Embertec Pty Ltd

South Australian Government
Supported Project

Efficient Targeting and Control of AC Loads

3rd of April 2023

Supported by

Government of South Australia

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Executive Summary

The Embertec® project is supported by the Government of South Australia. It presents a unique opportunity to assess the potential to utilise machine learning capabilities to profile householder temperature comfort and air conditioning (AC) demand with automated AC control, in an effort to mitigate critical grid constraints during peak load periods.

As the uptake of AC devices continues and as we move towards higher levels of variable renewable energy resources within our energy grid; the ability to schedule and orchestrate high energy consuming devices whilst ensuring householder comfort, convenience and also grid stability, is likely to be an important capability for a truly intelligent and 100% renewable energy grid.

The project will gather detailed power and voltage data from participant households in addition to leveraging temperature and humidity data gathered from within the property via the proprietary device called Emberpulse®. Embertec® is leveraging the existing Emberpulse® device together with its Pulse® analytics platform to deliver valuable customer energy insights, householder convenience and AC appliance control, both by the householder and via the Pulse® analytics platform.

Central to this project is to assess the ability to automate AC's within households in a manner which will deliver a cost effective and comfortable outcome for householders, whilst also working to address grid energy supply constraints and grid power price peaks. AC load is currently one of the most common and largest power loads within most residential properties today. Split system air-conditioning systems are becoming more prevalent and being put through greater use as we seek more comfortable working and living conditions and average ambient temperatures continue to increase. In addition, with a shift towards remote working, there is an increasing demand for AC use at home and therefore demand for energy from our electricity grid.

As our energy grid has a number of critical load limitations, the importance for us to better manage our energy demand as we move towards a more electrified world is of great importance. This project was designed to evaluate the potential for an intelligent approach when automating residential split system AC's. This commenced with determining which households would be best suited to automated AC control based on various power data and other sensory data collected from trial participant homes. Intelligent AC automation will lower the overall impact of increased AC penetration within our homes on the energy grid and demonstrate the potential for the broader adoption of intelligent appliance control.

Overall the project findings highlight that there exists the clear potential to dramatically reduce AC power load during critical periods by up to 90% for short durations. In addition, through the deployment of intelligent machine learning algorithms, this automated AC load control can be done with very little householder nuisance. Rotating AC control across groups of homes will also provide a more consistent load reduction during extended critical grid load periods without negatively impacting householder comfort.

As our energy use continues to shift towards electrification, in addition to the expected rise in electric vehicles; the management of residential energy demand will be of growing importance if we are to deliver on a 100% renewable energy grid.

Industry Engagement

Embertec® has long assisted Australian householders to lower their energy costs through a number of innovative product and technology offerings. This pilot required the engagement of 1,000 householders and the initial deployment of 1,000 Emberpulse® energy monitoring and advisory systems. To assist with community engagement to participate in this trial, Embertec® worked with RAA in the promotion of this offer to their members.

RAA members were given the opportunity to have an Emberpulse® device installed, free of charge at their premises. These householders would then attain all the energy monitoring and advisory benefits of the Emberpulse® system. The Emberpulse® device collected whole home and AC circuit power data, in addition to household temperature and humidity data.

As part of this trial, “behind the meter” data collected from participating households would be valuable to both South Australian Power Networks (SAPN) and the Australian Energy Market Operator (AEMO).

The deployment of Emberpulse® enabled the collection of power and voltage data which will be shared with SAPN and AEMO.

Energy consumption variation through automated control of AC systems, will be shared with AEMO to assist the assessment of demand response programs in residential settings.

Results from this trial will also assist in the design of future appliance energy management trials.

Tools & Training

In support of this trial, specialised deployment, calibration, training materials and technical support services were developed by Embertec®. A key component of the trial was the deployment of 1,000 Emberpulse® units within single family homes. To facilitate this, software was developed for in-field installation verification and calibration of energy meters. This platform provided a real-time interface between installation crews and technical support with respect to Emberpulse installations.

Embertec® developed a software application that provides installers the ability to check installations with respect to correctly installing circuit monitoring equipment. This platform delivered electronic registration and certification process for each installation.

The installation team comprised of 7 fully qualified electricians. Each electrician underwent a full day training program. Training was provided both in person at Embertec® offices and in the field. This process minimised installation challenges and also allowed for further vetting of installation personnel. Installers were trained on the products, their correct calibration processes and how to use the installation verification app to confirm proper installation prior to site departure.

The software further provided the Embertec® support team with installation issue alerts in the event power data was not being captured correctly.

Hardware installed at each property location:

Emberpulse unit	Submeter 3CT (2 per install)	Emberiq Smartplug
		

Participant Engagement & Selection

The target to reach 1,000 eligible households within a short period of time was a challenging endeavour. To achieve this a multi-pronged marketing and communications approach was developed. This included both direct mail to over 58,000 householders in addition to partnering with the Royal Automobile Association (RAA) to reach their 700,000+ members. Both methods yielded a suitable market response, delivering the required number of eligible householders. The direct mail promotion is shown below:

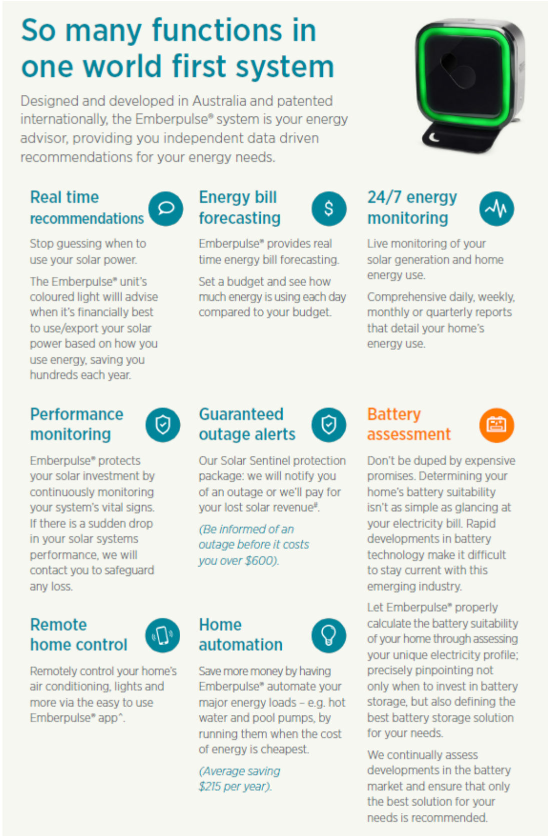
Of the eligible households, well over 25% were in solar households. It was important to acquire eligible solar households in this trial to properly reflect the effect of AC control in SA as over 30% of all SA residential homes currently have solar installed.

Overall the following household attributes were targeted in the trial group:

- 1,000 owner/occupier households
- Minimum of 25% (250 households) with solar installed in the trial group
- Controllable AC system present at the property
- Full-time internet connection

Given the obvious challenge in having householders sign up to a power monitoring and AC control trial, it was important to deliver the eligible participants a product offering that would provide upfront and ongoing value. The Emberpulse® product together with its Pulse® analytics platform is designed to utilise household power data to deliver actionable energy saving insights. These insights range from finding the cheapest available energy plans to assessing solar and battery suitability for householders tailored to their energy demands.

Below is an overview of the key features and benefits provided by Emberpulse® and Pulse® analytics that drove customer engagement and participation in this trial.



To streamline the customer sign-up and eligibility process, an online registration form was created for interested trial participants to provide required contact and household information. Customers were then contacted via our customer support centre to confirm eligibility and provide an overview of the trial itself.

Once householders confirmed their willingness to participate and their eligibility was determined, the installation of the Emberpulse® unit and metering of whole home and AC circuits was scheduled with our qualified and trained electricians.

Household Selection for Automated AC Control Phase

The first phase of the trial (post Emberpulse® install) entailed an assessment of the AC usage patterns of each of the trial participants, in addition to understanding the “ambient comfort levels” of each household. The importance of collecting this data was to ensure the second phase of the trial, which comprised of the distribution and installation of AC controller devices, was targeted at households where there was a higher potential of delivering valued AC control events for the householder and the energy grid.

The hypothesis was that not all households would deliver AC load control benefits to the energy grid, and thus the first phase of the trial was designed to assess the ability to use power, temperature and humidity data, collected via Emberpulse® to determine the most suitable homes for AC controller installation. This data was further assessed against National Energy Market (NEM) demand and price data to ascertain whether targeted AC control events would likely occur at times that would be suitable to manage grid constraints.

Challenges and opportunities of Covid-19:
Due to the Covid-19 pandemic, software developed by Embertec® to profile household AC usage, power demand and temperature comfort factors, required a significant rework. This was due to the significant variability in household occupancy and temperature malleability models pre and post Covid-19. Due to the prolonged household isolation period and common work from home directives from employers, a high percentage of householders were now working from home sporadically.

This led to significant variations in day to day AC energy demand. Due to this, additional algorithm development was required to determine the likelihood of householder presence during each day. Algorithms development was limited to data collected via Emberpulse®, which comprised primarily of power, temperature and humidity datasets. The target was to develop the capability to determine the likelihood of householder presence during the day and hence AC demand in order to forecast potential AC control opportunities.

Given this additional software development requirement, which was outside of the initial development plan, and the target to deliver the project within the agreed budget constraints, and amendment to the plan was negotiated and agreed with the SA Government.

In principle this amendment entailed reducing the number of AC controller deployments from 500 to 250, whilst also collecting data to determine the potential for load control events during the winter periods and expanding the model beyond summer months.

This looks to have been a useful compromise as it will expand the applicability of intelligent AC control beyond summer peak energy demand periods; especially as energy prices on the SA NEM have increased significantly during colder periods between 2021 and 2022, as shown below:

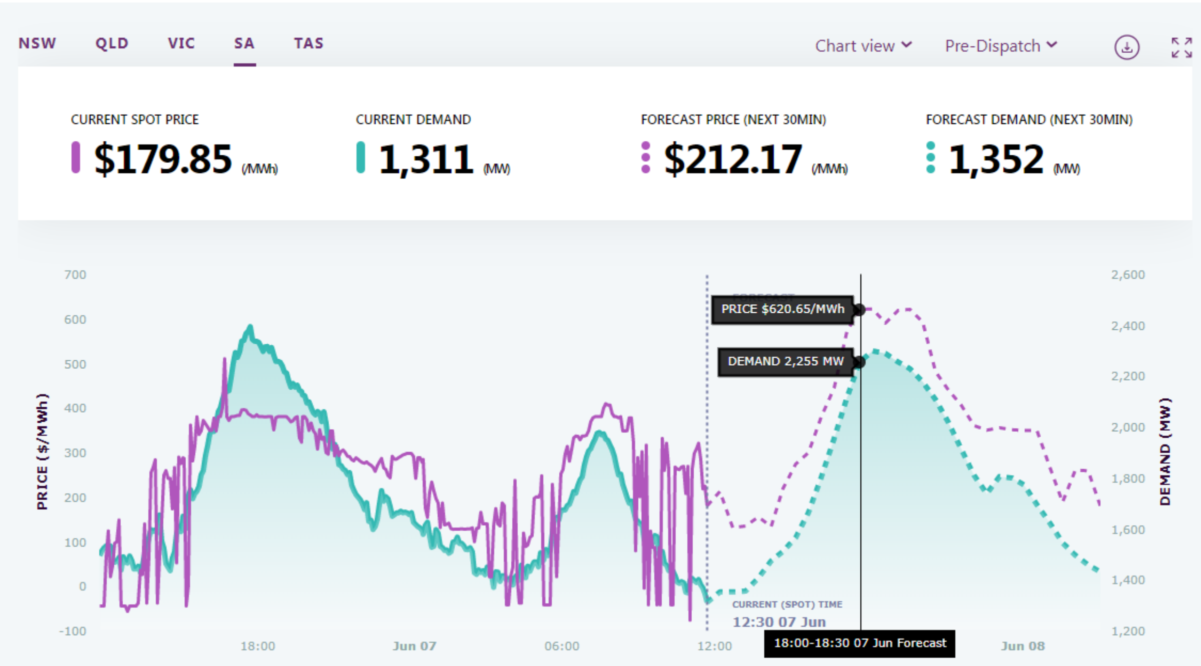
Daily Monthly Annual 2021 June

Date	Region	Average RRP	Peak RRP
2021/06	NSW	$160.04	$253.10
2021/06	QLD	$200.72	$324.63
2021/06	SA	$84.39	$96.91
2021/06	TAS	$68.88	$77.62
2021/06	VIC	$87.92	$107.34

Daily Monthly Annual 2022 June

Date	Region	Average RRP	Peak RRP
2022/06	NSW	$455.79	$542.01
2022/06	QLD	$430.02	$498.77
2022/06	SA	$327.16	$425.09
2022/06	TAS	$341.94	$423.44
2022/06	VIC	$329.85	$462.54

SA spot price: June 7th, 2022



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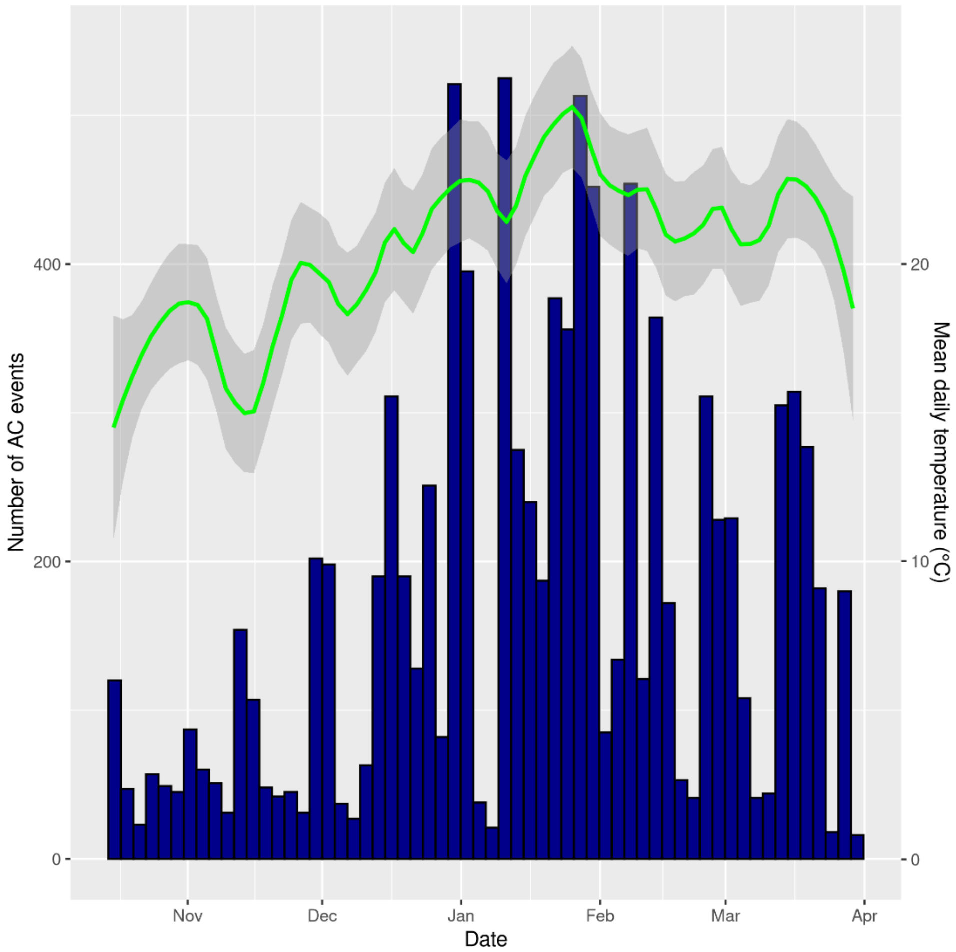
Initial household data assessment:

Over 10GB of data was collected during the course of the trial period. Of the 1,000 trial households the following high level outputs were obtained for the summer months between December 2020 and February 2021:

- 539 households maintained a steady and constant internet connection to the AWS cloud server.
- 376 of the 539 households showed regular power usage on the metered AC circuit
- Of these 376 households, the mean AC usage for the December 2020 to February 2021 period was 497 kWh, and the median usage was 380 kWh.

The histogram below (Chart 1) illustrates AC usage "events" against "mean daily temperature". Each "event" represents an individual AC switch on event. The illustration below is for the November 2020 to end March 2021 period. As expected, with an increase in mean daily temperature, AC events also increased across the trial households.

Chart 1:



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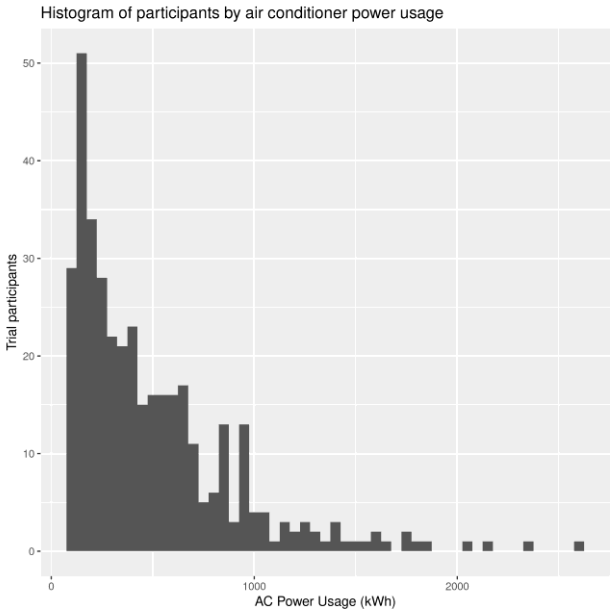
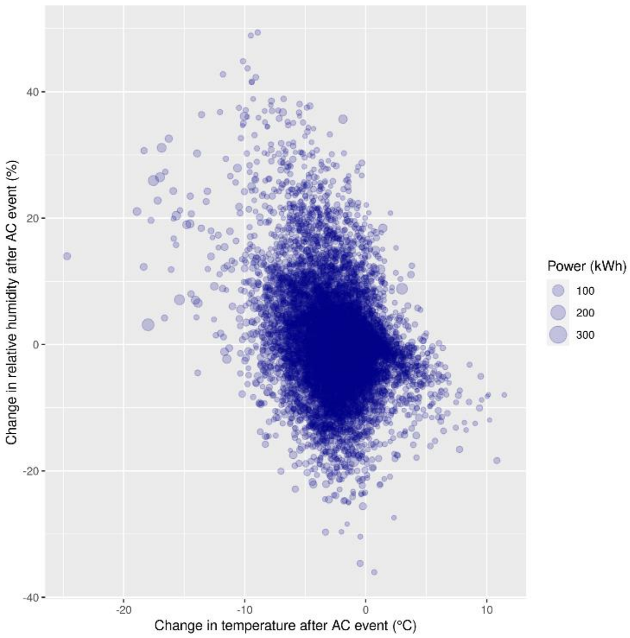
An assessment was conducted on the AC power demand across each participant household. This was to establish both an average AC power load across the field trial households and also to assist in selecting households that would have a greater impact in managing grid load through automated AC control.

Chart 2:



The long-run effectiveness of AC usage was also reviewed to understand the potential for different households to effectively deliver an appreciable change in household temperature and humidity during an AC event. This was also assessed against the energy consumption data of individual AC units.

Chart 3:



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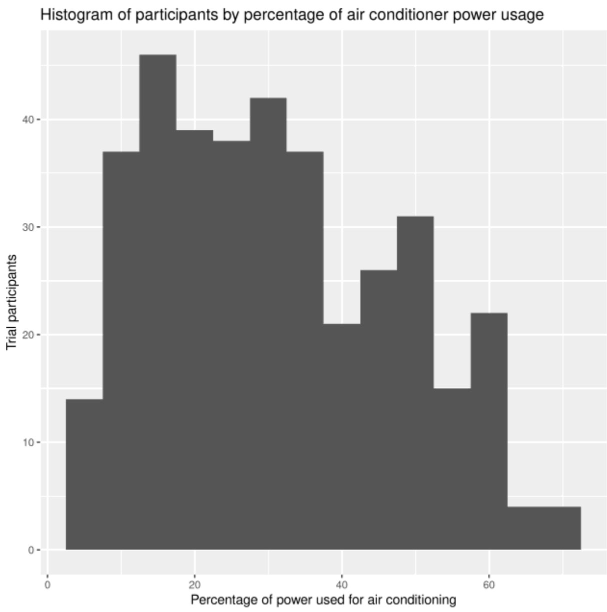
Furthermore, it was considered important to understand the effect of AC usage with respect to overall household energy consumption as a percentage of total energy usage. The histogram below looks at the evaluated trial participants to provide an indication of the net energy cost benefits through delivering a more efficient use of AC loads.

The majority of households use between 17% and 44% of their total energy consumption on air conditioning, with a mean of 31.0% and a median of = 28.7%. This demonstrates the importance of developing intelligent automated AC control solutions, as AC penetration continues to increase nationally.

Chart 4:



When determining the potential to control AC usage within households, it is important to ensure that the inside home temperature is at a comfortable level. To ascertain this, data was collected to determine the comfortable temperature range within each household.

The broader the comfortable temperature range the greater AC control malleability would be available during AC load control events. Chart 5 visualises the comfortable temperature ranges based on AC power usage and Emberpulse® temperature readings.

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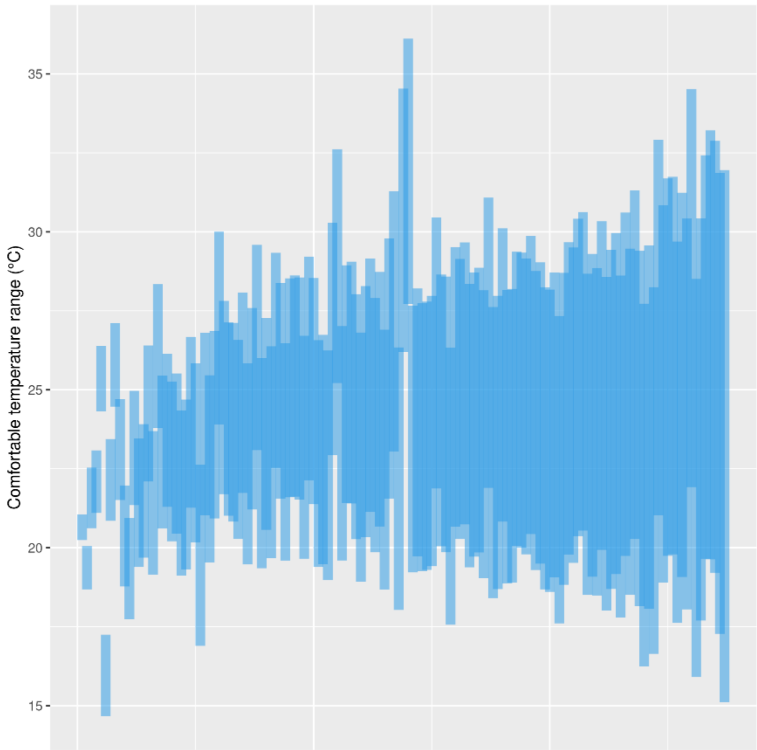
Based on 20th percentile where heating is used in winter and cooling is used in summer, the mean minimum comfortable temperature is 20.0°C in winter and the mean maximum comfortable temperature is 28.1°C in summer. This is based on Emberpulse® temperature sensor data.

Chart 5:



This data was utilised to provide a "ranking" for households which would be most likely to be suited to an AC controller for the second phase of the trial. There are a number of considerations when ranking households, firstly it depends whether we are talking about targets for medium term control (i.e. pre-cooling), or targets for short term control (i.e. fan mode). For medium term control, the best targets will be ones where our predictions are accurate; for this, we probably want households with narrow comfortable temperature ranges.

Someone that is usually only comfortable between 20 and 25°C will be more likely to use their AC when it reaches say 28°C and thus the prediction models will be better at predicting AC usage in these homes with less household data or "event data" needing to be collected. In other words, it is more difficult to predict when someone will use the AC if they are comfortable at a wide range of temperatures.

Similarly, households who have a wider temperature comfort window would be less likely to opt out of AC control events and have a more malleable AC control range when compared to other more narrow temperature comfort range households. We thus settled on a cross section of AC users across both narrow and wide temperature range comfort levels.

AC Use Forecasting

With respect to forecasting AC load control opportunities, a key component of this trial was to assess the ability to utilise a machine learning algorithm to reliably determine the likelihood of AC usage. The following data points were used to "feed" the machine learning algorithm:

- Day of week
- Hour of day
- Minute of day
- Weekend (true/false)
- Public holiday (true/false)
- School holidays (true/false)
- State lockdown due to COVID-19 (true/false)
- Emberpulse temperature (now and 15/30/45/60min ago)
- Emberpulse humidity (now and 15/30/45/60min ago)
- Outside temperature (now and 1/2/3/4/24hr ago)
- Outside humidity (now and 1/2/3/4/24hr ago)
- Outside apparent temperature (based on humidity and wind chill, etc.) now and 1/2/3/4/24 hr ago.
- Rainfall since 9am
- Whether AC is switched on (now, 15/30/45/60 min ago and 23/24/47/48 hr ago)
- Temperature measured by AC (now, 15/30/45/60 min ago and 24/48hr ago)
- Home power usage (now and 5/10/15/30/45/60 min ago)
- Power drawn by AC circuit (now and 15/30/45/60 min ago)
- Minimum and maximum power usage in the past 5 minutes
- Standard deviations of the power usage over the last 1/2/4/8/24 hours*
- Current solar power generation

Charts 6, 7 and 8 show the average AC power usage for participants with active use of the AC. It also illustrates the outside temperature, humidity, the mean voltage measured at the household power circuit in addition to the NEM electric price.

The charts also show the expected correlation between high ambient temperatures and AC usage, resulting in high AC power load in the trial households. Similarly a high NEM $/MW value is also seen during these increased AC load periods. This is expected and further supports the assumption that residential AC usage is an important factor which drives peak energy demand and pricing on the NEM.

Chart 6

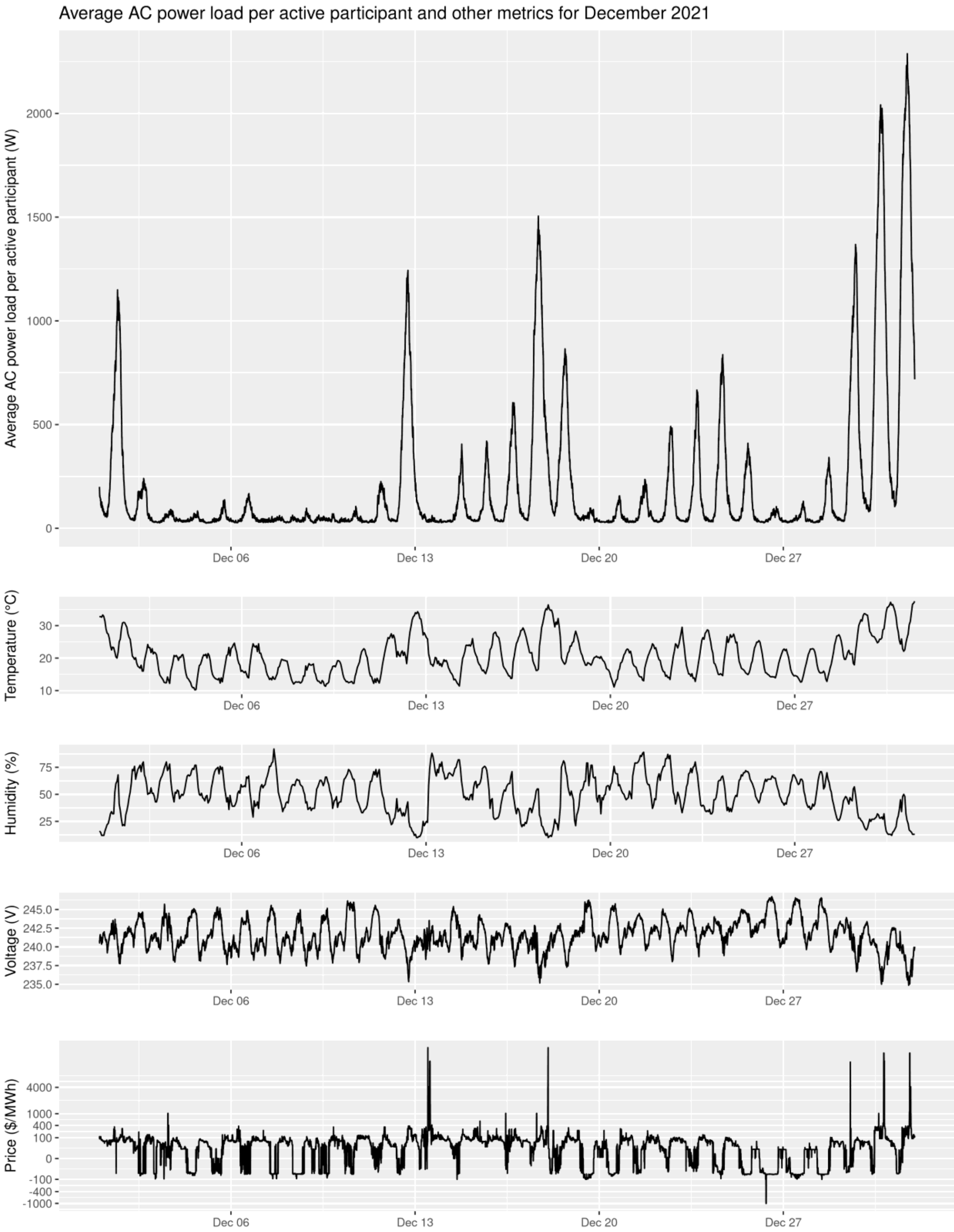

Average AC power load per active participant and other metrics for December 2021
Average AC power load per active participant (W)
2000
1500
1000
500
0
Dec 06
Dec 13
Dec 20
Dec 27
Temperature (°C)
30
20
10
Humidity (%)
75
50
25
Voltage (V)
245.0
242.5
240.0
237.5
235.0
Price ($/MWh)
4000
1000
400
100
0
-100
-400
-1000

Chart 7

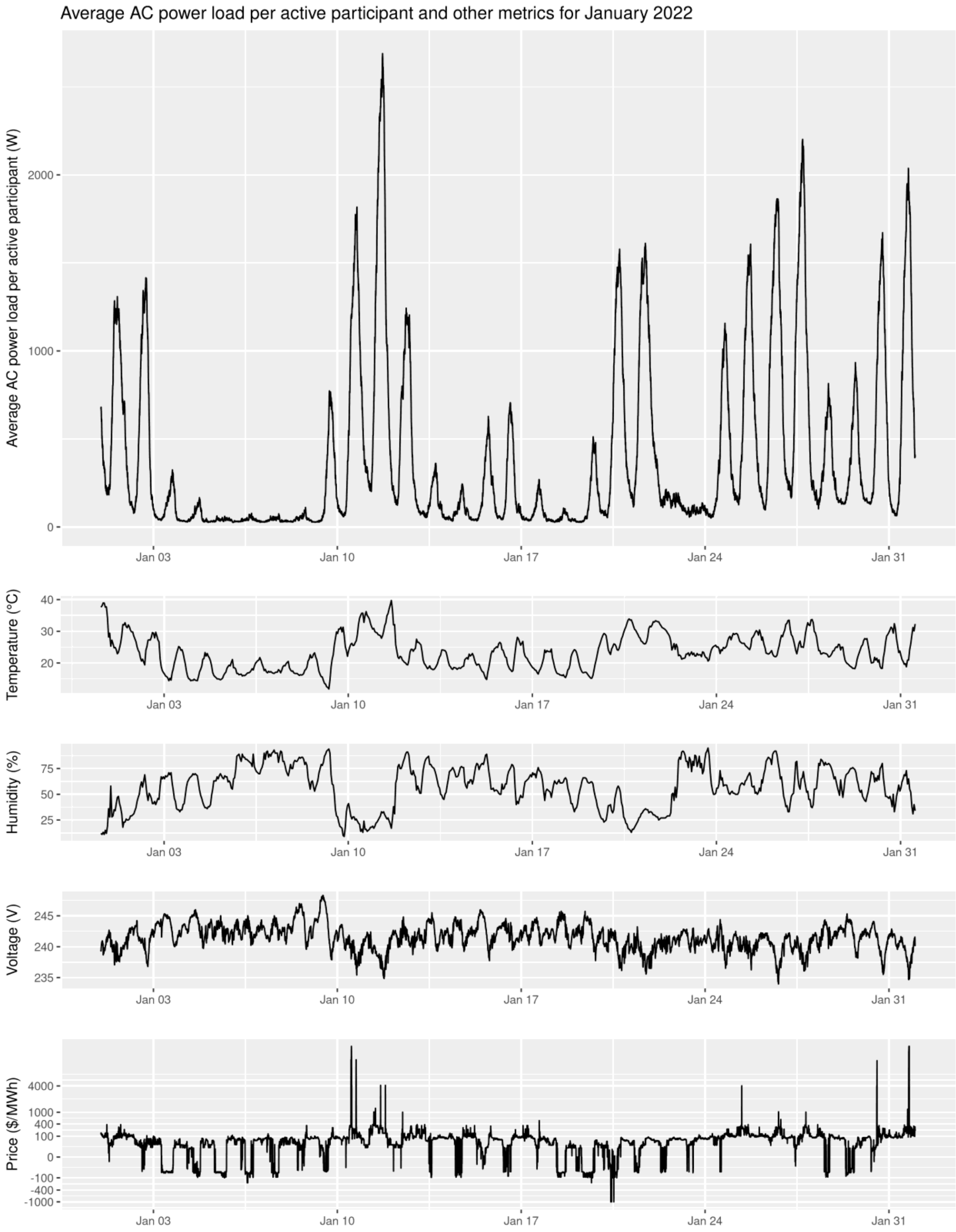


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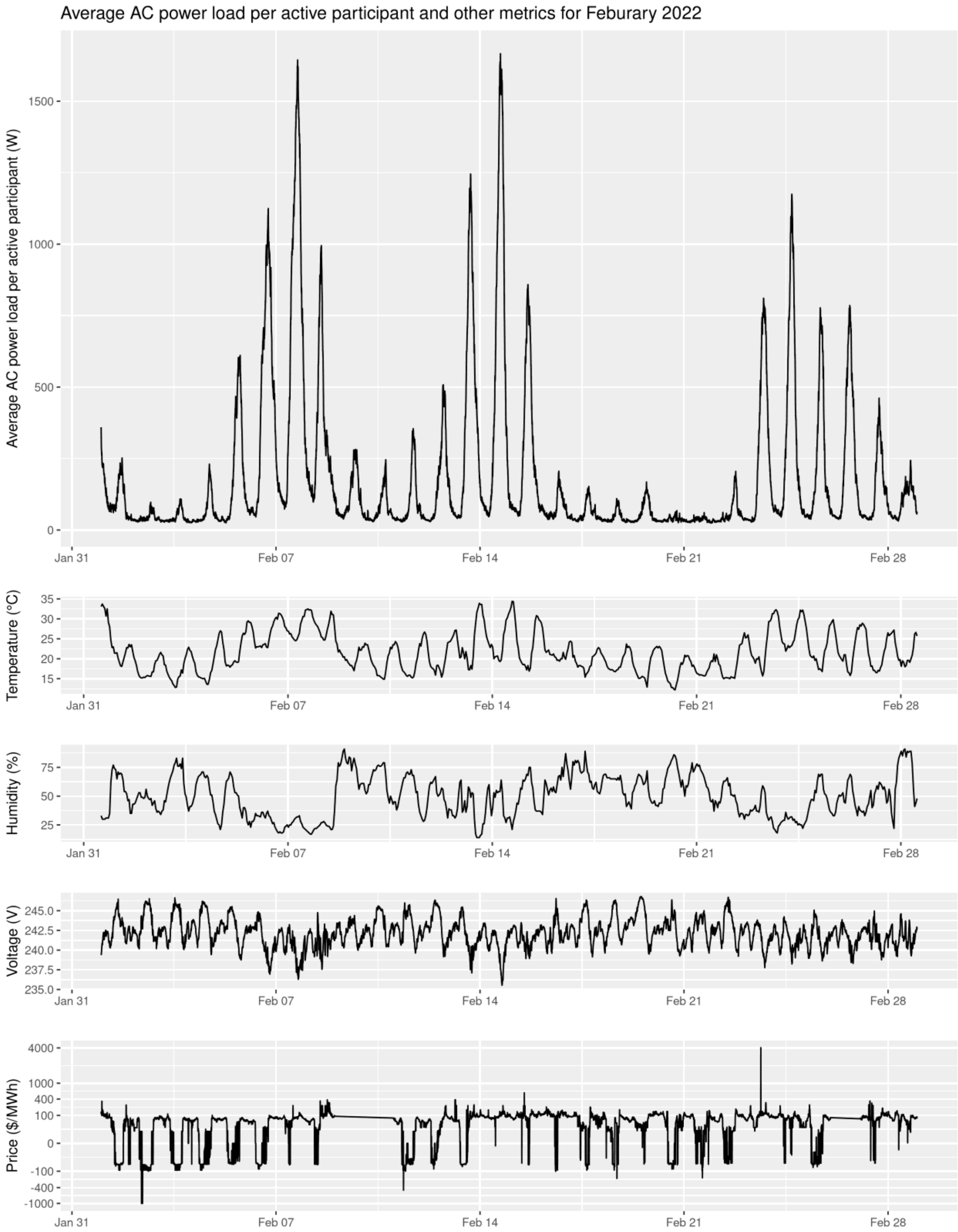
Chart 8



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As is typical with machine learning, the greater and more representative the data samples which are being fed into the model, the greater the reliability when forecasting AC usage. Our model evaluation found that using the stated data points from mid-November to December was not enough to deliver suitable confidence in forecasting AC usage. The machine learning algorithms were then run through to the end of January which improved AC usage forecasting.

Reliably forecasting AC usage and hence load availability from automated AC control many hours in advance, delivers greater value from an automated AC control platform to the energy grid. In essence, the more reliable and further out in time that the forecasted AC load control is, the more value automated AC load control can provide to the stability of the energy grid.

Our engineering team began with training individual household models for 24 hours in the future, however the confidence intervals were not initially suitable when using a few months of household data.

For our AI models to predict AC's being turned on one hour in advance, we can see the confidence/reliability increasing with additional training data. In January 2021 we used models that were trained using data only from mid-October to December. During this period there were very few AC usage events due to weather being unseasonably cooler than average, resulting in fewer AC events to "train" off of.

Chart 9 and 10 provide a comparison of aggregate model precision values in forecasting AC usage. Using data up to December the aggregate model precision value was 23% for predicting AC usage one hour in advance. This means that the model was currently predicting the timing that AC were being turned on 23% of the time.

Ideally we'd like precision to be higher so that we can be confident that when the model predicts an AC will be turned on, there is a high probability that it's true. By training the model using an additional months' worth of data (January 2021), the precision improved by 52%, to a precision value of 35%. With longer data collection periods and a higher number of AC event days, this precision value will continue to improve.

Chart 9

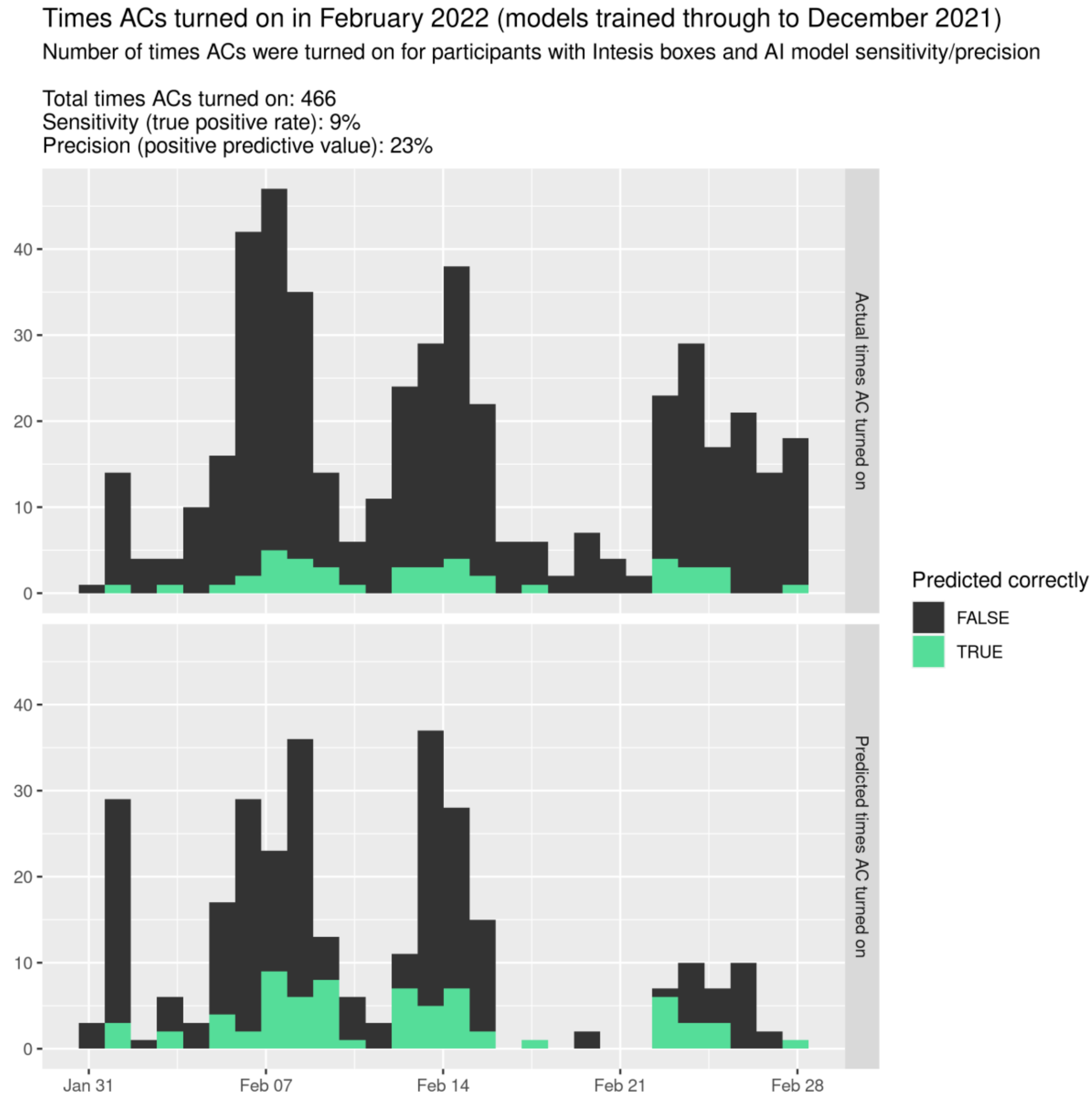

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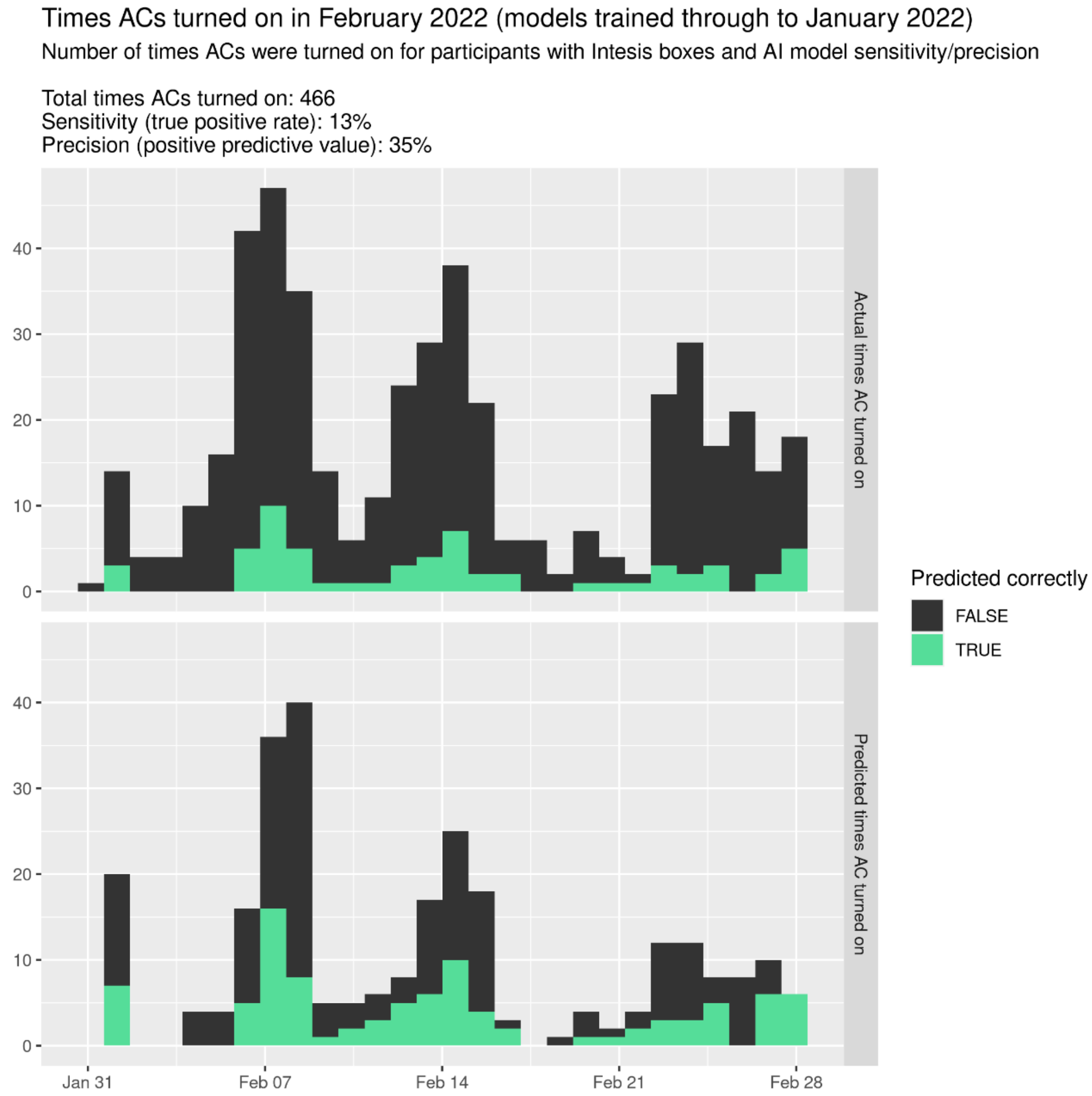
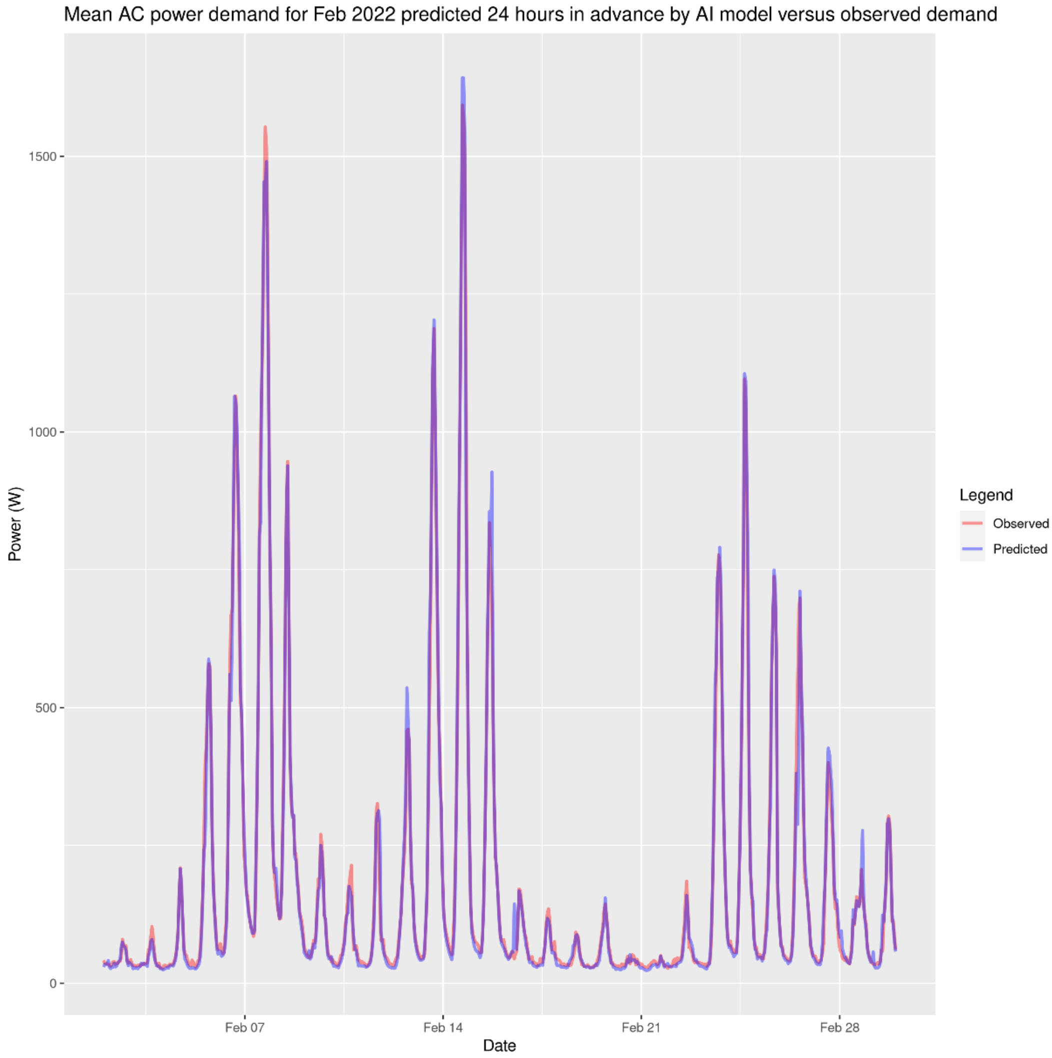
Chart 10



We then adopted an approach which forecasted aggregate demand across all the participants using air conditioners. This data was then used to train the machine learning model, to assess how accurately the model will now predict AC power demand 24 hours in advance. This is shown in Chart 11.

Chart 11



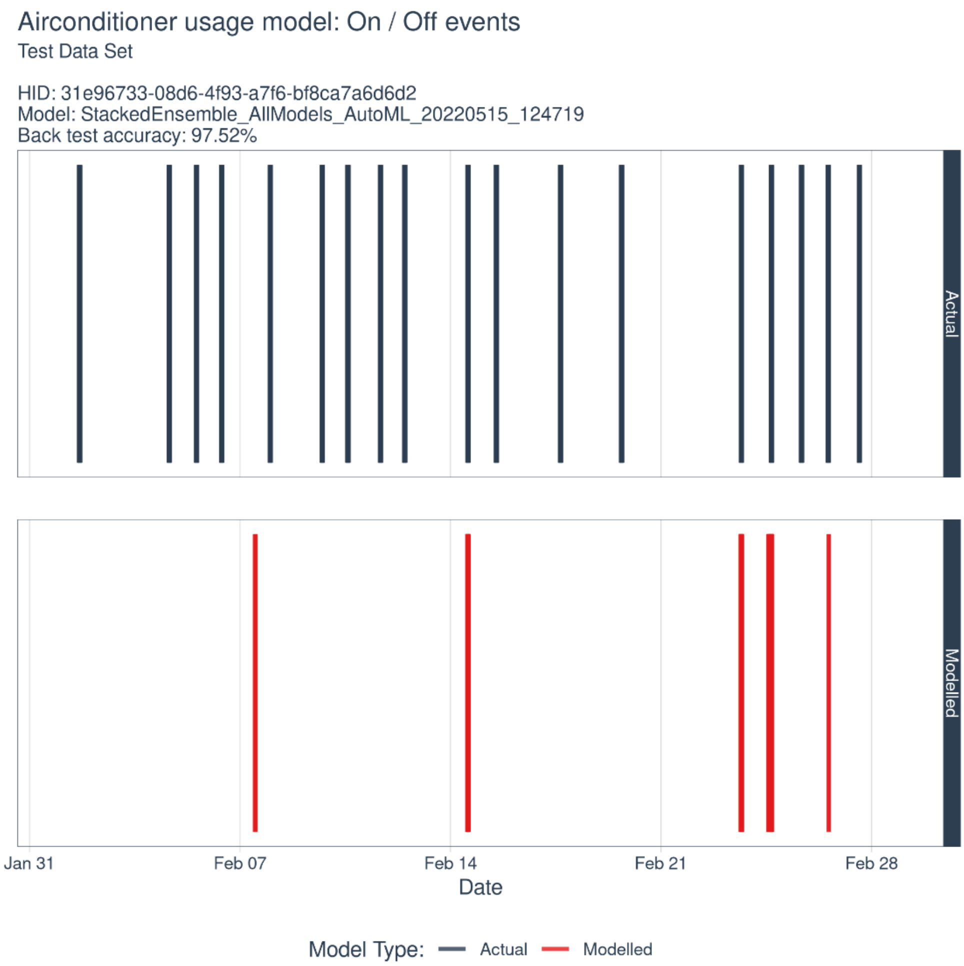
The model uses the observed power usage, temperature, humidity, wind speed and pressure over the past 24 hours, the hour of the day and the temperature forecast for the next 24 hours. This was done using weather forecast data supplied by www.WillyWeather.com.

The model was trained using data from December and January and then run against February data, which the model had never seen before. The observed performance was so impressive that our engineering team undertook a further peer analysis to double-check the model outputs; this was done to ensure we hadn't accidentally included the prediction variable in the model data. The accuracy of the 24 hour forecasting model was confirmed.

Given these observations, it was concluded that over time a machine learning approach would yield the appropriate level of AC use forecasting accuracy at both the aggregate and in time, at the individual household level.

A graphical illustration of the ongoing improvement in the machine learning algorithms forecasting accuracy is well depicted in Chart 12. It shows 2 out of 13 (15%) AC usage events were accurately predicted in the first half of February and then later 3 out of 5 (60%) AC events were accurately predicted by the model.

Chart 12



During the development of the AI forecasting model, it was seen that initial levels of intelligence built into the model was no longer sufficient post Covid-19. This was due to high variability in participant householders working from home. Thus a number of enhancements were built into the model which included:

- Hourly local district weather conditions including temperature, humidity, wind, cloud and rain (from WillyWeather)
- Variability in home power usage over the past several hours (an estimate for occupancy, which is more variable post-COVID)
- School holiday dates
- SA Government COVID-19 lockdown dates

With these new inputs we trained the AI to predict when the AC will go from OFF to ON, specifically we modelled the probability that an AC that is currently off will be turned on in next 30 to 60 minutes. This assessment was run on a subset of data (from mid-June to mid-July) not seen previously by the AI model:

- The plot reports 96.4% accuracy overall including true positives (we predicted the AC would turn on between 30 and 60 minutes ahead of time, and it did turn on as predicted) and true negatives (we predicted the AC would not turn on between 30 and 60 minutes from now, and it stayed off).

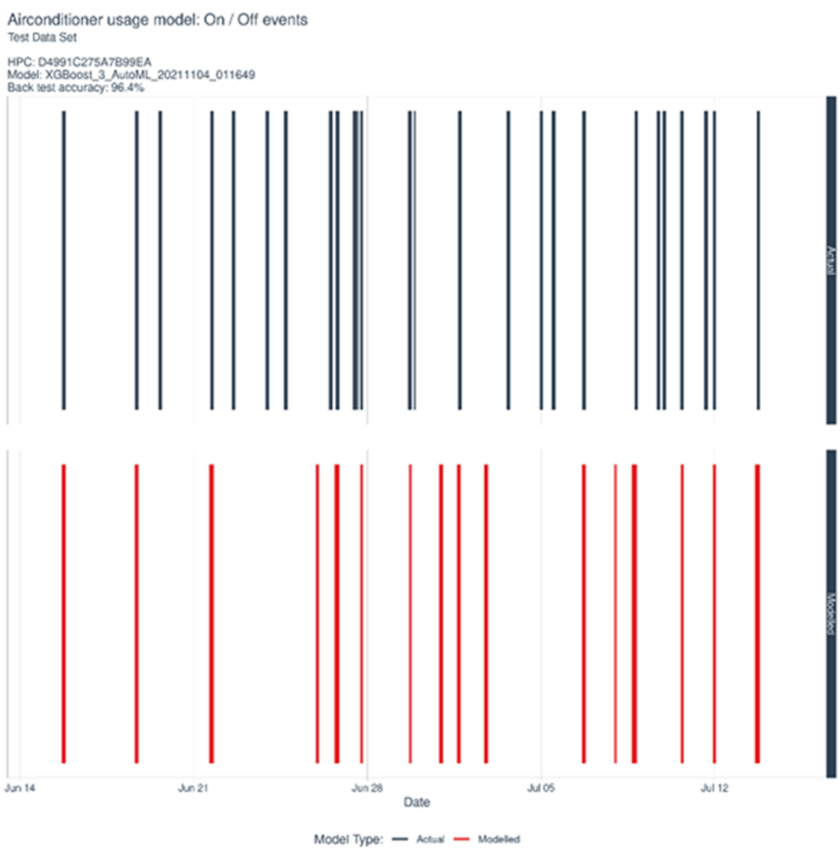
- There are 25 times the AC is turned on over this period. The model predicts 16 times that the AC goes from off to on, and 12 of these (75%) were correct.

- For AC control events we will only use these AI models to turn on the participant AC for pre-cooling when the predicted probability is over 75%

On average, combined true positive and true negative prediction rate was 94.4%, confirming richer dataset (local weather, variability in home power usage, school holiday dates and lockdown dates) improves the model.

We also trained an AI model without this data and got an average prediction rate of only 90.6%. Extra data points overtime have led to a vast improvement in the model and ability to cater for large variability in householder presence during a work week.

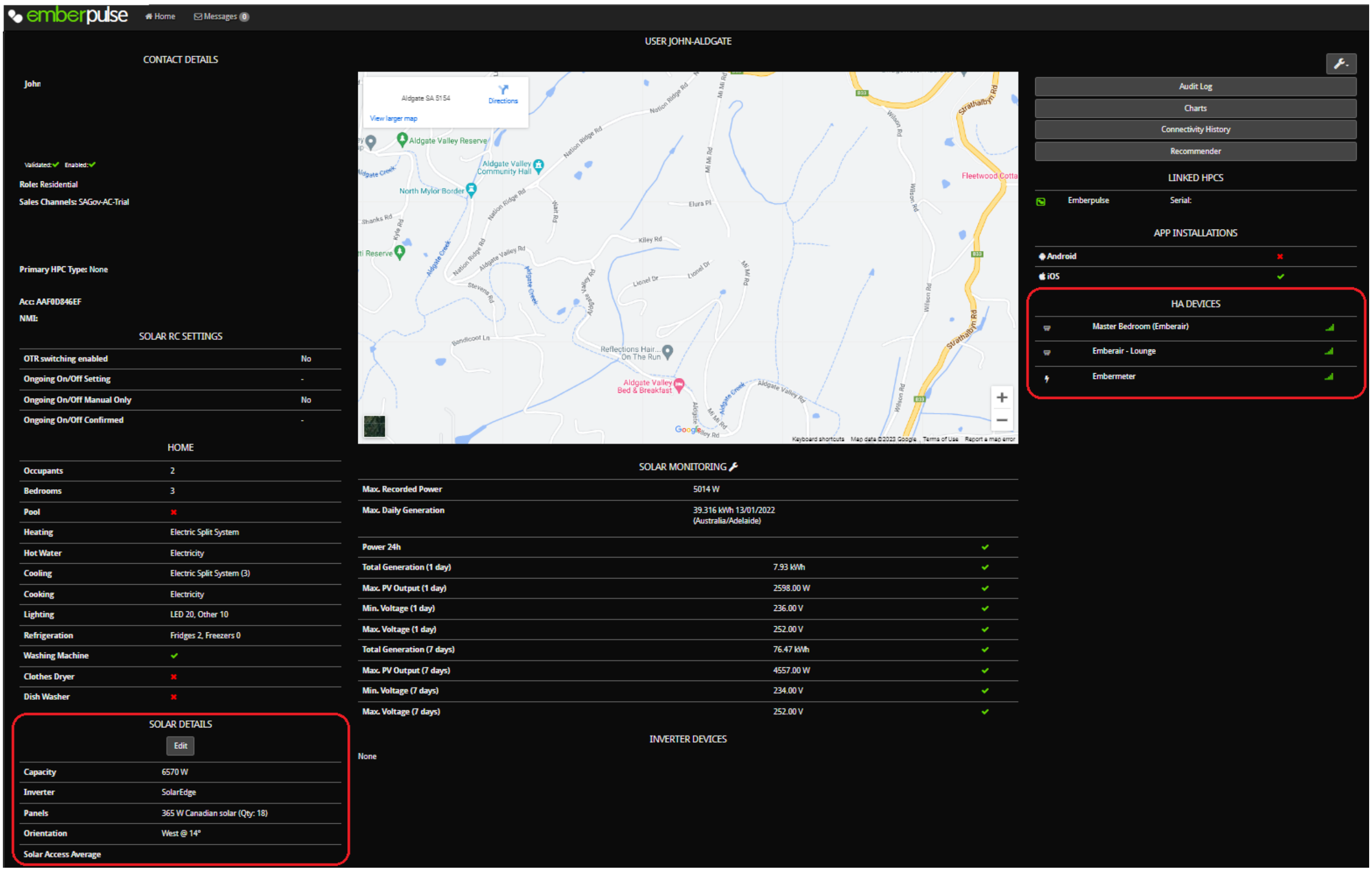
Chart 13:



A total of 211 AC controllers were deployed to 189 participating households. Participants for this phase of the trial were focused on homes where there was a reasonable level of AC usage during typical grid peak demand periods and where there would likely be AC load malleability potential.

The AC power load being monitored at each household enabled the analysis of AC usage during period when grid prices typically spike. Overall, of the 189 households who participated in the AC control phase of the trial, 58 of these were homes without solar systems as compared to 137 households who did have solar installed. This is important as solar penetration will have an impact on the level of grid support this technology will provide. In addition, solar penetration in residential homes continues unabated and is currently above 42% and growing.

An anonymized extract from the Emberpulse® dashboard that is collected on each trial participant is provided within this report. The circled red areas detail the solar status of the property including the solar system capacity and it also details "HA DEVICES" (Home Automation Devices). The device named "Emberair" is the AC Controller. The green signal strength icon denotes that the AC controller is currently online.



An assessment was conducted to understand the potential level of use of split system AC's in winter for heating purposes, in addition to cooling. The data showed that around 50% of all split systems were used for both heating and cooling.

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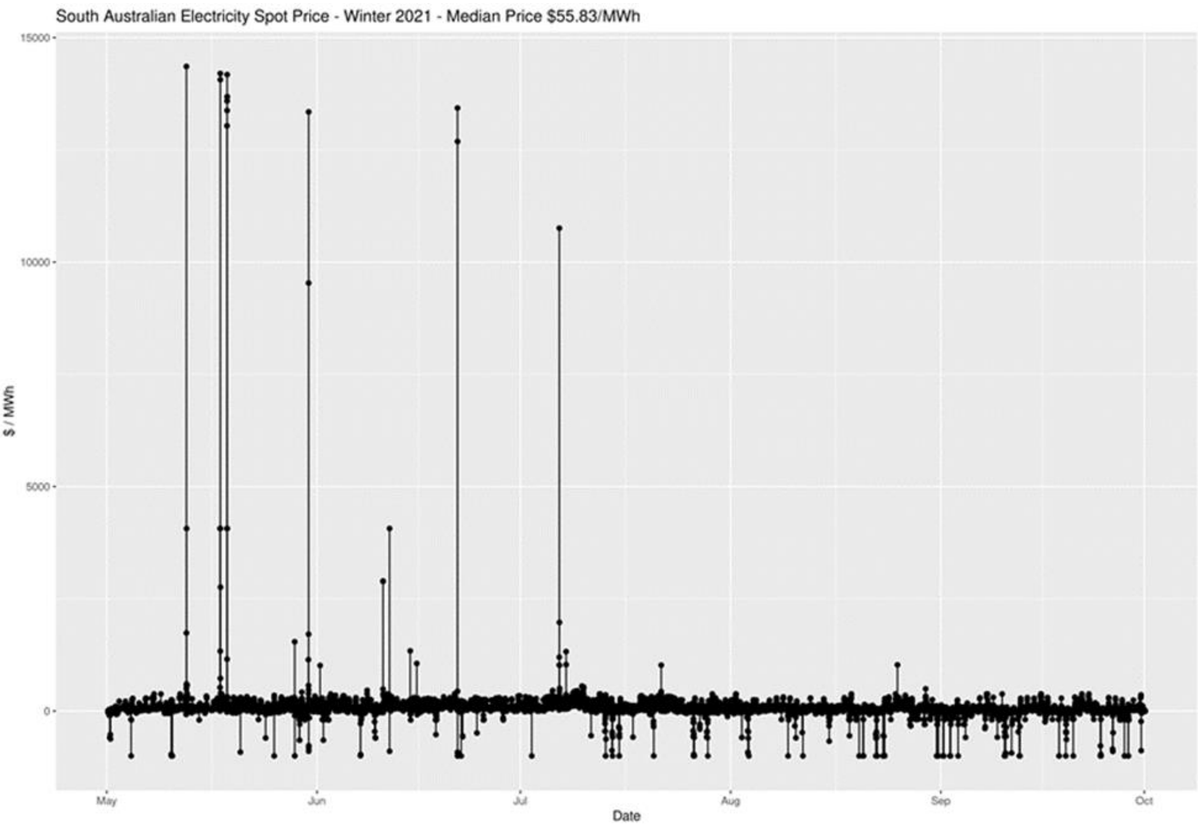
The model was expanded extensively to include 103 external to site and internally monitored individual data points. This was done to deliver greater accuracy in forecasting and assessing the potential to expand control into the winter months also. The ability to train the model will need to take place during the winter of 2022, but the preliminary data supports the ability to offer load management potential during the winter months.

Chart 14:



The automated AI AC load control software has been developed and deployed in the field and it is now awaiting hot weather to take action and monitor user feedback post automated control events.

A core part of this deployment is the need to monitor in real time the National Electricity Market. This included the following key steps:

- Actively monitoring the electricity spot price and forecast on the NEM
- When the spot price or forecast exceeds a threshold, we trigger load control event for a random sample of trial participants.

For testing as temperatures were fairly moderate at the time (spring) we validated the AC control functions based on historical temperature data during summer. Plotted below is a graphical representation of the spot prices in $/MWh for South Australia between May and September. Median spot price is $55.83/MWh and the maximum price for a 5 minute period in May, was $14,357.15/MWh.

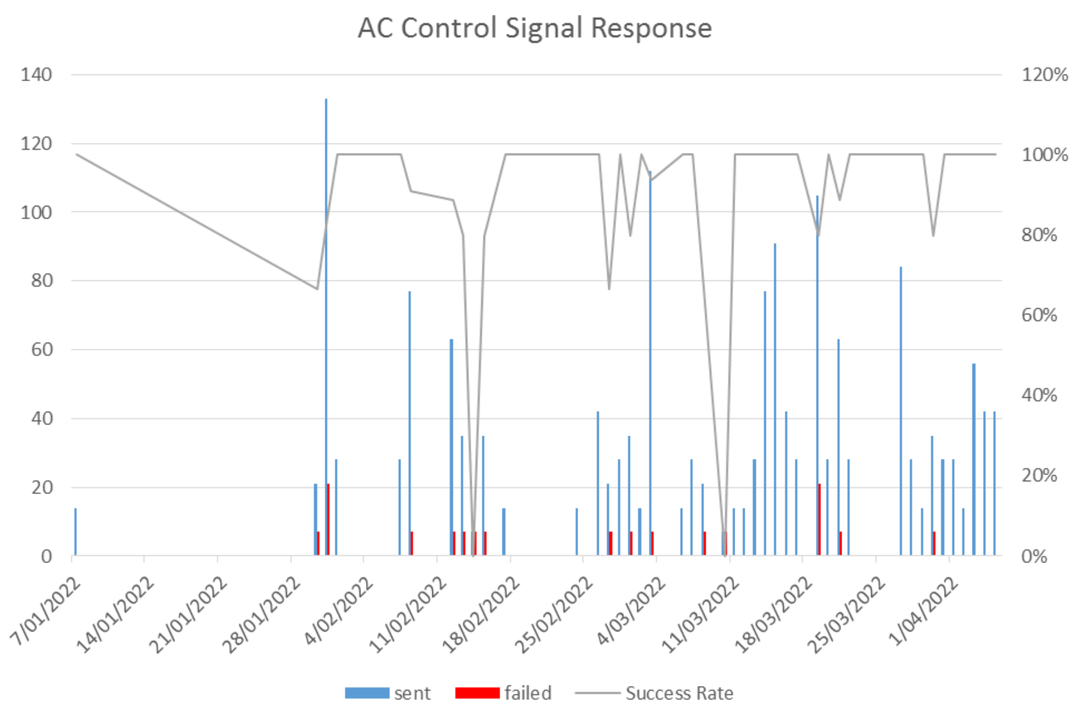
As part of the initial evaluation, a data gathering process was developed which would enable a snapshot assessment of the AI engine decision making process. Every 5 minutes a snapshot is provided to present the following:

- Current NEM price and price forecast for next 60 mins
- Max, Min and Ave NEM price forecast for next 60 mins
- NEM price trend (increasing or decreasing)
- Reports status of connected AC's
- Predicts which house temps are in the malleable range (i.e. AC's could be controlled)
- AI model then predicts which AC's have a probability of turning on
- Reports if any AC intervention has taken place
- Pre-cooling/heating, compressor off (fan mode), etc.
- House power/load

Below is a chart outlining the AC control events in terms of the events sent and the successful receipt and actions taken by the AC controllers. A successful action is defined as the AC controller being sent and undertaking the control command that was sent without being over-ridden. A "failed" event is when the AC controller either did not respond to the control signal, or it did respond and was over-ridden by the householder within a few minutes of the control command being sent and actioned.

This is important for a number of reasons. It details the number of AC's that were eligible for the control event because they were in an operational state (i.e. on and cooling when it was desired to be off or in a fan only mode) and in an actionable environment, i.e. the room where the AC was located was determined to at a sufficiently cool level for the householder.

Chart 15:



Of the 211 AC controllers installed, on average 39 (or 18.5%) of them were available to be controlled during the control events. 89% of these AC controllers responded to and maintained the control event. Thus 11% of the AC controllers either did not respond to the control event or they were over-ridden by the householder within a short time period.

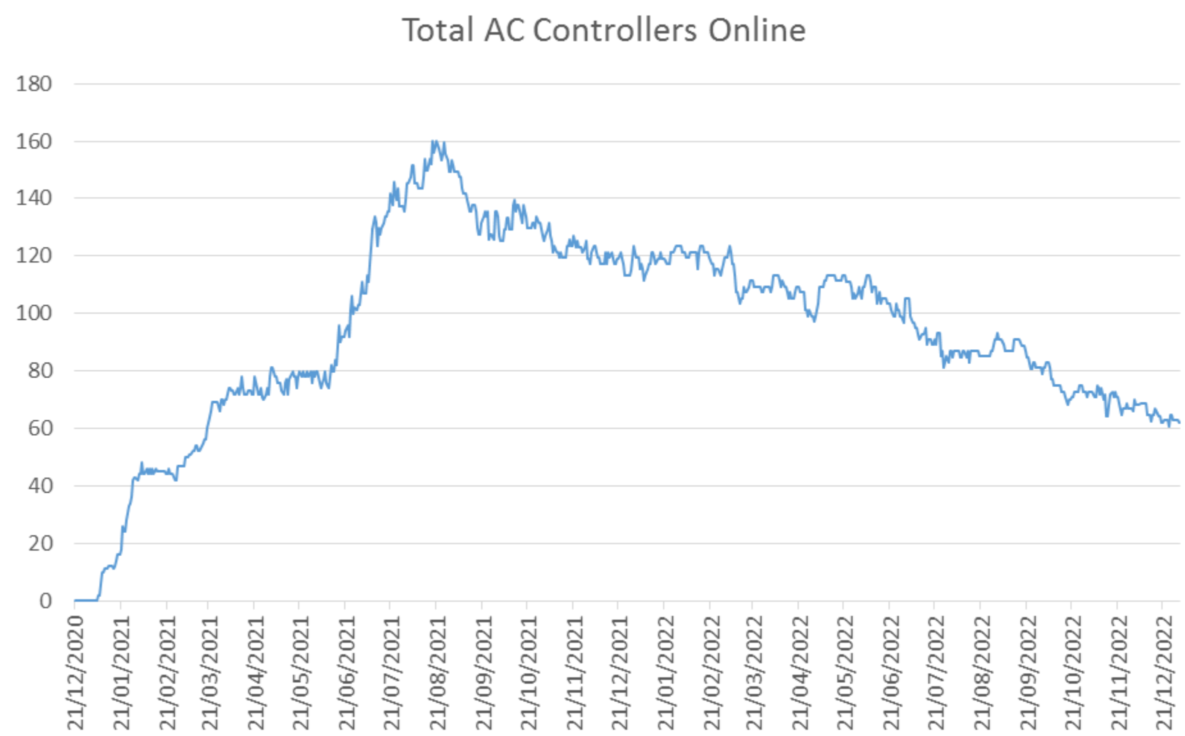
Over-ridden events suggest that the AI model which forecasts AC control availability is not 100% accurate based on there being a 89% success rate. However there is a hypothesis which suggests that striving for a 100% success rate may inadvertently eliminate some AC controllers from events where they would otherwise be available to participate without householder nuisance.

Thus a balance needs to be attained between attaining a suitable number of AC controllers participating in control events and not creating householder inconvenience through altering AC modes when conditions are not acceptable to the householder at the time or for the duration required for the control event.

As we have only had 3-4 days of a reasonably high temperature during this phase of the research, it did not yield much in terms of real world data and feedback on the AI engine performance. We expect this to change by mid-summer as ambient temperatures begin to increase on average.

One of the challenges with this research was maintaining an online status for the AC controllers so that they were able to collect data and receive control signals throughout the research project. The chart below illustrates the online status of the participant 211 AC controllers during the 21/22 period. At the peak, 158 of the 211 (75%) AC controllers were online at the same time.

Chart 16:



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AC Control Event Analysis

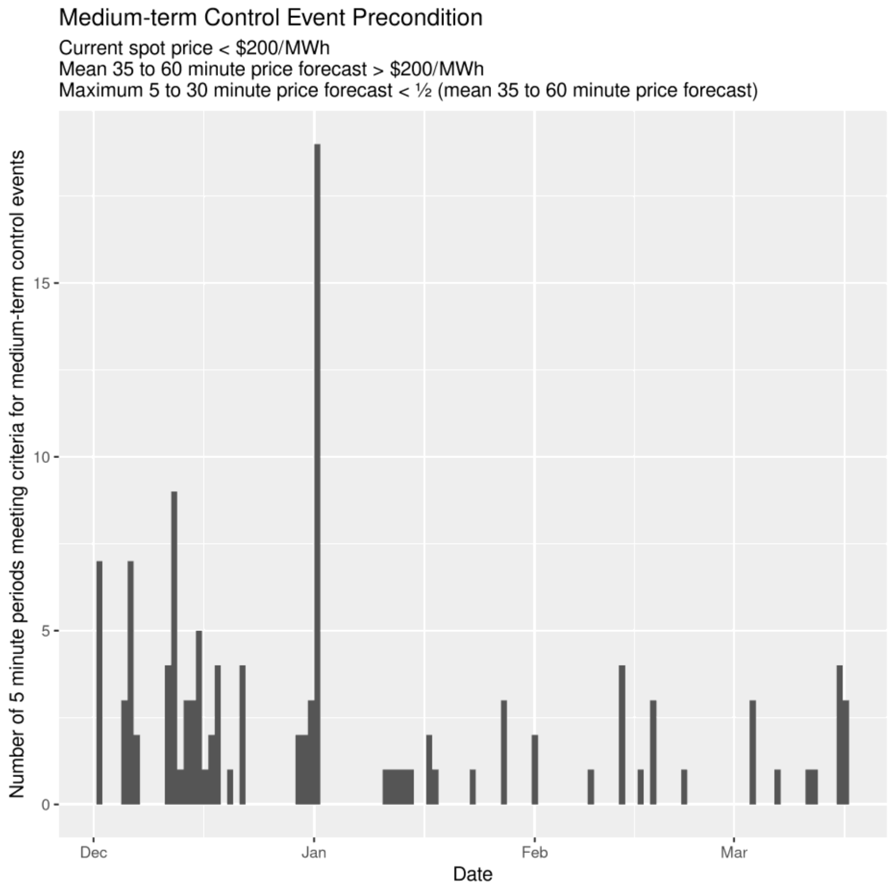
The AC control events targeted the following set of pre-conditions for each 5 minute SA NEM pricing window:

- The pre control event spot price was under $200/MW
- The mean forecast price 35 to 60 minutes from the control event is over $200/MW
- The maximum forecast price between the control event period and 30 minutes from the control event period, is less than half the mean forecast price 35 to 60 minutes from the control event period.

Unfortunately there were not as many opportunities as we would have preferred for AC control events to take place during the targeted control period. This was due to an unseasonably cool summer period which reduced AC usage, energy demand on the SA NEM and hence energy supply was not constrained to regularly drive up energy costs beyond $200/MW.

Chart 13 illustrates the dates on which these pre-conditions were met and the number of 5 minute windows where they were met.

Chart 17



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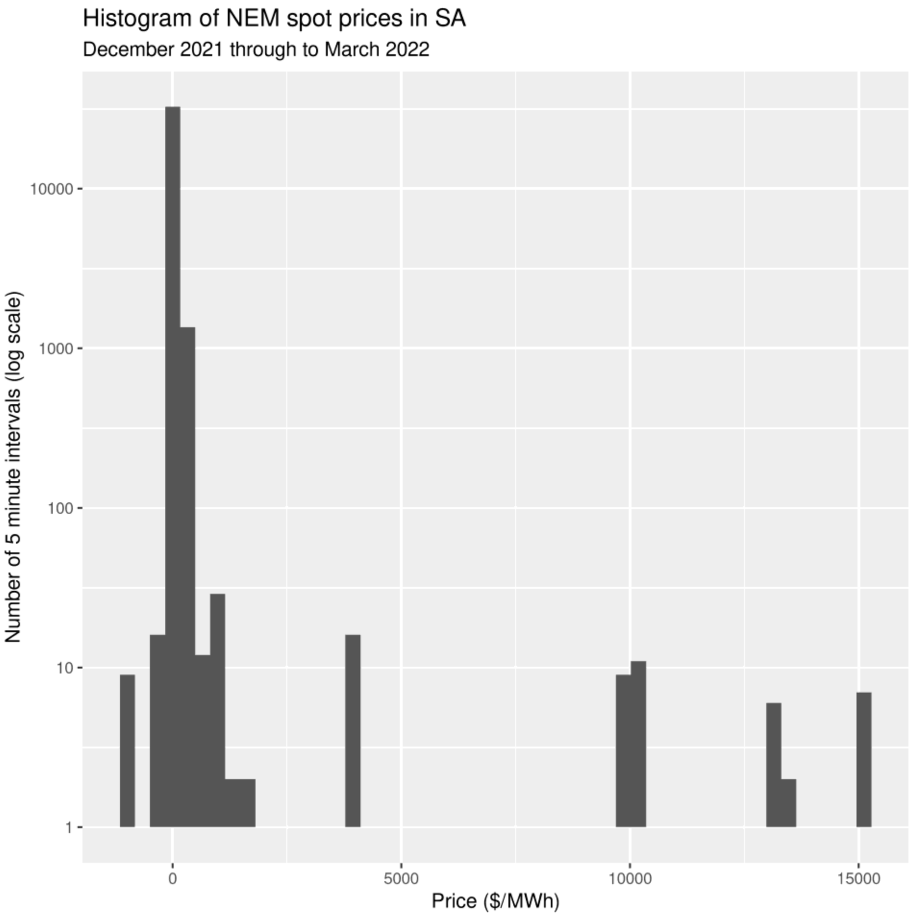
Specifically there were 63 instances of 5 minute periods where pre-conditions were met in December, 33 times in January, 10 times in February and 13 times in March. As the machine learning model was being trained during December and January, this left a small number of instances in February and March where the pre-conditions were met.

Between December and March there were relatively few instances of high spot prices on the SA NEM. In December, there were 46 five-minute intervals (almost 4 hours) with spot prices over $500/MWh. To put this into context, high price intervals represent only 0.5% of all price intervals during December. In January there were 36 (3 hours), in February there were 2 (just 10 minutes) and in March there were just 7 (35 minutes) of high price intervals. A histogram of spot prices can be seen in Chart 14 below.

Chart 18



Originally we started with the spot price threshold being $1,000/MW, however due to there being insufficient instances of these price points being reached, we lowered the price point to $200/MW. With the threshold at $200 there were 399 five-minute intervals exceeding this in December, 546 in January, 68 in February and 208 in March.

The main aspect of the trial was to assess the ability to automate AC loads in a comfortable manner for householders, which would lower grid load pressures when needed. Thus the NEM price point is a variable (there can also be others, i.e. voltage and frequency variables which may be dictated by SAPN) that can be adjusted in future applications of this platform to assist in delivering grid stability.

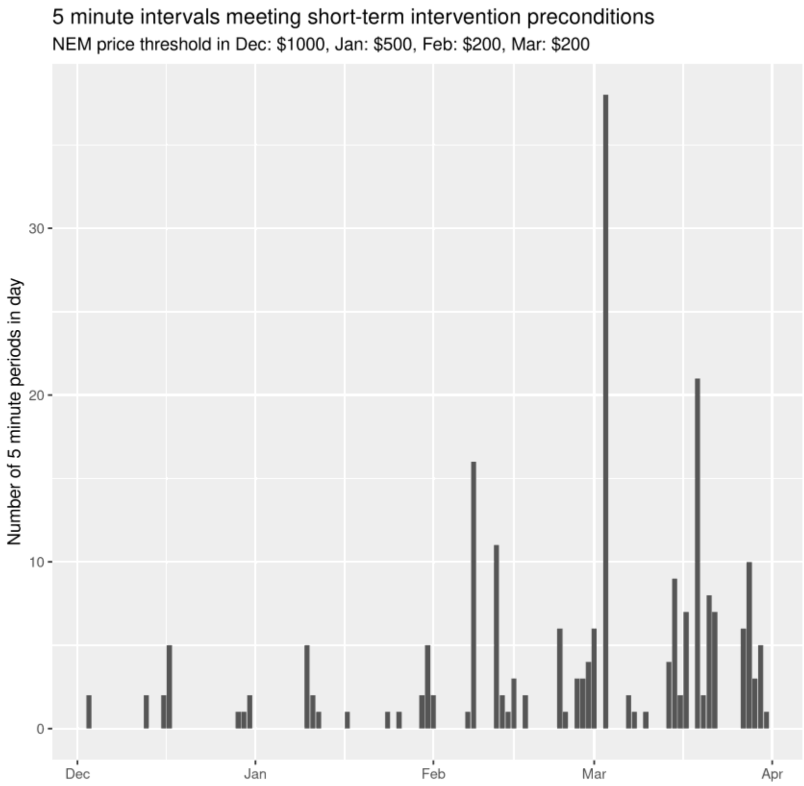
The target was to undertake between 5-10 AC load control events across the participant homes in total. The model was initially deployed to reduce energy consumption via switching off the compressor by putting the AC into fan only mode, which would circulate the cool air in the room. A number of household pre-conditions needed to be attained in order for the household to qualify to take part in the analysis.

The NEM price was the first pre-condition to be attained in order to begin qualifying for the control event. The graph below shows the number of 5 minute periods where the NEM price pre-conditions were met for short term AC interventions. These pre-conditions were:

- The current spot price was above the threshold ($1,000 in December, and then dropped to $500 in January and then $200 for February and March to increase the number of interventions as the spot price was unusually low during this implementation period.

- The mean forecast NEM price for the next 30 minutes needed to be more than the forecast mean NEM price for the 30 minutes after that. I.e. the aim was to only do short term interventions where the NEM price trend was "downwards", otherwise we might end up shifting load to a more expensive period.

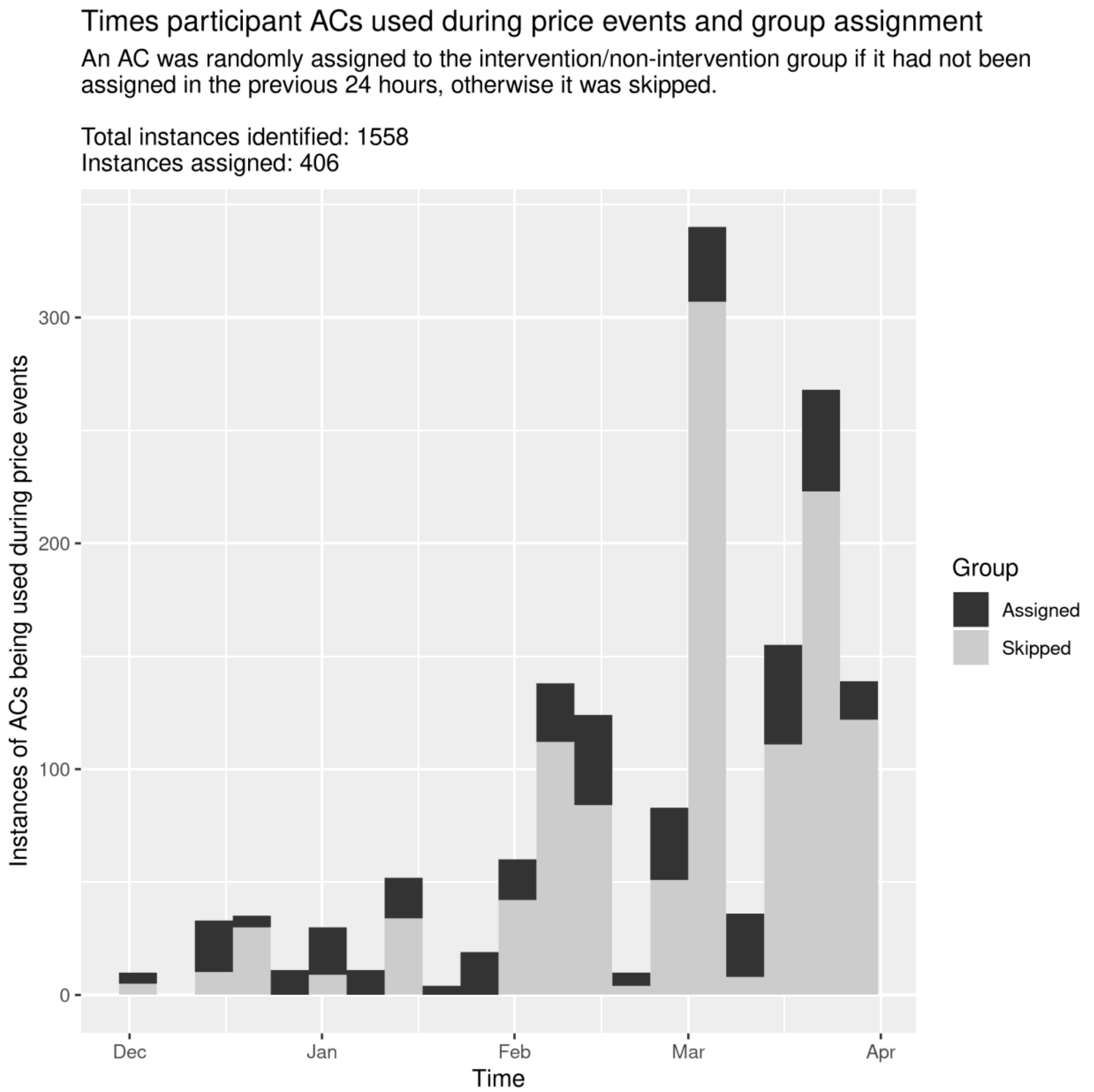
Chart 19



During the trial period there were 1,558 instances where we met the pricing pre-condition, the participant AC was “ON”, and the room temperature was under 26°C. When these instances occurred if there hadn't been an assigned event for that participant AC in the previous 24 hours, the AC’s were then assigned randomly with a 50% probability to either the intervention group or the non-intervention group.

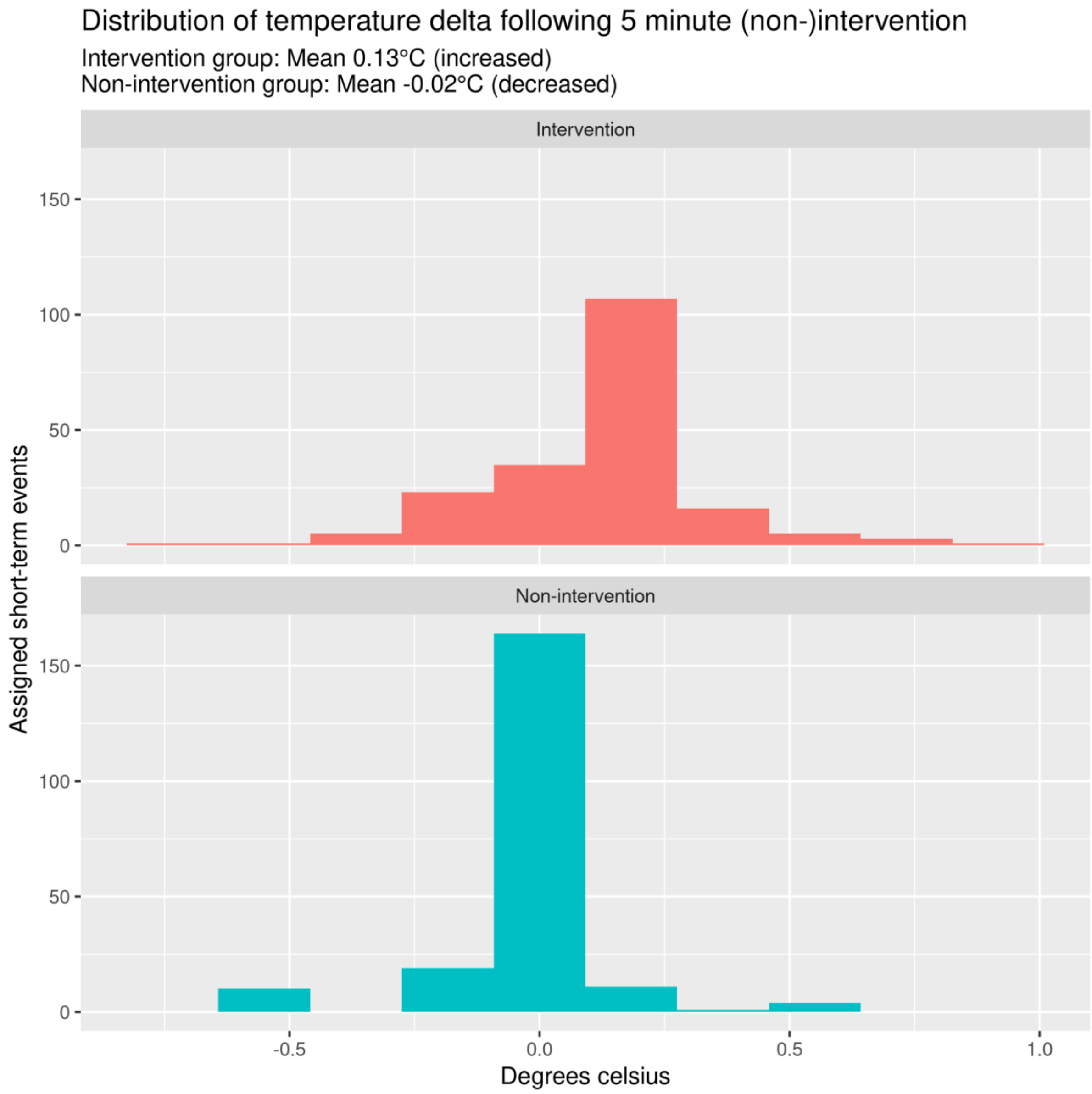
There were 406 assigned instances, 197 were executed as interventions, and 209 were tracked as non-interventions for a statistical control. The graph below illustrates these events and the participant AC's. As discussed earlier, the number of AC control events increased in the later months as we brought down the NEM price threshold from $1,000 to $200 in order to increase the sample size.

Chart 20:



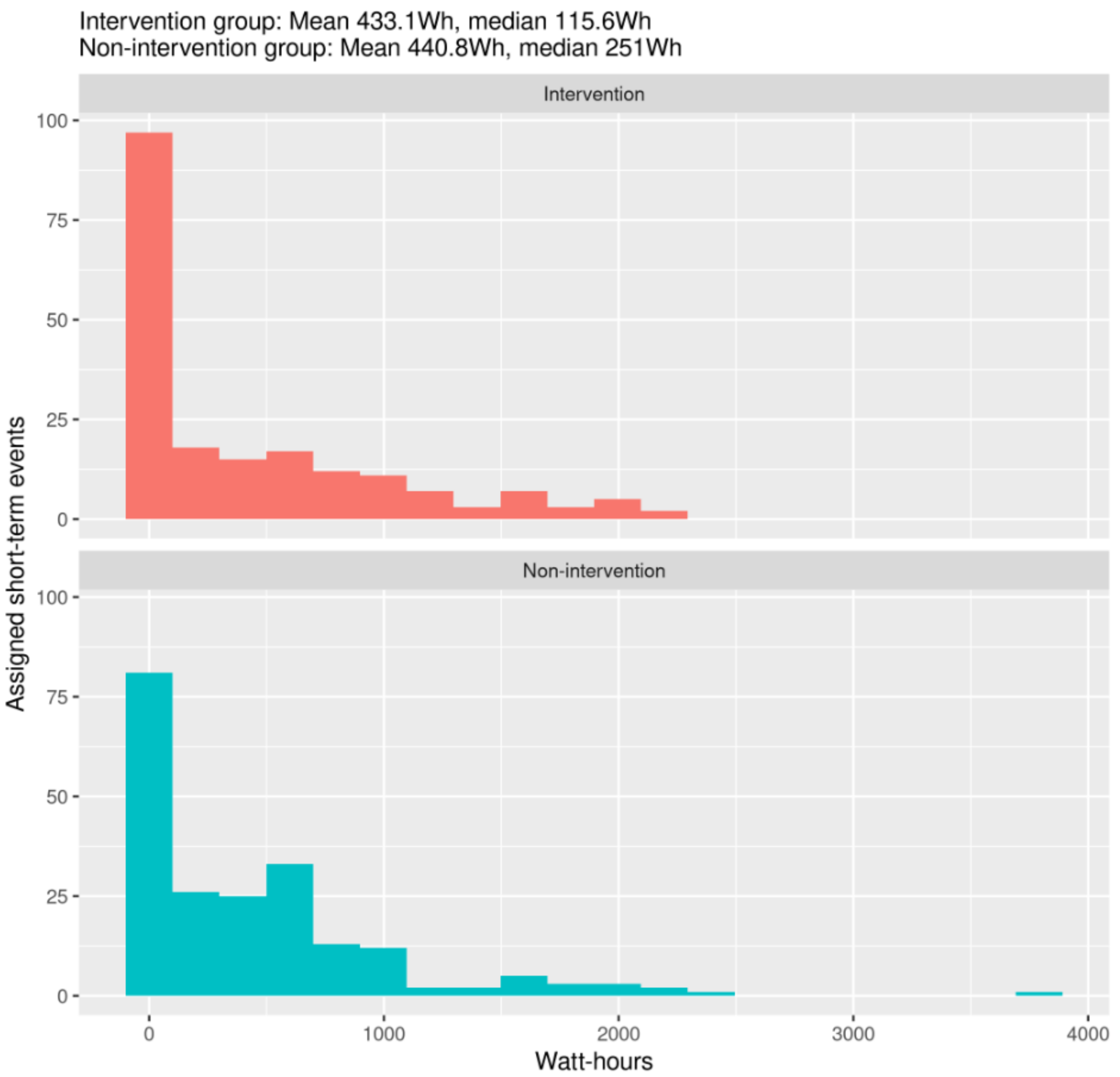
The Emberpulse® device and the AC controller were then used to monitor room temperature change during the intervention period. The graph below shows the change in temperature in the 5 minutes that the (non-) interventions were running. As expected, when ACs were placed into "fan-mode" for 5 minutes, there was a slight average increase in temperature observed by the AC. This difference was statistically significant ($p=2.2 \times 10^{-16}$) using a Wilcoxon rank sum test.

Chart 21:



When assessing the effect of the intervention on the amount of energy consumed by the non-intervention and the intervention groups, the following was observed.

Chart 22:



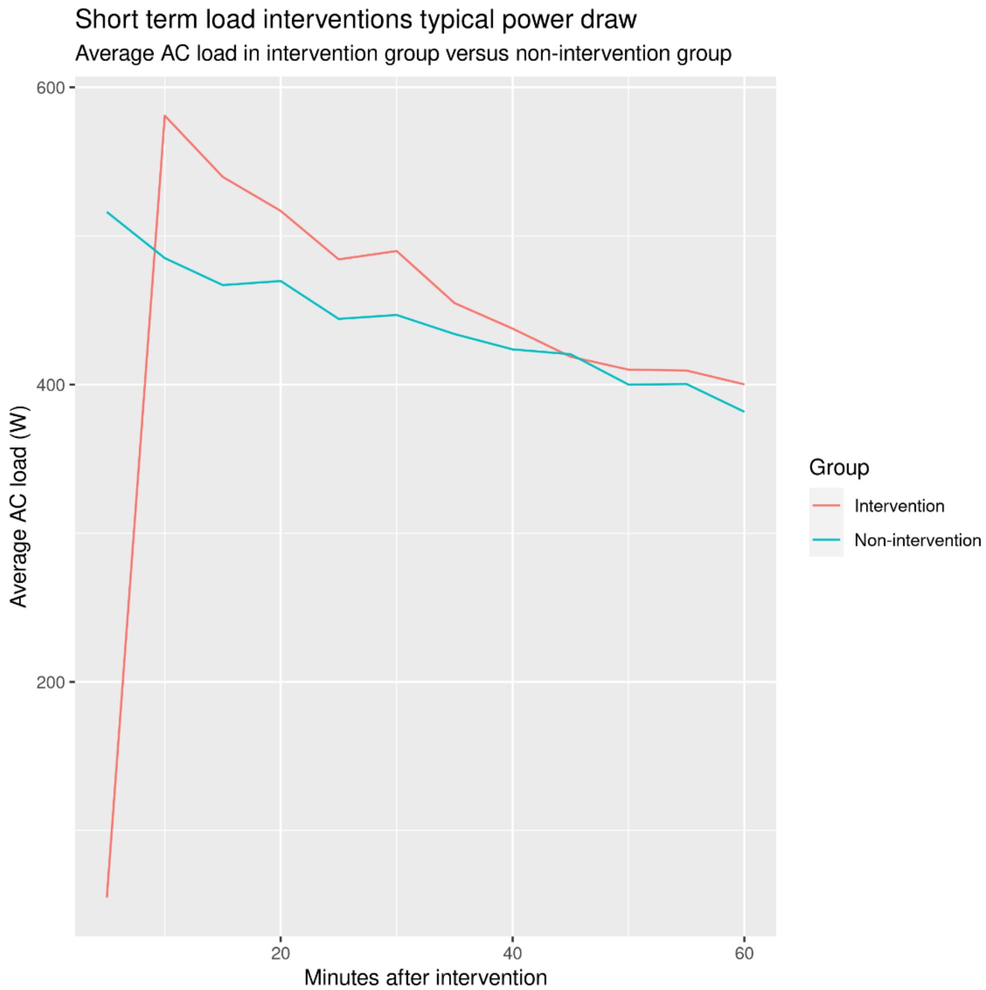
The histograms illustrates the total energy usage in the hour from the start of the intervention and non-intervention groups. While the mean of the intervention group was slightly lower, a Wilcoxon rank sum test found no statistical significance for this (p=0.65). This isn't too unexpected since the intervention is only for 5 minutes within the hour and the energy saved in the first 5 minutes is typically shifted to the remainder of the hour.

This is important as it suggests, short term interventions will not lead to an overall increase in AC energy usage due to a slight increase in room temperature with the fan mode being activated for 5 minutes. Thus, households participating in the intervention to curb load on the network will not be adversely affected financially, as there is no overall increase in energy usage post intervention.

When monitoring the mean AC load in watts in hour from the start of the intervention, we see that in the first 5 minutes there is, as expected, a large drop in AC load (the mean of the intervention group was only 10.6% of the mean of the non-intervention group.

This is a statistically significant variation by a Wilcoxon rank sum test ($p=1.5 \times 10^{-13}$). In the 5 minutes immediately following the intervention, average AC power was slightly higher in the intervention group. Overall delivering close to a 90% reduction in AC load across the intervention group compared to the non-intervention group, demonstrates a significant potential benefit in delivering an automated AC load control solution an a mass scale.

Chart 23:



Finally, an analysis was conducted on the energy consumed with respect to the average NEM price during the interventions compared to the non-intervention periods. As expected, on average the intervention sample consumed less energy and less cost over the same periods when compared to the non-intervention sites.

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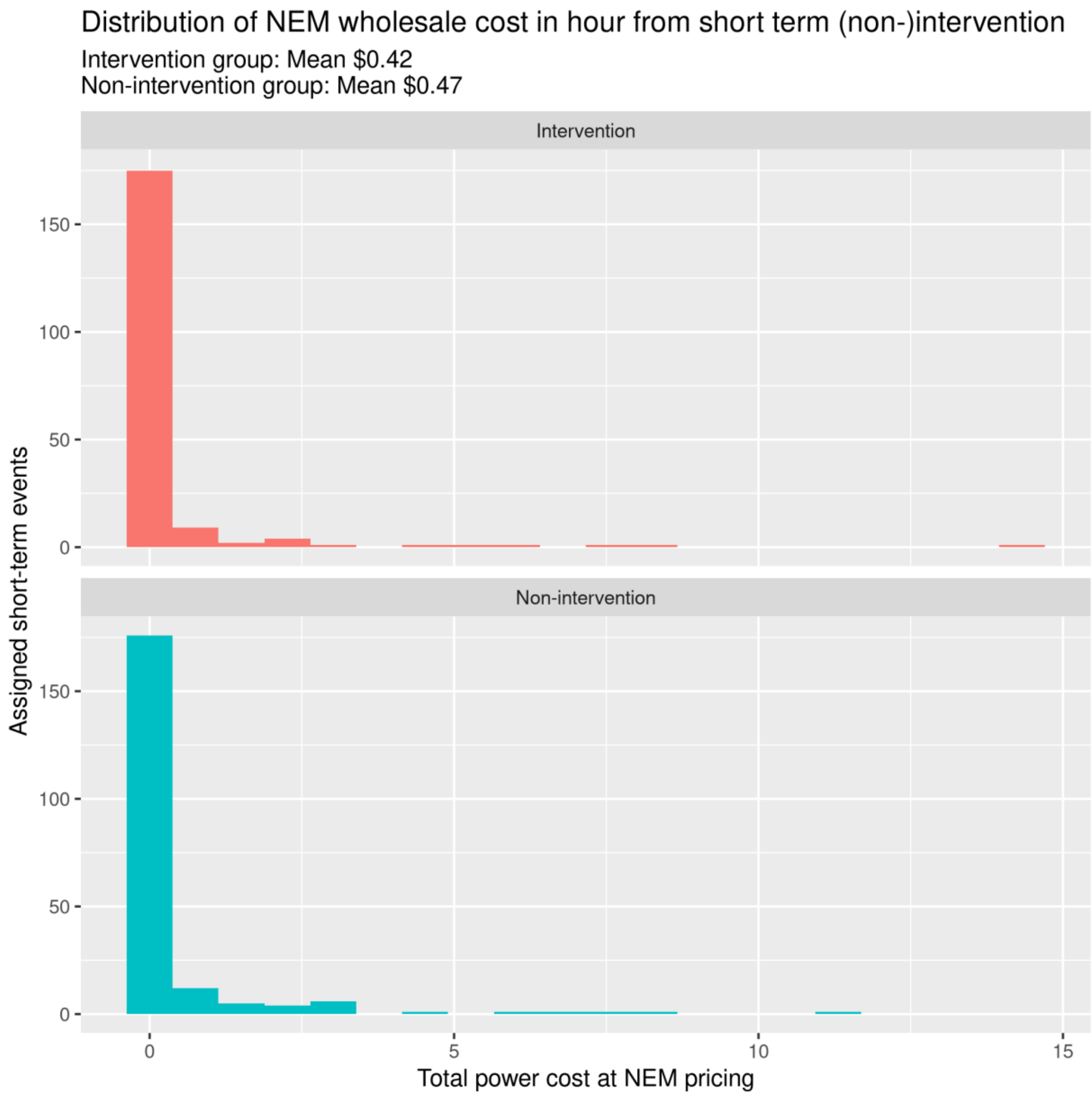
Although the relative means were quite low, 42 cents vs 47 cents between the intervention and non-intervention groups respectively, this still delivered a 10.7% decrease in energy usage for the full hour with only a 5 minute intervention.

Chart 24



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Consumer Research Survey

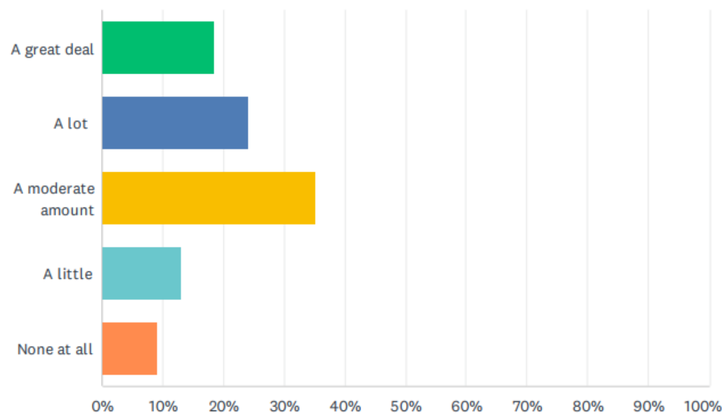
Following the AC control events, a survey was undertaken with the participant households to assess their level of comfort and convenience with Pulse® and the automated control of their AC provided by the Pulse® connected AC controller.

54 of the 189 households who participated in the second phase of the trial, responded to the online consumer survey. The results from the online questionnaire are detailed within this section of the report.

Overall, 90.7% of respondents stated that the Pulse® device provided useful feedback on their energy usage and would be used at some level.

Q1 How often each week would you look at the coloured light feedback of the Emberpulse?

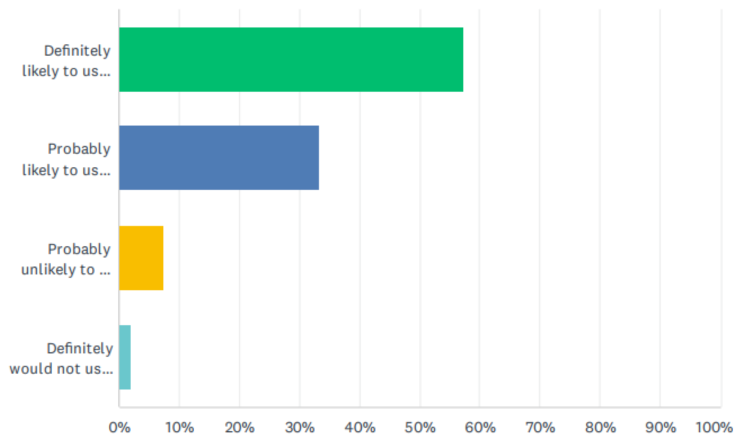
Answered: 54 Skipped: 0



The vast majority of respondents stated that they would use their split system AC on days when the weather was 30 degrees or hotter.

Q2 How likely would you use your Air-conditioner on hot days (over 30 degrees)?

Answered: 54 Skipped: 0



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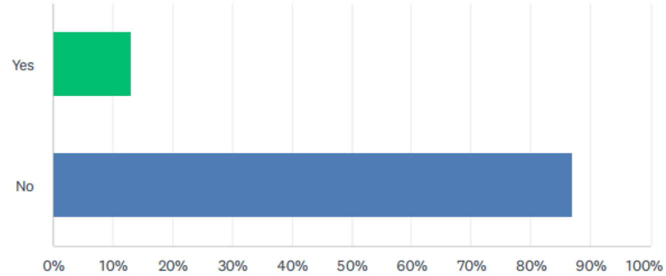
With respect to the ability for the AC to be automatically controlled without the householder realising that control had taken place, 87% of householders stated that they did not realise the AC had been controlled during the 5 month period when automated AC control was being undertaken.

Q3 Between November 2021 and March 2022 did you notice whether your air conditioner turned on or off at times other than when you specifically controlled it?

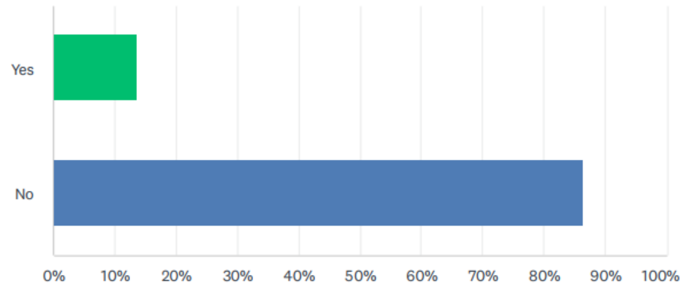
Answered: 54 Skipped: 0



When determining whether the automated AC control led to a negative householder comfort factor, 13.7% of respondents reported that their comfort was negatively affected during these control event periods. This would suggest that the machine learning algorithm was not set optimally for these householders and more householder data would be required for these homes to optimise the algorithm.

Q4 During periods when your air conditioner was controlled automatically by your Emberpulse, was your room temperature comfort negatively affected at all? i.e. Were you too hot or too cold during times when Emberpulse was controlling your air-conditioner?

Answered: 51 Skipped: 3



Interestingly, the percentage of householder who stated that they were negatively impacted by the automated AC control (13.7%) was almost identical to the percentage of householders who realised an automated AC control event was taking place (12.9%).

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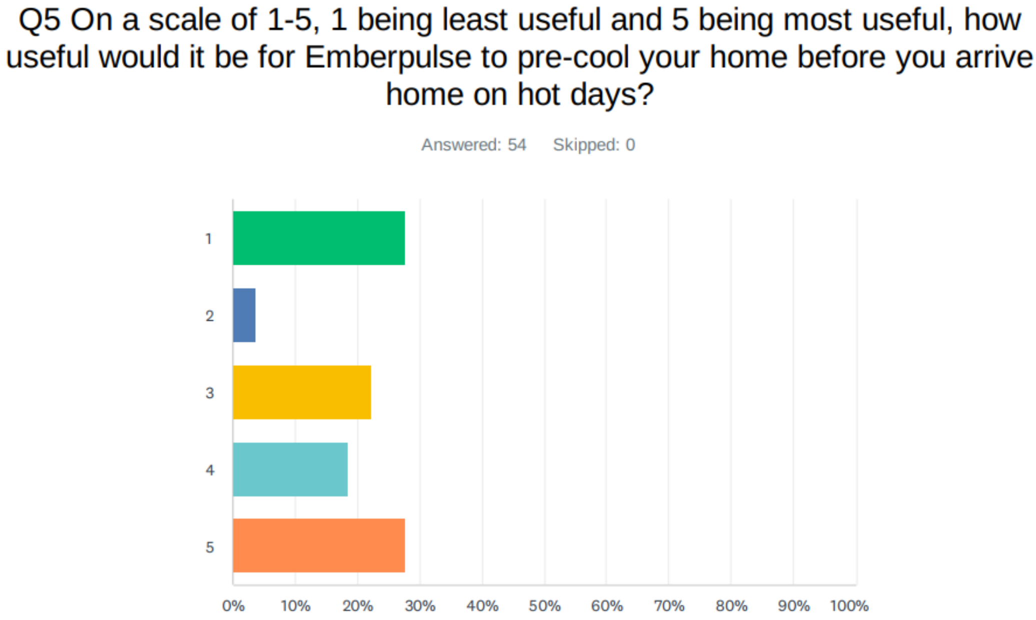
Overall, over two thirds of respondents stated that pre-cooling their home on hot days would be a welcomed feature of their split system AC.



Concluding Comments

Leveraging machine learning capabilities with appliance automation has the potential to unlock significant efficiencies within our energy grid. This project demonstrated the ability to develop tailored control solutions via machine learning for appliances, based on specific household demands.

Ascertaining the usage parameters of appliances based on their unique operational environment, is critical to deliver comfort, convenience and to do so at no net increase in energy costs to the householder. Delivering on these key areas for householders is of great importance if a level of appliance control is to be relinquished to intelligent automation platforms.

As our energy grid continues to shift towards renewable energy generation, the less controlled nature of renewables, due to wind and solar dominating our long term energy the energy production; will require greater levels of energy demand orchestration. Without controlling energy demand (through smart appliance controls), the level of surplus renewable energy generation required for a stable grid will significantly increase overall energy costs, when compared to a grid where large appliance orchestration is adopted and deployed correctly.

A successful deployment and adoption of automated appliance control mechanisms should be paired with financial reward mechanisms for householders in order to illicit broad market adoption in the intelligent & renewable energy grid.