Application of Artificial Intelligent Techniques to Predict the Performance of Solar PV Plant

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MEC4402: Final Year Project (FYP)

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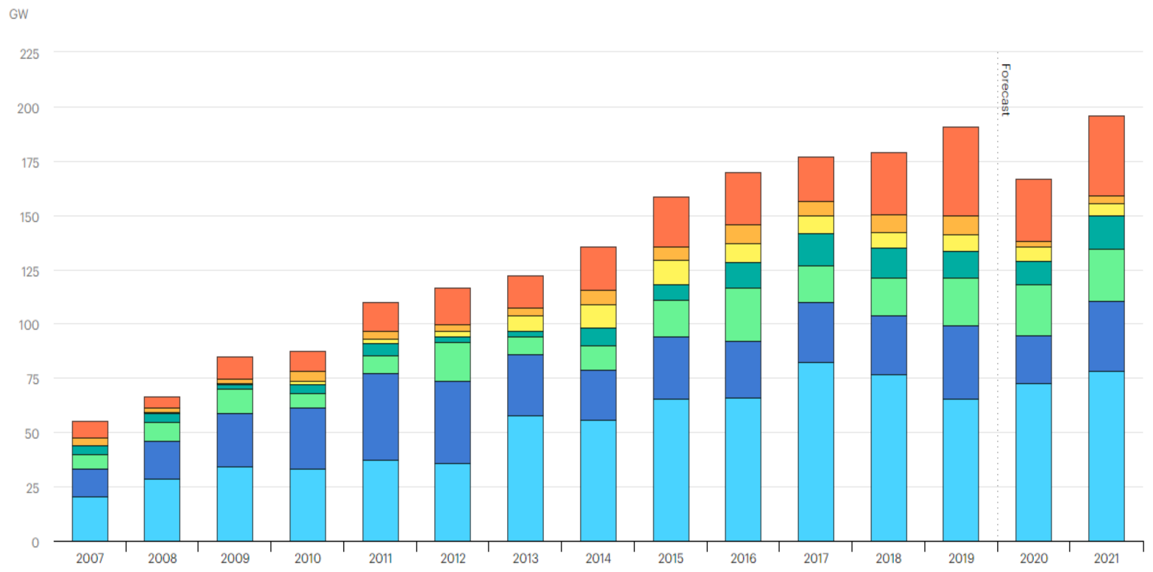
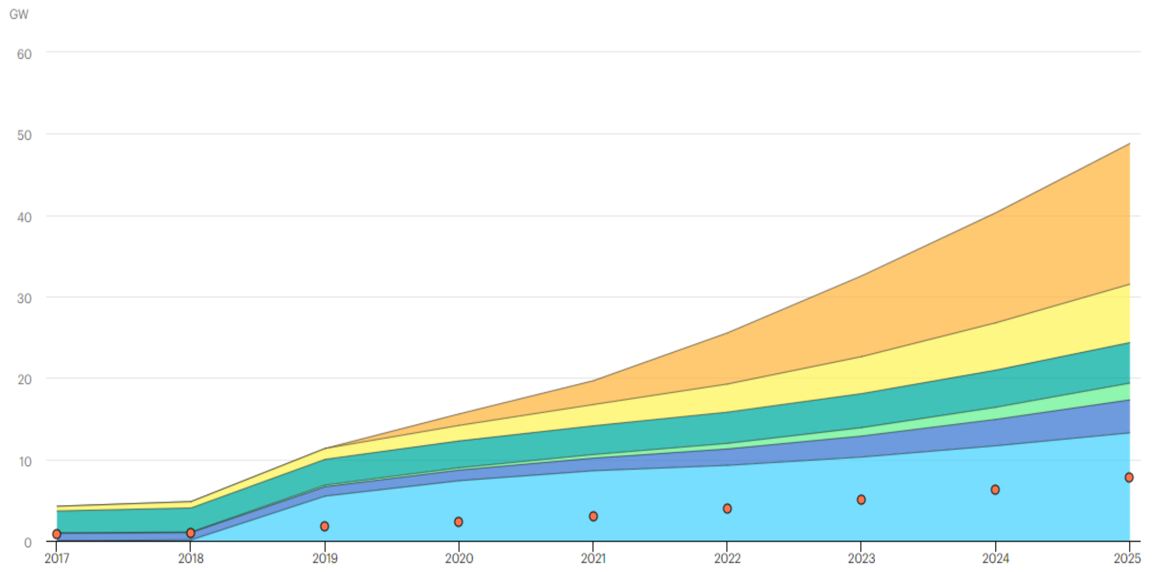
Introduction

Background

- Ever-growing electricity demand
- Use of renewable energy (RE) sources rising



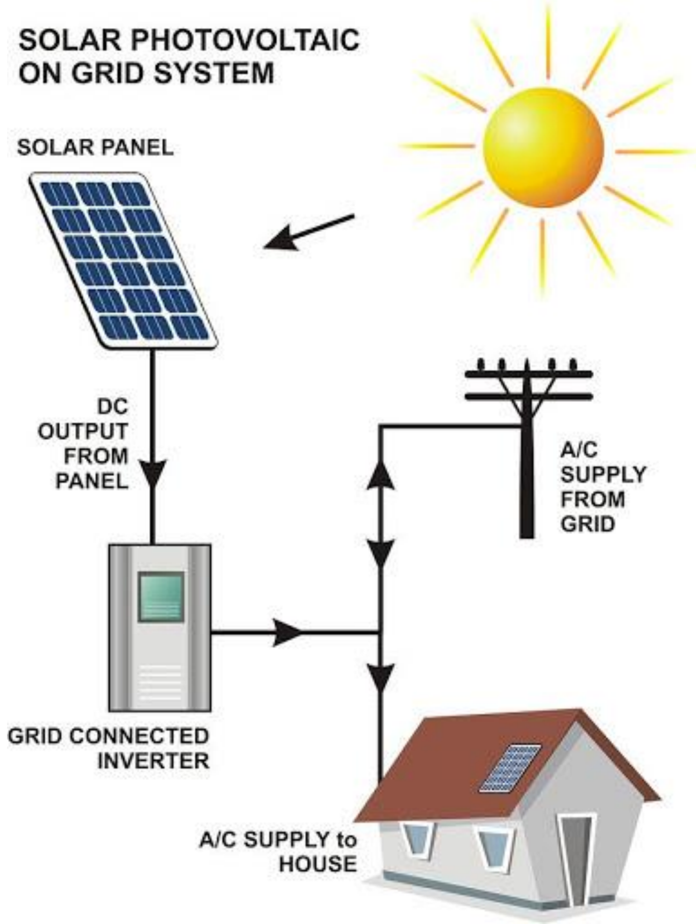
Renewable Energy Growth 2007-2021



ASEAN Solar PV Growth 2017-2025

What is Solar PV?

- Utilises radiant energy from the Sun
- Free electrons in solar cells excited by sunlight
- Charge build up yields electricity



Grid connected Solar PV process

Why an AI Forecasting Technique

- AI can deal with non-linear mapping and complex problems
- Accurate model would reduce uncertainties related to the operation and planning of PV systems

Performance Evaluation

- Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

- Mean absolute error (MAE)

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right|$$

- Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}{\sum_{j=1}^{n}(y_j - \mu_{\hat{y}})^2}$$

Literature Review

Author	Region	What has been done	Result
Jebli et al. (2021)	Morocco	Comparison study of RNN, LSTM and GRU	RMSE: RNN: 0.066 LSTM: 0.068 GRU: 0.089
Huang et al. (2020)	Shanghai, Jiangsu & Zhejiang	Compared MLP and LSTM models	RMSE: LSTM: 0.190 MLP: 0.285
Liu et al. (2021)	Thailand & Taiwan	Developed simplified LSTM	Average RMSE: 0.512
Park et al. (2021)	Korea	Developed and analysed the effect of LSTM with multiple layers	Cv(RMSE): Single-layer: 13.8% Multi-layer: 13.2%
Konstantiou et al. (2021)	Cyprus	Developed a stacked LSTM and introduces k-fold cross-validation	RMSE: 0.11368 K-fold RMSE: 0.09394±0.01616
Hossain and Mahmood (2020)	Florida	Developed and compared stacked LSTM using single step ahead and intraday rolling horizon	RMSE: Single-step ahead: 1.51 Multi-step ahead: 0.79
Akhter et al. (2021)	Kuala Lumpur	Developed a RNN-LSTM techniques for different types of PV module systems and compared to SVR and GPR	RMSE: Poly: 23.09 Mono: 19 Thin film: 22.014

Problem Statement

- Deep learning technique is relatively new
- No AI forecast model has been applied to Monash's grid connected solar PV plant
- Although previous researchers have developed AI models, many have focused only on ANN . Very few have considered predicting performance of solar power inspired by LSTM models, especially in this geographical region

Research Objectives and Scope

- To develop artificial intelligent (AI) models to make short-term predictions on the performance of Monash's grid connected solar PV plant
- To apply, compare and analyse an Artificial Neural Network (ANN) and Long-short Term Memory (LSTM) network models

Methodology

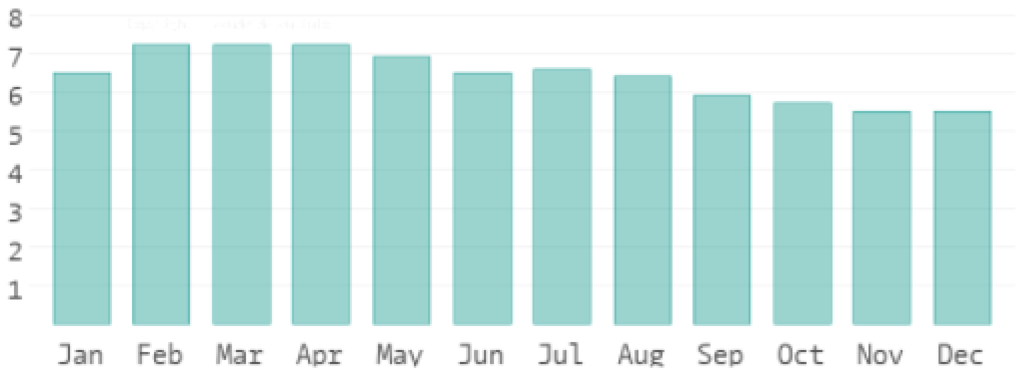
Monash Solar PV Plant

- PV cell type: Mono
- Max. Power Rating: 360 W
- Number of PV modules: 646
- Total area: 2169 m^2

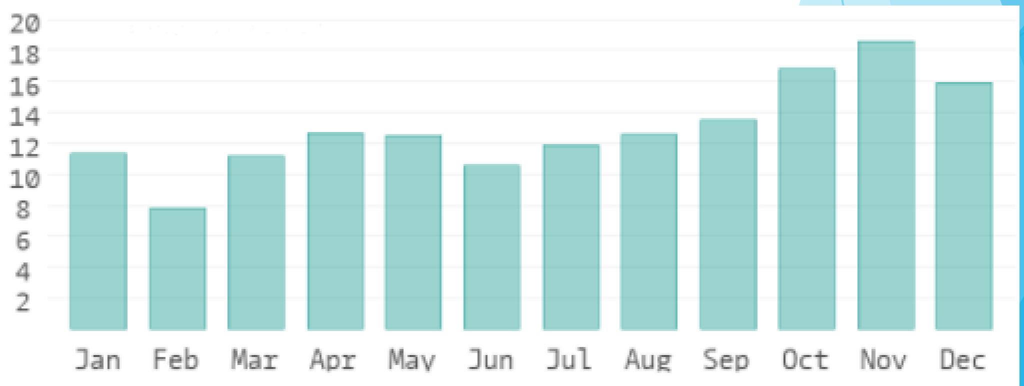
Monash Solar PV Installation at Rooftop

Dataset

- Entire year of 2019 (approx. 103680 observations)
- 5 minute resolution
- Peak power produced around noon
- Only interested in months February, June, August and November



Hour of sunshine per day in Malaysia,2019



Rainy days per month in Malaysia,2019

Data Pre-processing

- Missing Values

```
%only importing November 2019 data
Nov = readtable(file,opts1);
[filterNov, ia] = rmmissing(Nov);
NovCheck = ia(ia(:,1)==1); % expecting 29x3 = 87 rows to be removed
```

- Night-Time values

```
% obtain hour and minute index of each observation
h = hour(filterNov.Var1);
m = minute(filterNov.Var1);
% only keeping observations between 7 am to 8 pm
tabNov = filterNov((h >= 7) & (h < 20), :);
% remove first column - datetime format
matrixNov = tabNov(:,2:end);
% convert table to matrix
datasetNov = table2array(matrixNov);
[row, col] = size(datasetNov);
```

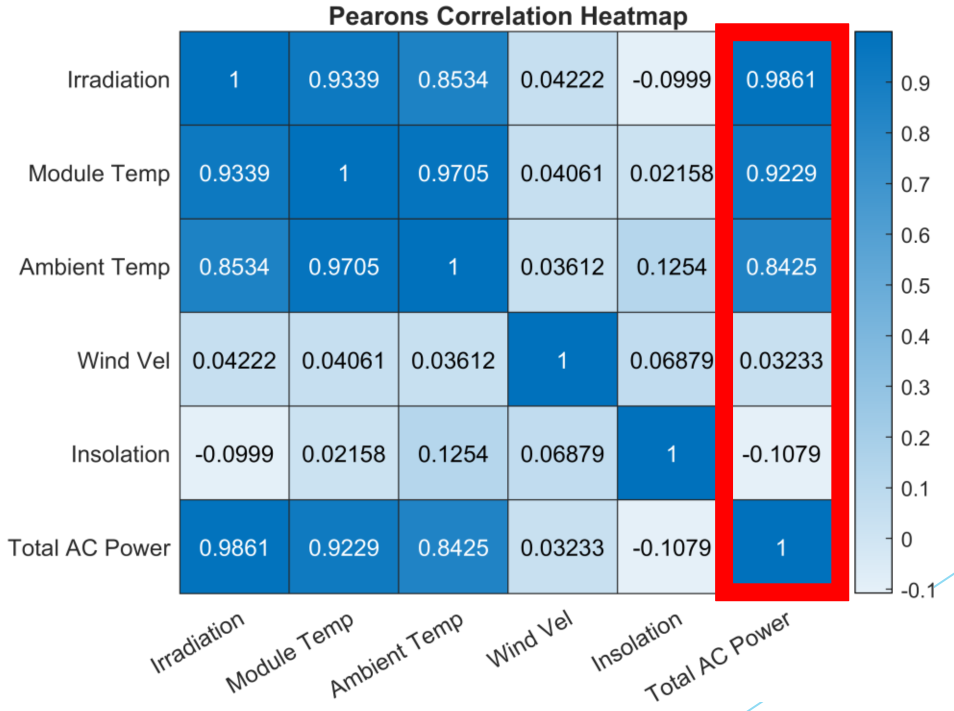
- Normalised

```
% normalize between range 0 to 1
dataNormalized = normalize(datasetNov,"range");
maxValues = max(datasetNov);
minValues = min(datasetNov);
```

Data Pre-processing

- Pearson's Correlation

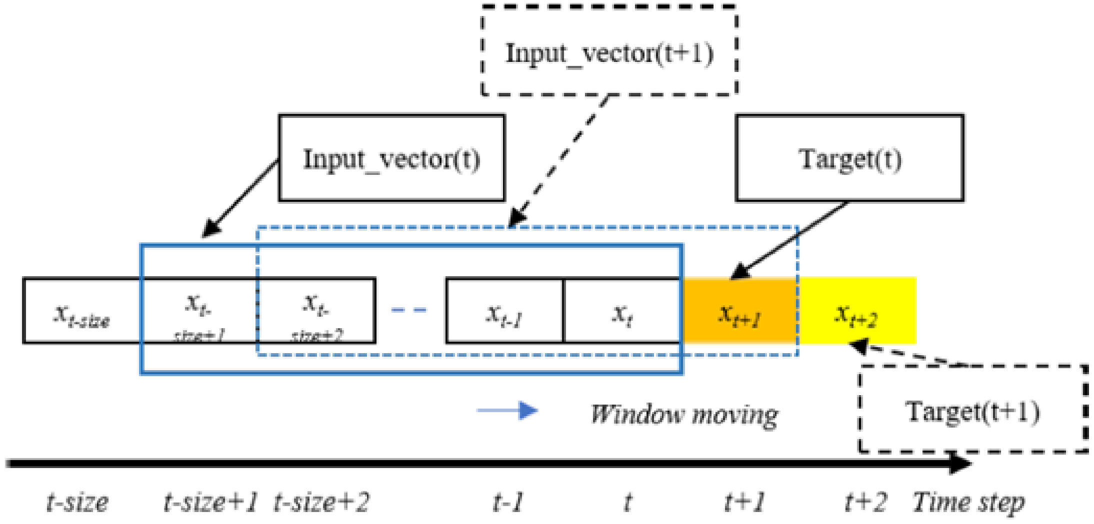
```
% finding correlation between all variables and total AC power
rIrradiation = corrcoef(irradiation,totalPower);
rModuleTemp = corrcoef(moduleTemp,totalPower);
rAmbientTemp = corrcoef(ambientTemp,totalPower);
rWindVelocity = corrcoef(windVelocity,totalPower);
rInsolation = corrcoef(insolation,totalPower);
rTotalPower = corrcoef(totalPower,totalPower);
% populating empty matrix with all correlations
matrix = zeros(6,6);
for i = 1:6
    for j = 1:6
        firstVar = datasetJan(:,i);
        secondVar = datasetJan(:,j);
        r = corrcoef(firstVar,secondVar);
        matrix(i,j)= r(1,2);
    end
end
% creating the heatmap
xlabel = {'Irradiation','Module Temp','Ambient Temp','Wind Vel',...
    'Insolation','Total AC Power'}
ylabel = {'Irradiation','Module Temp','Ambient Temp','Wind Vel',...
    'Insolation','Total AC Power'}
h = heatmap(xlabel,ylabel,matrix);
h.Title = 'Pearons Correlation Heatmap';
```



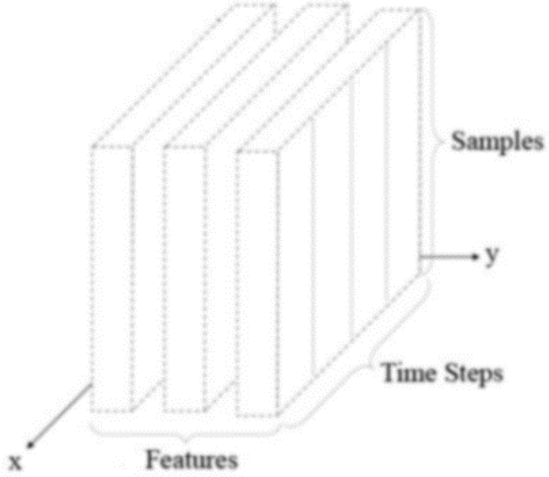
Heatmap showing correlation with Total AC Power

Input Matrix

- LSTM requires input data matrix to be 3-D
- Moving window mechanism



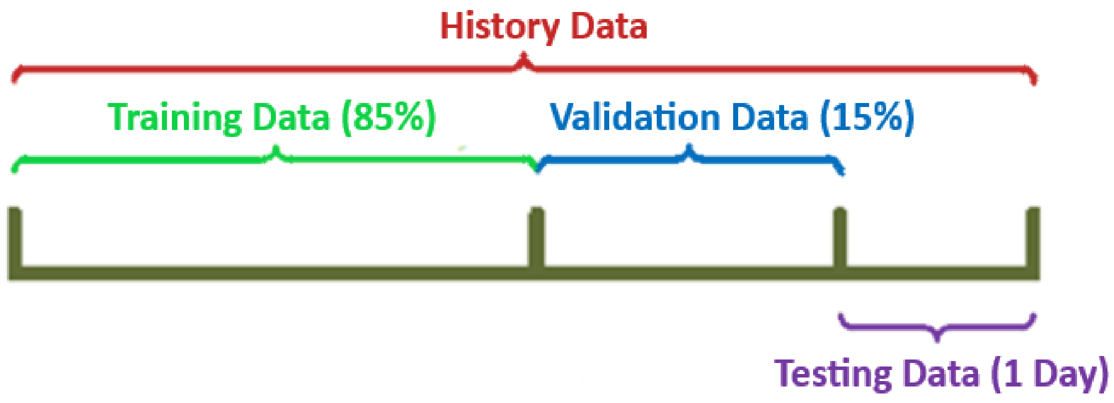
Input matrix mechanism



LSTM input 3-D array

Splitting the Dataset

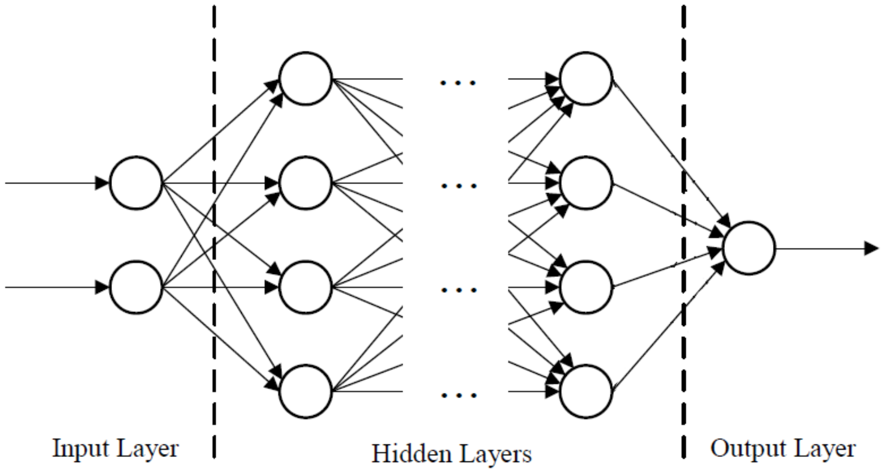
- Data is split sequentially not randomly
- Ratio is to avoid over-fitting
- Both validation and testing data are “unseen” data
- Validation for tuning hyperparameters



Visualisation of history data split

ANN

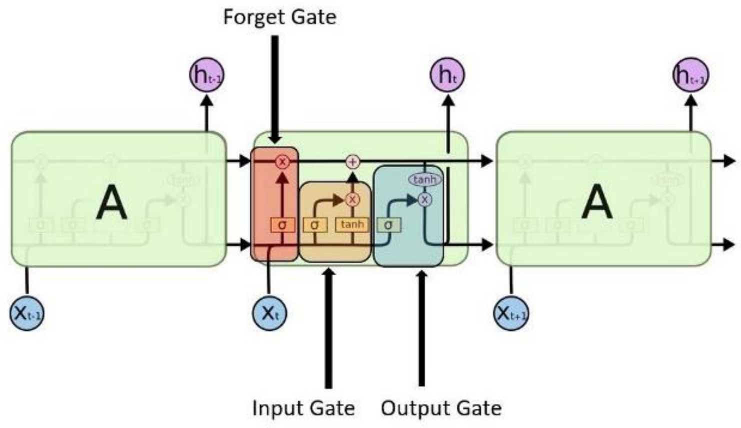
- Replicates information processing mechanism of human brain
- Back-propagation algorithm
- Suitable for many applications and treated as benchmark



ANN schematic diagram

LSTM

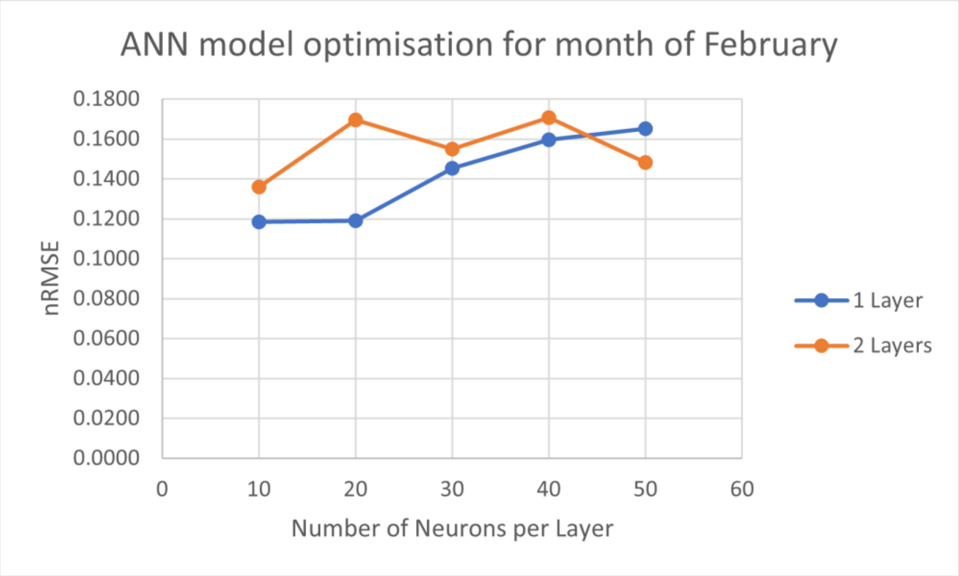
- Modified version of recurrent neural network (RNN)
- Overcomes gradient disappearance and gradient explosion problems
- Excellent performance in long-range dependency problem involving nonlinear relationships

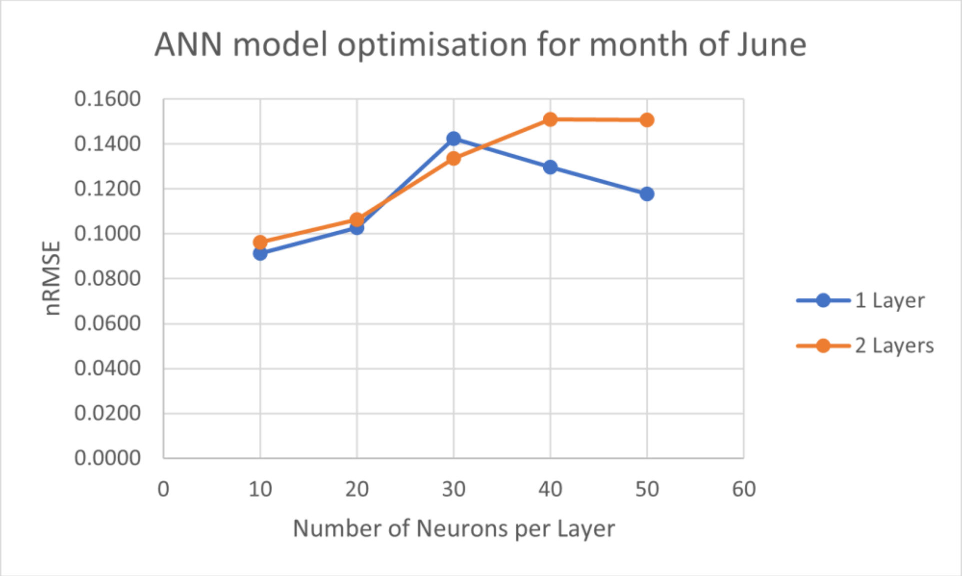


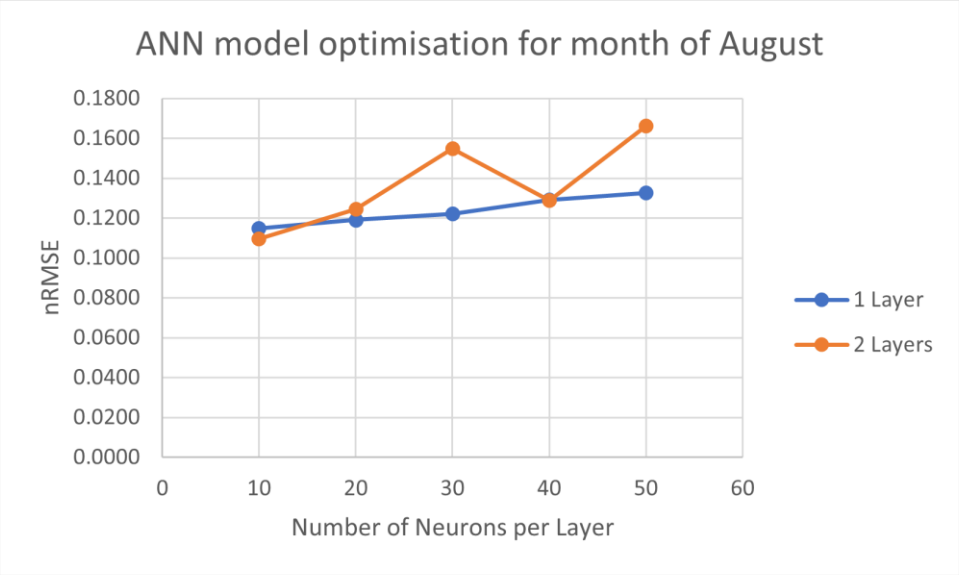
LSTM network and cell architecture

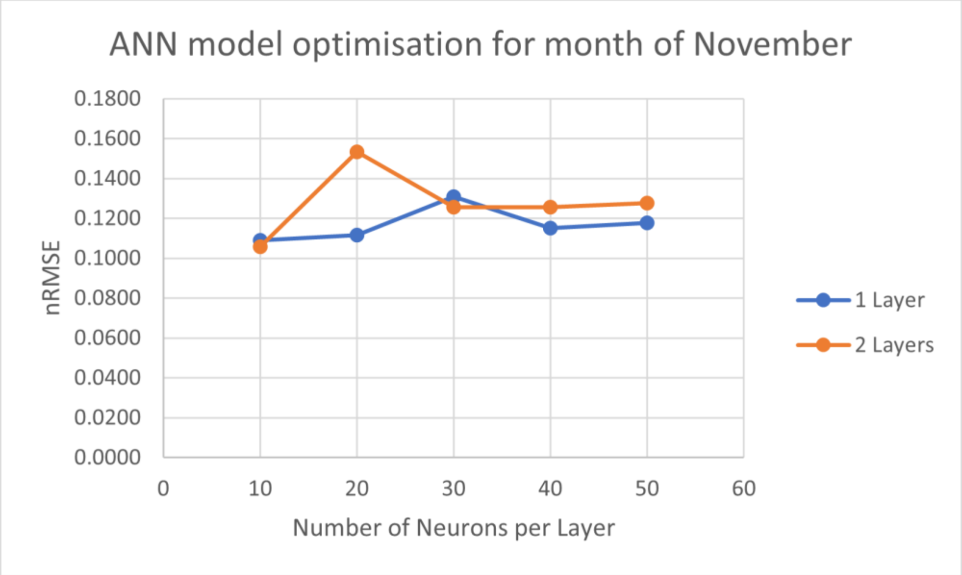
Optimisation

ANN

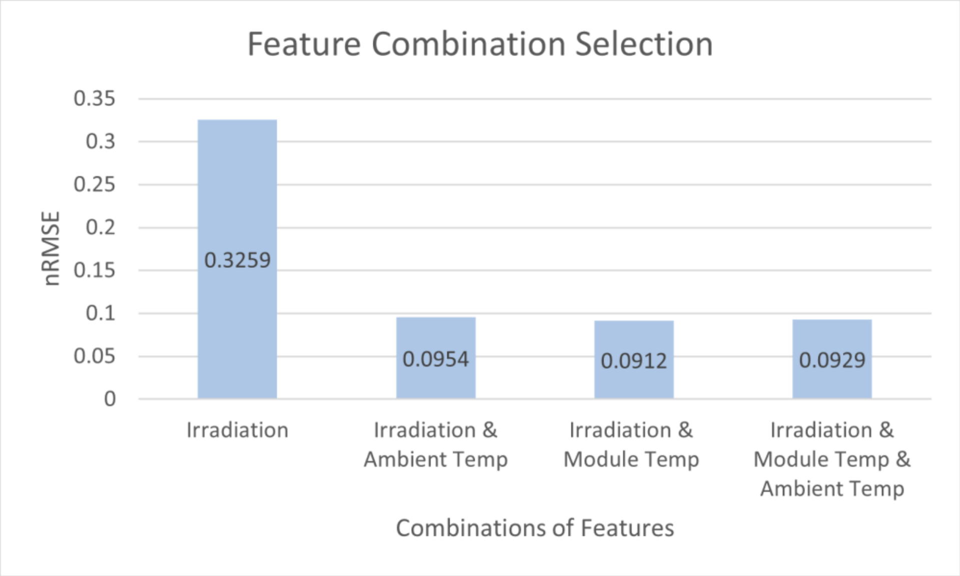

ANN model optimisation for month of February
0.1800
0.1600
0.1400
0.1200
0.1000
0.0800
0.0600
0.0400
0.0200
0.0000
nRMSE
0
10
20
30
40
50
60
Number of Neurons per Layer
1 Layer
2 Layers

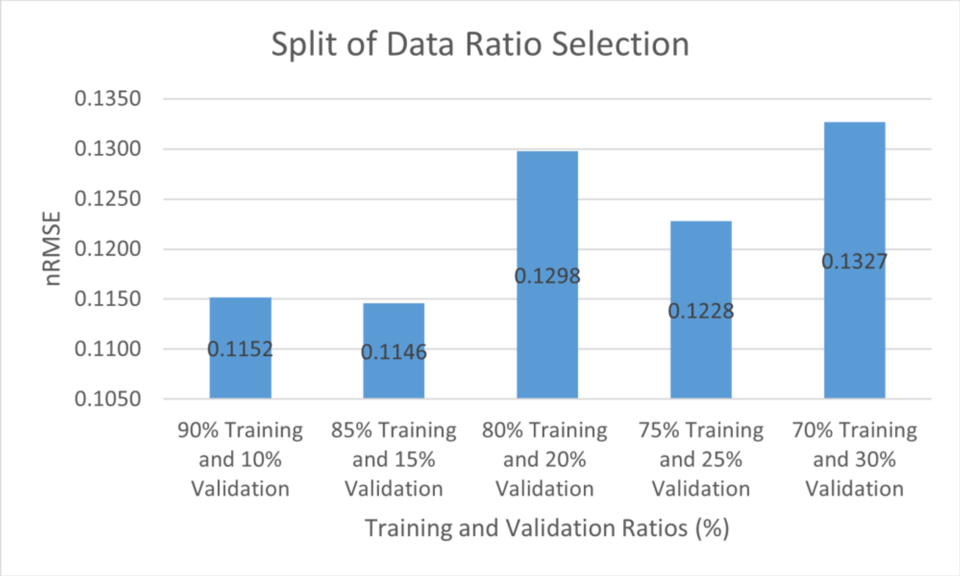

ANN model optimisation for month of June
0.1600
0.1400
0.1200
0.1000
0.0800
0.0600
0.0400
0.0200
0.0000
nRMSE
0
10
20
30
40
50
60
Number of Neurons per Layer
1 Layer
2 Layers

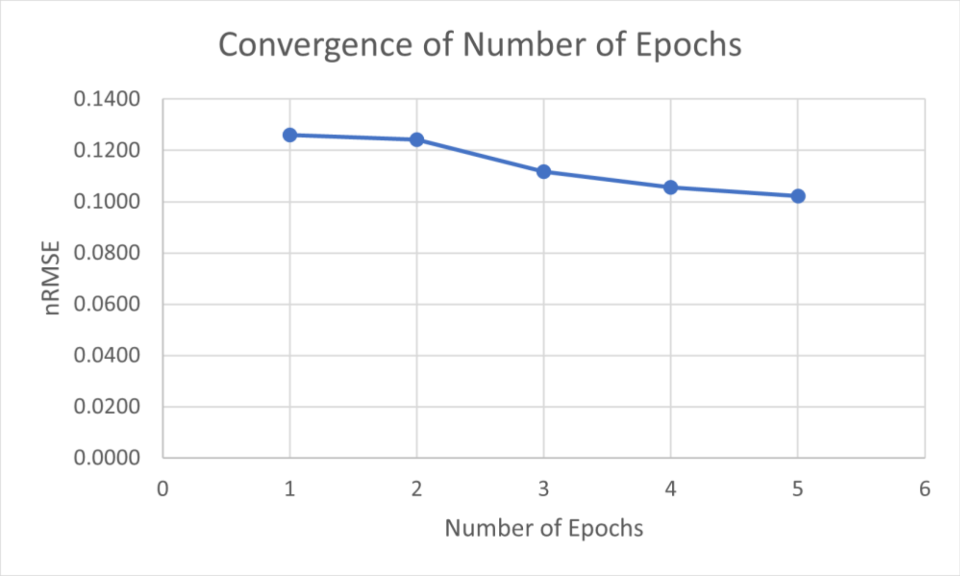

ANN model optimisation for month of August
0.1800
0.1600
0.1400
0.1200
0.1000
0.0800
0.0600
0.0400
0.0200
0.0000
nRMSE
0
10
20
30
40
50
60
Number of Neurons per Layer
1 Layer
2 Layers

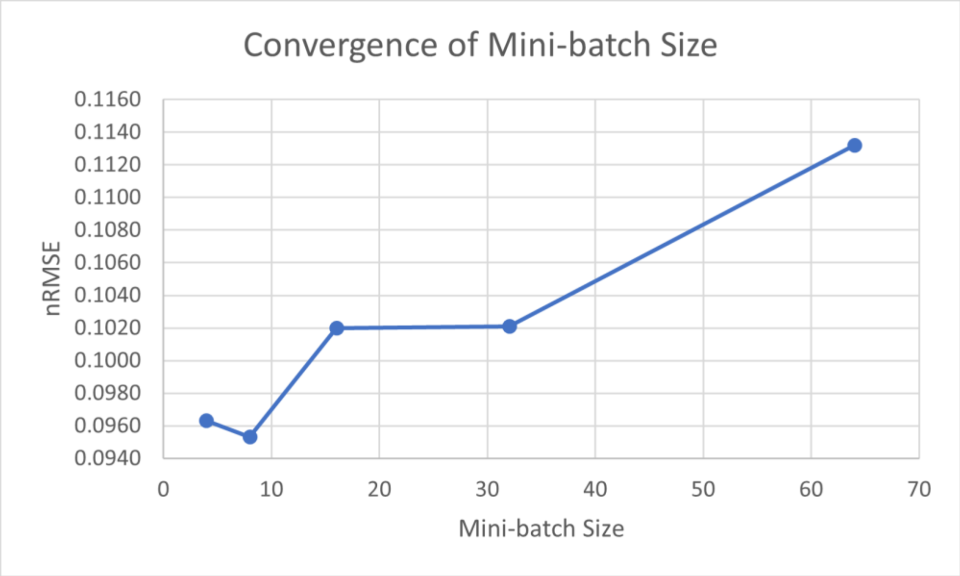

ANN model optimisation for month of November
0.1800
0.1600
0.1400
0.1200
0.1000
0.0800
0.0600
0.0400
0.0200
0.0000
nRMSE
0
10
20
30
40
50
60
Number of Neurons per Layer
1 Layer
2 Layers

LSTM

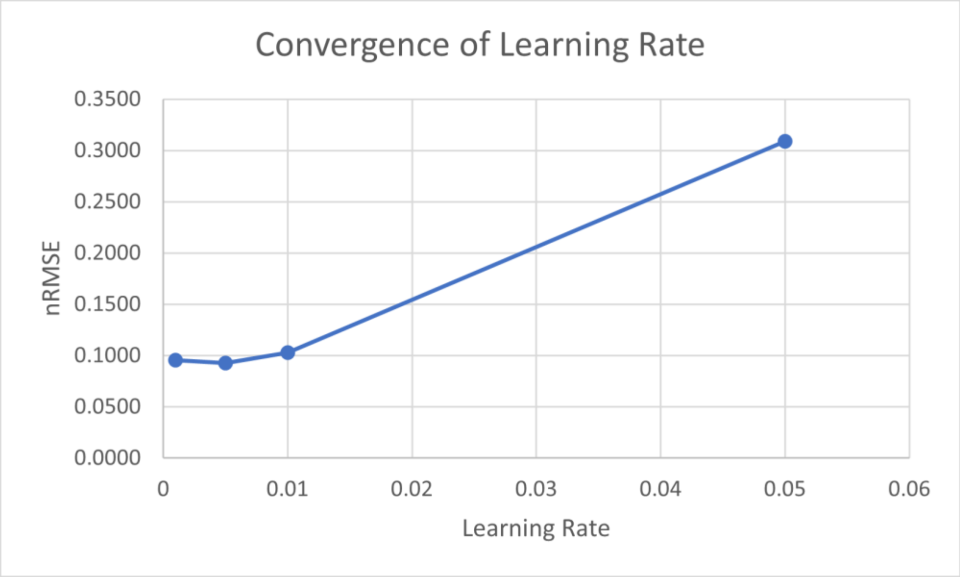

Feature Combination Selection
nRMSE
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0.3259
0.0954
0.0912
0.0929
Irradiation
Irradiation & Ambient Temp
Irradiation & Module Temp
Irradiation & Module Temp & Ambient Temp
Combinations of Features


Split of Data Ratio Selection
nRMSE
0.1350
0.1300
0.1250
0.1200
0.1150
0.1100
0.1050
0.1152
0.1146
0.1298
0.1228
0.1327
90% Training and 10% Validation
85% Training and 15% Validation
80% Training and 20% Validation
75% Training and 25% Validation
70% Training and 30% Validation
Training and Validation Ratios (%)

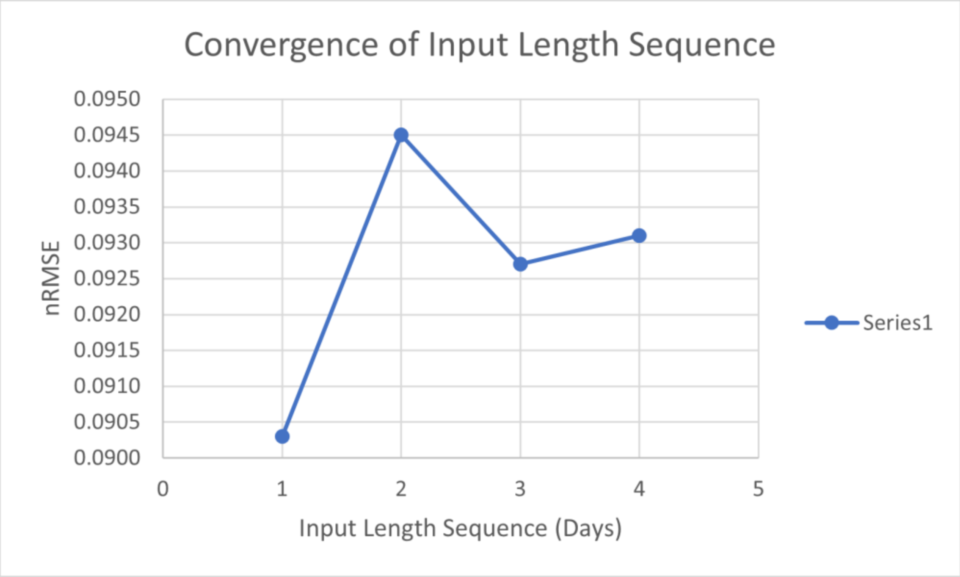

Convergence of Number of Epochs
nRMSE
0.1400
0.1200
0.1000
0.0800
0.0600
0.0400
0.0200
0.0000
0
1
2
3
4
5
6
Number of Epochs


Convergence of Mini-batch Size
nRMSE
0.1160
0.1140
0.1120
0.1100
0.1080
0.1060
0.1040
0.1020
0.1000
0.0980
0.0960
0.0940
0
10
20
30
40
50
60
70
Mini-batch Size

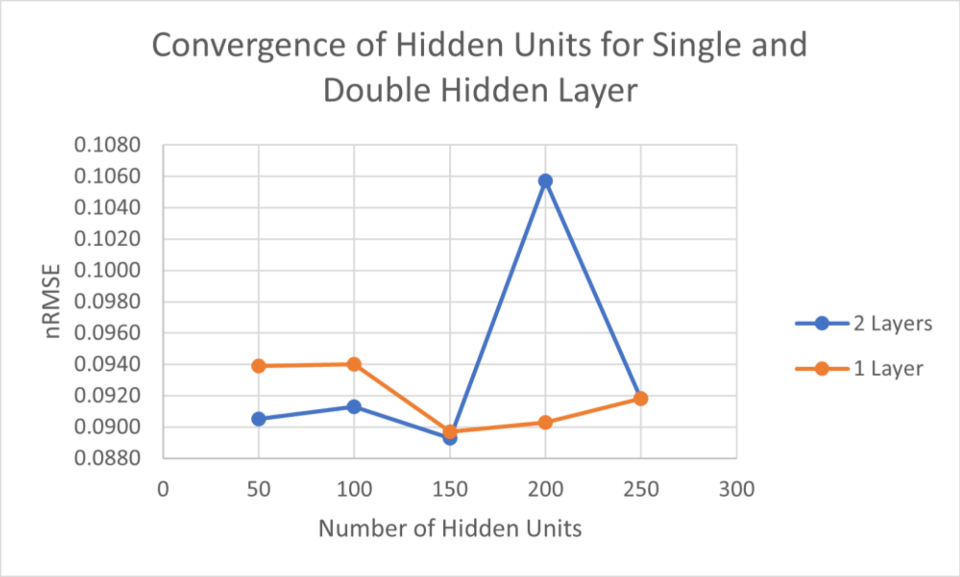
LSTM



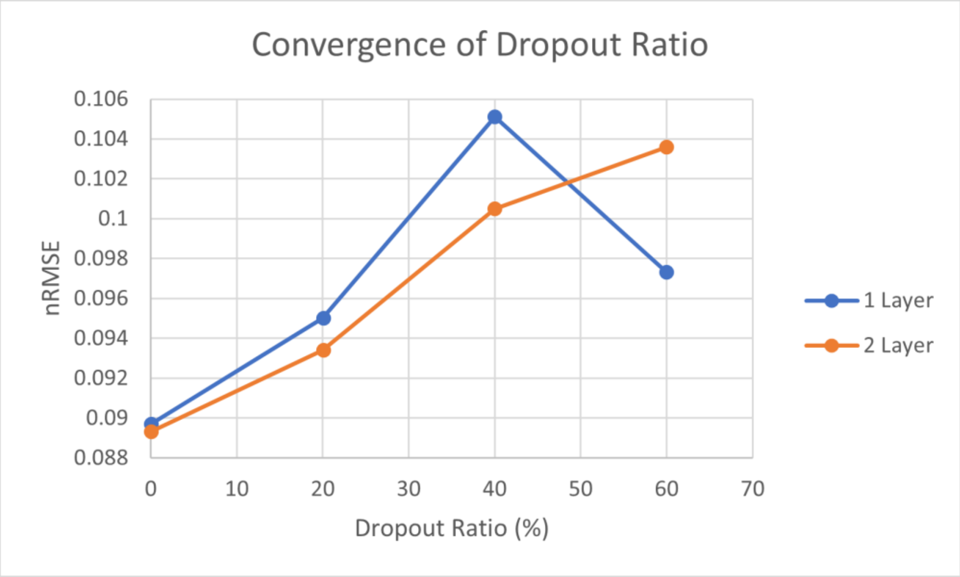
Convergence of Learning Rate
nRMSE
0.3500
0.3000
0.2500
0.2000
0.1500
0.1000
0.0500
0.0000
0
0.01
0.02
0.03
0.04
0.05
0.06
Learning Rate



Convergence of Input Length Sequence
nRMSE
0.0950
0.0945
0.0940
0.0935
0.0930
0.0925
0.0920
0.0915
0.0910
0.0905
0.0900
0
1
2
3
4
5
Input Length Sequence (Days)
Series1

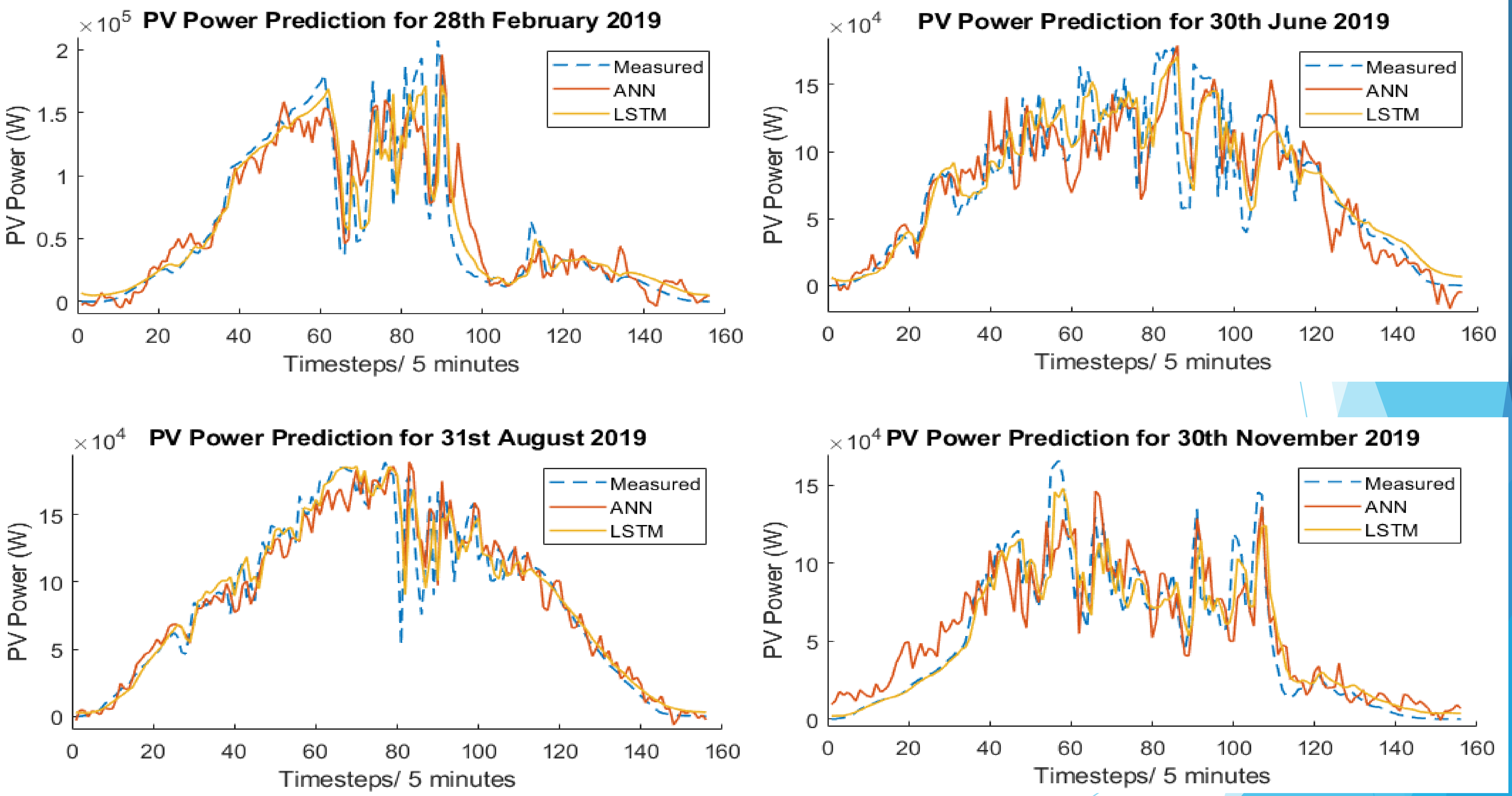


Convergence of Hidden Units for Single and Double Hidden Layer
nRMSE
0.1080
0.1060
0.1040
0.1020
0.1000
0.0980
0.0960
0.0940
0.0920
0.0900
0.0880
0
50
100
150
200
250
300
Number of Hidden Units
2 Layers
1 Layer



Convergence of Dropout Ratio
nRMSE
0.106
0.104
0.102
0.1
0.098
0.096
0.094
0.092
0.09
0.088
0
10
20
30
40
50
60
70
Dropout Ratio (%)
1 Layer
2 Layer

Results


PV Power Prediction for 28th February 2019
PV Power Prediction for 30th June 2019
PV Power Prediction for 31st August 2019
PV Power Prediction for 30th November 2019
Measured
ANN
LSTM
PV Power (W)
Timesteps/ 5 minutes

Quantitative Performance Evaluation of all ANN and LSTM models

Month	Model	nMAE	nRMSE	R^2
February	ANN	0.0438	0.1237	0.8007
	LSTM	0.0055	0.1107	0.8404
June	ANN	0.0088	0.1198	0.7719
	LSTM	0.0035	0.1141	0.7892
August	ANN	0.0088	0.0975	0.9007
	LSTM	0.0068	0.0938	0.9066
November	ANN	0.0225	0.0975	0.7927
	LSTM	0.0005	0.0734	0.8821

Computational Time

Computational time taken in seconds

Model	February	June	August	November
ANN	75	84	108	30
LSTM	1361	166	260	382

- ANN computational time is lower than LSTM
- Dependent on hyperparameters
- LSTM model for February takes much longer due to 7 day input sequence compared to 1 day for others

Conclusion

Conclusion

- LSTM network reacts better to fluctuations and follows trend more closely
- LSTM is superior to ANN for time series regression problems
- The developed AI models can be used for real-time forecasting of power of solar PV plants in Malaysia or similar geographical location

Future Works

- Different architectures of LSTM models could be utilised
- Hybridisation with other DL methods or optimisation techniques
- Extend forecast horizon to longer term forecasting

Acknowledgements

I would like to express my sincere gratitude to my supervisor Dr. Arshad for the continuous support and many insights provided during the numerous consultation sessions over the past year. His assistance and guidance went a long way in helping me successfully complete this research project. Finally, I would like to thank Monash for the education imparted over the last four years and also for providing the data used in this study.

References

1. Jebli, F.-z. Belouadha, M. I. Kabbaj, and A. Tilioua, "Deep Learning based Models for Solar Energy Prediction," ASTESJ, Journal Article vol. 6, no. 1, pp. 349-355, 2021. [Online]. Available: internal-pdf://ASTESJ_060140.pdf.
2. D. Huang et al., "Prediction of Solar Photovoltaic Power Generation Based on MLP and LSTM neural networks," in 2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2): IEEE, pp. 2744-2748.
3. C.-H. Liu, J.-C. Gu, and M.-T. Yang, "A Simplified LSTM Neural Networks for One Day-Ahead Solar Power Forecasting," IEEE Access, vol. 9, pp. 17174-17195, 2021.
4. M. K. Park, J. M. Lee, W. H. Kang, J. M. Choi, and K. H. Lee, "Predictive model for PV power generation using RNN (LSTM)," Journal of Mechanical Science and Technology, vol. 35, no. 2, pp. 795-803, 2021.
5. M. Konstantinou, S. Peratikou, and A. G. Charalambides, "Solar Photovoltaic Forecasting of Power Output Using LSTM Networks," Atmosphere, vol. 12, no. 1, p. 124, 2021.
6. M. S. Hossain and H. Mahmood, "Short-term photovoltaic power forecasting using an LSTM neural network," in 2020 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), 2020: IEEE, pp. 1-5.
7. "Understanding RNN and LSTM", Medium, 2021. [Online]. Available: https://aditi-mittal.medium.com/understanding-rnn-and-lstm-f7cdf6dfc14e. [Accessed: 31- May- 2021].
8. "Renewable electricity capacity additions, 2007-2021, updated IEA forecast – Charts – Data & Statistics - IEA", IEA, 2021. [Online]. Available: https://www.iea.org/data-and-statistics/charts/renewable-electricity-capacity-additions-2007-2021-updated-iea-forecast. [Accessed: 31- May- 2021].
9. "ASEAN total installed capacity 2017-2025 – Charts – Data & Statistics - IEA", IEA, 2021. [Online]. Available: https://www.iea.org/data-and-statistics/charts/asean-total-installed-capacity-2017-2025. [Accessed: 31- May- 2021].
10. Scholtz, Louise & Muluadzi, Khodani & Kritzinger, Karin & Mabaso, Mbali & Forder, Stephen. (2017). Renewable Energy: Facts and Futures The energy future we want.
11. "We are doing our part", Malaysia, 2021. [Online]. Available: https://www.monash.edu.my/news-and-events/pages/latest/articles/2019/we-are-doing-our-part. [Accessed: 31- May- 2021].
12. "Climate and temperature development in Malaysia", Worlddata.info, 2021. [Online]. Available: https://www.worlddata.info/asia/malaysia/climate.php. [Accessed: 01- Jun- 2021].

Thank You