

Retargeting Demand Response for Carbon Positive Flexible Buildings

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ABSTRACT

Buildings account for ~75% of electricity demand and yet, for the most part, they are unresponsive to (and disengaged from) variations in the generation and greenhouse gas (GHG) emissions intensity of electricity supplies. Mismatches between electricity supply and demand can lead to network instability and price volatility. These effects become evident at low levels of non-dispatchable renewable energy penetration and more pronounced as the proportion increases.

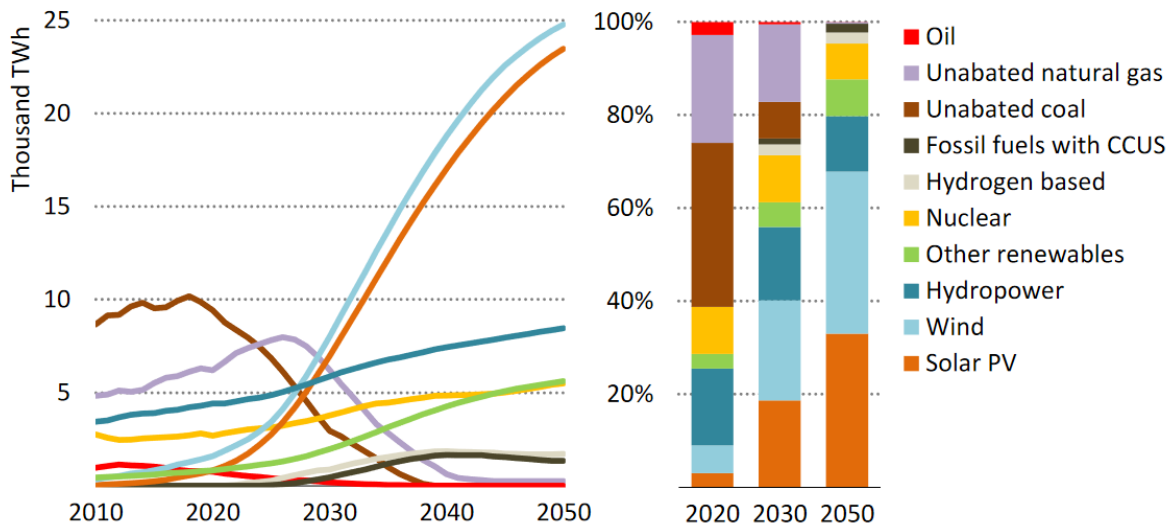
This paper presents analysis of a demand response (DR) intervention at a large office building in downtown Sydney, Australia that was intended to achieve a 4-hour ‘load shift’ of approximately 6% of the building’s total daily consumption. Aside from the capacity benefit the DR provided to the electricity network, it was found that the intervention also reduced total electricity consumption for the 24-hour period by 1.7%, implying a ‘roundtrip’ efficiency of >100%. Furthermore, a 1.4% greenhouse gas (GHG) emission reduction was calculated using real-time emissions factors. When the same intervention was juxtaposed onto an adjoining electricity network dominated by wind and solar generation, it was found that the GHG emission reduction would have been 5.3%.

The paper highlights opportunities to achieve enhanced indoor environmental quality, lower electricity cost (assuming access to wholesale prices) and lower GHG emissions by introducing automatic load shifting from periods of high carbon intensity to periods when electricity grids are cleanest. The findings indicate that large non-residential buildings can meet up to 20% of the world’s projected battery storage requirements through application of targeted DR measures.

Introduction

According to the International Energy Agency, for the global economy to reach net zero greenhouse gas (GHG) emissions by 2050, annual clean energy investment worldwide will need to more than triple by 2030 to around USD \$4 trillion. This ambition will require huge increases in electricity system flexibility by 2030—such as demand response, behavioral changes, batteries and ‘zero-carbon-ready’ buildings, among many other things—to stabilize loads and maintain reliable supplies (IEA 2021).

The IEA has set out clear milestones—more than 400 in total, spanning all sectors and technologies—for what needs to happen, and when, to transform the global economy from one dominated by fossil fuels into one powered predominantly by renewable energy like solar and wind. Investment in solar and wind generation will be crucial. In 2020, solar and wind accounted for 29% of global electricity generation; however, by 2050 this contribution will need to rise to nearly 90% (IEA 2021), as illustrated in Figure 1.



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Figure 1. Proportion of solar and wind generation needs to rise dramatically. *Source: IEA, 2021.*

Unlike ‘dispatchable’ sources of electricity generation like conventional power stations which can ramp production up and down to match network demand (taking their signal from the wholesale price), electricity generated from wind and solar is typically ‘non-dispatchable’ which means it enters and exits the wholesale market regardless of network demand or the price. Under conventional electricity network operating conditions if demand in the market is high relative to supply, prices increase and ‘dispatchable’ sources enter to ‘firm’ up the system. However, this does not happen with non-dispatchable sources that generate in proportion to the availability of wind and sunshine. Significant growth in the proportion of supply coming from non-dispatchable sources without a proportional increase in the flexibility of demand will therefore lead to price volatility and network instability (Leerbeck et al. 2020).

This situation was illustrated in dramatic fashion in the state of South Australia when during the southern hemisphere summer of 2020/21, South Australia’s electricity network became the world’s first large-scale grid to run on 100% solar power for more than an hour (Parkinson, 2021). In South Australia, utility-scale solar farms account for 5% of the entire generation capacity but in addition, approximately 35% of South Australian households have rooftop solar (Keane, Harmsen, and Tomevska 2021) taking the capacity accounted for by solar to approximately 25%. Wind currently accounts for 34% of generation capacity and 42% of total generation in South Australia. As Figure 2 shows, the impact of this growth in solar generation capacity has had a profound impact on the daytime price of electricity in South Australia driving it down to an average USD –\$9 between 1000 hrs and 1530 hrs during the late 2021/21 summer period of January to March 2021 (AEMO 2021).

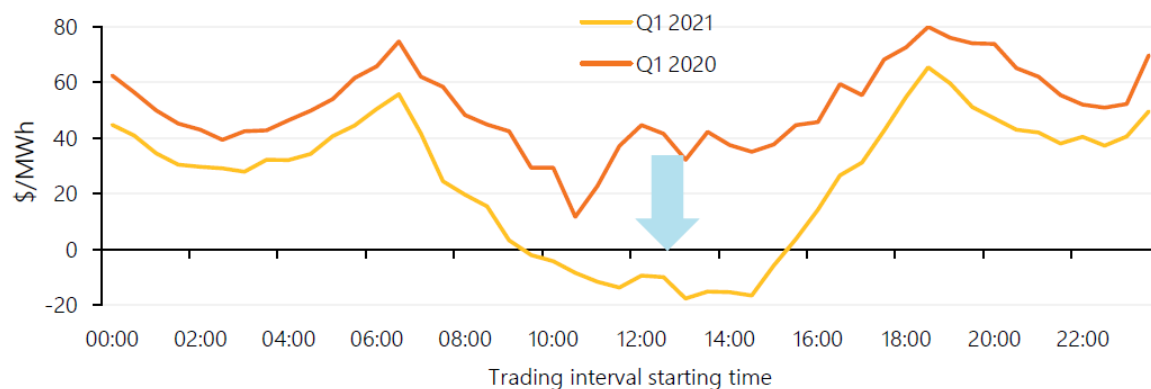


Figure 2. South Australian average underlying electricity price (\$AUD) by time of day – Q1 2021 and Q1 2020. Source: AEMO, 2021.

The response of the system operator and regulatory bodies, fearful of large-scale blackouts arising from very low operating demand, was equally dramatic. After introducing ‘emergency’ powers in September 2020, the market operator for the first time deliberately ‘tripped’ the supply from 12,000 solar generation units on March 2021 to increase network demand by 60 MW and maintain stability of the grid (Keane, Harmsen, and Tomevska 2021).

Negative price and low / unstable demand events are becoming increasingly common around the world, and they usually correspond with times of maximum renewable energy generation and, therefore, lower GHG emission electricity. This is again reflected in the experience of South Australia where the average wholesale price paid for energy generated by rooftop solar panels during 2021 was 1/10th of what gas generators supplying the same market, typically in the evening, were paid (McConnell et al. 2022). The message from these electricity markets, currently, is that consumers are not ‘carbon active’ and consequently are prepared to pay a premium for convenience over clean energy. Unless this changes the levels of investment in renewable energy generation required to decarbonize electricity will not be realized.

In the United States, buildings account for approximately 75% of electricity use and 40% of all primary energy use and associated greenhouse gas (GHG) emissions (DoE 2015), so they have the potential to make a significant contribution to balancing supply variability. Grid-integrated and *zero-carbon-ready buildings* (a term used extensively in IEA 2021) can provide a flexible resource for electricity systems, using connectivity and automation to manage network demand and the operation of energy storage capacity. This flexibility can, in turn, underpin the economic case for investments in renewable electricity generation infrastructure. Much of the technology and knowhow comes from Demand Response (DR) a well-established discipline for managing network constraints under times of maximum demand and there is much experience and evidence from DR programs around the world (Roussac and Huang 2018).

Flexible and grid-integrated commercial office buildings are a great fit for renewable energy, particularly solar energy, because most of their energy-consuming operations occur during the day. Figure 3 illustrates the demand profile of an office building in California reflected in its GHG emissions profile calculated using the ‘static’ emissions factor provided by the Energy Information Administration (EIA). On sunny days on networks with significant solar generation capacity there is an obvious negative correlation between a typical office building’s demand profile and the GHG emissions profile of the grid which reflects the contribution of solar

power. This is also illustrated in Figure 3. The relationship does not completely offset, however, with the resultant peaks in the morning and evening (green line) providing an opportunity to focus DR measures to drive demand towards the middle of the day when the GHG intensity of the grid is at a minimum.

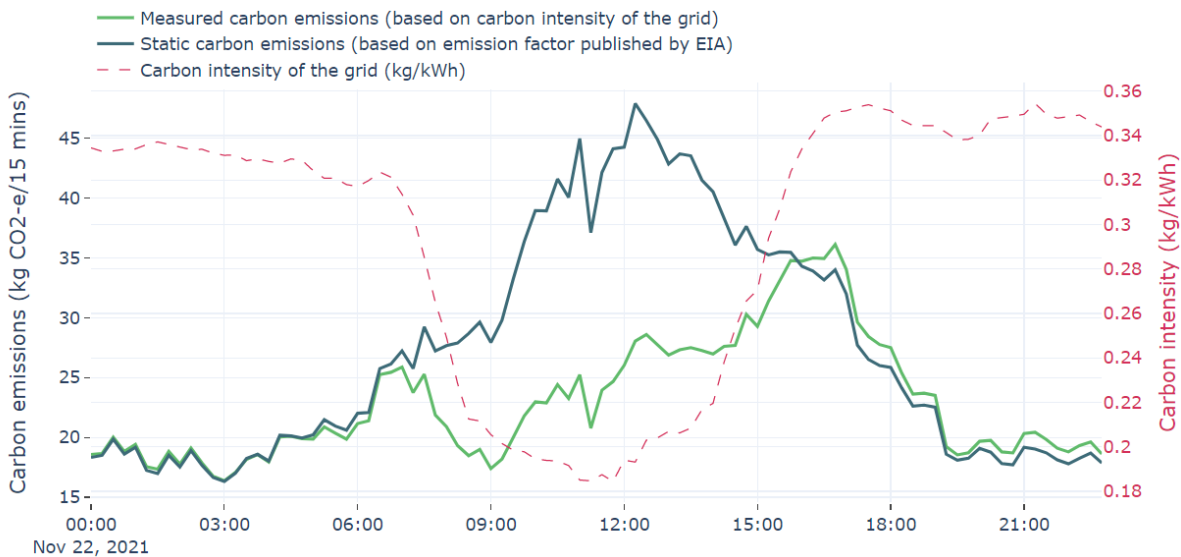


Figure 3. Profile of electricity demand for a commercial office building in the Bay Area, California and the carbon intensity of the electricity grid on November 22, 2021. For more explanation see Buildings Alive 2021.

Conventional energy efficiency approaches focus on reducing electricity use without regard to the timing. This was appropriate when most electricity supplies were generated from fossil fuels. Grid-integrated and zero-carbon-ready buildings that can shift their electricity demand away from times of high carbon intensity to times of low carbon intensity can access lower wholesale electricity prices and at the same time drive demand to support renewable energy generation. In most cases buildings are not directly exposed to wholesale electricity prices due to their fixed retail contracts; however, by virtue of the emerging economic benefits, pressure on policy makers, regulators and retailers to develop measures to pass through market signals can be expected to increase over time. All of this requires insight into real-time price and GHG emissions factors; without it building operators are not able to actively manage their impacts. This paper addresses many of the emerging opportunities and challenges.

Methodology

Carbon Intensity Calculations

Electricity is generated from a mixture of fuels. Different fuel types have different GHG emission factors (measured in units of CO₂-equivalent/MWh) which are published by authoritative sources (see for example EIA 2022). There are two widely recognized approaches to calculating the GHG emissions intensity of electricity supplies: average and marginal. The average emissions intensity corresponds to the overall, e.g., region-wide electricity production including net imports feeding into a grid at a given point in time. The marginal intensity factor

reflects the GHG intensity of the marginal generator, i.e., the last and least economical generating unit contributing to the supply. There has been some debate about whether one should use marginal emission factors or average emission factors to evaluate the carbon savings when performing DR (Finenko and Cheah 2016; Evans and Sidat 2018). In this study we focus on average carbon intensity based on our view that the load from individual commercial buildings is inconsequential when compared to the overall demand on generators, thus making no discernible difference to the generation fuel mix (Lowry 2018).

We calculate the average grid carbon intensity using a weighted sum of the emission factors for different fuels according to their contribution to the generation mix. If there is power exchange between two grid systems, the GHG emissions intensity of the imported electricity is also considered. General speaking, the calculation of GHG emissions intensity requires the following three data sets:

- The total generation (MWh) output from each relevant generating system.
- The GHG emissions per unit of electricity (t CO₂-e /MWh) generated by each relevant generating system.
- Imported generation (MWh) and its GHG emissions intensity, calculated as per the above two points.

When the above data sets are available, the GHG emissions intensity can then be calculated using the following equations:

$$CDE_{II} = \frac{\sum_i CDE_i + E_{import} * EF_{import}}{\sum_i E_i + E_{import}} \quad (1)$$

$$CDE_i = E_i \times EF_i \quad (2)$$

Where CDE denotes Carbon Dioxide Equivalent emissions (t CO₂-e) from a generating system, CDE_{II} denotes grid carbon intensity (kg CO₂-e /kWh), E denotes generation output (MWh) from a generating system, E_{import} is imported generation (MWh), and EF_{import} = Carbon intensity of the imported electricity.

Figure 4 compares the real-time carbon intensity calculation results in Victoria, Australia when the power exchange is considered (red line) or not (blue line). It shows that the carbon intensity will be overestimated by ~10% without considering the power import from its neighboring grids, especially Tasmania which has a high proportional of hydro power. Figure 4 also shows the most significant deviation occurred at ~6:00pm, October 12, which is the time when the power import from Tasmania reached a peak.

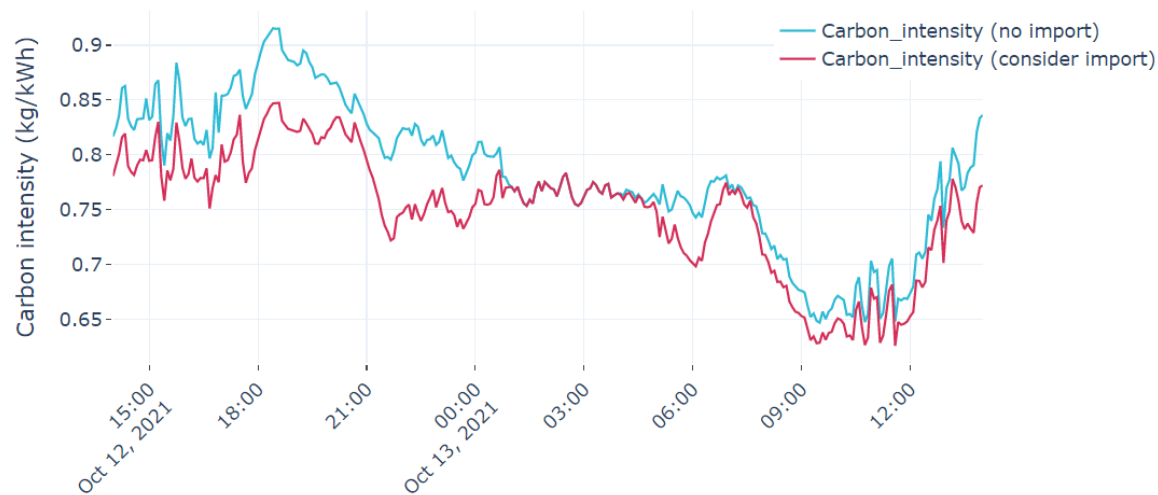


Figure 4. Carbon intensity of electricity grid in Victoria, Australia when power exchange is considered (red line) and not (blue line).

Demand Prediction Model

In our previous work, we demonstrated a peak demand model which can accurately predict a building's electricity demand for any 15-minute interval up to 120 hours (5 days) in advance (Roussac and Huang 2018). A similar modelling approach is applied in this work and the descriptions of all input variables are listed in Table 1. The predicted grid demand is the building's electricity demand. Observed and forecast weather data are used as inputs and were obtained from the Australian Bureau of Meteorology (BOM), or equivalent. An outline of the algorithm is as follows:

1. Obtain historical data from database and prepare in a format that can be used for training.
2. Remove outlier days, weekends, and public holidays from training set.
3. Drop the days when the ambient temperature and/or relative humidity were below a certain threshold to reduce under-fitting on extreme days. The threshold is determined based on discontinuity analysis applied to historical data.
4. Split the data into training and validation sets to train and validate a random forest regression model.
5. Specify the depth of the decision trees, the number of iterations, the learning rate value and the accuracy forecast.
6. Calculate various statistics to assess model performance and return to 4, until the best modelling result is generated.

Table 1. Description of input variables for peak demand forecast model

Description	Units/value
Output variable	
Electricity demand	kW
Input variables	
Forecast dry bulb temperature	°C
Previous days' ambient temperature	°C
Forecast moisture content	%
Forecast solar irradiance	W/m ²
Day of week bin	[1,2,3,4,5,6,7]
Time of day indicator	[1,2,...,96]
Time of year indicator	[1,2,...,365]

GHG Emissions Intensity Forecast Model

Reliable GHG emissions intensity forecasts are essential for operators of grid integrated and zero-carbon-ready buildings to anticipate periods of low and high carbon intensity. With accurate forewarning, building operators can utilize active efficiency strategies to minimize their buildings' carbon footprint. Forecasting grid GHG emissions intensity is challenging and an active field of research. In this study, we applied Lasso Estimated AutoRegressive (LEAR) modeling to predict the GHG emissions intensity. A similar model structure has been applied for wholesale electricity price forecasting in (Uniejewski, Nowotarski, and Weron 2016). The input features used for GHG emissions intensity forecast are listed in Table 2. Before model training, we convert the 5-minute interval carbon intensity data into 15-min interval data to match the granularity of the building energy data. We used two years' worth of historical data to train the LEAR model and performed a cross validation to test the developed model.

Table 2. Description of input variables for the GHG emissions intensity forecast

Description	Units/value
Output variable	
GHG emissions intensity	kg/kWh
Input variables	
Forecast grid electricity demand	MW
Forecast dry bulb temperature	°C
Forecast moisture content	%
Previous day's grid demand	MW

Previous three days' GHG emissions intensity	kg/kWh
Day of week bin	[1,2,3,4,5,6,7]

Figure 5 illustrates day-ahead GHG emissions intensity forecasting for ten consecutive days on the South Australian grid. It shows that the variation in GHG emissions intensity can be forecast using the LEAR model.

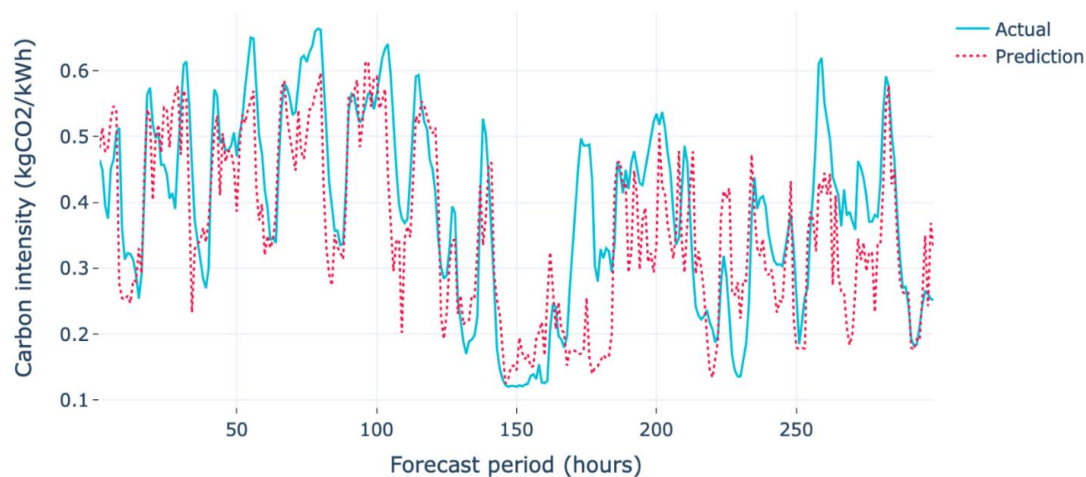


Figure 5. GHG emissions intensity forecast for Adelaide's electricity grid (red line) versus actual (blue line).

Demand Shift Illustration

For this study, we focus on a DR intervention undertaken at a large commercial office building in downtown Sydney, Australia during an extremely hot 39°C (102°F) summer's day on January 31, 2019 (see Roach and Roussac 2020 for more details and explanation of the baselining method). We chose to focus on this day because it represents a good example of an effective demand response in a large office building under extreme conditions prior to COVID-19 lockdowns impacting building occupancy and operations. As Figure 6 illustrates, the 1°C (1.8°F) lowering of the internal temperature setpoint from 09:00 to 13:45 reduced network demand by approximately 200kW below the counterfactual (forecast based on 'business as usual') during the period 14:00 – 18:00 when the setpoint was returned to its normal level, equivalent to the introduction of 800kWh of energy storage. This 4-hour 'storage capacity' represents approximately 6% of the building's total daily consumption which, if extrapolated across similar building typologies globally, suggesting buildings can meet up to 20% of the world's projected battery storage requirements through application of active efficiency measures (IEA 2020). Furthermore, there was no 'net' energy penalty incurred, with the building's total consumption for the 24-hour period being 1.7% lower, implying a 'roundtrip' efficiency of >100%, possibly due to more efficient cooling outside of peak outdoor temperature hours.

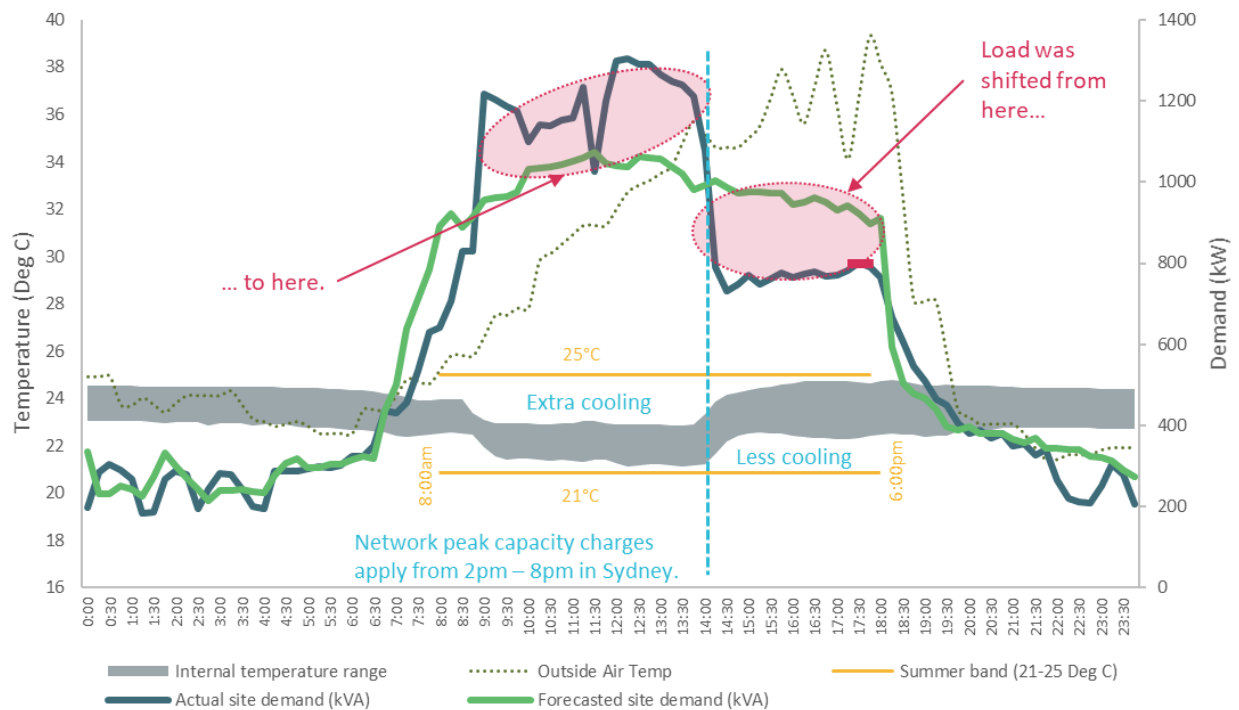


Figure 6. Electricity demand profile and internal temperature range on January 31, 2019. Without extra cooling running during the middle of the day the load profile was forecast to follow the green line. By increasing demand before 2pm the building was able to reduce demand later in the afternoon (dark blue line). *Source: Roach and Roussac 2020.*

Results And Discussion

As electricity grids decarbonize with the introduction and increase in non-dispatchable renewable generation sources, emissions profiles calculated by using the conventional ‘static’ (e.g., EIA factor) approach begin to vary from the profiles generated by considering ‘dynamic’ variations in the electricity networks’ generation mix. This has important implications for building controls and operating strategies targeting real-time GHG emissions reductions because the emissions reduction opportunity is directly tied to the intra-daily variability in grid emissions intensity. To investigate this, the demand response observed from the office building on January 31, 2019 and described in Figure 6 above was juxtaposed with different places and times.

As expected, the intraday variability in GHG emissions intensity of the electricity grid makes a significant difference to the value of the DR intervention in GHG emissions terms. This is demonstrated in Figure 7. Plotted on the left-hand side is the building in Sydney on the day of the intervention. Plotted on the right-hand side is the same building—identical in every way—but analyzed as though it were in Adelaide, South Australia, under near-identical weather conditions which occurred on December 14, 2020. The shading behind the plots on the top row indicates the GHG emissions intensity of the grid on the two days. As can be observed, the emissions from the grid in Sydney changed only marginally during the day reflecting a very low renewable energy contribution relative to fossil generation, principally coal. The GHG emissions

intensity of the grid in Adelaide was very different, being relatively low throughout the day up until 16:00 when the contribution of wind and solar energy dropped off and was replaced by gas.

The effect of this variability in emissions intensity throughout the day is reflected in the second row in Figure 7. The emissions profiles, i.e., GHG emissions calculated by multiplying grid GHG emissions intensity with demand at each 15-minute interval, in Sydney closely resembled the demand profile whereas in Adelaide the profile looked completely different.

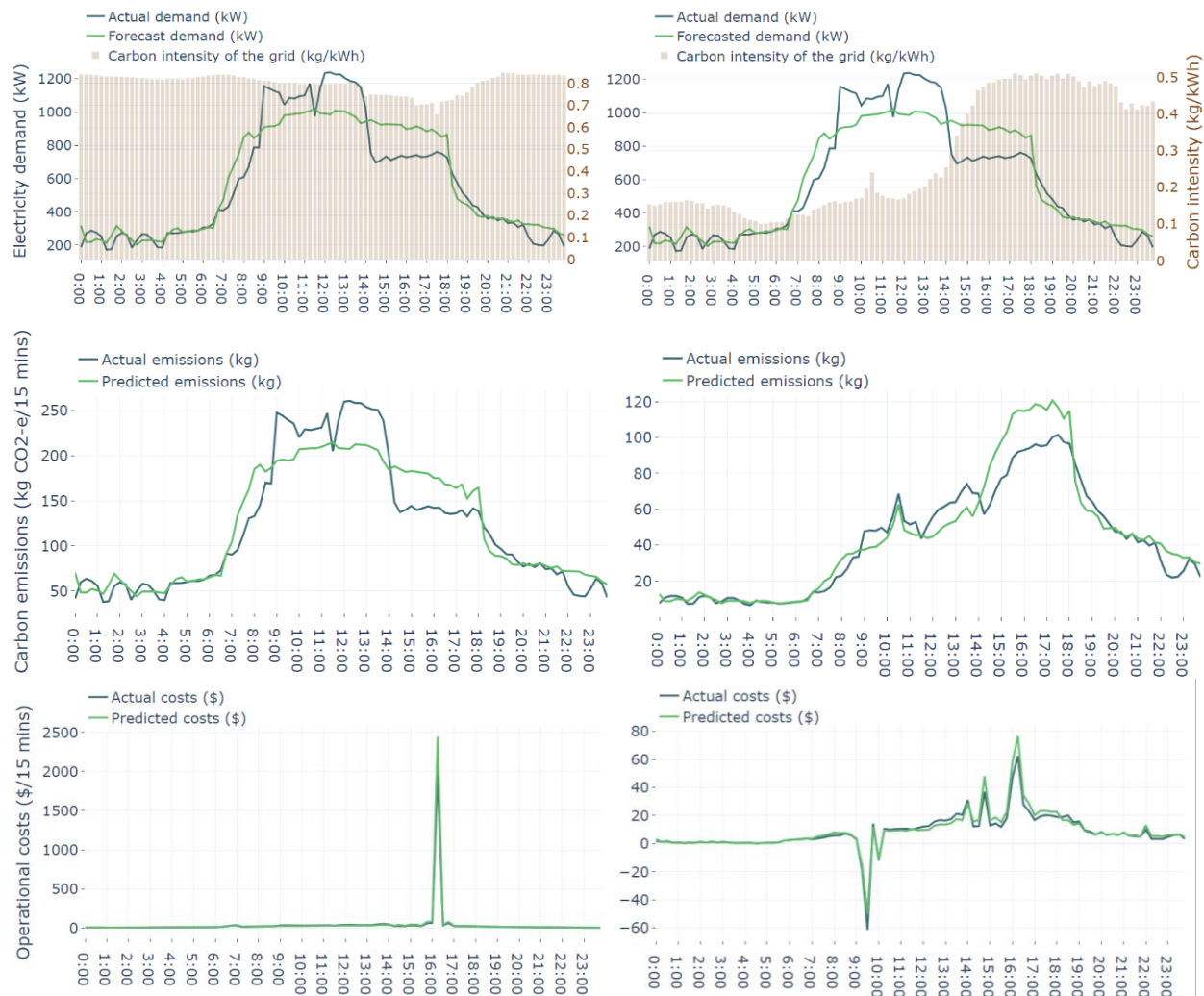


Figure 7. Demand response results when considering grid GHG emissions intensity and wholesale electricity price in Sydney, Australia (left column) and in Adelaide, South Australia (right column).

When we examine the difference (second row) between “actual” GHG emissions profiles and those “predicted” using the methodologies outlined above, we can see the effect of the load shift in Sydney was insignificant compared to the value of the demand response in pure demand (kW) terms. In Adelaide, by contrast, the energy and emissions ‘penalty’ from intervening to increase demand early in the day to avoid ‘peak demand’ late in the day was almost non-existent. The relative GHG reductions and the building’s operational cost savings based on the fluctuating wholesale electricity price are illustrated on the third row of Figure 7 and presented in Table 3.

Table 3. Comparison of carbon savings and costs savings when performing the same demand response behavior under two grid systems

	Ratio of average GHG intensity level between morning and afternoon	Peak demand reduction (kW)	Full day GHG saving based on 15-min interval grid GHG emissions intensity (%)	Costs savings based on wholesale electricity price (%)
Adelaide grid (12/14/2020)	1:2	201	5.3%	9%
Sydney grid (01/31/2019)	1:0.7	201	1.4%	1.3%

On January 31, 2019, there was a significant price spike on the wholesale market for electricity in Sydney (see row three of Figure 7) which occurred due to the extreme weather conditions. It is notable that despite this, total savings would have been considerably higher if the DR intervention were to have occurred in Adelaide under equivalent conditions, rather than Sydney. The reason is the Adelaide grid's abundance of PV-generated electricity under hot / sunny conditions and, consequentially, the difference in emissions intensity of the two networks. This difference is expressed in the ratio of average GHG intensity level between morning and afternoon which is also reflected in the consistently lower price of electricity in Adelaide during times of low GHG emissions intensity.

Electricity networks increasingly display a correlation between wholesale price and GHG emissions intensity, reflecting the proportion of non-dispatchable energy sources feeding the grid and the impact that has on net operating demand, i.e., more generation relative to demand drives down price, and vice versa (Middleton 2021). For this reason, we expect to see the overall system / societal value of DR continue to increase as renewable energy investment increases over coming years. Figure 8 shows the fuel mix of the two grids considered in the above analysis and the relative market prices.

22 Mar 2021 – 27 Mar 2022				22 Mar 2021 – 27 Mar 2022			
	Energy GWh	Contribution to demand	Av.Value \$/MWh		Energy GWh	Contribution to demand	Av.Value \$/MWh
Sources	73,295		\$102.88	Sources	14,718		\$80.16
Solar (Rooftop)	5,268	7.3%	\$51.57	Solar (Rooftop)	2,302	16.5%	\$23.61
Solar (Utility)	4,024	5.6%	\$72.84	Solar (Utility)	690	4.9%	\$66.72
Wind	5,401	7.5%	\$82.43	Wind	5,796	41.5%	\$51.52
Hydro	2,677	3.7%	\$184.00	Battery (Discharging)	91	0.7%	\$182.65
Gas (OCGT)	353	0.5%	\$295.01	Gas (Reciprocating)	291	2.1%	\$193.99
Gas (CCGT)	1,111	1.5%	\$136.25	Gas (OCGT)	250	1.8%	\$220.15
Distillate	0.4	0.0006%	\$898.72	Gas (CCGT)	2,552	18.3%	\$105.19
Coal (Black)	48,900	67.7%	\$99.95	Gas (Steam)	1,243	8.9%	\$120.18
Imports	5,561	7.7%	\$87.63	Distillate	13.5	0.10%	\$1,219.88
Loads	-1,462			Imports	1,489	10.7%	\$78.31
Exports	-1,085	-1.5%	\$223.43	Loads	-866		
Pumps	-377	-0.5%	\$37.06	Exports	-752	-5.4%	\$37.10
Net	71,833			Battery (Charging)	-114	-0.8%	\$38.07
Renewables	17,369	24.1%		Net	13,852		
				Renewables	8,788	62.9%	

Figure 8. Contribution and wholesale market value of different generation sources for the 12-month period March 2021 – March 2022 in Sydney (left column) and in Adelaide (right column). *Source:* McConnell et al. 2022

Over the past two years, the proportion of solar energy supplying Sydney has grown substantially whereas in Adelaide it has remained relatively constant. This may point to the benefits of developing more effective grid-integrated buildings policies and programs. As mentioned in the introduction, network operators have acted to ‘curtail’ (disconnect) solar energy generation in Adelaide during sunny conditions to maintain grid stability, whereas in Sydney this has not occurred. Furthermore, solar generators (particularly professionally run utility-scale solar farms) on the grid servicing Adelaide have held back investments and voluntarily curtailed on a regular basis when market prices have edged below zero, explaining the significant difference in average value (\$/MWh) achieved between Solar (Utility) and Solar (Rooftop) (Keane, Harmsen, and Tomevska 2021).

Different networks and climates present different opportunities and challenges for GHG emissions-focused DR. In jurisdictions where solar energy is dominant and predictable, like California and South Australia (Adelaide), techniques for shifting load to the middle of the day include opening up outside air intakes to increase fresh air volumes and improve indoor environmental quality (IEQ). In locations where wind energy is more dominant, techniques will be more dependent on sophisticated and reliable medium-range forecasting to inform the operation of thermal and battery storage, often during the middle of the night. These differences are illustrated in Figure 9, below.

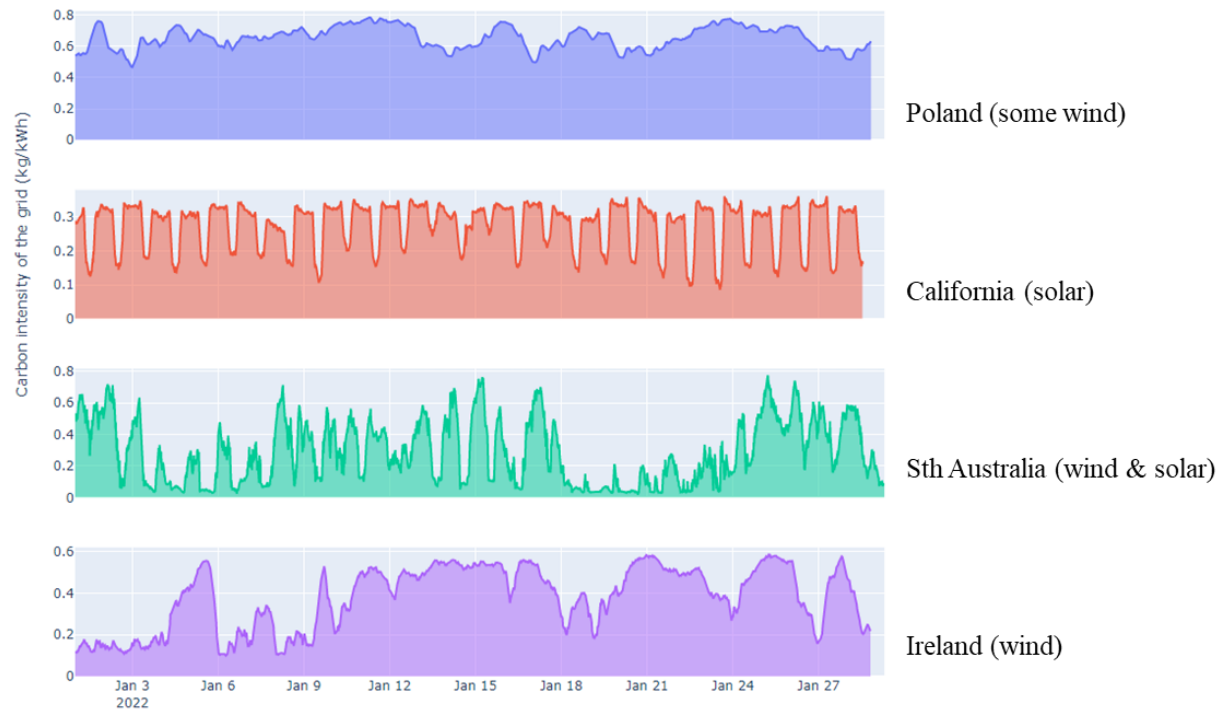


Figure 9. GHG emissions intensity of grids in California, Poland, South Australian and Ireland during January 2022 reflecting contributions of different renewable energy sources.

Most of the world's buildings procure electricity from retailers acting as price buffers between the consumer and producer: low wholesale prices do not pass through to customers on fixed contracts, peak prices don't either. As this changes, the economic and environmental value of smart building information and control systems that can interact with the grid and provide flexibility services to support local renewables by shifting plant and equipment loads, and optimizing battery and electric vehicle (EV) charging, will become increasingly clear. This should drive a change in DR thinking and practice. Conventional DR focused on 'peak demand' events which occur infrequently and can therefore be addressed deliberately (and manually) by building operators will become less viable and less valuable. GHG emissions-focused DR, in contrast, will become an every-day, every-hour, concern. This will require automation and integration. It also requires market signals which can incentivize demand flexibility to reduce emissions and shift 'carbon aware' load which will in turn support greater investment in renewable energy generation.

Conclusions

GHG emissions-focused DR can make a significant contribution to reducing GHG emissions, stabilizing electricity networks, supporting investment in renewable energy generation and reducing the cost of operating buildings. If we do not address the opportunity to make electricity use in buildings more flexible and efficient, the challenge of decarbonizing the energy system will be made significantly more difficult and more costly.

This paper demonstrates that existing and conventional commercial buildings with existing and conventional technology and control systems can play a major role in supporting the

decarbonization of electricity networks globally, and do so at a profit. Comparing building performance patterns across different grid signatures shows that carbon impact is predictable, and highly variable depending on fuel mix. Grids with high levels of renewables need load flexibility to maintain stability, and this also offers an opportunity to directly manage and reduce carbon impacts at the building level.

References

- AEMO (Australian Energy Market Operator). 2021. *Quarterly Energy Dynamics Q1 2021*. aemo.com.au/-/media/files/major-publications/qed/2021/q1-report.pdf?la=en
- Buildings Alive. 2021. *Net Zero Carbon: The hidden ingredient*. buildingsalive.com/net-zero-carbon-the-hidden-ingredient/
- Department of Energy (DoE). 2015. *Quadrennial Technology Review: An Assessment of Energy Technologies and Research Opportunities*. U.S. Department of Energy, Washington, DC. www.energy.gov/quadrennial-technology-review-2015
- EIA (Energy Information Administration). 2022. *State Electricity Profiles*. www.eia.gov/electricity/state/california/
- Evans, B., and S. Sidat. 2018. “The use of temporal factors for improved CO₂ emissions accounting in buildings”. *Building Services Engineering Research and Technology* 39 (2): 196-210. doi.org/10.1177/0143624417753297
- Finenko, A., and L. Cheah. 2016. “Temporal CO₂ emissions associated with electricity generation: Case study of Singapore”. *Energy Policy* 93: 70-79. doi.org/10.1016/j.enpol.2016.02.039
- IEA (International Energy Agency). 2020. *Innovation in Batteries and Electricity Storage*. IEA. Paris. www.iea.org/reports/innovation-in-batteries-and-electricity-storage
- . 2021. *Net Zero by 2050*. IEA. Paris. www.iea.org/reports/net-zero-by-2050.
- Keane, D., N. Harmsen, and S. Tomevska. 2021. “Solar panels switched off by energy authorities to stabilise South Australian electricity grid”. *Australian Broadcasting Corporation (ABC)*, March 17. Retrieved from www.abc.net.au/news/2021-03-17/solar-panels-switched-off-in-sa-to-stabilise-grid/13256572
- Leerbeck, K., P. Bacher., R. Junker, G. Goranović, O. Corradi, R. Ebrahimi, A. Tveit, and H. Madsen. 2020. “Short-term forecasting of CO₂ emission intensity in power grids by machine learning”. *Applied Energy*, 277, p.115527. doi.org/10.1016/j.apenergy.2020.115527

- Lowry, G. 2018. “Day-ahead forecasting of grid carbon intensity in support of heating, ventilation and air-conditioning plant demand response decision-making to reduce carbon emissions”. *Building Services Engineering Research and Technology*, 39(6), pp.749-760. doi.org/10.1177/02F0143624418774738
- McConnell, D., S. Holmes à Court, S. Tan, and N. Cubrilovic. 2022. *OpenNEM project*. opennem.org.au/
- Middleton, E. 2021. “Exploring the correlation between the carbon intensity of the UK’s electricity and the wholesale price”. *Elgar Middleton*. www.elgarmiddleton.com/exploring-the-correlation-between-the-carbon-intensity-of-the-uks-electricity-and-the-wholesale-price/
- Parkinson, G. 2021. “‘World first’: South Australia achieves 100pct solar, and lowest prices in Australia”. *RenewEconomy*, January 29. reneweconomy.com.au/world-first-south-australia-achieves-100pct-solar-and-lowest-prices-in-australia/
- Roach, C., and A.C. Roussac 2020. “It Takes A City: Harnessing the Demand Response Potential of Commercial Buildings”. In *Proceedings of the 2020 ACEEE Summer Study on Energy Efficiency in Buildings*, Pacific Grove, California: ACEEE.
- Roussac, A.C., and H. Huang. 2018. “Forewarned Is Forearmed: Reducing Peak Demand in Commercial Buildings with Behavior Science”. In *Proceedings of the 2018 ACEEE Summer Study on Energy Efficiency in Buildings*, Pacific Grove, California: ACEEE.
- Uniejewski B, J, Nowotarski, and R. Weron. 2016. “Automated Variable Selection and Shrinkage for Day-Ahead Electricity Price Forecasting”. *Energies*; 9(8):621. doi.org/10.3390/en9080621