Electrical Distribution Network Energy Consumption Forecasting based upon Victorian MRIM Meter Data

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Agenda

Institute of Data

Bio

KHONG FWU CHIN

UNIVERSITY OF MELBOURNE

- **Bachelor of Science** (Electrical Systems major)
- **Master of Engineering** (Electrical Engineering)

  Key Interests:

    Power Systems

    Digital Systems

    Control Systems

    Electrical Network Analysis

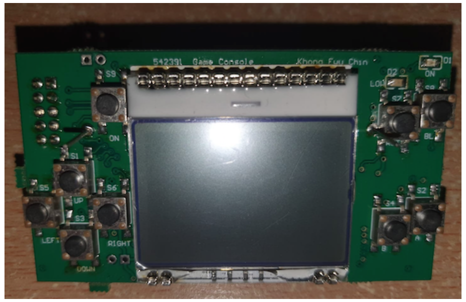
PROJECTS

- **Evaluation** - High Accuracy GNSS Camera Position System for Unmanned Aerial Vehicles
- **Design and Assembly** - Miniature Game Console

COMMUNITY PROGRAMS

- **Endeavour Volunteer**
  - Visit schools to promote the area of engineering
  - Volunteer Assistant Manager at Endeavour Exhibition
- **Research Bazaar**
  - AutoCad Inventor

GPS Device



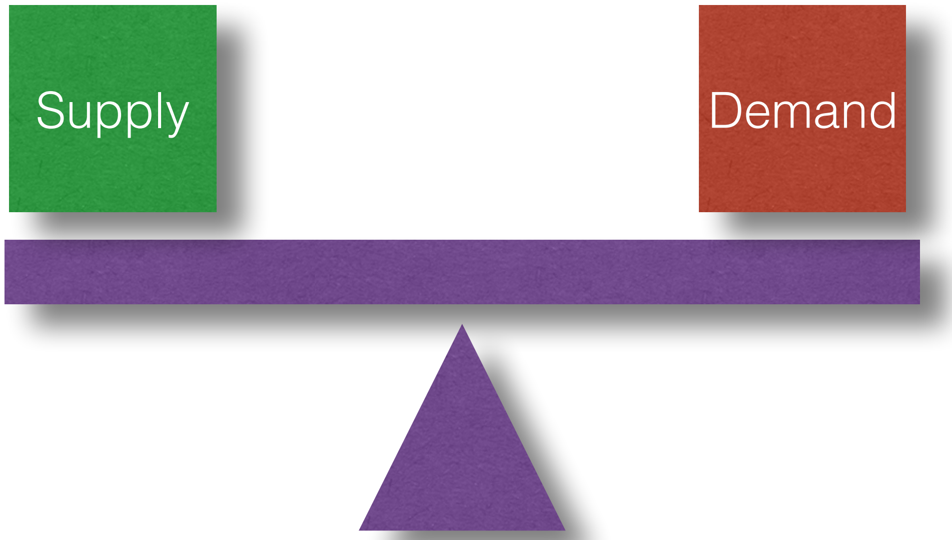
Miniature Game Console

Project

Background

Matching Electrical Energy Consumption with the Right Level of Supply is CRUCIAL

- **Oversupply**
    - Cannot be massively stored
    - Expensive
    - High maintenance
    - Limited lifespan
- **Undersupply**
    - Overload supply line
    - Cause blackouts



Supply and demand has to be balanced at every moment

Project

Description

Objective - Utilising Time Series Models

- Forecast Energy Consumption for an Electrical Distribution Network on a Daily Basis
- Based on Historical Data

Rationale

- Reliable forecasting allows better management of electrical network.
- Using Historical Data:
    - Alleviate the dependence on weather data
      (Weather data are forecasts as well)

Data

Source

- Acquired from Australian Energy Market Operator (AEMO) - CitiPower
- Contains aggregated half hour energy (VAL01 - VAL48) and the daily total (DAILYT)
    - Measured in kWh
- Recorded from Victorian MRIM Meter Data
- Null Checks (missing values) and Summation Checks were conducted

SETTD	PROFILEAREA	DAILYT	VAL01	VAL02	VAL03	...	VAL44	VAL45	VAL46	VAL47	VAL48	DCTC
01/04/2014	CITIPOWER	6363749.701	83948.634	75686.720	70851.453	...	121154.389	113845.677	111219.265	111446.631	106211.512	MRIM
02/04/2014	CITIPOWER	5630825.535	93503.589	84693.357	79590.499	...	95684.746	91694.112	91698.657	93790.379	89377.501	MRIM
03/04/2014	CITIPOWER	5173891.385	77688.455	69851.785	65002.304	...	94635.246	90432.761	90406.507	92838.823	89320.024	MRIM
04/04/2014	CITIPOWER	5044050.180	77761.113	69530.046	64437.280	...	93741.476	91659.930	93286.271	96403.437	92482.282	MRIM
05/04/2014	CITIPOWER	4383318.300	80930.298	72390.242	66461.934	...	91474.783	91223.017	94194.091	98842.620	95486.413	MRIM

SETTD	PROFILEAREA	DAILYT	VAL01	VAL02	VAL03	...	VAL44	VAL45	VAL46	VAL47	VAL48	DCTC
26/09/2019	CITIPOWER	5357014.025	104634.319	94261.824	85886.697	...	119627.636	117257.730	116889.511	116537.564	111083.906	MRIM
27/09/2019	CITIPOWER	5219544.620	99948.011	90329.481	82614.079	...	132064.546	128539.473	127118.810	126562.299	120734.248	MRIM
28/09/2019	CITIPOWER	5036389.054	109579.556	99327.006	90975.407	...	125324.594	122525.891	121376.335	121272.505	115959.738	MRIM
29/09/2019	CITIPOWER	4993439.774	105339.777	95979.319	88359.469	...	130184.465	123603.663	119416.449	117391.576	111069.642	MRIM
30/09/2019	CITIPOWER	6030581.529	100149.694	90839.884	83260.137	...	146284.126	136462.910	129778.602	125565.504	118117.204	MRIM

Victorian MRIM Meter Data Installed by CitiPower from 01 April 2014 till 30 September 2019

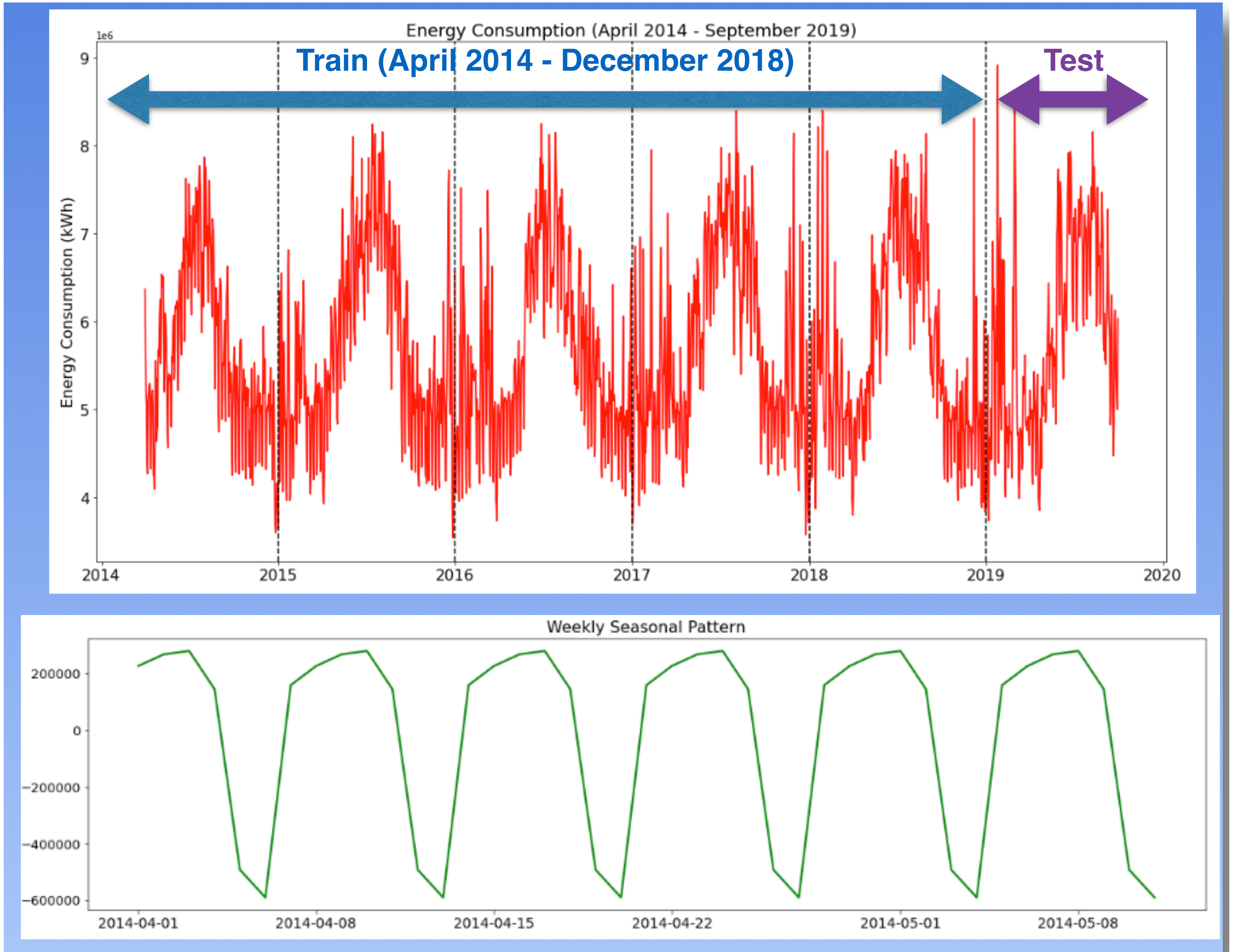
Data

Analysis

- **Time Series Data**
  - Sequence of data in order of time
- **Yearly Seasonality**
  - Behaviour is similar each year
- **Weekly Seasonality**
  - Observed after decomposition analysis
- **Dickey - Fuller Test**
  - Determines the stationarity of the data
  - p-value < 0.05 means data is stationary and ensures model robustness
  - Results: p-value = 0.019962

```
ADF Statistic: -3.200387
p-value: 0.019962
Critical Values:
        1%: -3.434
        5%: -2.863
        10%: -2.568
```

Dickey - Fuller Test



Yearly (Top) and Weekly (Bottom) Seasonal Patterns are observed from the data

Models

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5 Basic Models (9 Variations) - Python Package

Low — COMPLEXITY — High

ARIMA

- Auto Regressive Integrated Moving Average
- Captures complex relationships as it takes error terms and observations of past values
- Regressing a variable on past values

- 2nd variation using walk-forward validation

2 Variations

SARIMA

- ARIMA

  +

  ONE seasonal component

- Two variations were built on a YEARLY and WEEKLY seasonality respectively

2 Variations

SARIMAX

- ARIMA

  +

  ONE seasonal component

  +

  Exogenous variables
  - External factor (Eg. weather, *additional seasonal component*)

- 2nd variation using walk-forward validation

2 Variations

Prophet

- Developed by Facebook in 2017
- Works best with time series that have strong seasonal effects and several seasons of historical data.
- Fits with yearly, weekly, and daily seasonality, plus holiday effects.

- 2nd variation using walk-forward validation

2 Variations

LSTM

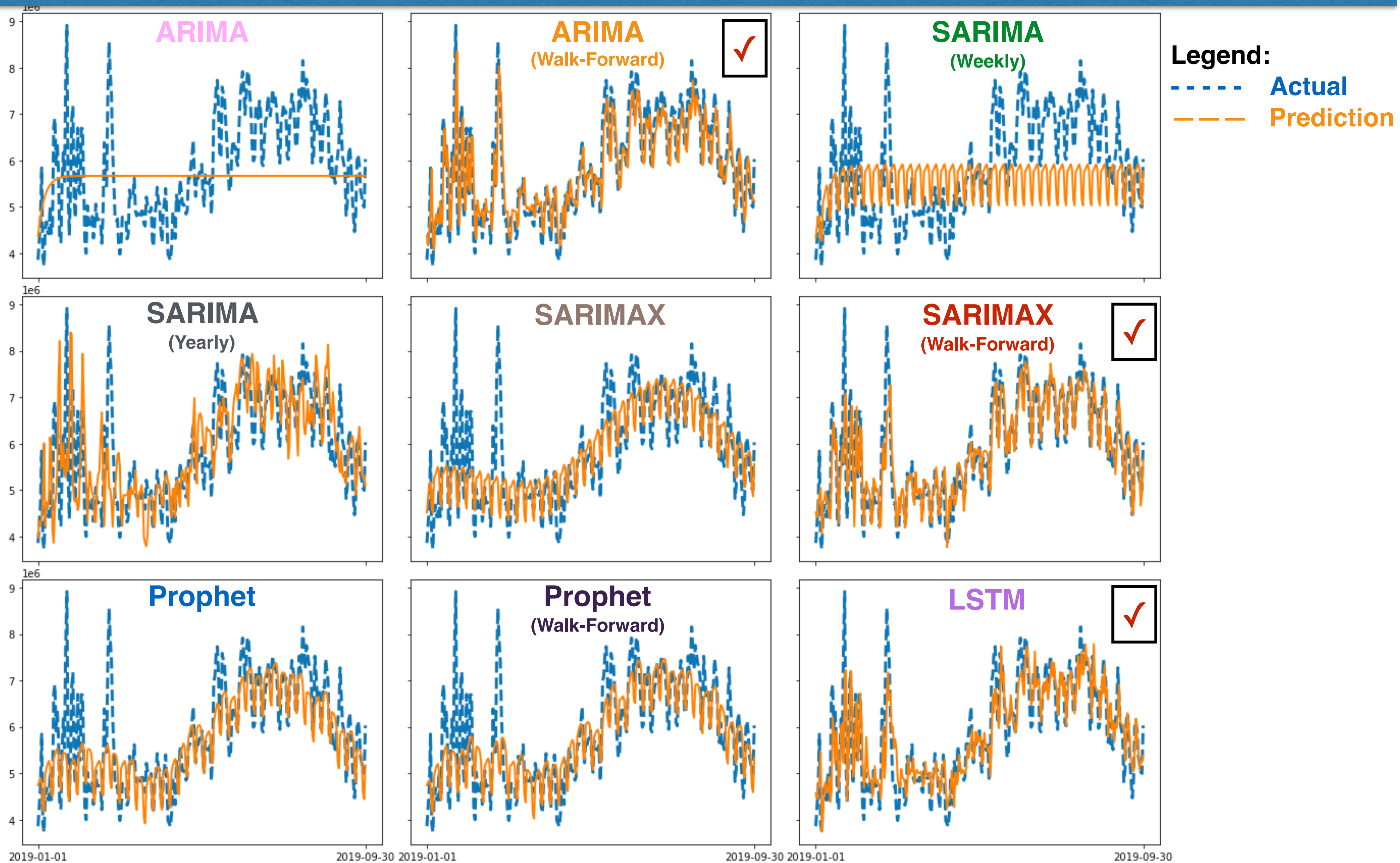
- Long Short Term Memory
- Recurrent Neural Network
- Learn from a series of past observations predict the next value in the sequence

- Modelled using walk-forward validation

1 Variation

Model Evaluation

Prediction vs Actual



Model Evaluation

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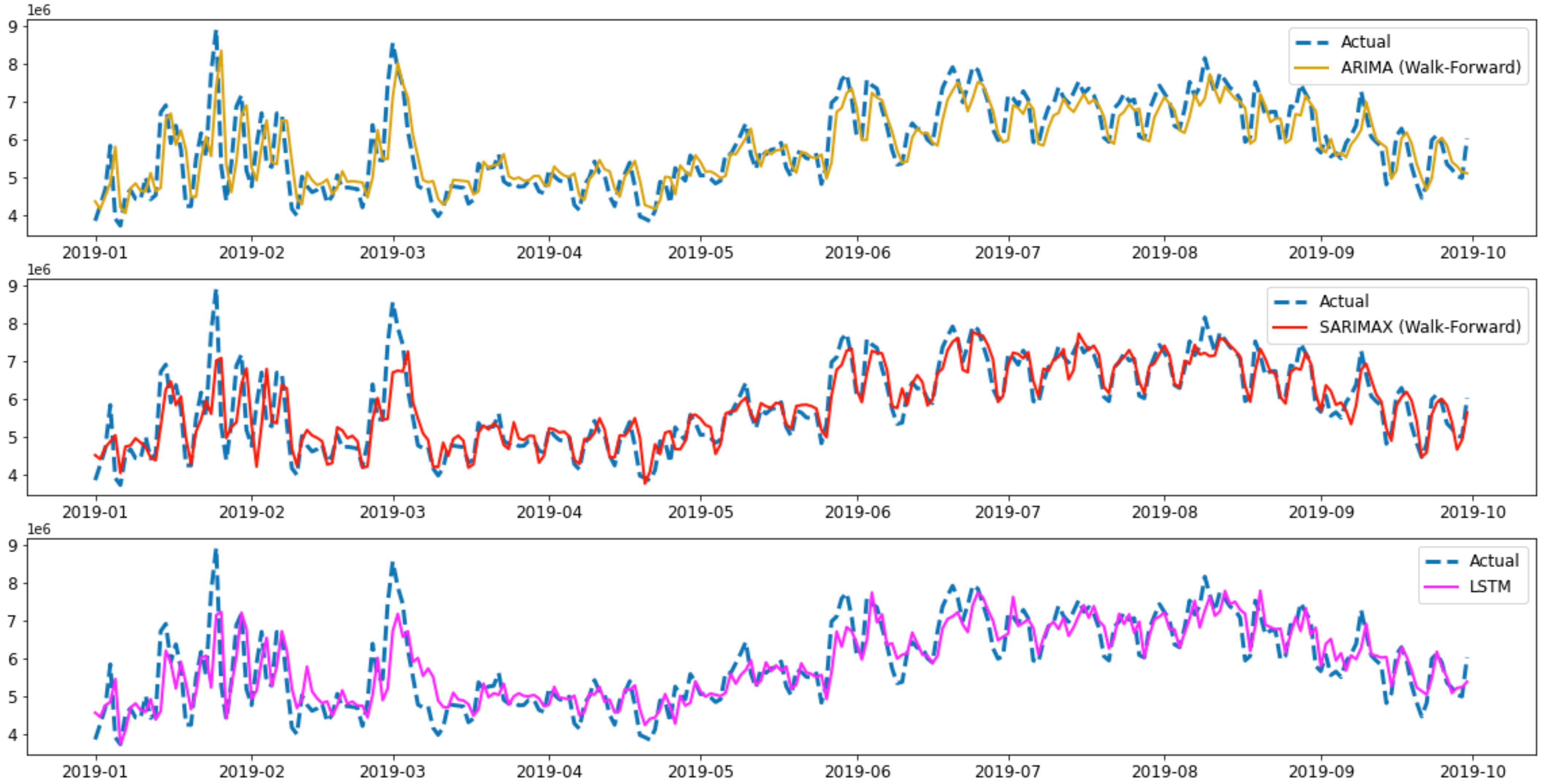
Top 3 Predictions - Visualisation



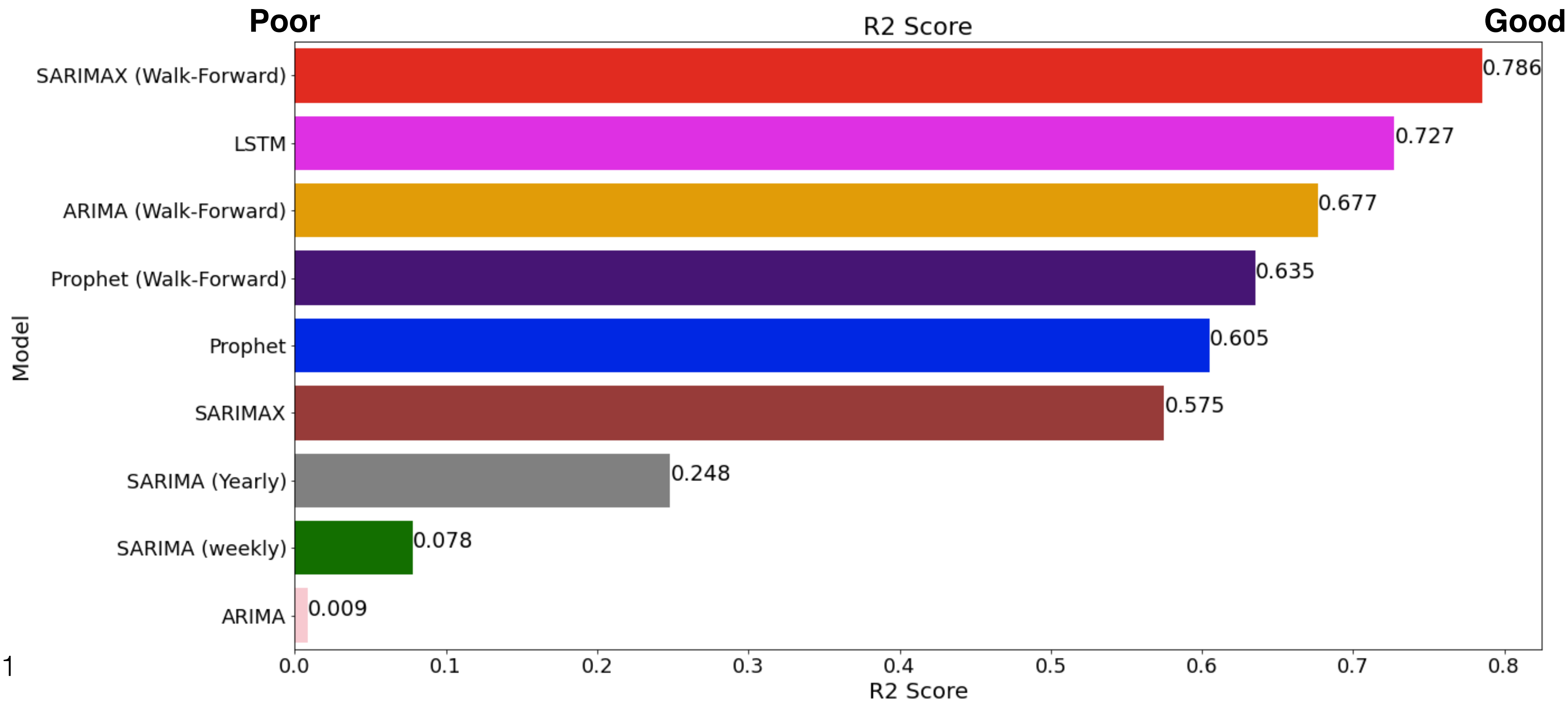
Model Evaluation

R2 Score*

- **SARIMAX (Walk-Forward) performs the best at 0.786**

Note: *

- *R2 Score measures how the models captures behaviour of the power consumption, in comparison with the actual values*
- *The closer R2 Score is to 1, the better*



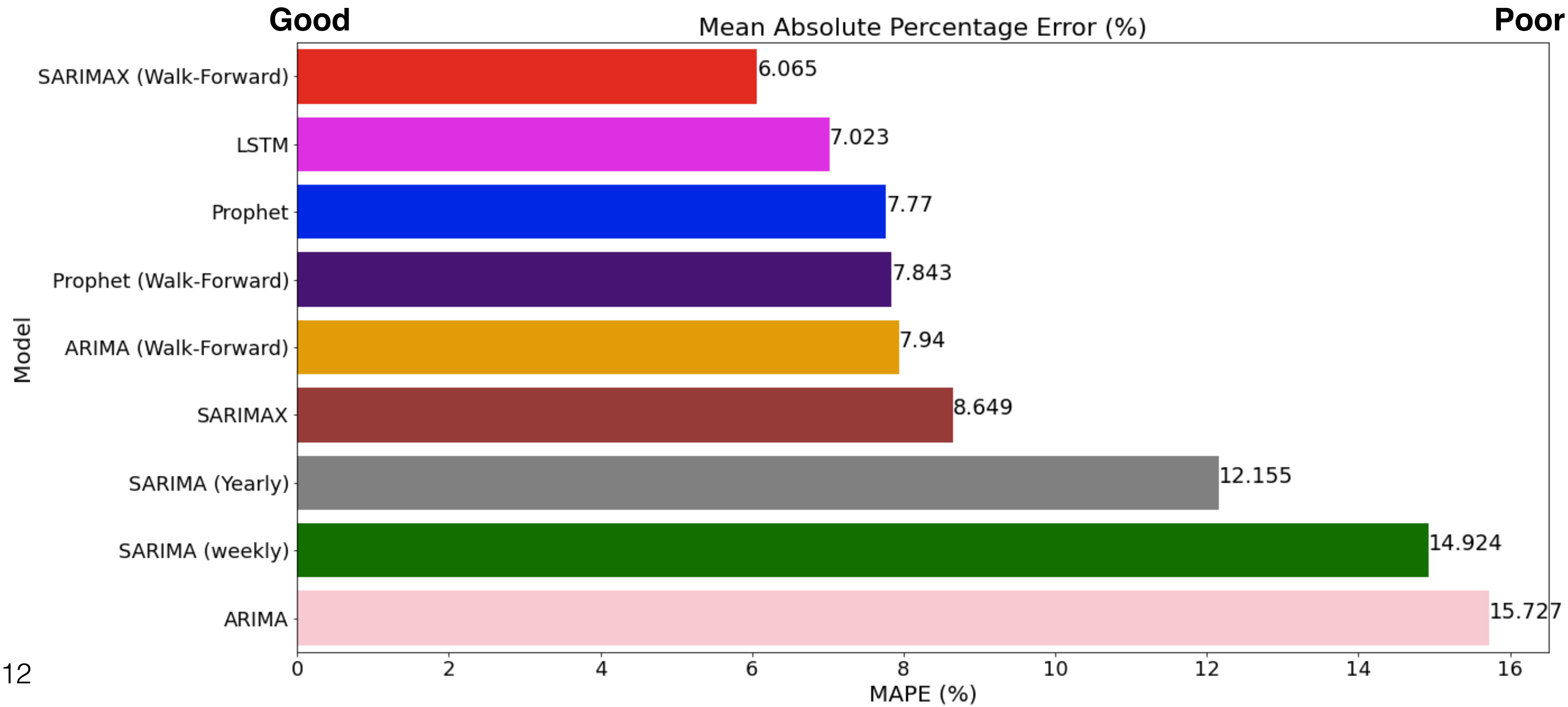
Model Evaluation

Mean Absolute Percentage Error *

- **SARIMAX (Walk-Forward) performed the best , 6.065%**
- With the walk-forward approach:
  - Improved ARIMA from 15.7% to 7.94% (49% Improvement)
  - Improved SARIMAX from 8.649% to 6.065% (30% Improvement)

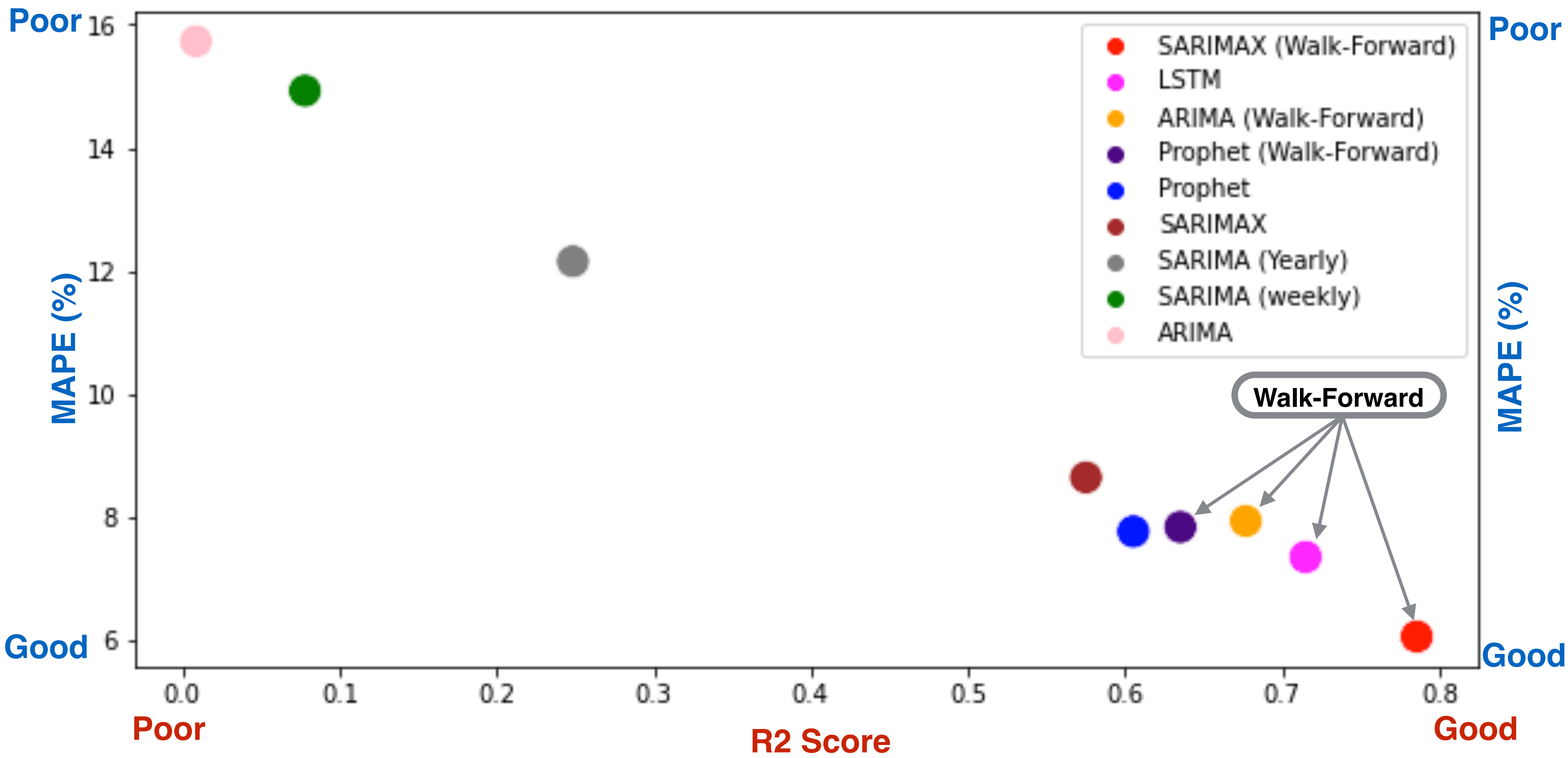
*Note: **

- *The lower the MAPE, the better*



Conclusion

- **Best Model for Daily Forecasting: SARIMAX (Walk-Forward)**
  - Largest R2 Score (0.786)
  - Smallest MAPE (6.065%)
- **For longer period of forecasting, Prophet can be a viable model**



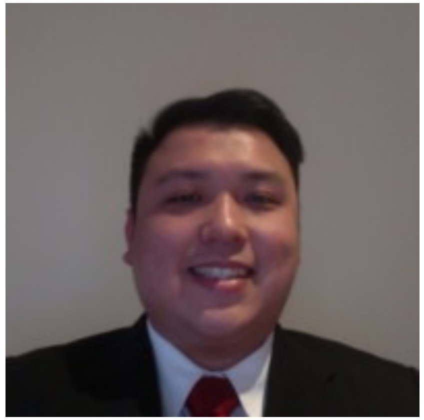
Further Work

1. **Calibrate and verify models for other electrical distribution networks**

2. **Explore models available in Amazon Web Services (AWS) and Microsoft Azure**

3. **Automate process of retraining the model from sensors**

Thank You



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