
Design Project EEE F377

AI in Renewable Energy Forecasting

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Introduction

Photovoltaic (PV) Energy Generation:

- The process of converting sunlight directly into electricity using photovoltaic cells

Importance of forecasting Photovoltaic Energy Generation:

- Grid Stability and Management
- Cost Efficiency and Profitability
- Enhanced Integration of Renewable Energy

Problem Statement

- > Accurately forecasting PV energy generation is challenging due to the variability of solar resources
- > To develop and analyze hybrid deep learning model that combines multiple forecasting techniques to improve the accuracy of short-term PV energy predictions
- > Leverage historical weather and solar data to later utilize the developed model on real-time data

Literature Review

Models used	Data Used	Benefits	Disadvantages	Results
Multi-level fusion and self-attention transformer-based model	<ul style="list-style-type: none">• 2 years data• Power generation data• toal consumption• Key weather features	<ul style="list-style-type: none">• Can perform better even with missing data in most important features• Can capture complex patterns and generalize well	<ul style="list-style-type: none">• 100% probability dropout layer - constraint the model ability to generalize to anomalies in data	<ul style="list-style-type: none">• RMSE: 0.0460• MAE: 0.0245
WPD-LSTM-CNN	<ul style="list-style-type: none">• 4 months data• Power gen. and wind speed	<ul style="list-style-type: none">• Better generalizability to outliers	<ul style="list-style-type: none">• Random initialization could lead the model to converge to suboptimal solutions	<ul style="list-style-type: none">• MAE: 40.6• RMSE: 79.6• MSE: 6336.4• R2: 0.99
LSTM-Convolutional encoder	<ul style="list-style-type: none">• 1 year data• Active power• Temp, humidity, wind speed, GHI, DHI	<ul style="list-style-type: none">• Can process long durational input sequences• High accuracy in all forecasting categories	<ul style="list-style-type: none">• High computational complexity	<ul style="list-style-type: none">• MAE: 0.217• RMSE: 0.602

GHI: Global Horizontal Irradiance; DHI: Diffuse Horizontal Irradiance

Literature Review

Models used	Data Used	Benefits	Disadvantages	Results
BiLSTM	<ul style="list-style-type: none">• Battery Type• Ambient Temperature• Charge Cycles	<ul style="list-style-type: none">• Can perform better even with missing data in most important features• Can capture complex patterns and generalize well	<ul style="list-style-type: none">• 100% probability dropout layer - constraint the model ability to generalize to anomalies in data	<ul style="list-style-type: none">• RMSE: 0.0460• MAE: 0.0245
GBDT-BiLSTM	<ul style="list-style-type: none">• Historical PV generation• Total Irradiation• Temp., humidity, pressure, precipitation, wind speed	<ul style="list-style-type: none">• Solves the problem of time scale limitations• Reduces cumulative errors• Solves vanishing gradient problem	<ul style="list-style-type: none">• May have difficulties with longer forecast horizons• Hourly update constraint with Teacher Forcing	<ul style="list-style-type: none">• MAE: 0.112• MSE: 0.141• MASE: 0.102

Data Used

> 3 months historical energy + solar + weather data (May, June, July) is used for training and testing the models

> Key features include:

- Energy delta
- Global Horizontal Irradiance
- Temperature
- Pressure
- Humidity

	Energy delta[Wh]	GHI	temp	pressure	humidity
Time					
2021-05-01 00:00:00	0	0.0	1.9	1016	96
2021-05-01 00:15:00	0	0.0	1.9	1016	96
2021-05-01 00:30:00	0	0.0	1.9	1016	96
2021-05-01 00:45:00	0	0.0	1.9	1016	96
2021-05-01 01:00:00	0	0.0	2.6	1015	97

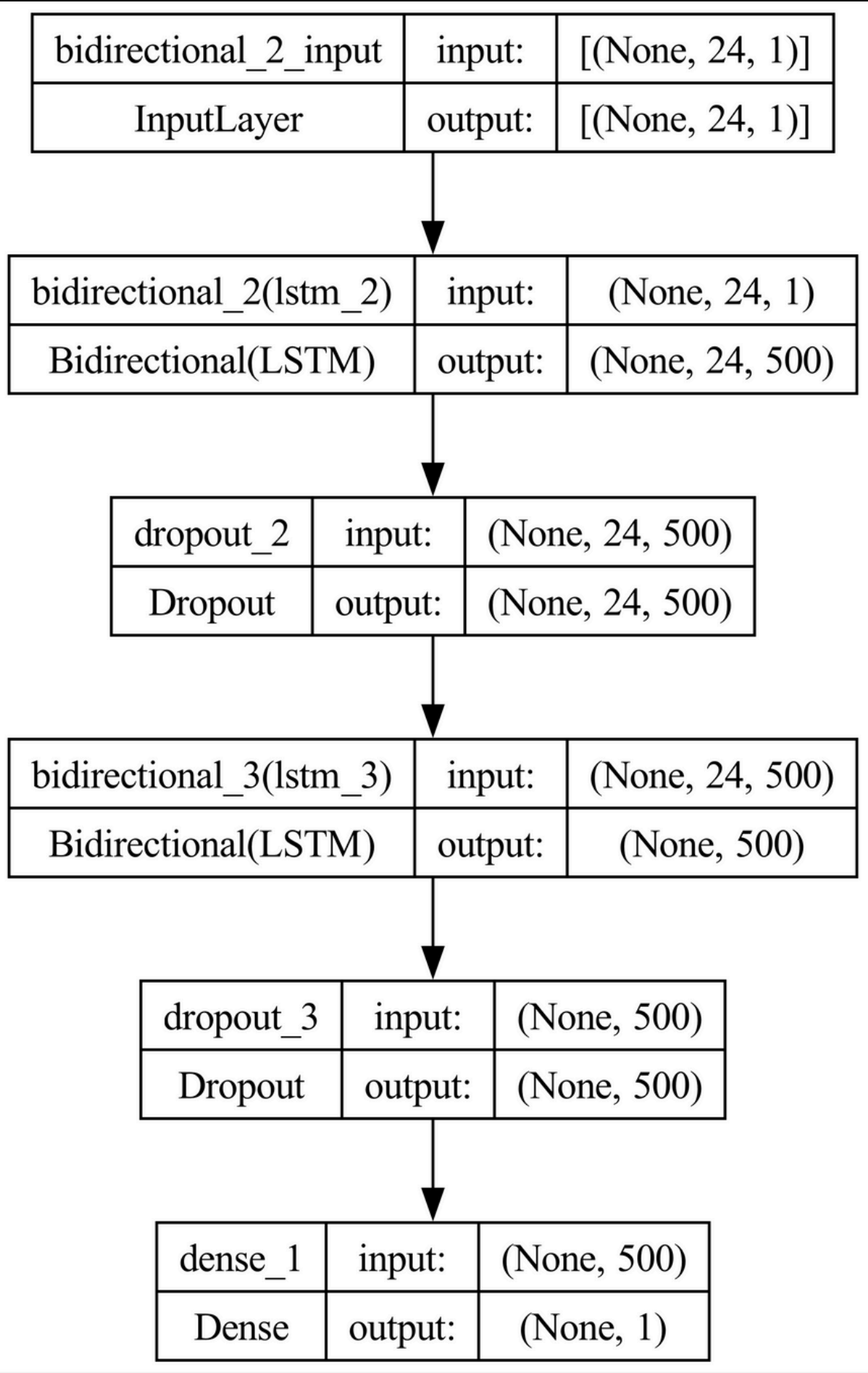
Models Used

BiLSTM model:

- 5 layers architecture (2 Bidirectional LSTM + 2 dropout layers + 1 dense layer)
- Each layer has 250 neurons, functioning on ReLU activation function
- Trained on 10 epochs with batch size of 64
- Mean Squared Error loss function
- Adam optimizer is used for hyperparameter tuning

Teacher Forcing mechanism on 4 hybrid gradient boosting models with BiLSTM:

- > GBDT-BiLSTM
- > XGBoost-BiLSTM
- > CatBoost-BiLSTM
- > LightGBM-BiLSTM



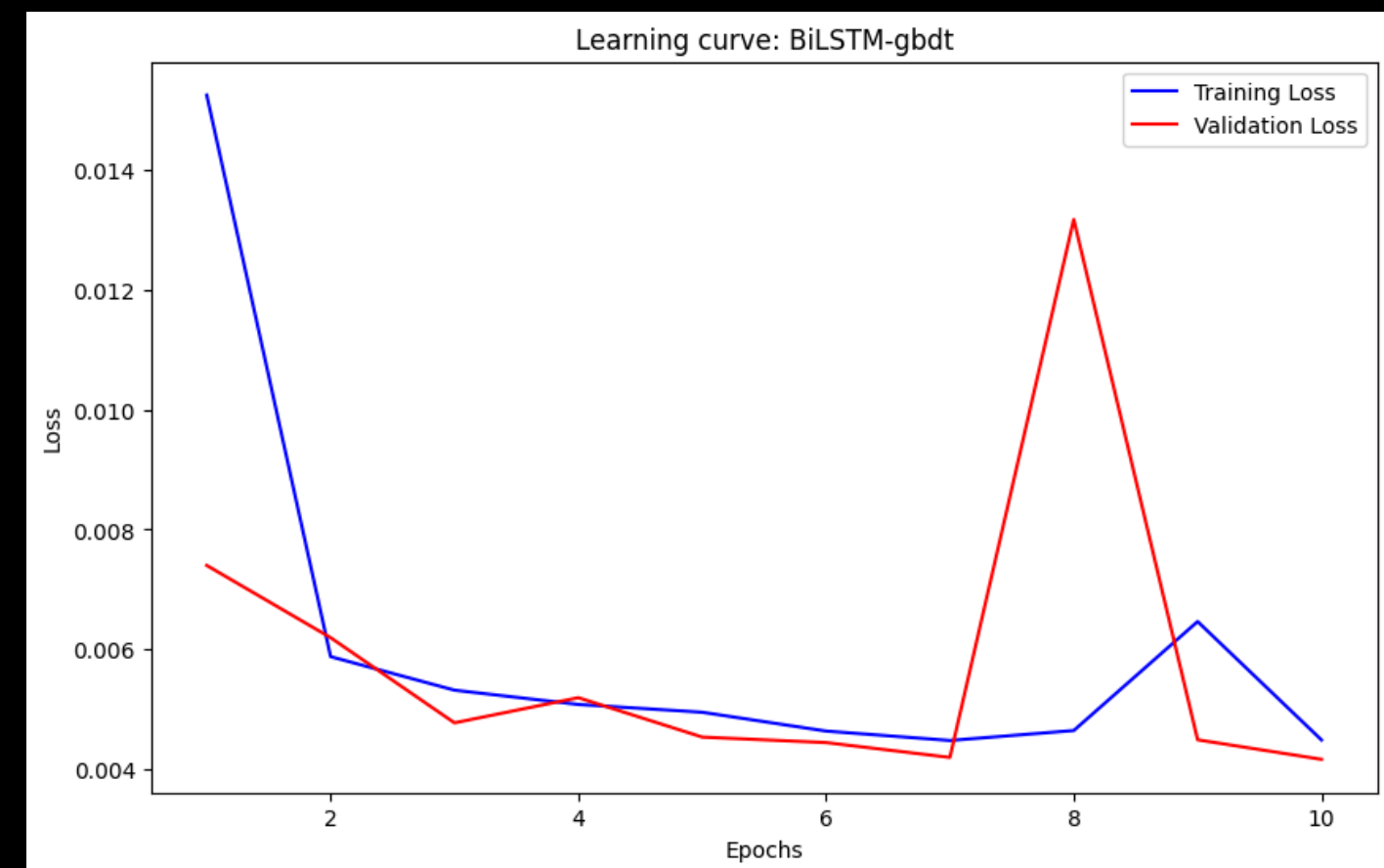
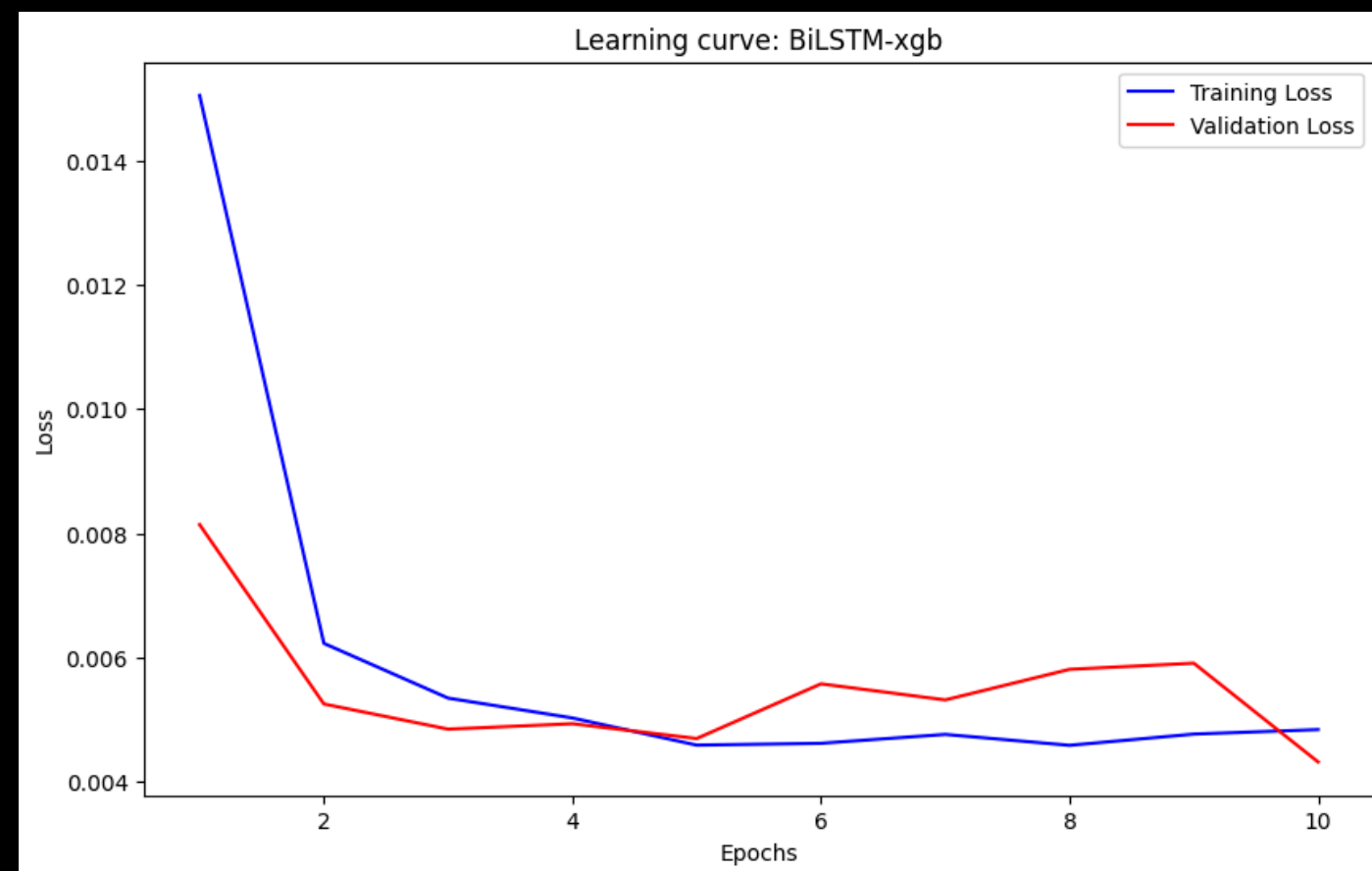
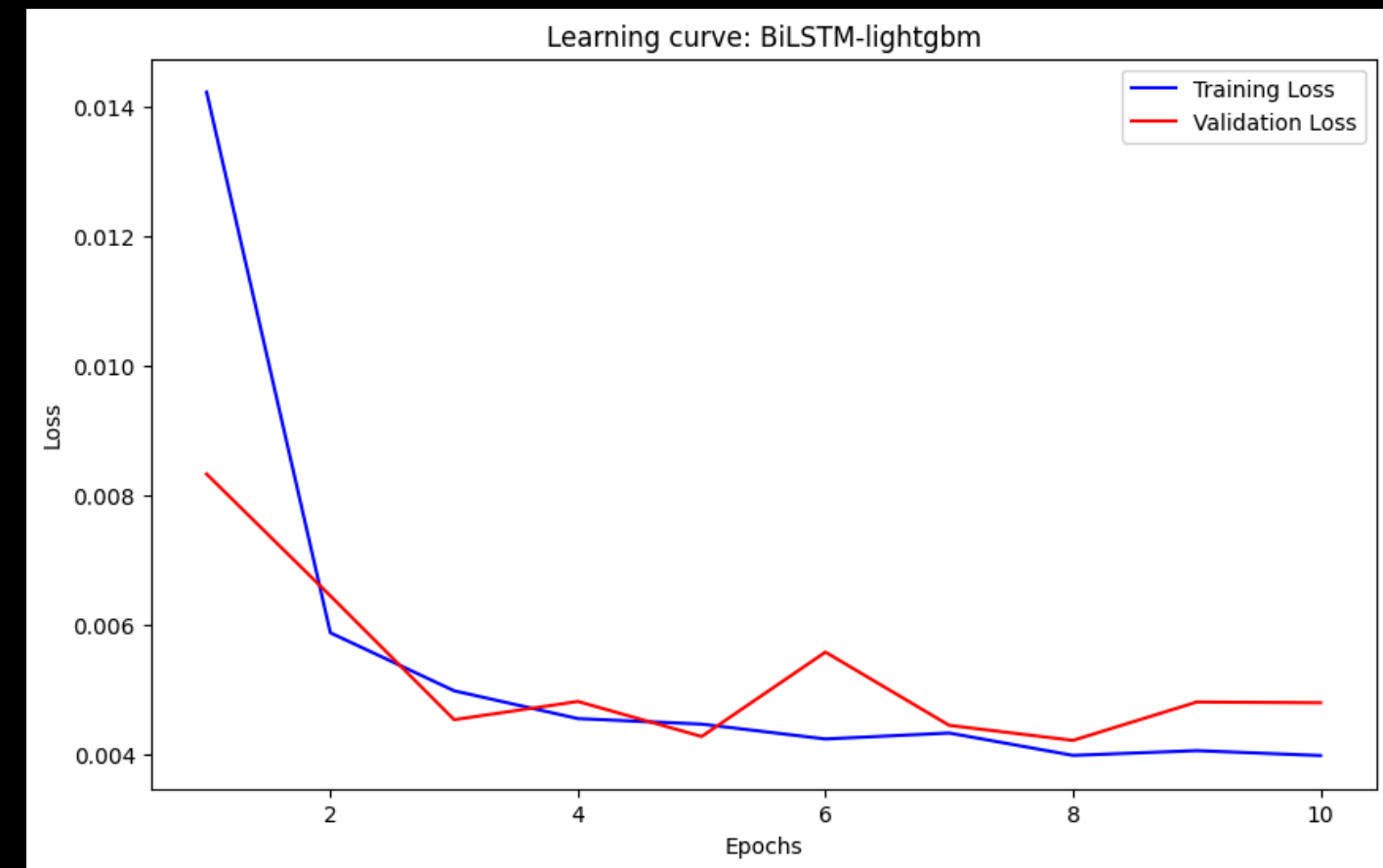
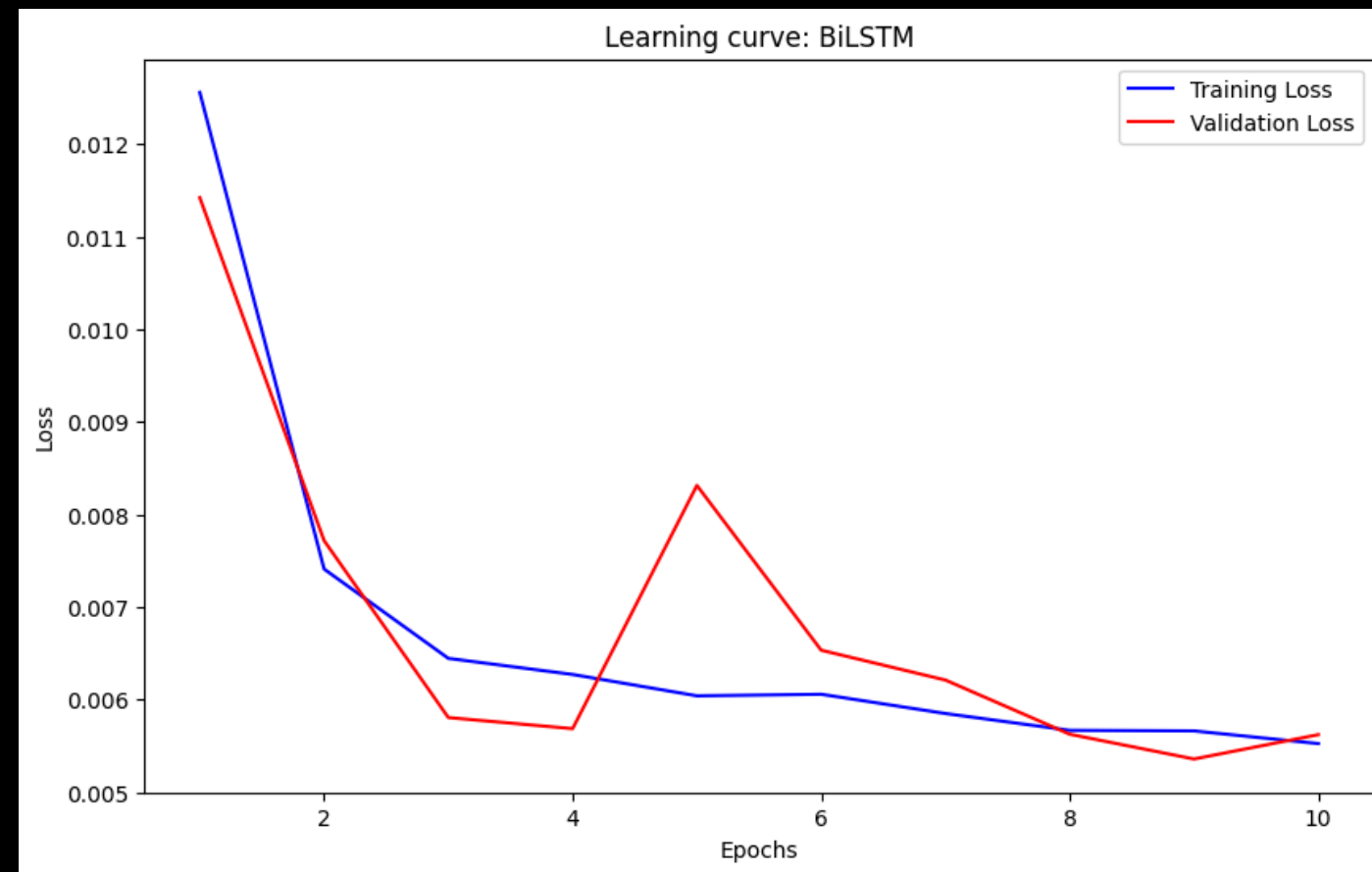
Results using only energy delta + GHI

Model	MAE	MSE	RMSE	R2
BiLSTM	179.264314	122170.675042	349.529219	0.899611
GBDT-BiLSTM	15.6850	669.6340	25.8772	0.9263
XGBoost_BiLSTM	10.8162	441.6858	21.0163	0.9514
CatBoost-BiLSTM	14.0843	610.8645	24.7156	0.9309
LightGBM-BiLSTM	11.0640	447.2854	21.1491	0.9510

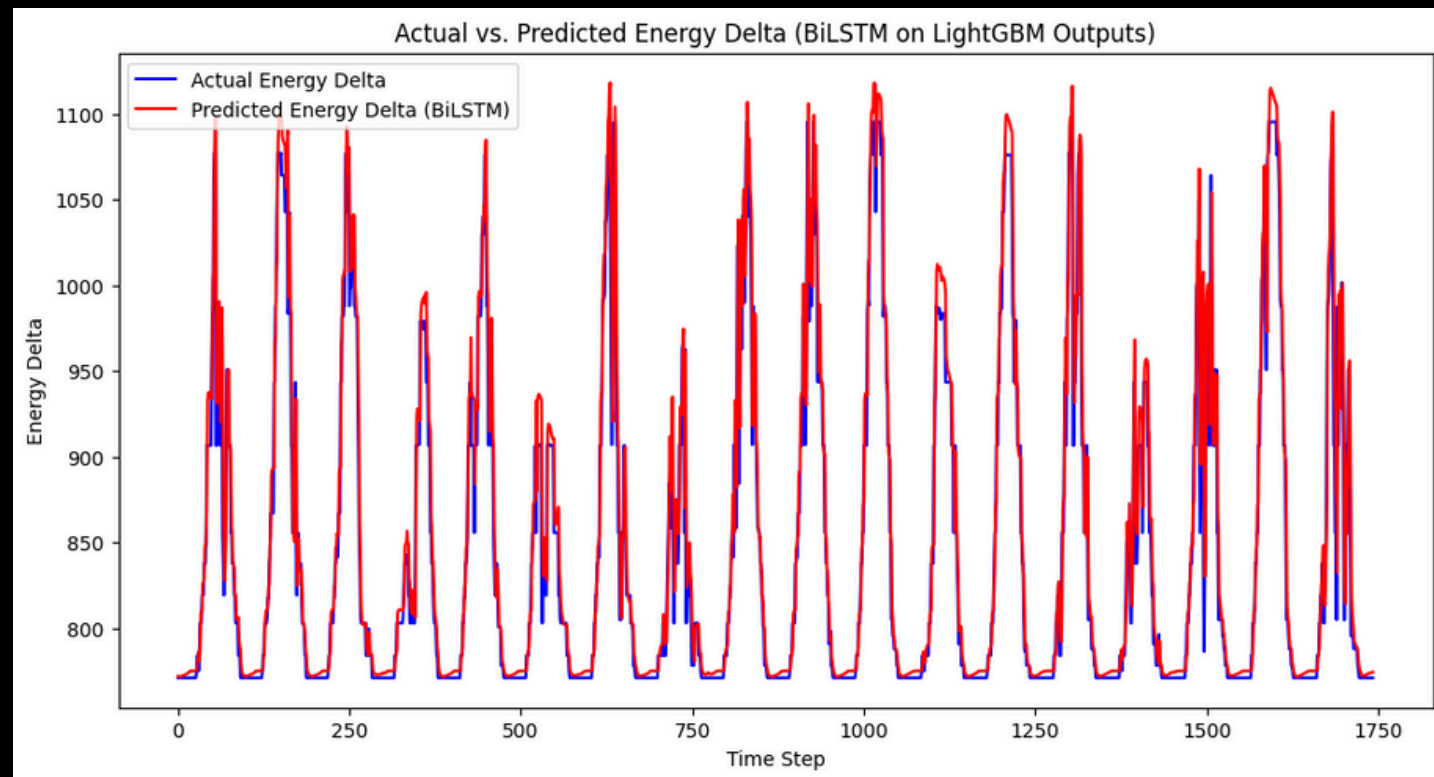
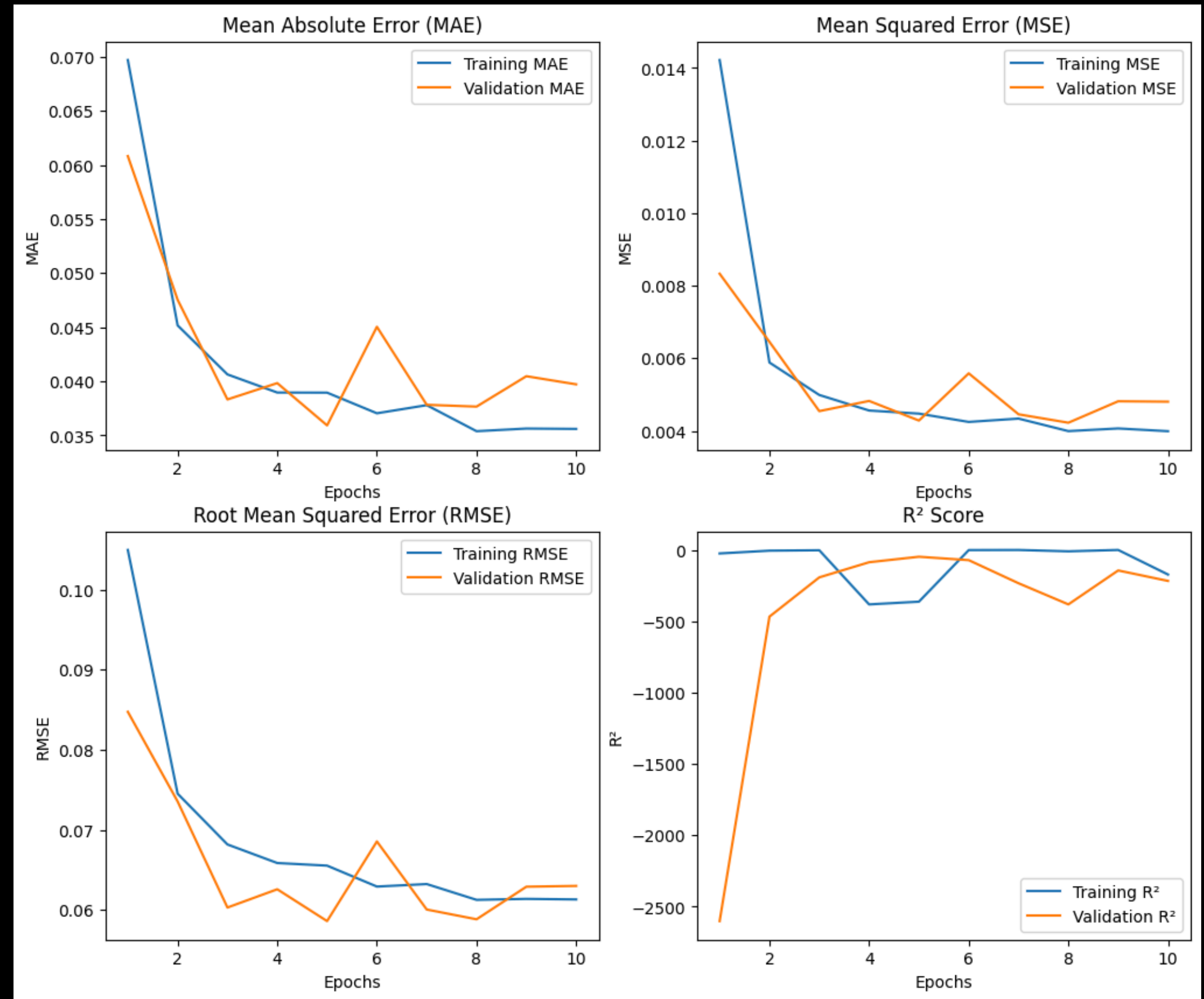
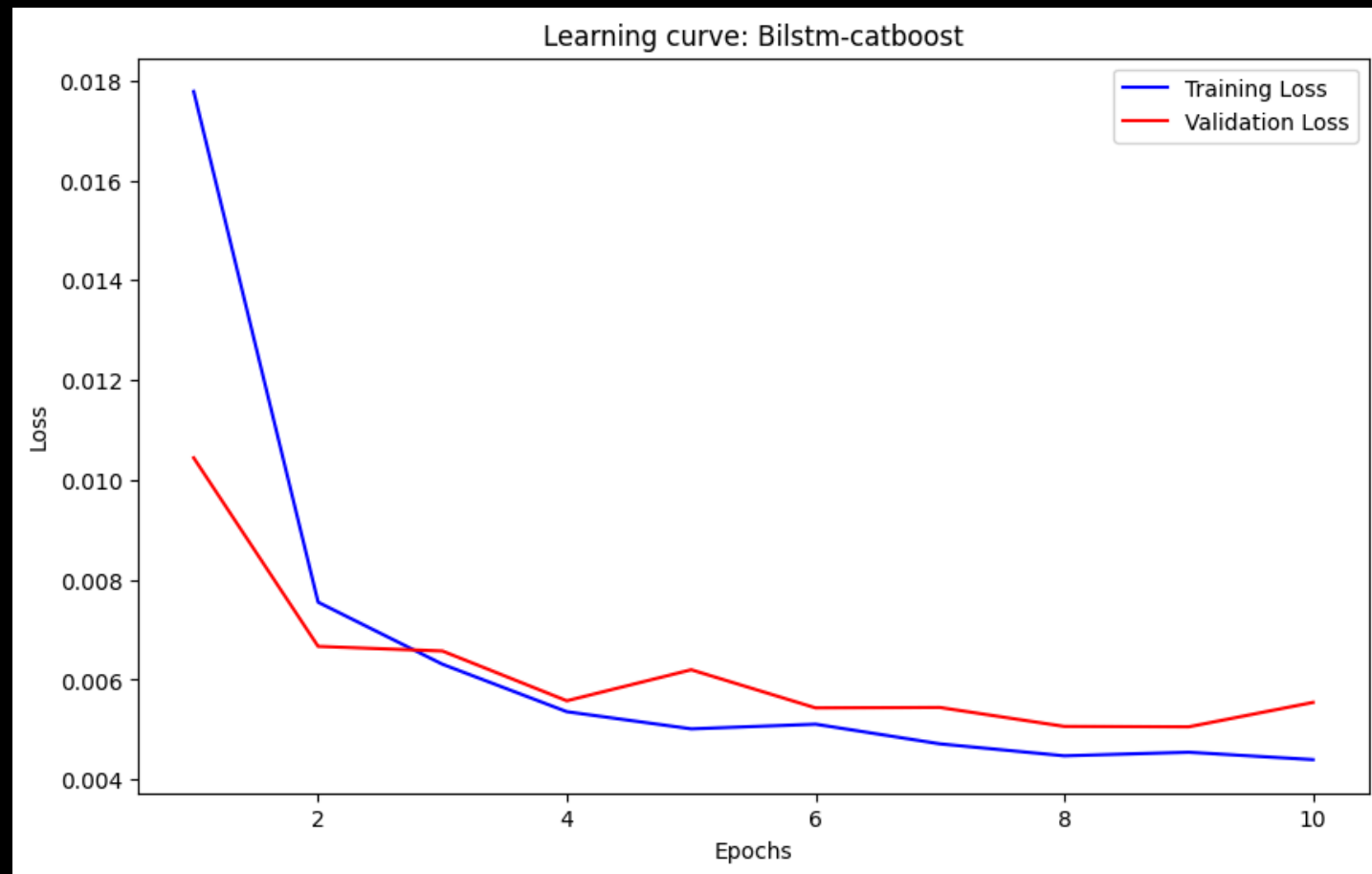
Results after adding weather data

Model	MAE	MSE	RMSE	R2
BiLSTM	179.264314	122170.675042	349.529219	0.899611
GBDT-BiLSTM	14.455092	633.9615	25.178593	0.928841
XGBoost_BiLSTM	12.196121	537.4874	23.183773	0.940582
CatBoost-BiLSTM	11.279689	468.5298	21.645548	0.945520
LightGBM-BiLSTM	13.774397	564.8327	23.766210	0.937324

Learning Curves with all features



Results from CatBoost-BiLSTM





Thank you