

EUROCON 2021



Peak Demand Management and Schedule **Optimisation for Energy Storage through the** Machine Learning Approaches

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European Union European Structur



Presentation outline

- Introduction
- Literature survey
- Case study
- Machine Learning (ML) models
- Forecast results
- ES optimization
- Conclusion
- Acknowledgement







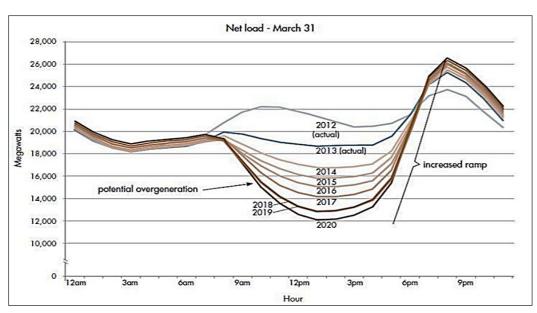


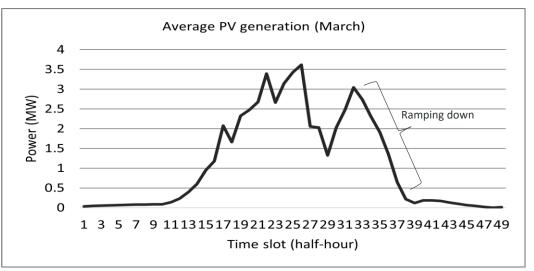
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Introduction

- Electricity demand uncertainity (ramping up evening peak)
- PV generation variability
- Need of accurate forecasting
- Schedule optimization for energy storage (ES)
- Better preparedness against ES duty cycle mismatch volatility

Could Machine Learning be useful?







Literature survey

Models for PV generation forecasting

- Seasonal ARIMA
- ANN-Multivariate
- CNN-SRP (Super Resolution Perception)
- ANN
- LSTM
- CNN-LSTM

Models for electrical demand forecasting

- ARMA
- RNN
- CNN-LSTM
- LSTM
- CNN+LSTM-AE
- Bi-GRU
- Bi-LSTM



Case Study

Problem Statement:

Optimise the duty cycle of energy storage device (battery) through forecasted PV and load demand data (half-hourly)

Aim: Flatten the peak demand curve



Total PV capacity: 5MW



Total battery capacity: 6MWh

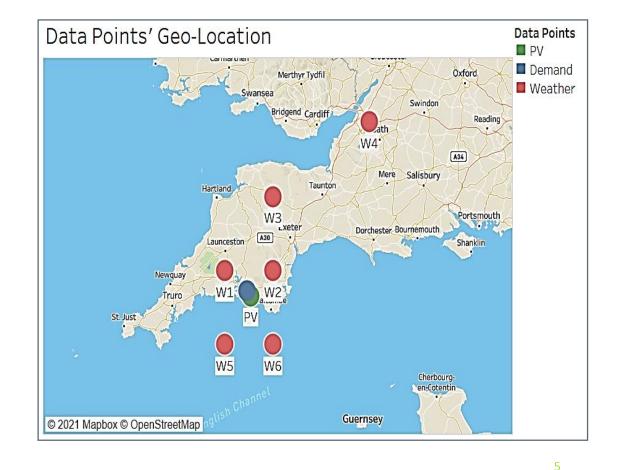


Devon Substation, Plymouth, UK

Constraints:

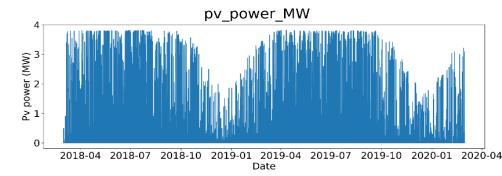
Battery must charge only until 15:30 (@ max charging rate of 2.5MW/hh)

Battery must discharge only during 15:30 to 21:00 (@ max discharging rate of 2.5MW/hh)





Data Analysis



Correlation Heatmap_PV

1.00

- 0.50

- 0.25

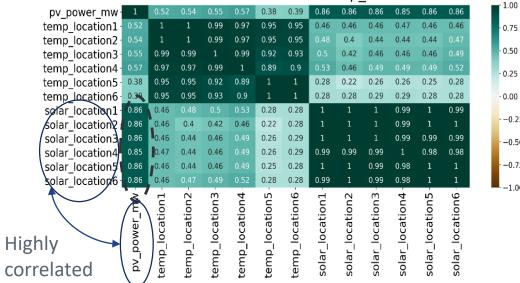
- 0.00

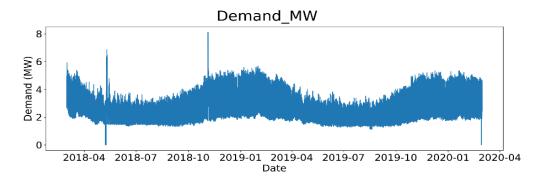
-0.25

-0.50

- -0.75

-1.00



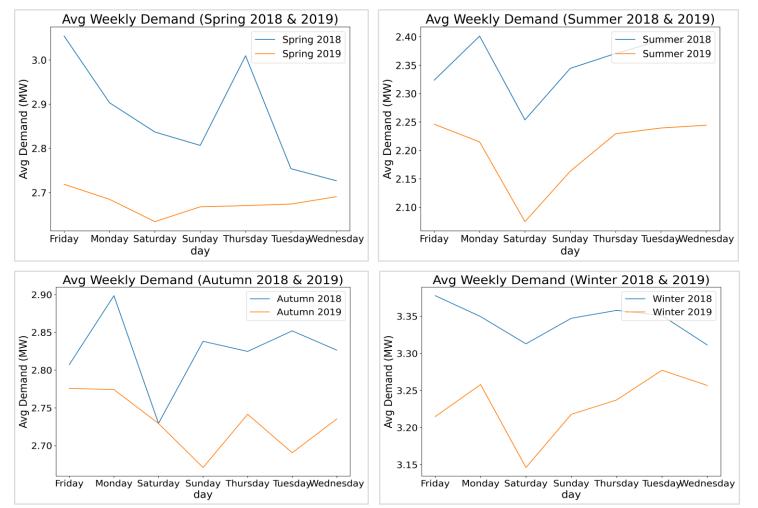


Correlation Heatmap DEMAND

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demand 1	0.086	0.093	0.1	0.12	0.013	0.017	0.25	0.25	0.24	0.23	0.25	0.25	1.00	,
temp_location1 0.08		1	0.99	0.96	0.95	0.94	0.45	0.44	0.45	0.44	0.44	0.44	- 0.75	j
temp_location2 0.093	1	1	0.99	0.97	0.95	0.95	0.45	0.45	0.45	0.45	0.45	0.45		
temp_location3 0.1	0.99	0.99	1	0.98	0.92	0.92							- 0.50	1
temp_location4 - 0.12	0.96	0.97	0.98		0.89	0.89							- 0.25	ŝ
temp_location - 0.013	0.95	0.95	0.92	0.89			0.28	0.28	0.28	0.28	0.28	0.28	0.25	
temp_location ^{5 - 0.017}	0.94	0.95	0.92	0.89		1	0.27	0.27	0.28	0.28	0.27	0.27	- 0.00)
solar_location - 0.25	0.45	0.45			0.28	0.27				0.99	1	0.99		
solar_location2 - 0.25	0.44	0.45			0.28	0.27				0.99	1	1	0.2	25
solar_location 3 - 0.24	0.45	0.45		0.5	0.28	0.28	1	1	1	0.99	0.99	0.99	0.5	50
solar_location4 0.23	0.44	0.45			0.28	0.28	0.99	0.99	0.99	1	0.99	0.99		
solar_location5 0.25	0.44	0.45			0.28	0.27			0.99	0.99		1	0.7	15
solar_location6 - 0.25	0.44	0.45			0.28	0.27	0.99		0.99	0.99	1	1	1.0	20
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No \ ^{\vee} /	temp_location1	temp_location2	temp_location3	temp_location4	temp_location5	temp_location6	solar_location1	solar_location2	solar_location3	solar_location4	solar_location5	ŏ.		
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Data Analysis



Seasonal variation of load demand for 2018 & 2019

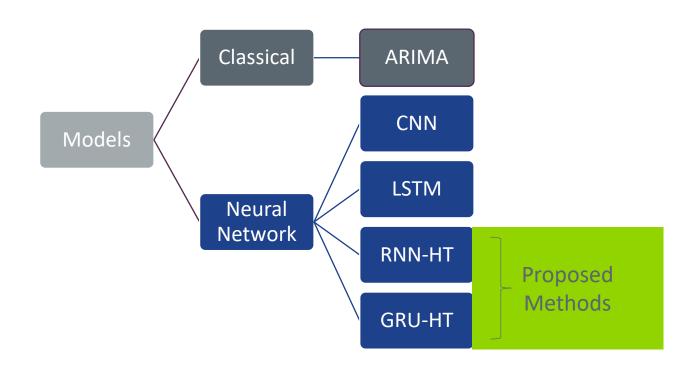
Spring	01/03/2018 to 31/05/2018
Summer	01/06/2018 to 31/08/2018
Autumn	01/09/2018 to 30/11/2018
Winter	01/12/2018 to 28/02/2019

Small dataset given for model training



ML Models

Neural network models with Bayesian hyperparameter optimization approach or Hyperparameter Tuning (HT)



Model Evaluation:

$$RMSE = \sqrt{\left(\frac{1}{N}\sum_{i=1}^{N} \left(\widehat{P}_{i} - P_{i}\right)^{2}\right)}$$

$$nRMSE = 100 \sqrt{\left(\frac{1}{N} \sum_{i=1}^{N} \left(\frac{\widehat{P}_{i} - P_{i}}{P_{installed}}\right)^{2}\right)}$$

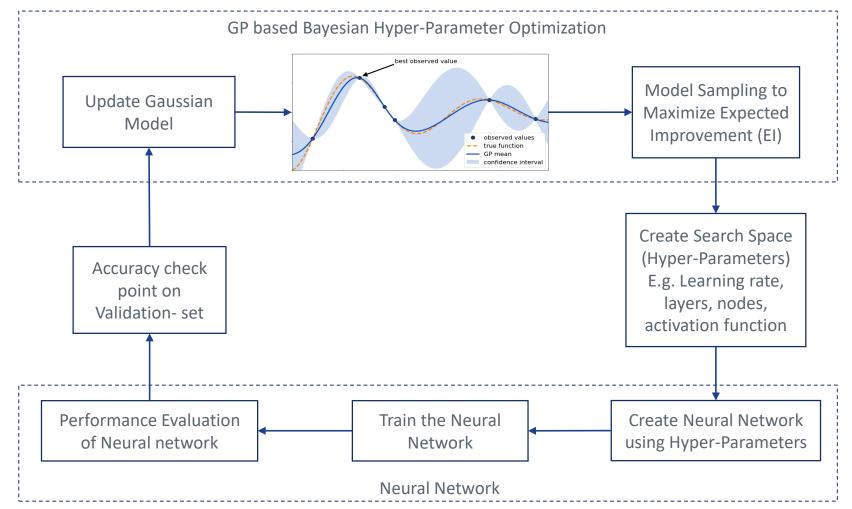
N is the number of samples;

 \hat{P}_i and P_i are the predicted and measured power at the time *i*;

Pinstalled is the installed capacity.



Bayesian optimization for HT



Source: Pedersen, M.E.H.: Hyper-parameter optimization (2018). <u>https://github.com/Hvass-Labs/TensorFlow-Tutorials</u>



Bayesian optimization for HT

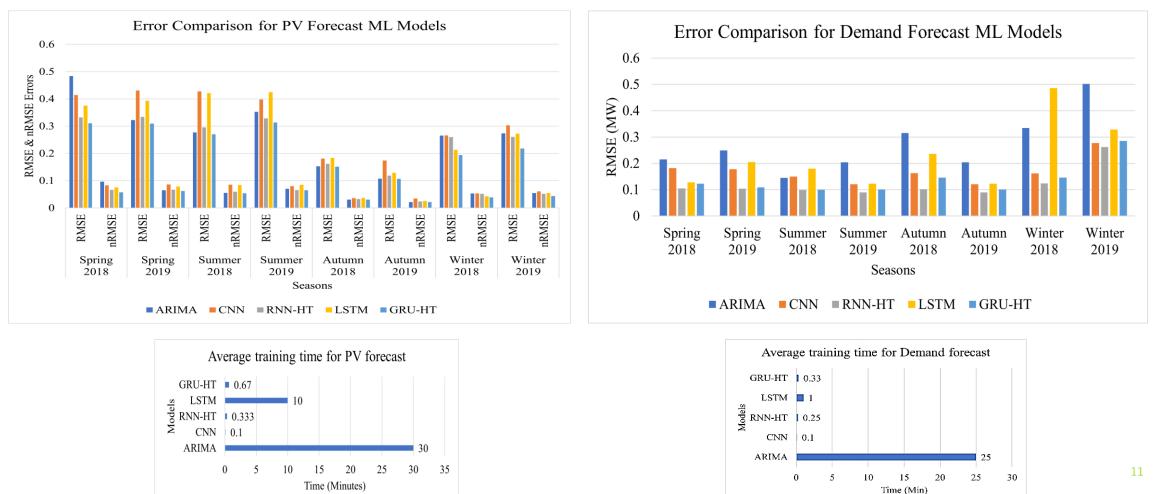
Advantages

- Parallel processing of all the possible hyperparamters combinations
- Faster than manual hit and trial selection approach
- Maximise the model's predictive accuracy

Hyperparameters	HT values				
Number of units	128, 128, 64				
Number of hidden layers	2				
Activation function	Leaky ReLU				
Max epochs	100				
Batch Size	Single shot batch (all data points at once)				
Optimizer	Adam				
Learning rate	0.5				
Dropout rate	0.3				



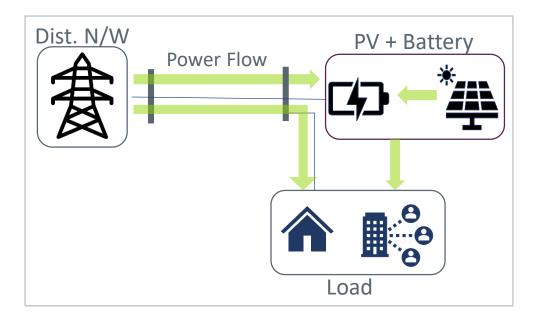
Forecast results

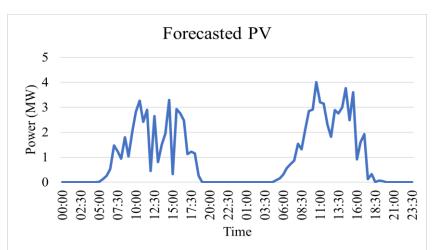


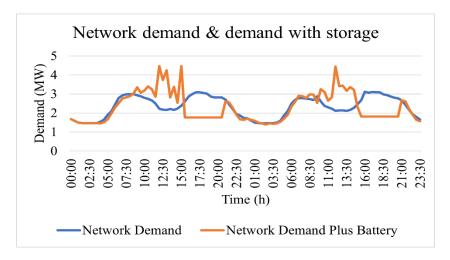


ES Optimization

Baseline Model: Basic RNN Model Best Model: GRU-HT for PV Forecasting RNN-HT for Demand Forecasting

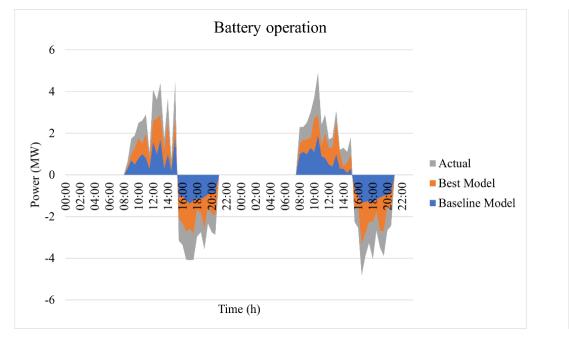


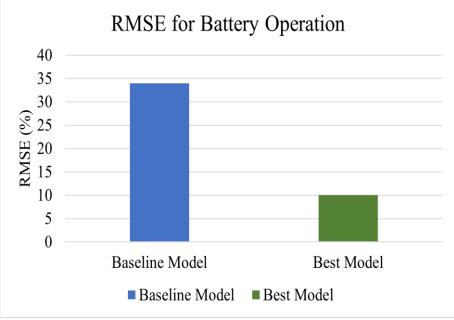






ES Optimization







Conclusion

- Bayesian optimization based HT provides more accurate forecasting results
- Best model for **multivariate** forecasting **GRU-HT**
- Best model for univariate forecasting RNN-HT
- Models worked well with small training dataset
- Future schedule of storage optimization is 24% more accurate than standard models
- Computational time is very less and hence can be a better tool for real-time forecasting



Acknowledgement

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Thank You For any queries, you can reach me at Rohit Trivedi@ierc.ie



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