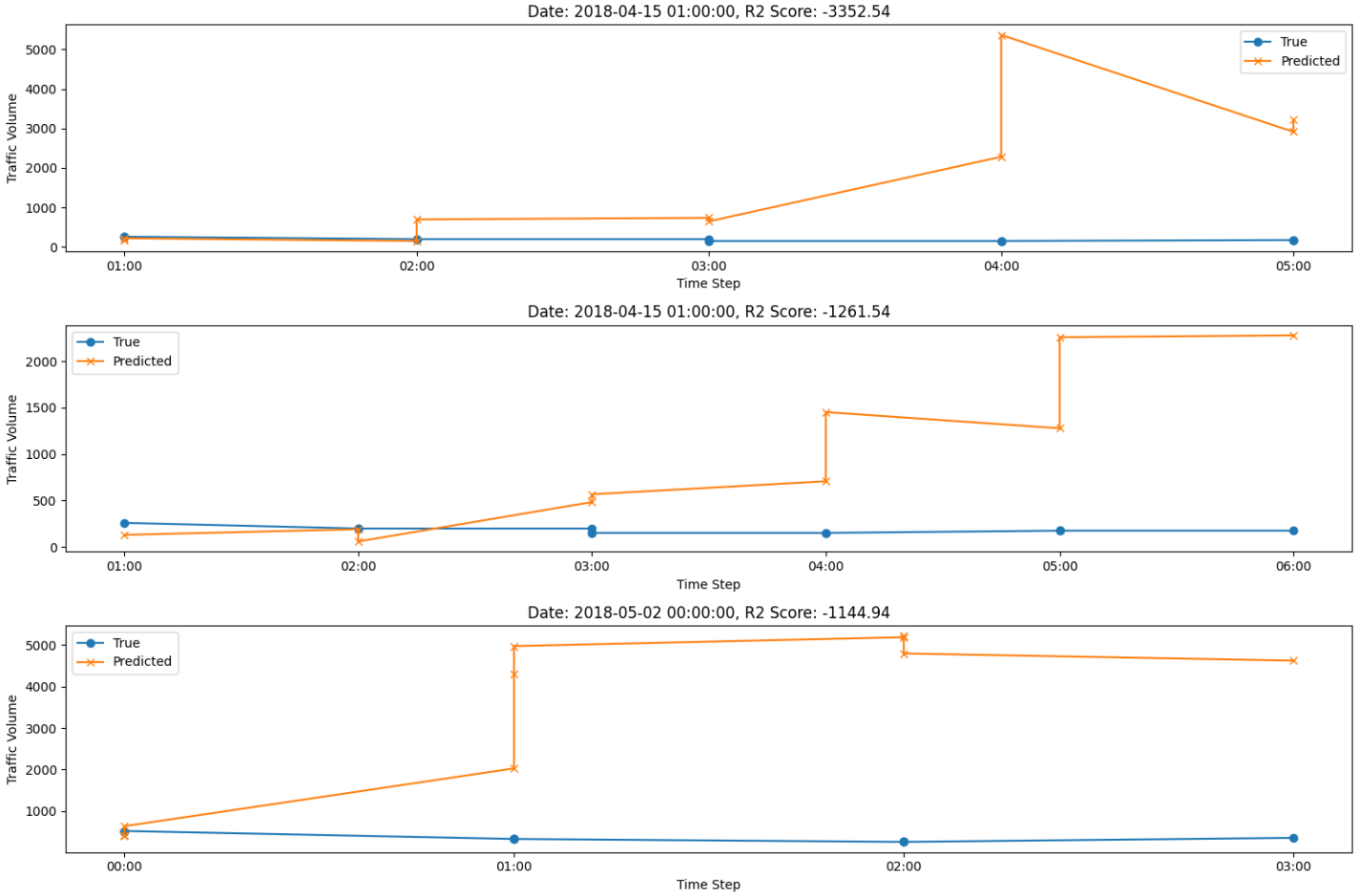
Worst predicted days for DeepNN.



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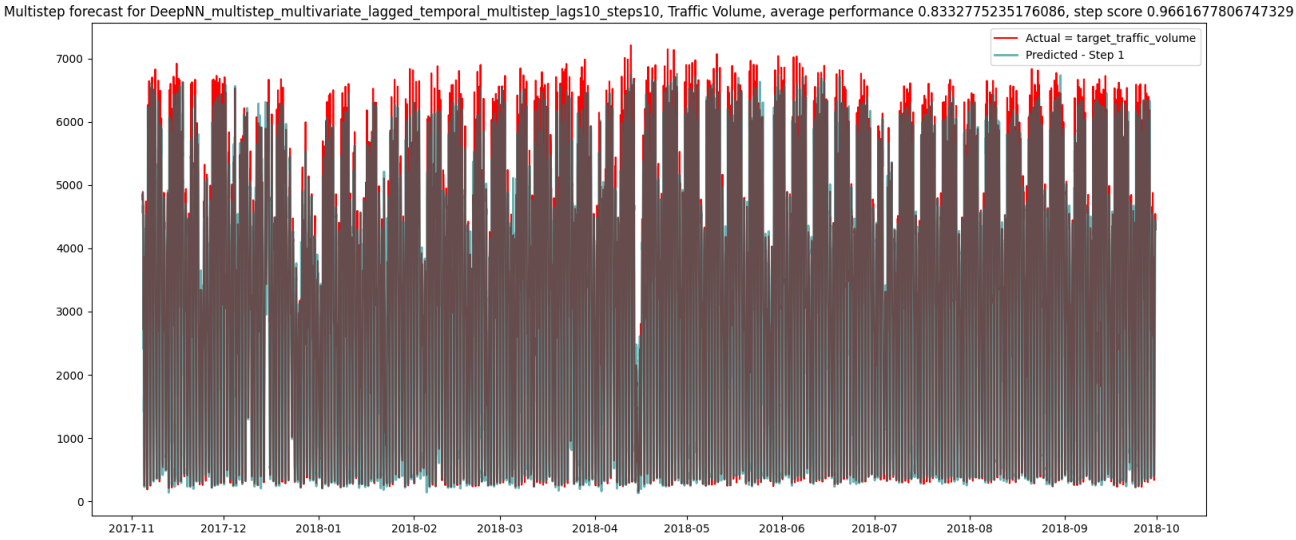
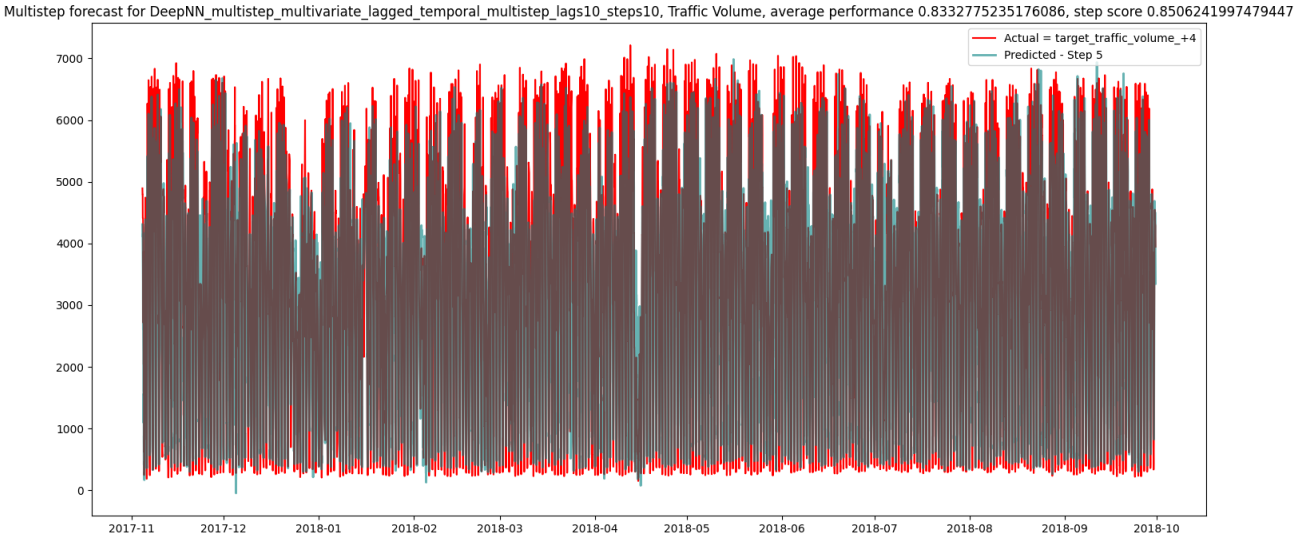
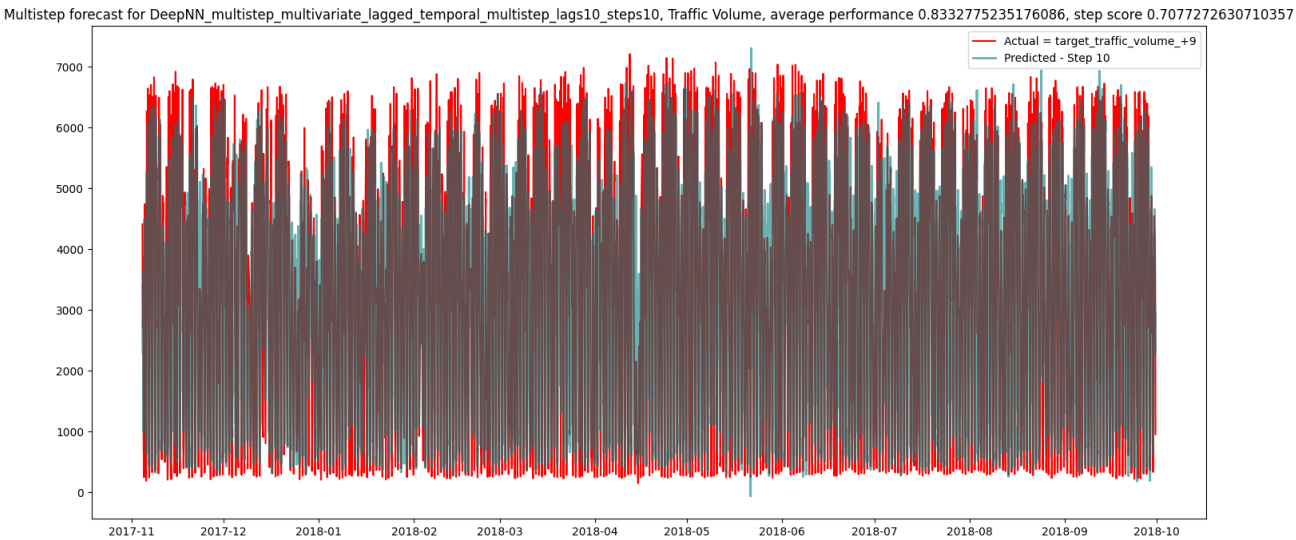
Steps plots for DeepNN forecasts over time







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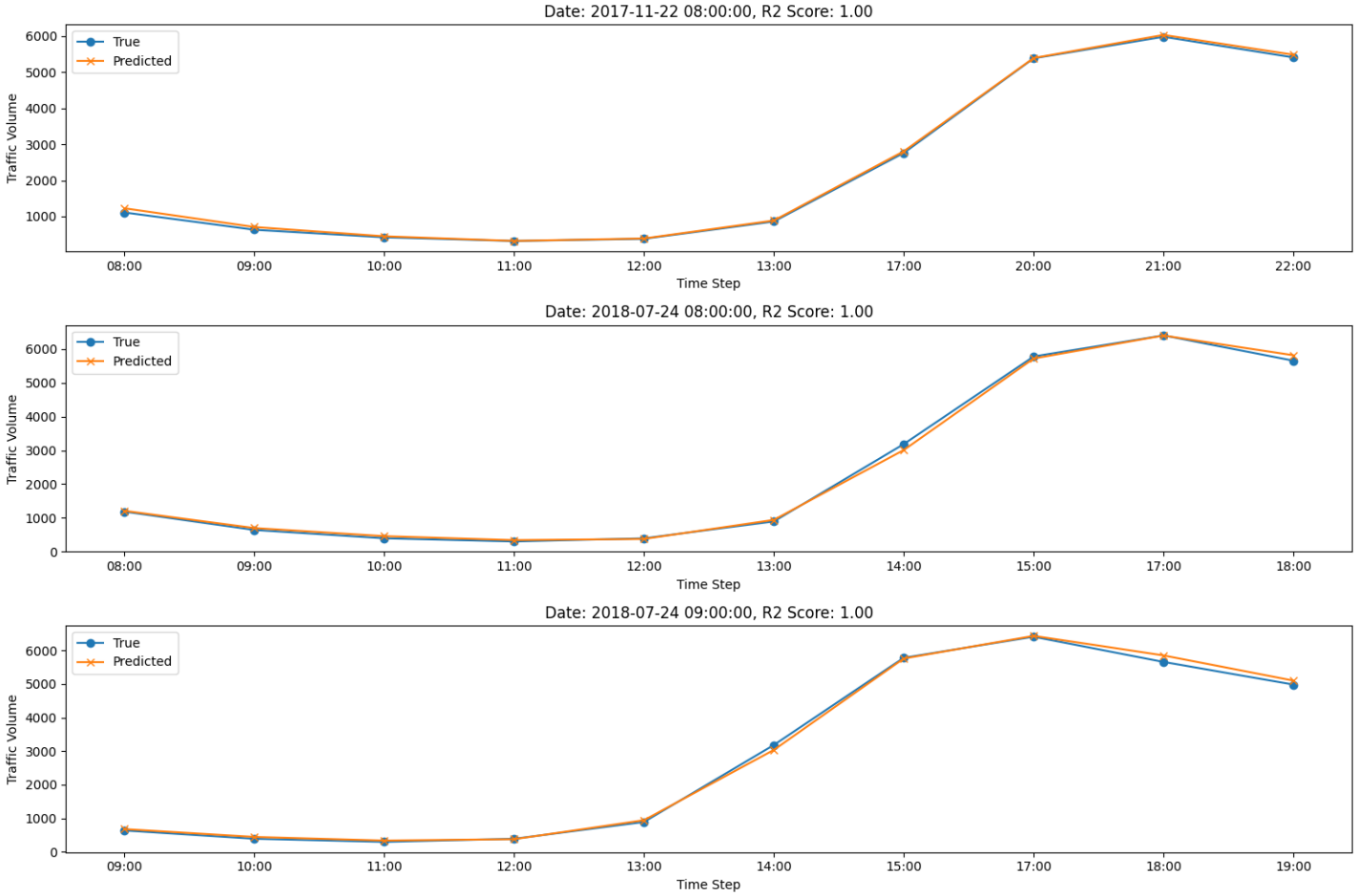
The best model for recursive forecasting.

The best model for recursive forecasting is the DeepNN model.
The model has been trained on the multivariate_lagged_temporal_lags10 dataset.

The best score for the recursive forecasting is 0.7752858400344849.

Best predicted days for DeepNN.



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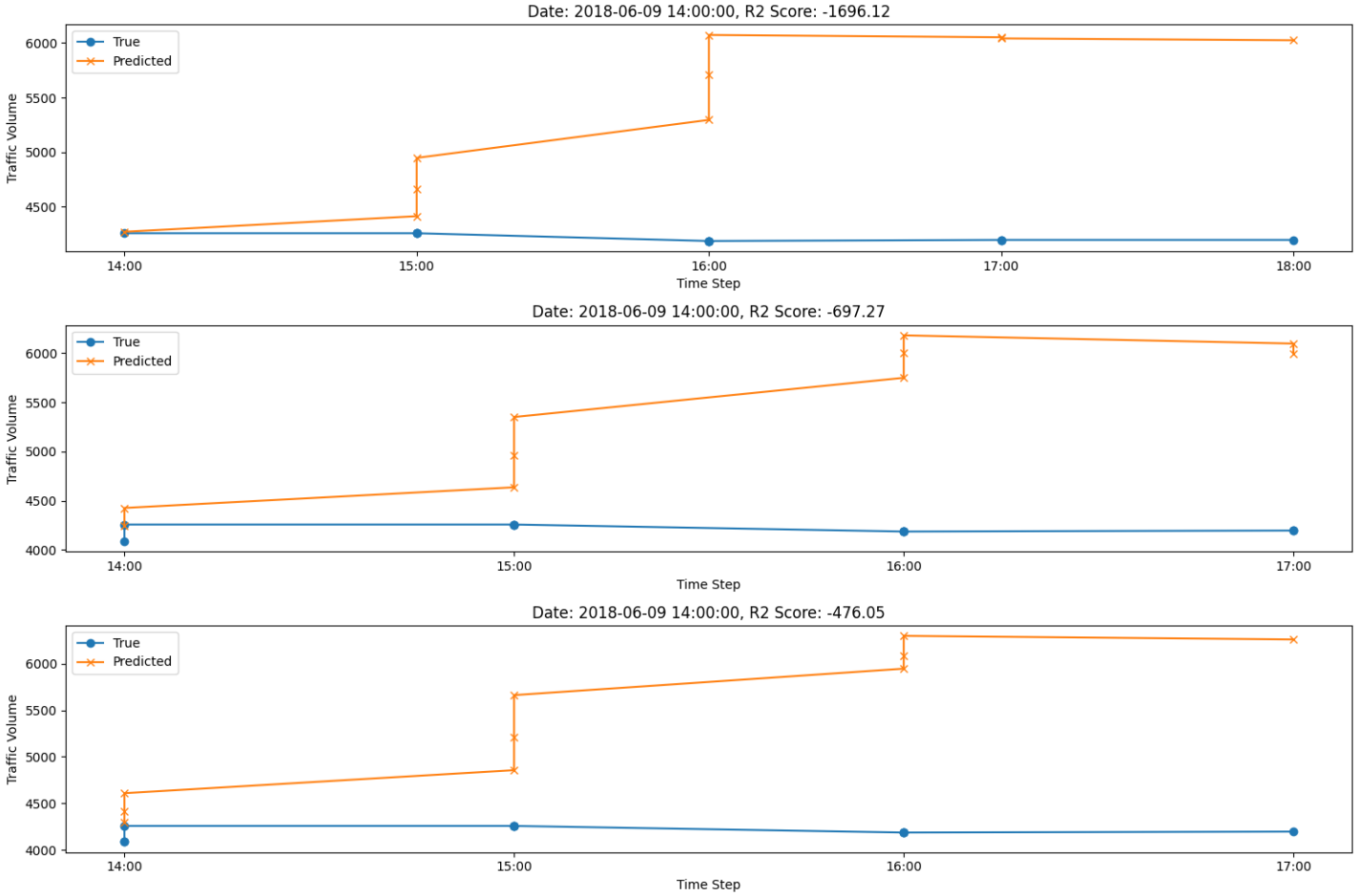
Worst predicted days for DeepNN.



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Steps plots for DeepNN forecasts over time