Optimisation of behind the meter DER generation assets within network constraints: A roadmap to successful DR program (Project-69)

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Contents

- What is ‘Demand Response’?
- Project Overview
- WP-1: Machine Learning based Energy Demand Prediction for Demand Response Market
- WP-2: Unlocking the Potential of Backup Generators in Demand Response
- Recommendations

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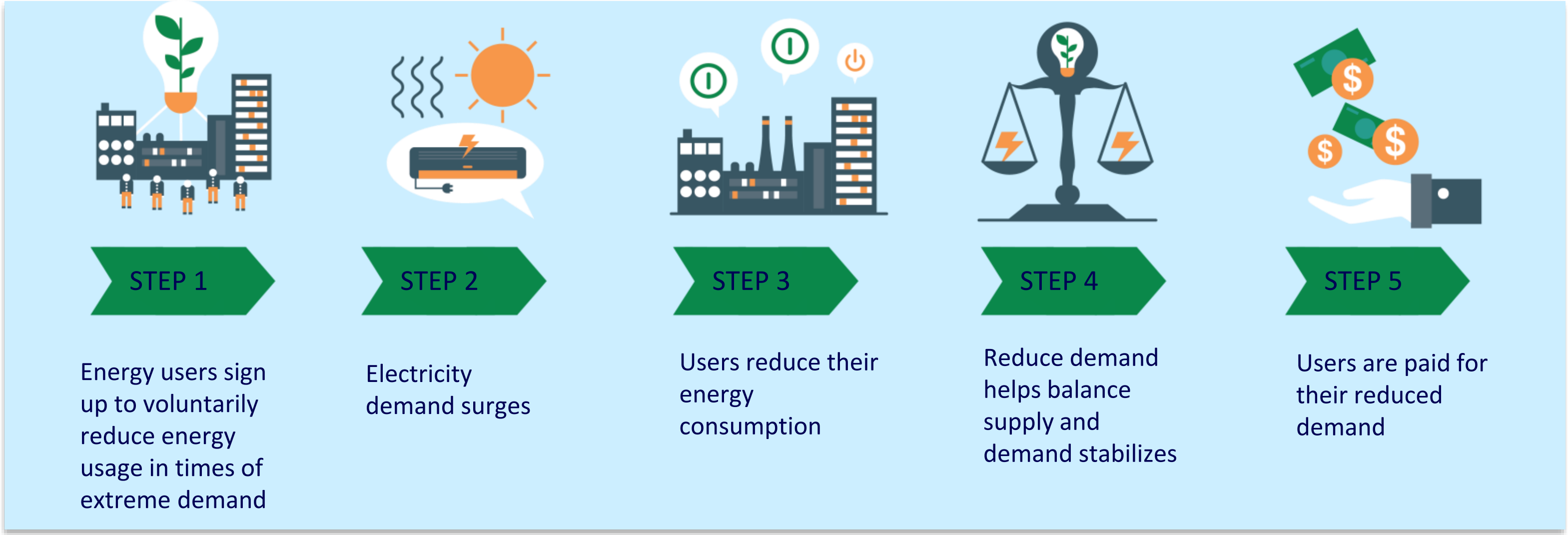
What is 'Demand Response (DR)'?

- Reducing demand when requested by participants in the market
- It helps reduce costs and increase reliability



Project Overview

WP-1: Machine learning for C&I customers' baseline improvement

- Identify the correlation between the C&I customer demand and weather parameters
- Apply machine learning techniques to improve the C&I customer baselines/ demand prediction

WP-2: Unlocking the potential of participation of backup generators in demand response

- Identify the main factors contributing to back-up generator export limitations
- Identify the strategies to improve back-up generator export limits
- Feasibility study of biodiesel for backup generators

WP-3: Identify tariffs that can incentivise the uptake of batteries

- Developing a battery optimization tool for a C&I customer
- Analysing battery behaviour at site level and its network impact
- Recommendations for the network tariff structure to increase uptake of batteries

Roadmap for successful implementation of demand response for C&I customers

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Work Package 1

Machine Learning based Energy Demand Prediction for Demand Response Market

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Motivations

- Baseline is used to calculate the monetary benefits for participants
- The existing simple DR baseline method is based on averaging the power consumption on 10 days before the event
- This averaging method is not able to use auxiliary variables (e.g. temperature) as inputs to improve the baseline
- Our aim is to use Machine Learning (ML) models for demand prediction and study impact on the DR monetary benefits
- The ML model is able to find hidden patterns in data series

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Machine learning models for demand predication

Goal:

- Investigate the potential of ML for building an easily understandable and interpretable model that can lead to higher accuracy against the baseline model!

Methodology:

- Two ML-based models are considered
- Feed in historical energy demand data and other informative factors and produce the future demand as output

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ML-based models

Model #1:

Linear Regression (LR) model

$$\hat{y} = a_1 x_1 + \cdots + a_n x_n + b$$

Model #2:

Polynomial regression (NLR) model

$$\hat{y} = a_o + \cdots + a_n x_n^2 + b_1 x_1 \ldots + b_n x_n + c$$

$\hat{y}$: predicated value ; x_i : power consumption ; a_i, b_i, c: cofficients to be learned

ML demand prediction framework

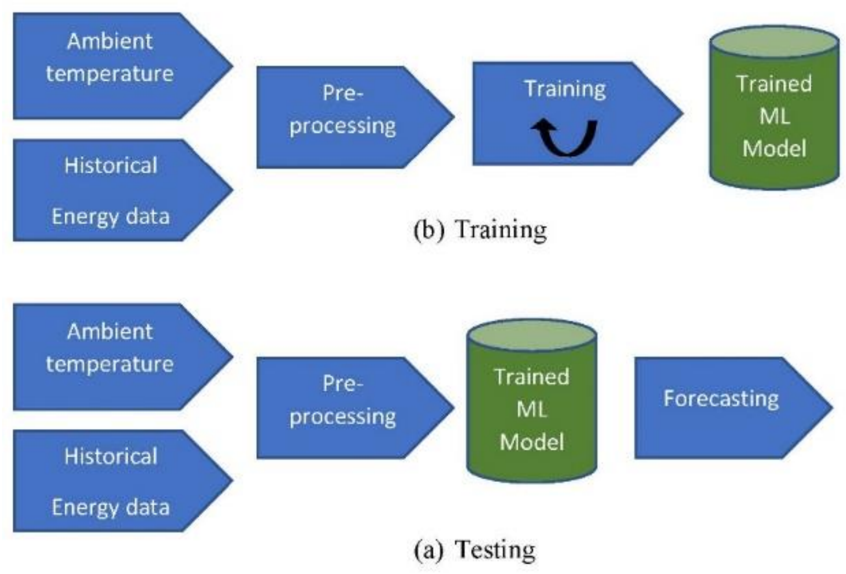

Fig 1. The general framework of the ML model for demand response

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Experimental results

Dataset 1:

The data is collected every 30 minutes for different periods

- It also includes the power consumption of an event day (actual DR event), which has been excluded during the training and testing of the ML prediction models

Table 1. C&I portfolios and their data availability of dataset 1.

C&I customer	**Data availability**	
	From (dd/m/y)	*To* (dd/m/y)
Chemical Plant	10/11/2020	14/01/2021
Telecom	10/11/2020	10/06/2021
Telecom VIC	1/01/2021	25/05/2021
University	22/12/2019	31/01/2020
Water Utility 2	22/12/2019	31/01/2020
Water Utility 5	1/01/2020	31/01/2020

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Experimental results

Dataset 2:

- This dataset was collected every 30 minutes from 01/04/2018 to 31/12/2020.
- The participant is a large water utility, but they have not participated in the DR event (it is used for prediction only)

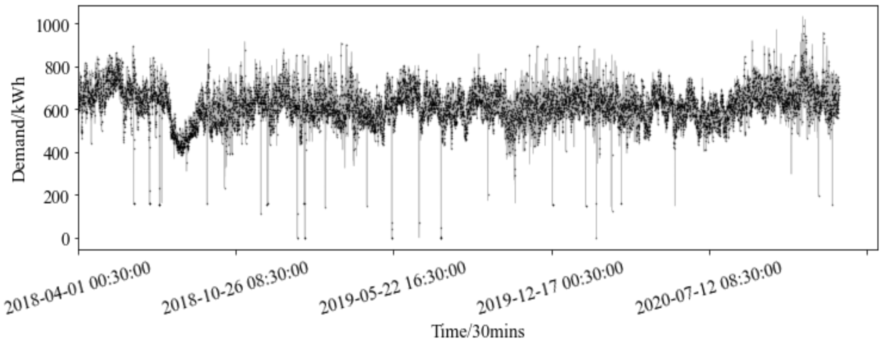
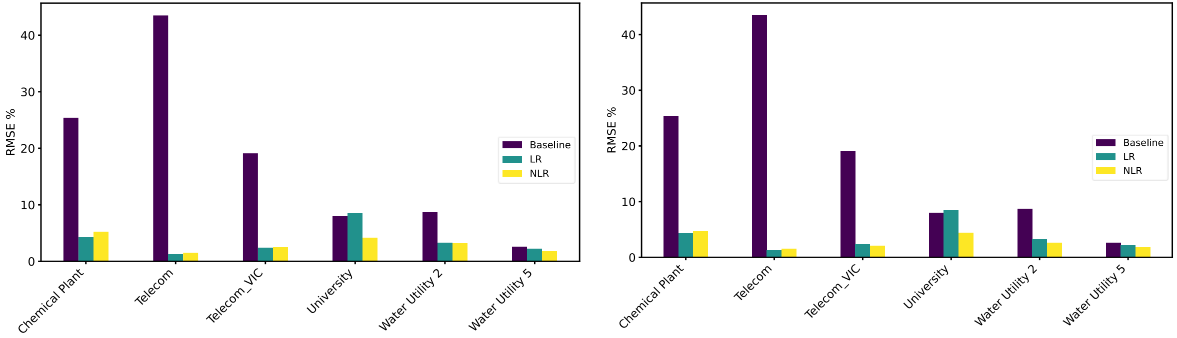


Fig. 2 Demand data from 01/04/2018 to 31/12/2020.

Experimental results

Case study 1 (dataset 1)

- The accuracy in term of RMSE of the different predictive models and baseline models are reported.
- For each model, the following settings are explored to verify the effectiveness of weather-related data on the demand prediction: 1) energy consumption, 2) energy consumption and temperature.



(a) without temperature (b) with temperature

Fig. 3: Dataset 1 testing RMSE performance for average baseline and LR, NLR.

Experimental results

case study 1 (dataset 1)

- We investigate the C&I ML predication compared to the Baseline at DR event.

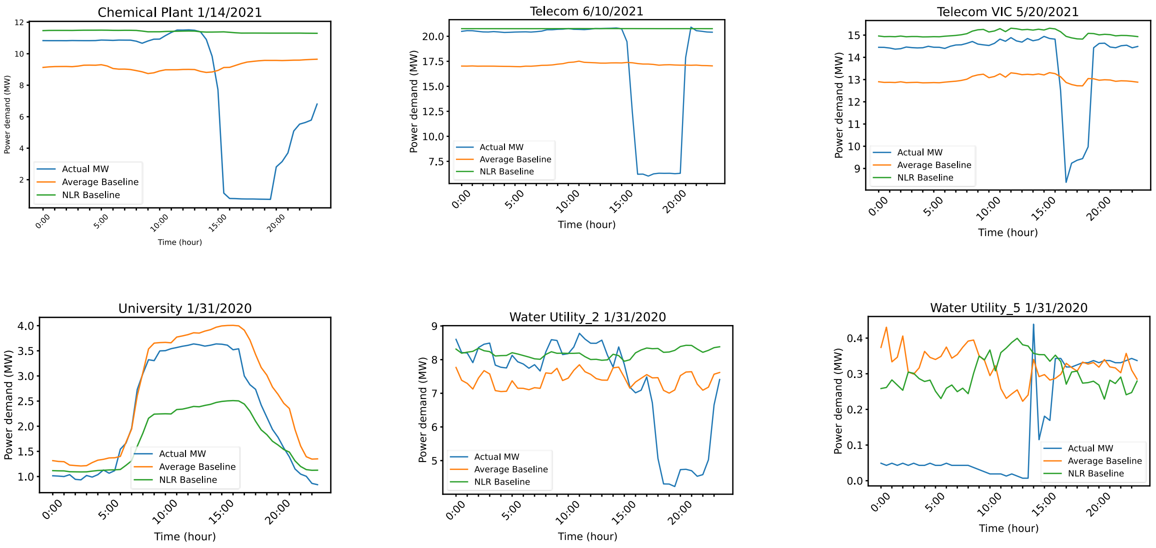


Fig. 4: Demand response predictions for the NLR model compared to the baseline for the dataset 1 with 6 C&I customer portfolios.

Impacts on monetary benefits

Customer	Percentage of the difference in the benefit (ML-baseline comparing to Average baseline)
Chemical Plant	+28.3 %
Telecom	+47 %
Telecom VIC	+87 %
University	-60.7 %
Water Utility 2	+16.0%
Water Utility 5	+44.9%

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Experimental results

case study 2 (dataset 2)

- We use the data before 28/12/2020 (training set) to train the model and the data from 28/12/2020 to 30/12/2020 (testing set) to test the trained model.
- We design two different models:
  - Model 1 uses the same historical time stamps as the baseline, but can add more exogenous factors
  - Model 2 uses the time stamps before the predicted time stamps as inputs with a time window (TW) – the number of previous time stamps denoted as TW, e.g., using 7:00, 7:30, 8:00, 8:30, 9:00, and 9:30 data to predict 10:00 for the same day

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Experimental results

case study 2 (dataset 2)

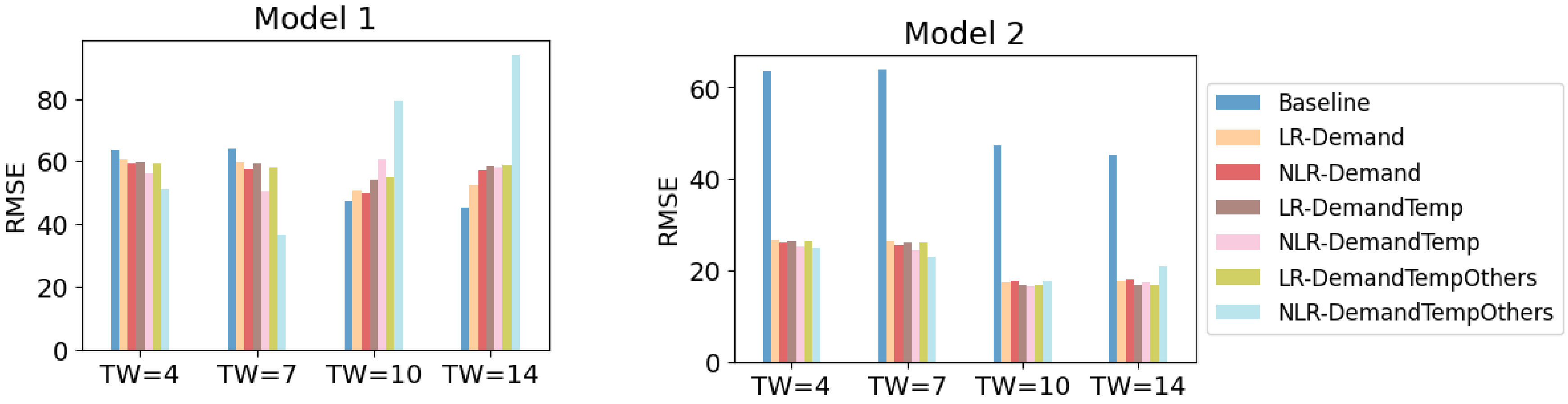

Fig. 5: The testing RMSE performance of the baseline, LR and NLR predictors for the Demand, DemandTemp and DemandTempOthers scenarios for Model1 and Model2 (Dataset 2).

Study Summary

- How to engage C&I customers with DR programs more effectively?
- Baselines!
- Explainable ML for more accurate baselines
- More data is required to confirm the true benefits to customers

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Work Package 2

Unlocking the Potential of Backup Generators in Demand Response

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WP-2 Motivation and Objectives

- Identify the main factors contributing to back-up generator export limits
- Identify the strategies to improve back-up generator export limits
- Conducting research on the most economic ways to synchronise backup generators, while meeting regulatory and DNSP requirements
- Feasibility study of biodiesel for backup generators

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Identify the Main Factors Contributing to Back-up Generator Export Limitations

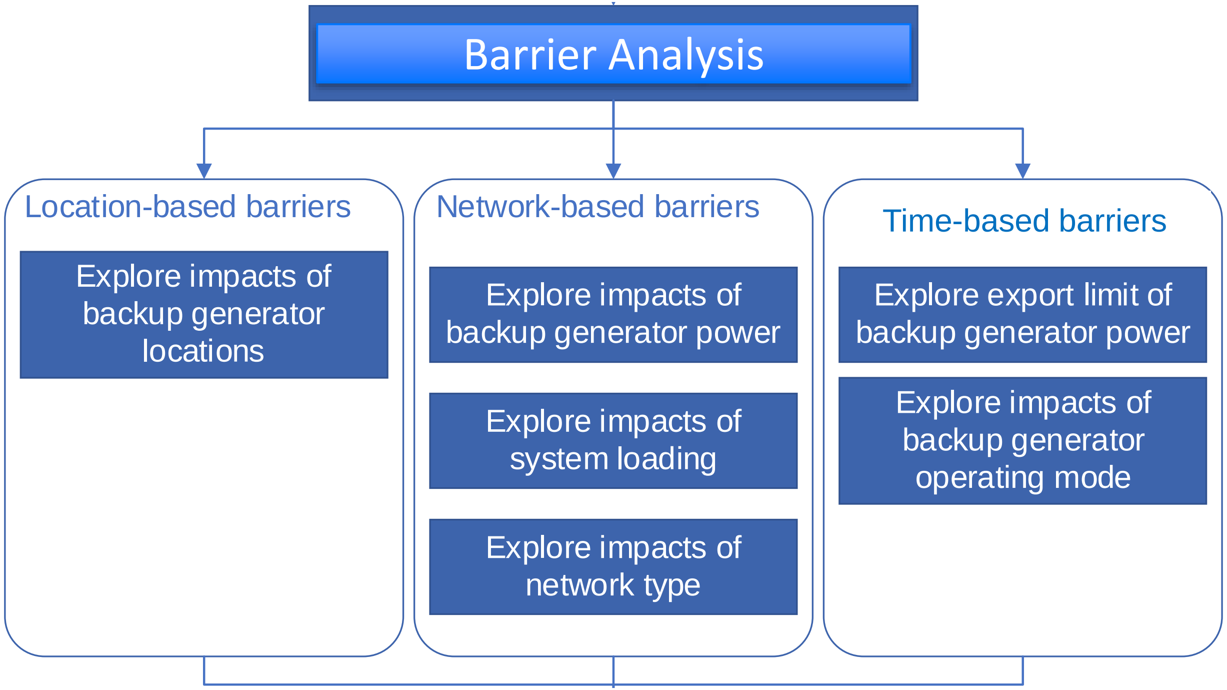

Fig. 6. Barriers to backup generator export.

Voltage limit

Thermal limit

Short-circuit current limit

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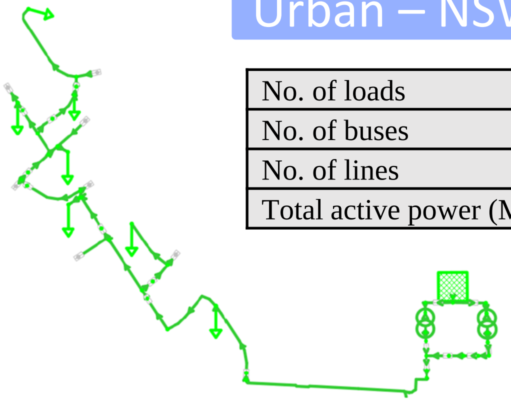
MV Network Models

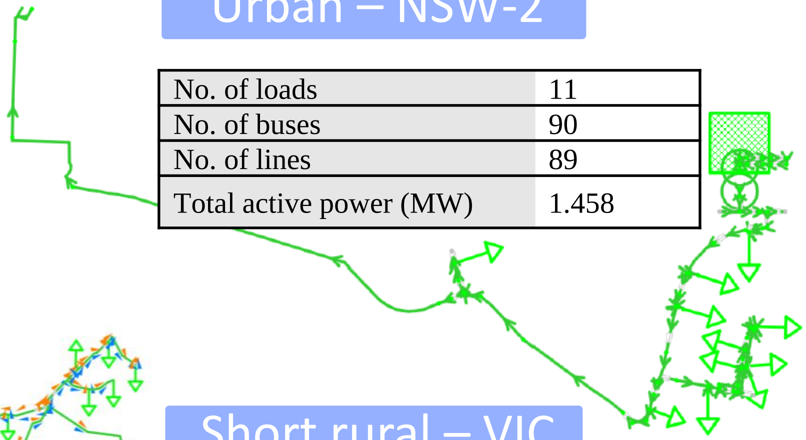
CSIRO National Feeder Taxonomy Study

Urban – NSW-1



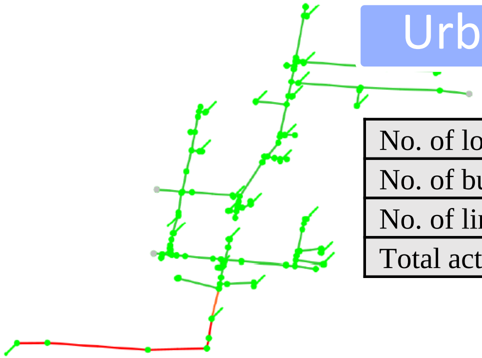
No. of loads	7
No. of buses	57
No. of lines	55
Total active power (MW)	0.926

Urban – NSW-2



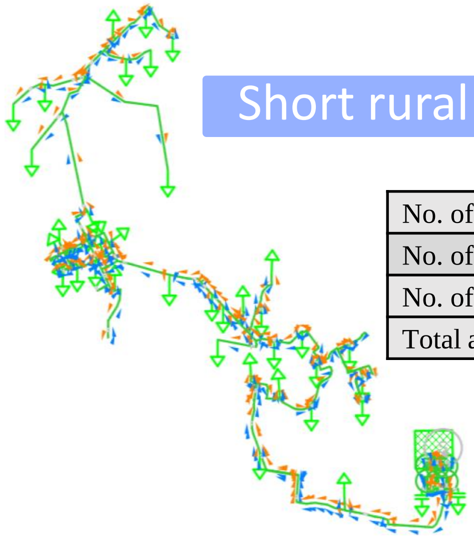
No. of loads	11
No. of buses	90
No. of lines	89
Total active power (MW)	1.458

Urban – VIC



No. of loads	26
No. of buses	191
No. of lines	187
Total active power (MW)	12.001

Short rural – VIC



No. of loads	39
No. of buses	263
No. of lines	263
Total active power (MW)	5.367

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Impact of Back-up Generator Location

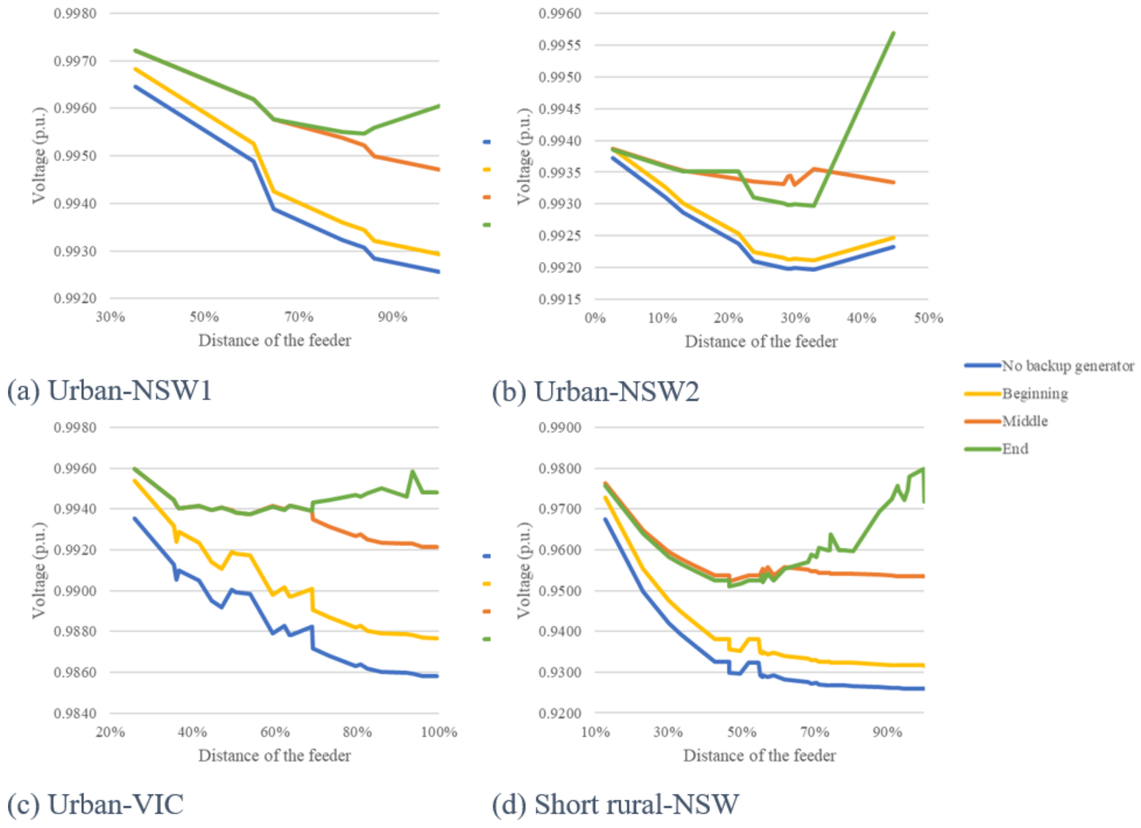

Fig. 7. Terminal voltage with different backup generator locations.

Impact of System Loading

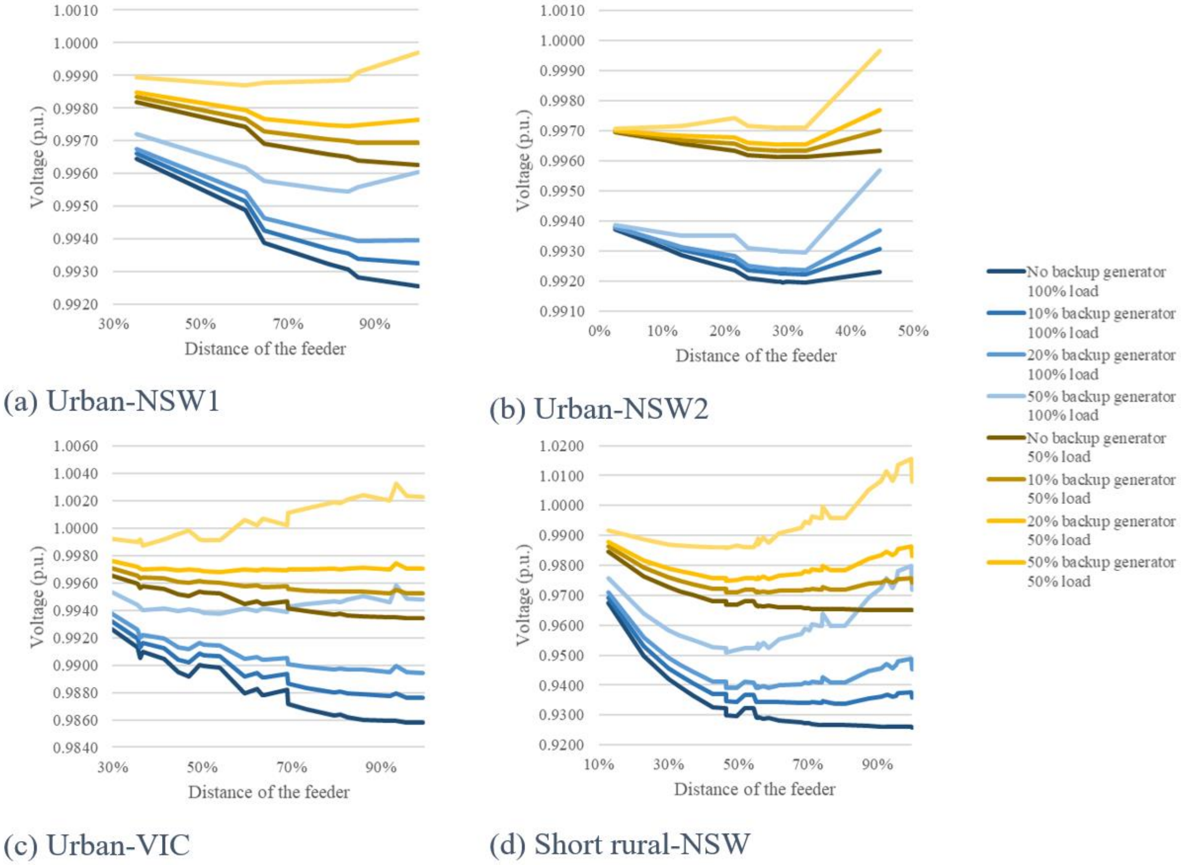

Fig. 8. Terminal voltage with different system loading.

Dynamic Export Limit of Backup Generators

Estimation of dynamic export limits for backup generators using time-series load-flow simulations.

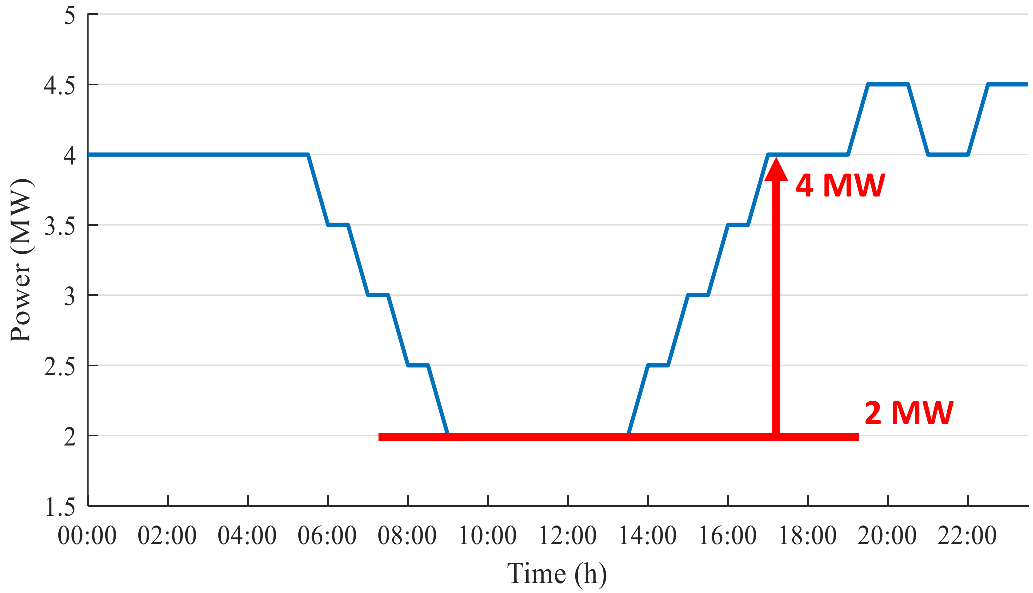

Fig. 9. Dynamic backup generator export limit

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Flexible Operating Modes for Backup Generators

Proposing new operating strategies for backup generators (e.g. voltage control mode)

- **P-Q control:**
  - Accurately control active and reactive power output
  - With constant P and Q setpoints, the terminal voltage is dynamic
- **P-V control:**
  - Accurately control terminal voltage to be a constant
  - Increase line loading

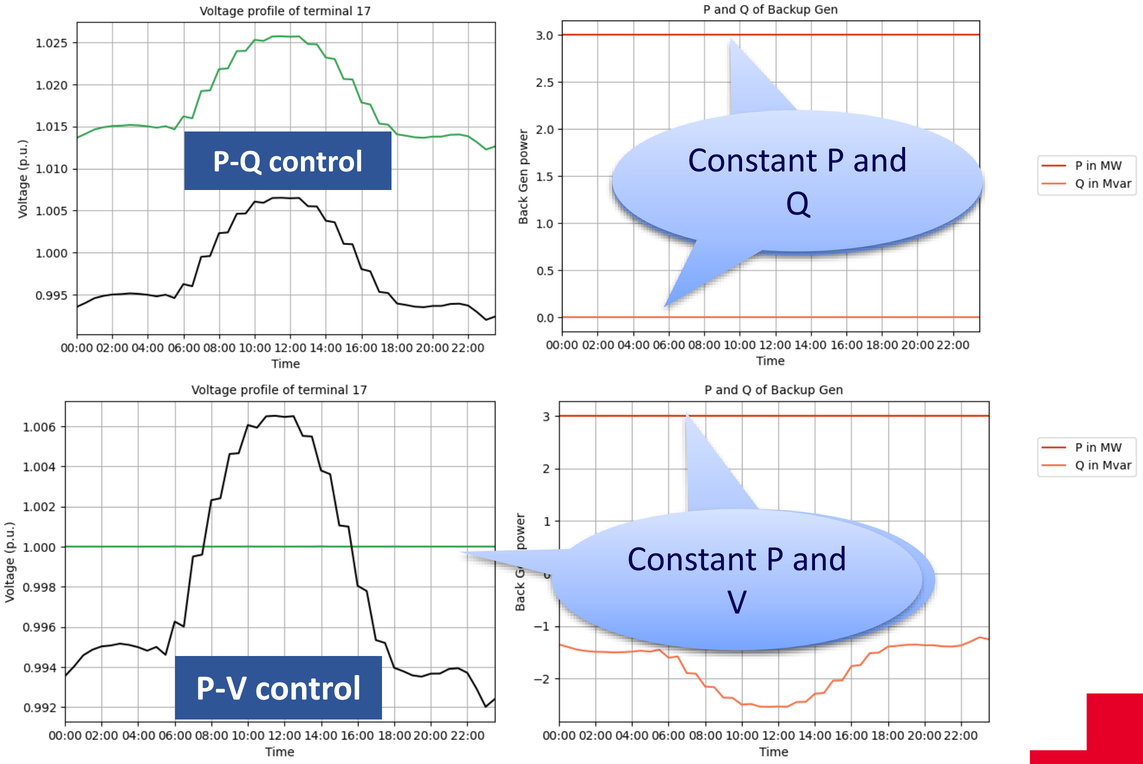

Fig. 10. Operating mode of backup generator

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Project Recommendations

Recommendations

Machine Learning Techniques for Baseline Calculations –

- Machine learning techniques can be applied to weather dependent loads. In particular, loads that are strongly depending on temperature, such as shopping malls, universities, etc.

Dynamic Export Limits for Backup Generators –

- Dynamic export limit can increase the energy export capacity and consequently increase the potential for grid and network support services, without impacting the grid stability.

Flexible Operating Modes for Backup Generators –

- It is recommended assessing the operating mode flexibility when conducting backup generator connection studies, as it could bring benefits to the distribution network operator (e.g., assist to reduce network bottlenecks).

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Recommendations

Consistent inter-tripping and Synchronisation Standards

- The lack of standardisation leads to complexity and uncertainty in enabling export from behind the meter generators. It also hinders the ability to identify new solutions that are lower cost but still meet the operational requirements for the network companies.
- Inter-tripping and technical synchronisation requirements can be standardised to achieve consistency across all DNSPs. That will encourage facilitate the process of enabling exports and a higher capacity for C&I customers to participate in DR programs.

Recommendations

Biodiesel for Backup Generators

- Biodiesel can be used as a low carbon emission fuel for back-up generators. There are ready made units that can be procured in Australia and a complete supply chain exists from the manufacturer to the retailer.
- State and federal governments can provide subsidies to C&I customers to procure biodiesel ready generators and also appropriate technology to upgrade their back-up generators to operate with biodiesel. This would also include support on the relevant operation costs with the aim of increasing the uptake until it becomes a standard solution

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