MINISTRY OF ECONOMY
DEPARTMENT OF STATISTICS MALAYSIA

Time Series Modeling of Start-Stop Battery Electric Vehicle Charging

11Th MALAYSIA STATISTICS CONFERENCE
"Data and Artificial Intelligence: Empowering the Future"
19Th September 2024
Organized by:
MINISTRY OF ECONOMY DEPARTMENT OF STATISTICS MALAYSIA
BANK NEGARA MALAYSIA CENTRAL BANK OF MALAYSIA
MALAYSIA INSTITUTE OF STATISTICS
MyStats 2024

INTRODUCTION

- The Battery Electric Vehicles (BEVs) has reached maturity and expected to replace the Internal Combustion Engine (ICE) Vehicles.
- Relying solely on stored energy from electric charges in their battery packs, BEVs propel their electric motors without the need for traditional combustion engines.
- Meeting this growing demand requires electricity utility providers to enhance electricity generation capabilities and upgrade distribution grids for BEVs charging stations.

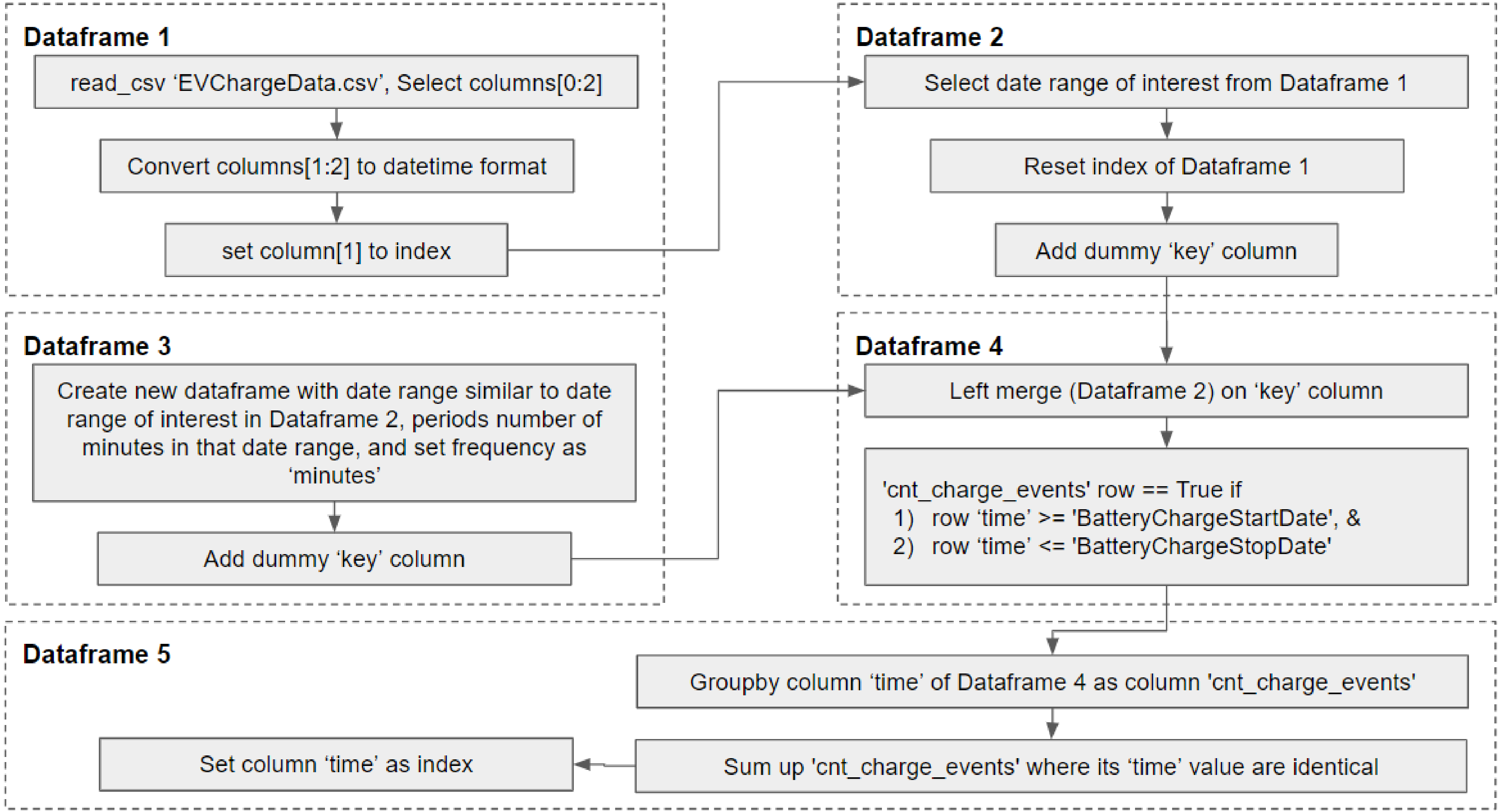
INTRODUCTION

- Manufacturers of BEVs and charging stations typically record charging sessions at start and stop points. This data can be valuable for forecasting electricity demand, as it provides insights into usage patterns.
- BEV charging data often exhibits non-stationary and unstable characteristics, posing significant challenges for forecasting (Dokur et. al).
- The raw data need to be transformed into a continuous time series format for effective modeling of charging behavior, enabling trend and seasonality forecasting.

METHODOLOGY

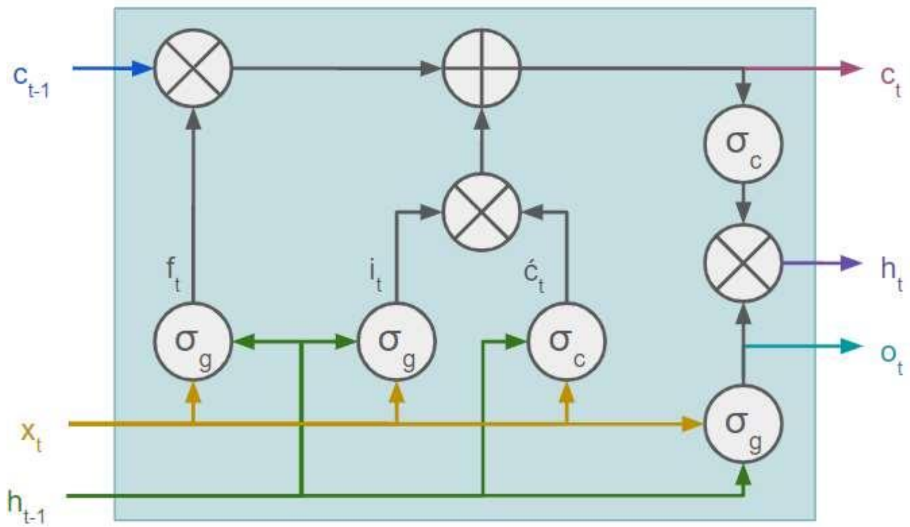
- Secondary data for this study was sourced from the My Electric Avenue project in the UK where 209 Nissan Leaf BEVs were leased to participants and its usage behavior is recorded.
- Using data from January 1, 2014 to December 15, 2014, the transformation involves counting simultaneous charging by augmenting data between start and stop times.
- The final transformed data will be suitable to be used in the LSTM model for modeling and forecasting electric load demand from BEV during active charging session.

METHODOLOGY



METHODOLOGY

- The hidden LSTM layer is structured as a sequential single layer, encompassing 125 units of LSTM cells. In the training process, the data was divided into sequences of 60 data points, each associated with a single expected output.



$$f_t = \sigma_g(W_f * x_t + U_f * h_{t-1} + b_f)$$

$$i_t = \sigma_g(W_i * x_t + U_i * h_{t-1} + b_i)$$

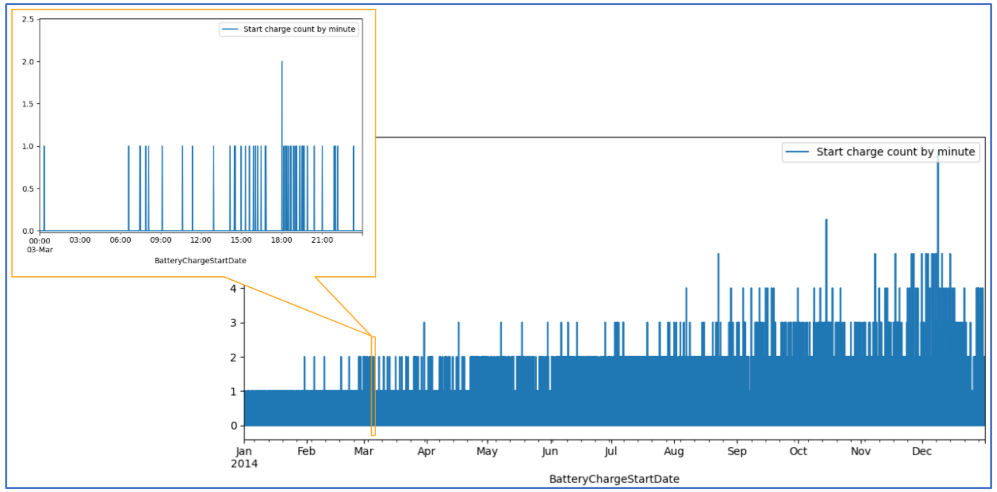
$$o_t = \sigma_g(W_o * x_t + U_o * h_{t-1} + b_o)$$

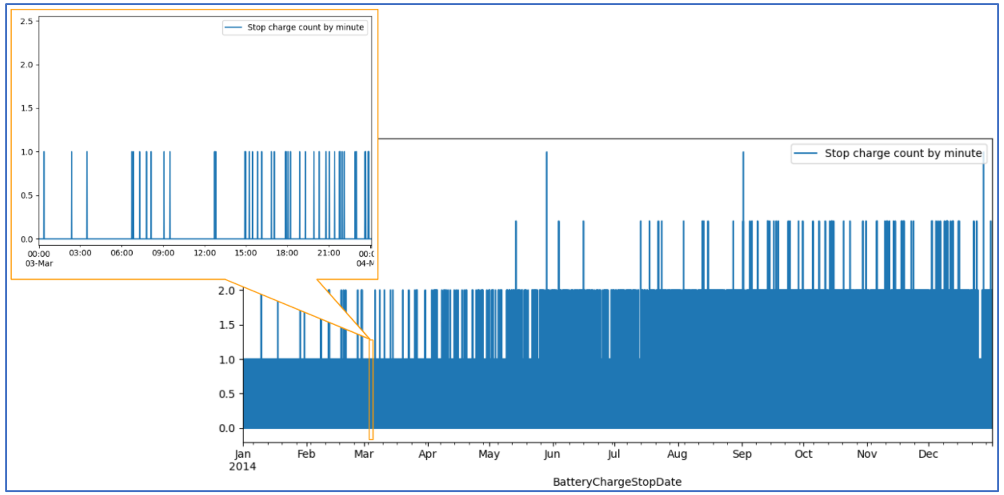
$$\acute{c}_t = \sigma_c(W_c * x_t + U_c * h_{t-1} + b_c)$$

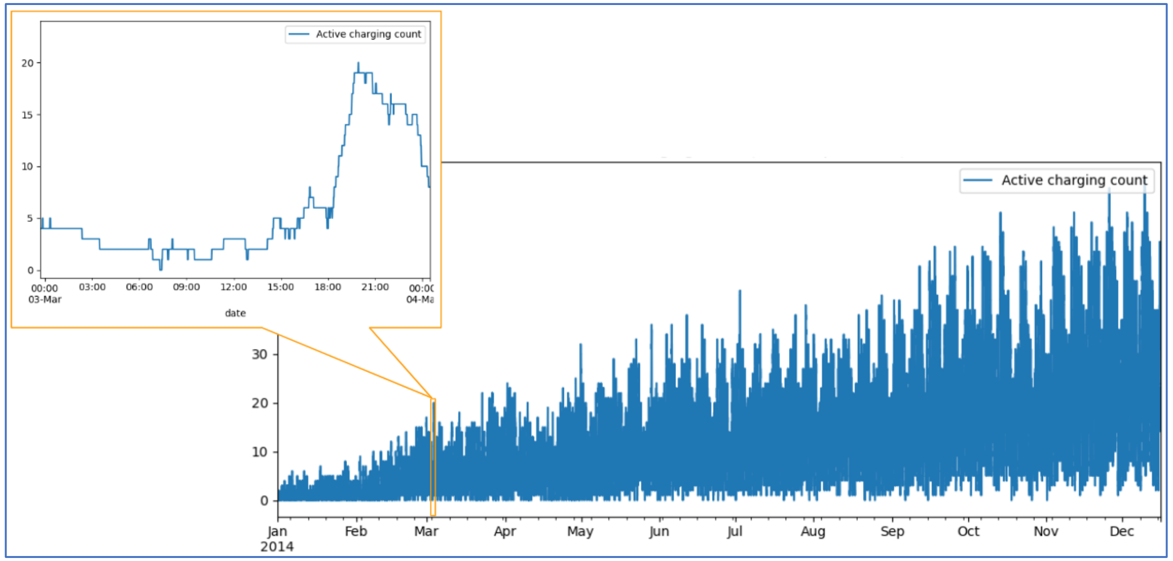
$$c_t = f_t \cdot c_{t-1} + i_t \cdot \acute{c}_t$$

$$h_t = o_t \cdot \sigma_c(c_t)$$

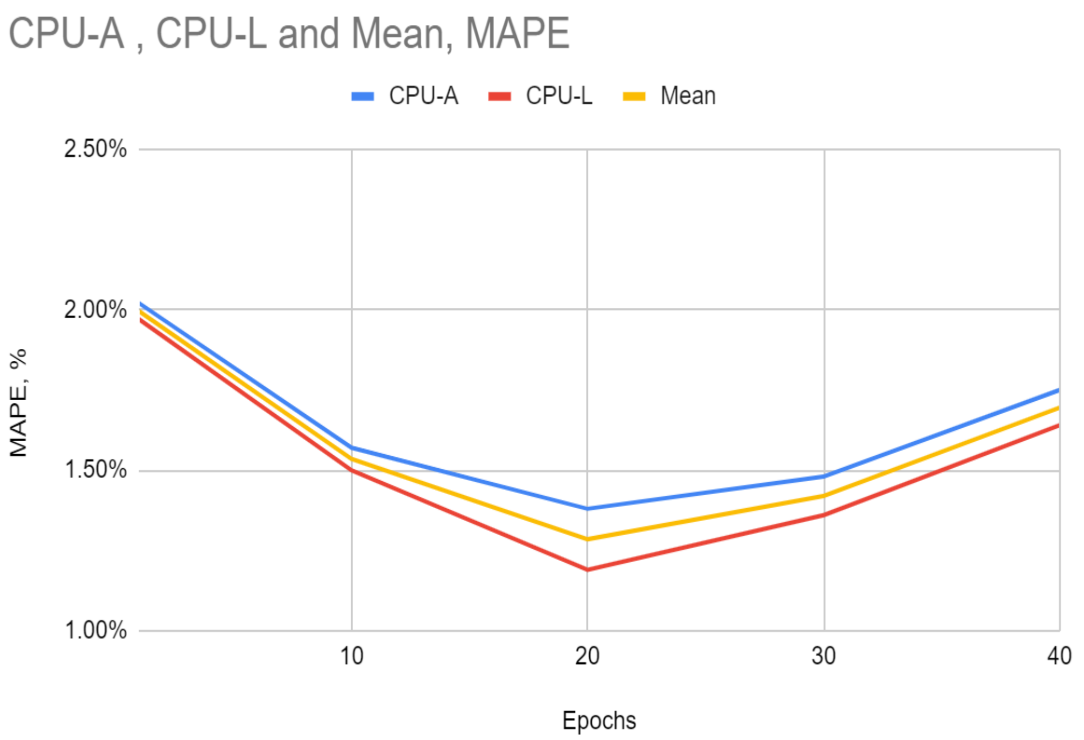
RESULTS

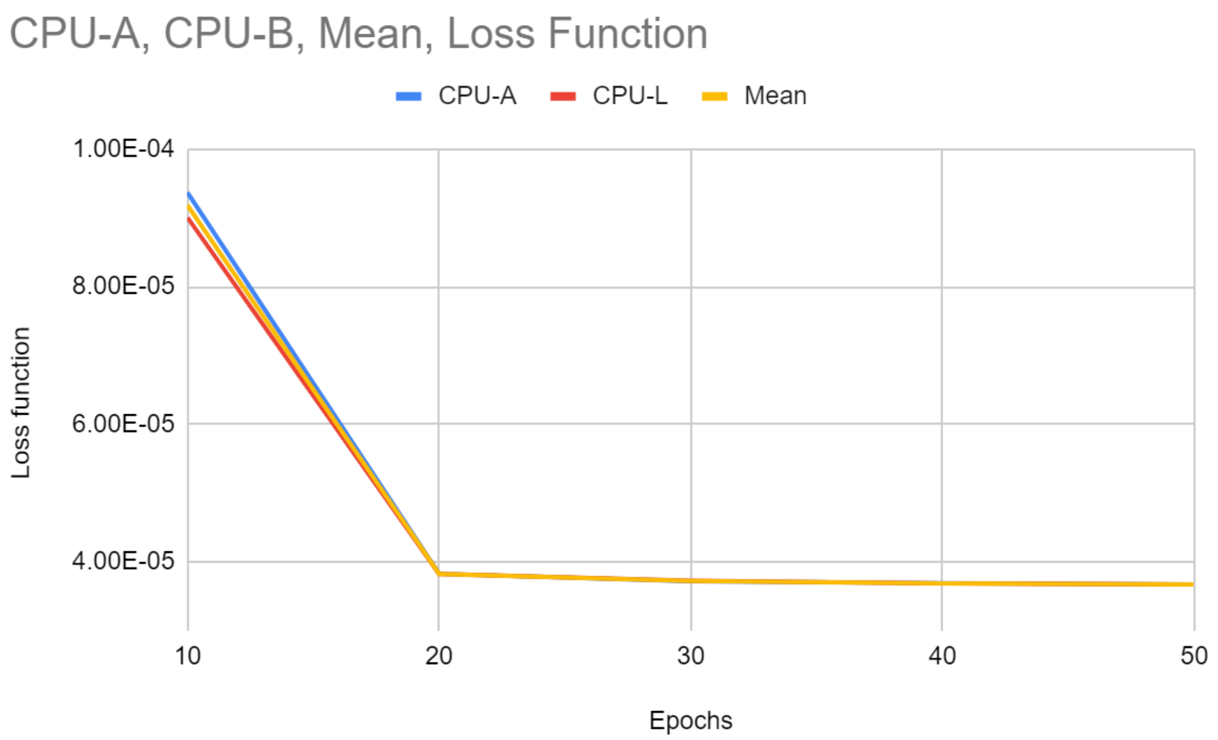

Start charge count by minute
BatteryChargeStartDate
Start charge count by minute
Jan
2014
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
BatteryChargeStartDate


Stop charge count by minute
Stop charge count by minute
Jan
2014
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
BatteryChargeStopDate


Active charging count
date
Active charging count
Jan
2014
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

RESULTS


CPU-A , CPU-L and Mean, MAPE
CPU-A
CPU-L
Mean
2.50%
2.00%
1.50%
1.00%
MAPE, %
10
20
30
40
Epochs


CPU-A, CPU-B, Mean, Loss Function
CPU-A
CPU-L
Mean
1.00E-04
8.00E-05
6.00E-05
4.00E-05
Loss function
10
20
30
40
50
Epochs

CONCLUSIONS

- The transformed data from BEVs has been found suitable for time series modeling using the LSTM method.
- This indicates that the data retains the necessary patterns and characteristics, making it effective for accurately predicting future trends in BEVs charging behavior through advanced modeling techniques like LSTM.
- The LSTM method proposed in this study achieved:
  - CPU-A: MAPE of 1.38%, RMSE of 0.51 (after 20 epochs)
  - CPU-L: MAPE of 1.19%, RMSE of 0.51 (after 20 epochs)

ACKNOWLEDGEMENT

- This research was funded by Universiti Malaysia Pahang Al-Sultan Abdullah (grant number RDU233008) under a special publication grant from the Research and Innovation Department, and Doctorate Research Scheme (Salleh, S.).

Thank you