ITISE 2022

Fakultät Ingenieurwissenschaften

Limitation of Deep Learning Algorithm for Prediction Power Consumption

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8th International Conference on Time Series and Forecasting, Gran Canaria, Spain, 27–30 10 juin 202

Outline

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2. Deep Learning Algorithms
3. Train Model
4. Simulation and Results
5. Conclusion

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Introduction

Power consumption prediction is a difficult time series forecasting task because power consumption has irregular trend elements.

Prediction power consumption

- Power production planning
- Energy management system
- Take the decision to buy or sale electricity

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Introduction

- Prediction power consumption has been examined using traditional and artificial techniques.

- Statistical methods showed weaknesses in predicting and capturing the nonlinear behavior of energy consumption data.

- Machine learning algorithms suffer greatly from overfitting .

- Are deep learning algorithms able to predict power consumption accurately?

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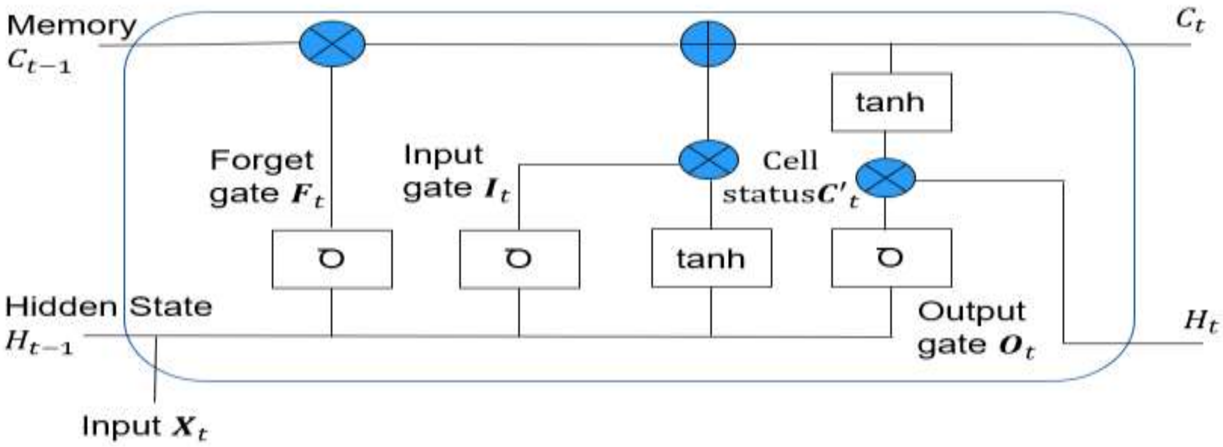
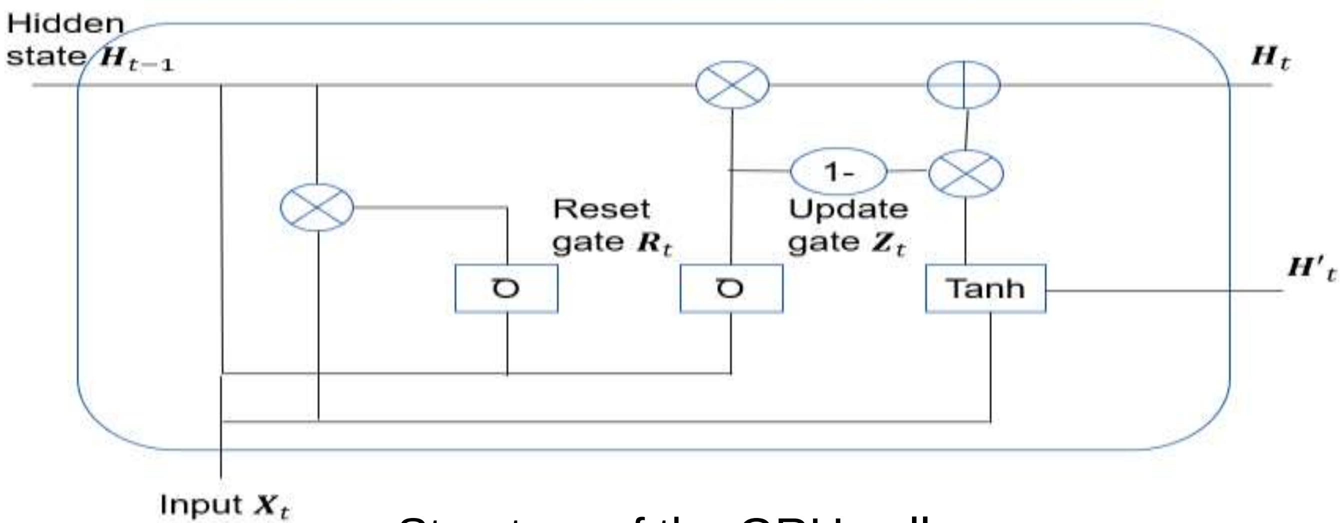
Deep Learning Algorithms



Structure of the LSTM cell

- The complex structure of the LSTM cell finds a solution to the problem of vanishing gradients and disappearance [1].
- The LSTM model has four key elements: input gates, cell status, forget gates and output gates.

Deep Learning Algorithms



Structure of the GRU cell

- GRU architecture has only two gate layers, a reset gate and an update gate[2].
- Update gate checks if the memory of the previous cell remains active.
- Reset gate is used to combine the input sequence of the next cell with the memory of the previous cell.

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Deep Learning Algorithms

Convolutional neural network

- Convolution layer
- Pooling layer
- Fully connected layers

- Convolution layer is the first layer to extract feature map from an input sequence.
- Pooling layer reduce the resolution of the feature map between the hidden layer and the memory cells.
- Fully connected layers combine these feature map together to create a model.

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Train Model

- IHEPC is a household dataset from the UCI machine learning repository[3].
- Measurements of electric power consumption at a one-minute sampling rate over four years.
- It contains more than 2 million values, with a total of around 26,000 missing values.
- 75% of the data is used as a training set and 25% of data is used as a test set.

IHEPC household dataset

Train Model

Known sequence : $[X_{1,} X_2 ,\ldots., X_n , X_{n+1}]$; $\mathrm{n} = 15$

Input sequence :X = $[X_{1,} X_2 ,\ldots., X_n]$

Expected output : Y = $[X_{n+1}]$

- Train our model to predict the $\mathrm{n} + 1$ value of our input sequence

X = $[X_{1,} X_2 ,\ldots., X_n]$ ⟹ Model ⟹ Y' = $[X_{n+1}]$

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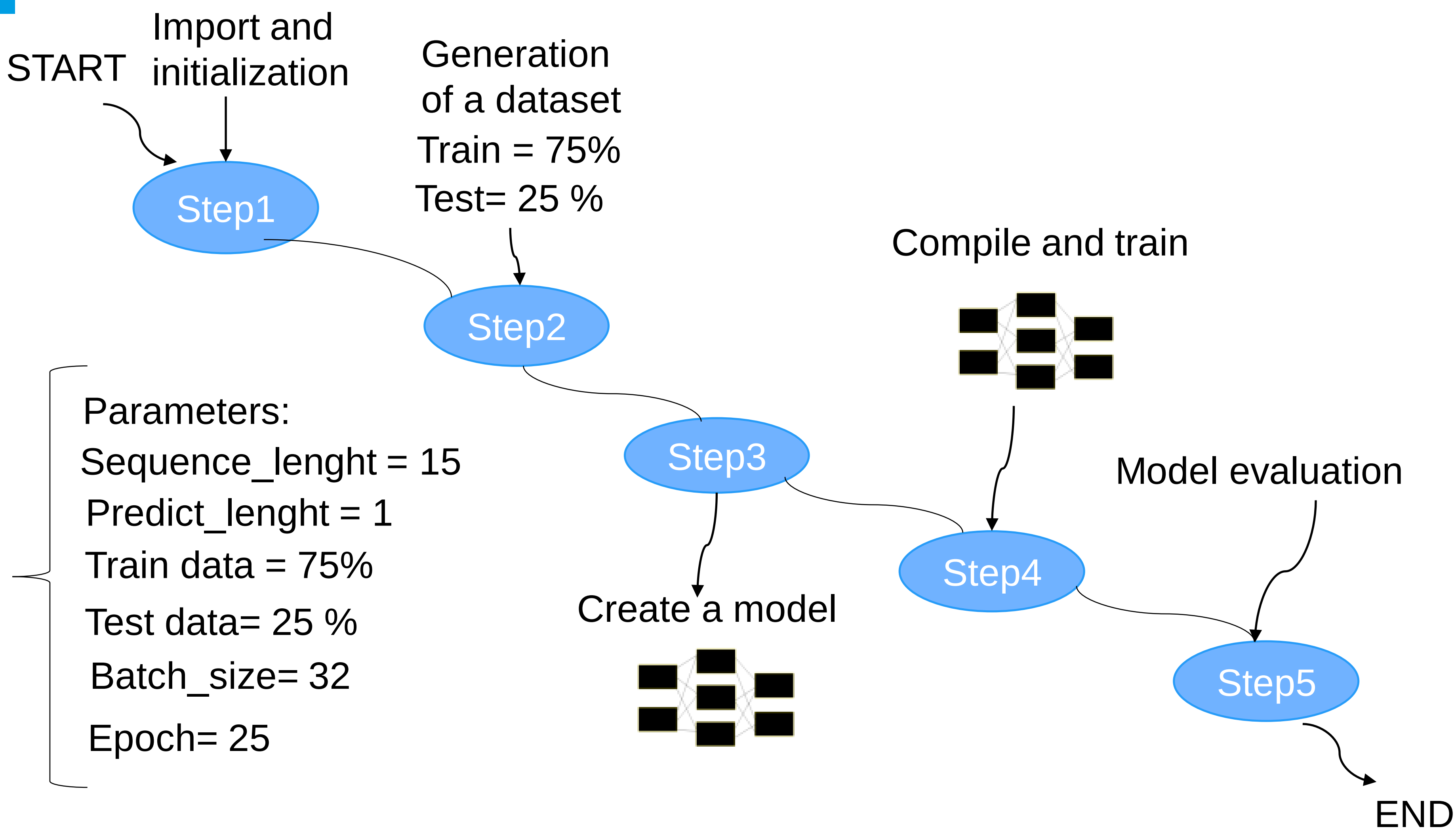
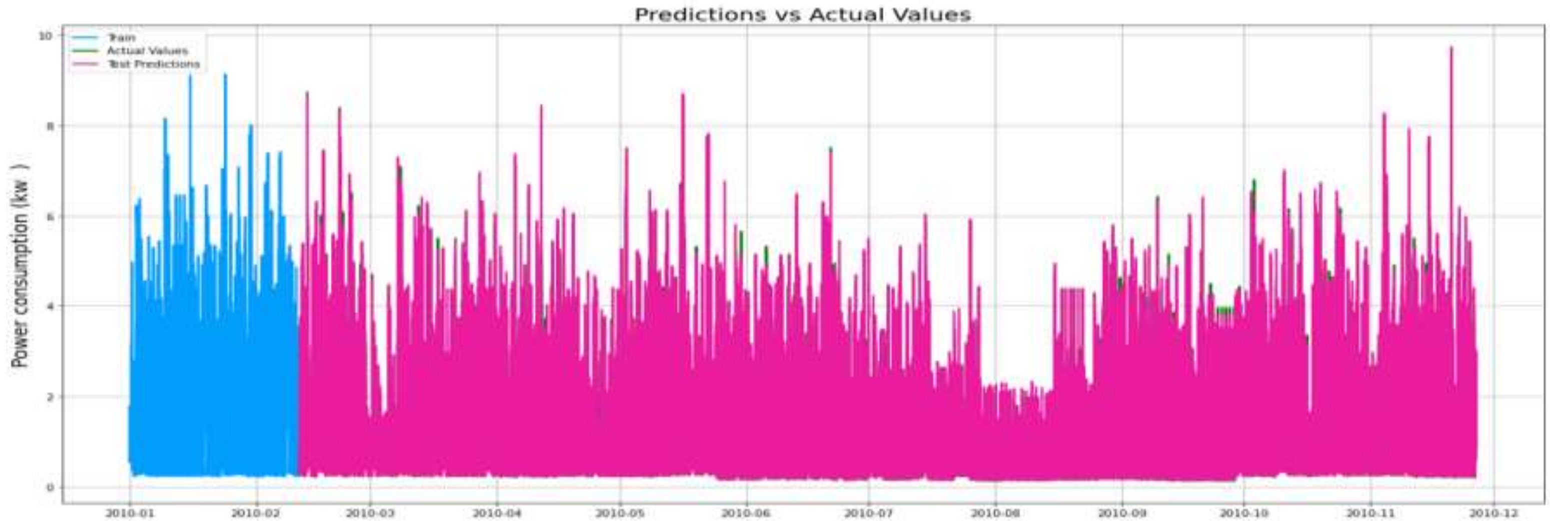
Train Model


START
Import and initialization
Step1
Generation of a dataset
Train = 75%
Test= 25 %
Step2
Parameters:
Sequence_lenght = 15
Predict_lenght = 1
Train data = 75%
Test data= 25 %
Batch_size= 32
Epoch= 25
Step3
Create a model
Compile and train
Step4
Model evaluation
Step5
END

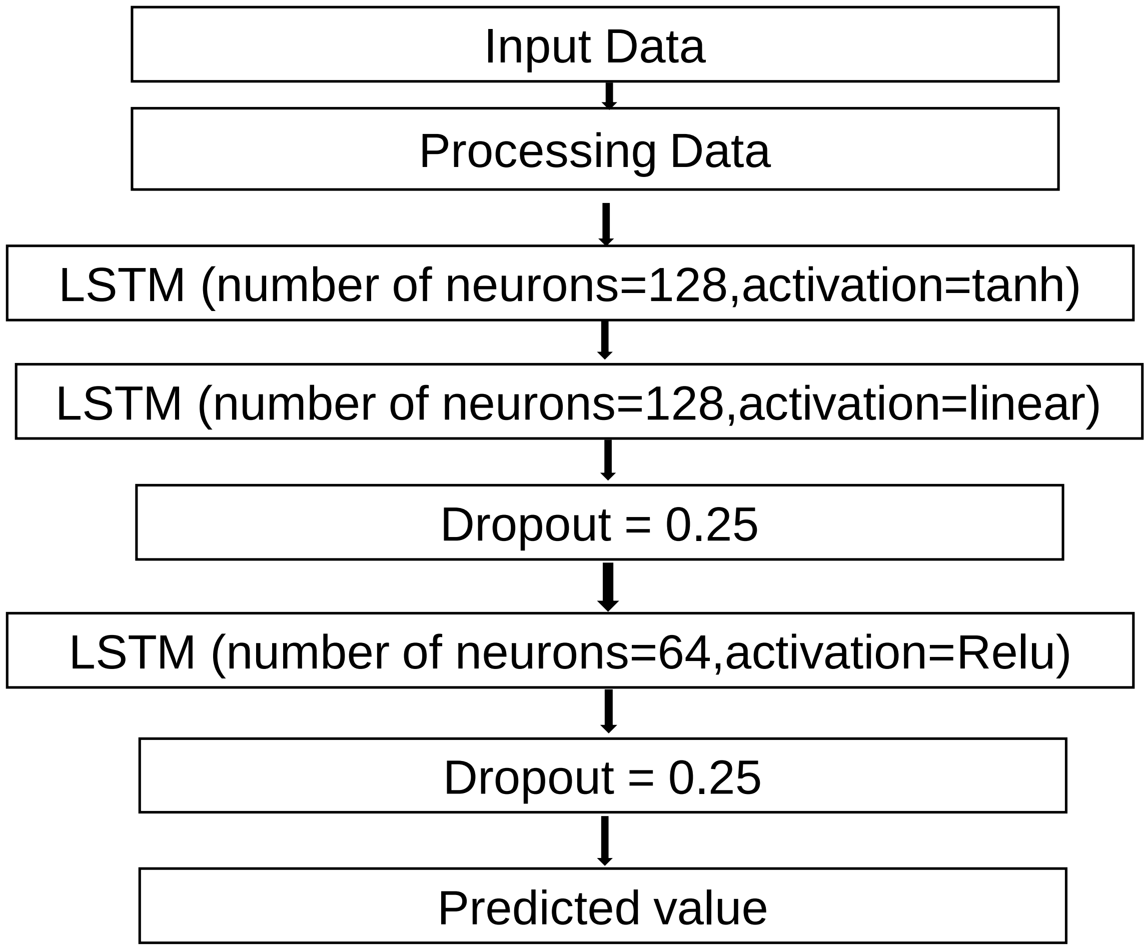
Simulation and Results

Deep learning algorithms	RMSE	MSE
CNN	0.23	0.05
LSTM	0.21	0.04
GRU	0.22	0.04
3-LSTM-Layers	0.19	0.03



Prediction performance of 3-LSTM-Layers model over IHEPC dataset

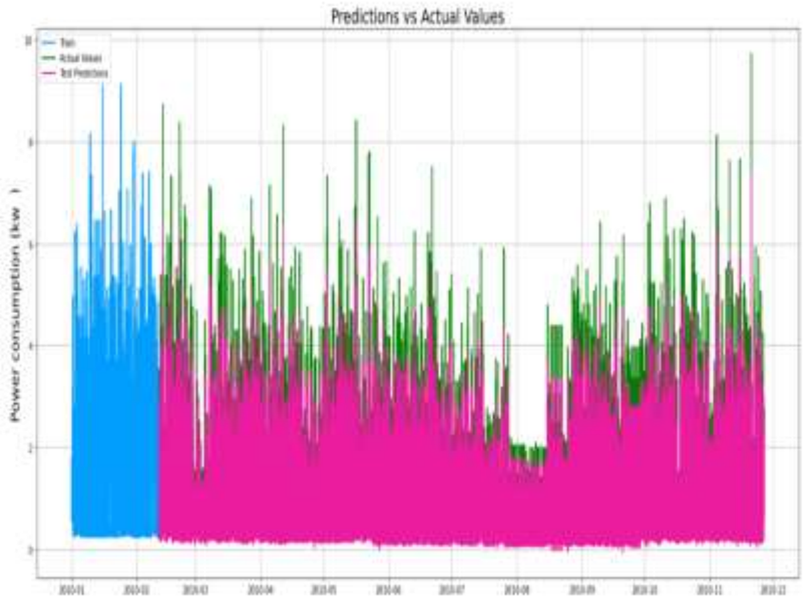
Simulation and Results



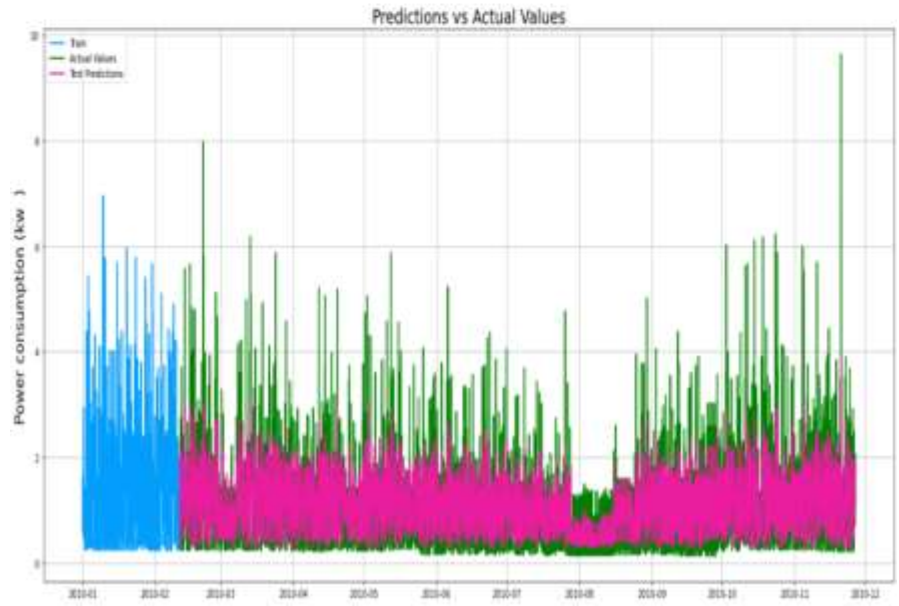
Architecture of 3-layer LSTM model

Simulation and Results

Time stamp	RMSE	MSE
1 min	0.19	0.03
5 min	0.34	0.11
15 min	0.46	0.21
60 min	0.77	0.59



Prediction performance of 3-LSTM-Layers model over 15 min time stamp



Prediction performance of 3-LSTM-Layers model over 60 min time stamp

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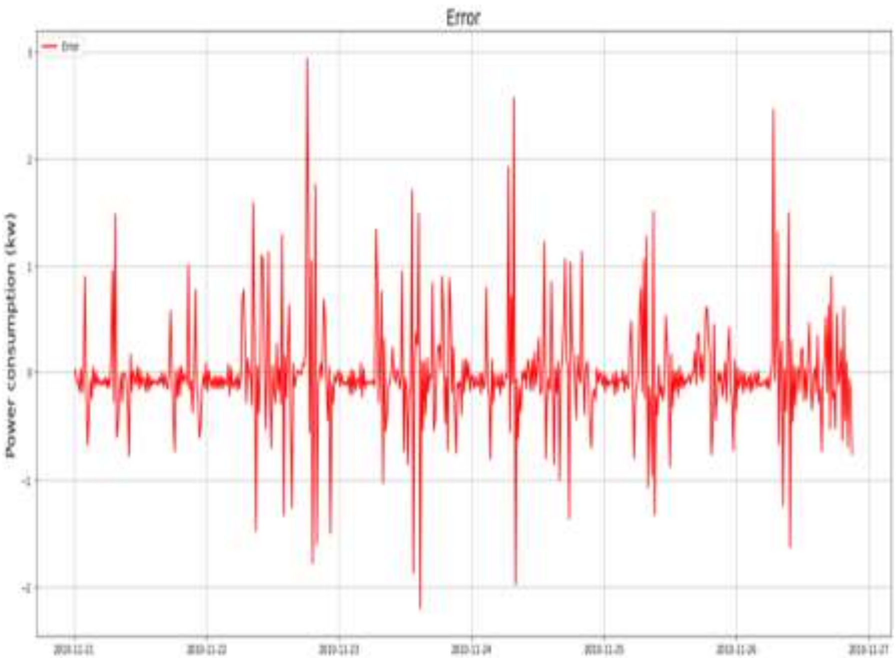
Simulation and Results



Error prediction of 3-LSTM-Layers model over 15 min time stamp

Error prediction of 3-LSTM-Layers model over 60 min time stamp

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Conclusion

- A comparative study has been established to predict energy consumption using the IHEPC dataset.

- Power consumption prediction depends on database complexity.

- Deep learning algorithms are not always reliable and accurate for power consumption prediction.

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[1] Yan, Ke; Li, Wei; Ji, Zhiwei; Qi, Meng; Du, Yang (2019). A Hybrid LSTM Neural Network for Energy Consumption Forecasting 1 of Individual Households. IEEE Access, 7(), 157633–157642.

[2] Sajjad, Muhammad; Khan, Zulfiqar Ahmad; Ullah, Amin; Hussain, Tanveer; Ullah, Waseem; Lee, Miyoung; Baik, Sung Wook 21 (2020). A Novel CNN-GRU based Hybrid Approach for Short-term Residential Load Forecasting. IEEE Access, (), 1–1.

[3] Dua, D. and Graff, C. (2019). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.