Market Performance Quarterly Review

July-September 2021

Information Paper

Executive summary

This review covers a broad range of topics in the electricity market. It is published quarterly to provide visibility of the regular monitoring undertaken by the Electricity Authority. This report covers the September 2021 quarter using data from 1 July 2021 to 30 September 2021.

The country entered lockdown to prevent the spread of Covid-19 on 18 August 2021 with lockdown restrictions changing as Covid Alert Levels changed. Weeks outside of lockdown showed higher levels of electricity demand than weeks during lockdown. Overall national grid demand has increased despite the effects of lockdown.

Meridian has shown the greatest growth in retail market share followed by Contact. Trustpower's retail business sale to Mercury is on track to be completed by late 2021/early 2022.

Restricted fuel supplies and high winter demand resulted in high wholesale spot prices at the beginning of the quarter. Increasing hydro storage and decreasing demand going into summer brought lower spot prices by the end of the quarter.

As hydro storage has increased short term forward prices have decreased. Long term forward prices have seen minimal change.

Included is a look at forecasting New Zealand's national electricity demand using machine learning techniques.

Contents

Figures

1 Demand

1.1 On 18 August 2021 the country entered lockdown due to the appearance of the Delta Covid variant in the community. National electricity demand decreased from the effects of lockdown which dampened business and commercial related activities as well as from the effects of warmer weather entering into summer.

1.2 Figure 1 shows national daily grid demand over the September quarter. Coloured blocks delineate the points at which the country shifted to different Covid Alert Levels during the 2021 lockdown. An average of daily demand across 2011 to 2020 is included for comparison.

1.3 Differences in daily demand pre-lockdown compared to during lockdown averaged to ~9 per cent.

1.4 When comparing daily demand for the September quarter between 2021 and the 2011-2020 historical average, daily demand in 2021 was on average 2.7 per cent higher than historical average demand. When comparing daily demand between years excluding the period during lockdown (1 July – 21 August) daily demand in 2021 was on average 4.4 per cent higher. When comparing the period during lockdown (22 August – 30 September) demand in 2021 was on average 0.4 per cent higher, showing how despite the effects of Covid, demand in 2021 has followed the historical trend of increasing electricity demand.

1.5 Outside of the effects of lockdown daily demand has decreased entering into summer with the increase in daylight hours and warmer weather reducing demand from winter levels. Weekly demand decreased from 865.5 GWh at the beginning of the quarter to 774.7 GWh by the end of the quarter.

1.6 Reconciled demand for each month July, August and September was 3,911.1 GWh, 3,735.5 GWh and 3,501 GWh respectively. Compared to the equivalent 2011-2020 mean demand reconciled demand in July was 3 per cent higher, demand in August was 0.7 per cent lower and demand in September 0.4 was per cent higher.

Figure 1: Daily Grid Demand, Jul-Sep 2021 vs Historic Avg.
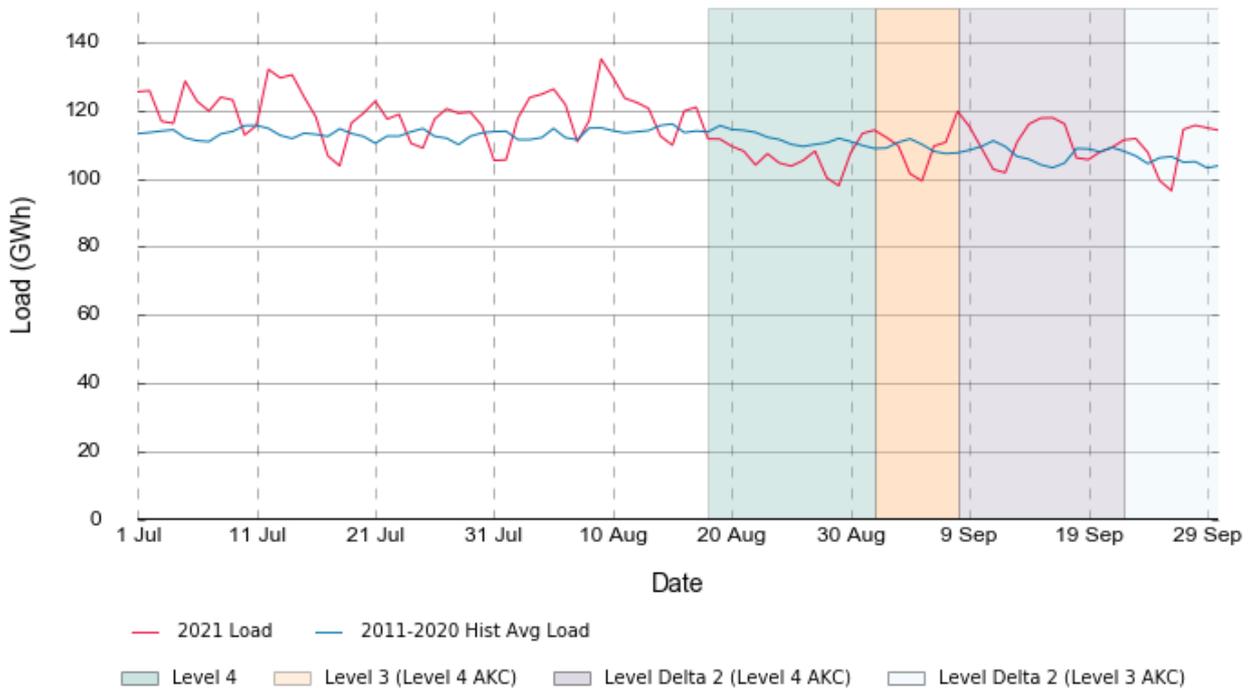
1.7   Figure 2 shows monthly reconciled demand from 1 July 2020 to 30 September 2021 broken down by the categories residential and business. Residential demand is defined as having no ANZSIC code in the registry. Business demand is calculated by removing residential demand from total reconciled demand. Compared to the same time last year July 2021 demand was similar to demand in 2020. In August 2021 and September 2021 however business demand decreased, and residential demand increased, by approximately, ~100 GWh, compared to August and September in 2020, the difference can be attributed to lockdown restricting people to their residences compared to before lockdown.

Figure 2: Reconciled Demand Residential v Business
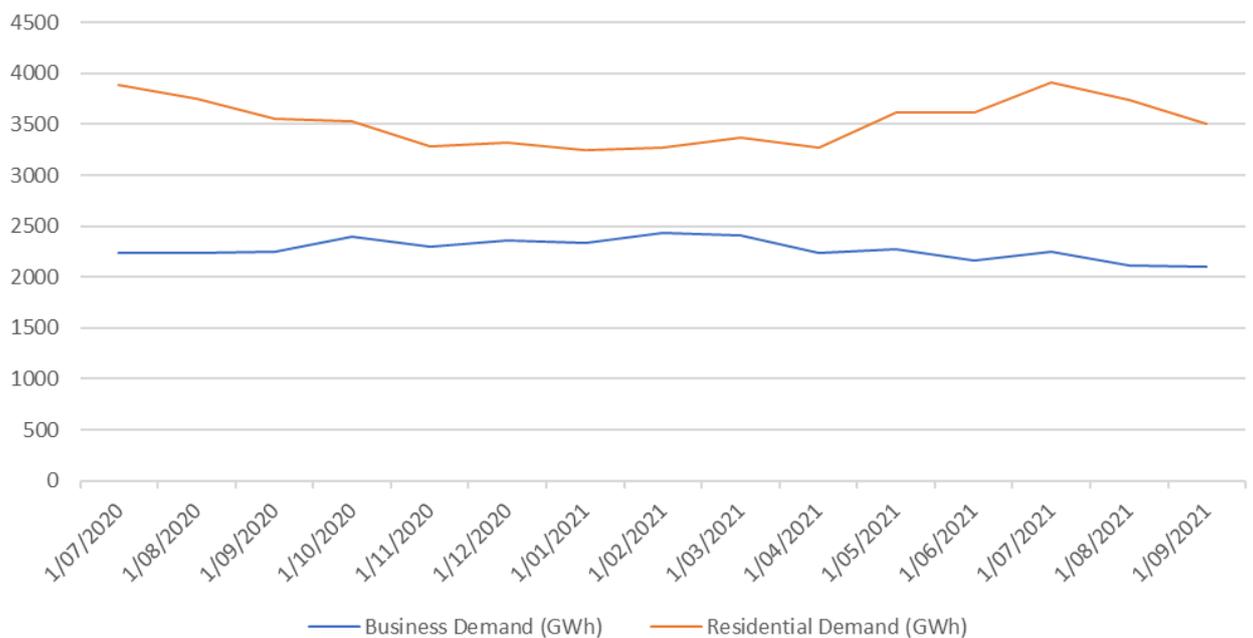
1.8   Figure 3 shows daily demand of major users. Outside of the five largest retailers Meridian, Genesis, Contact, Mercury and Trustpower, NZ Aluminium Smelters (NZAS) was the largest single user of electricity, followed by the medium sized retailers Powershop and Nova then NZ Steel.

1.9   While Meridian maintained its average rate of demand the four other largest retailers saw a decline in their demand from the beginning of lockdown. Demand from the largest industrial users NZAS and NZ Steel remained steady throughout lockdown. Residential and businesses saw greater changes in their demand from the effects of lockdown than large industrial users.

Figure 3: Daily Demand Major Electricity Users
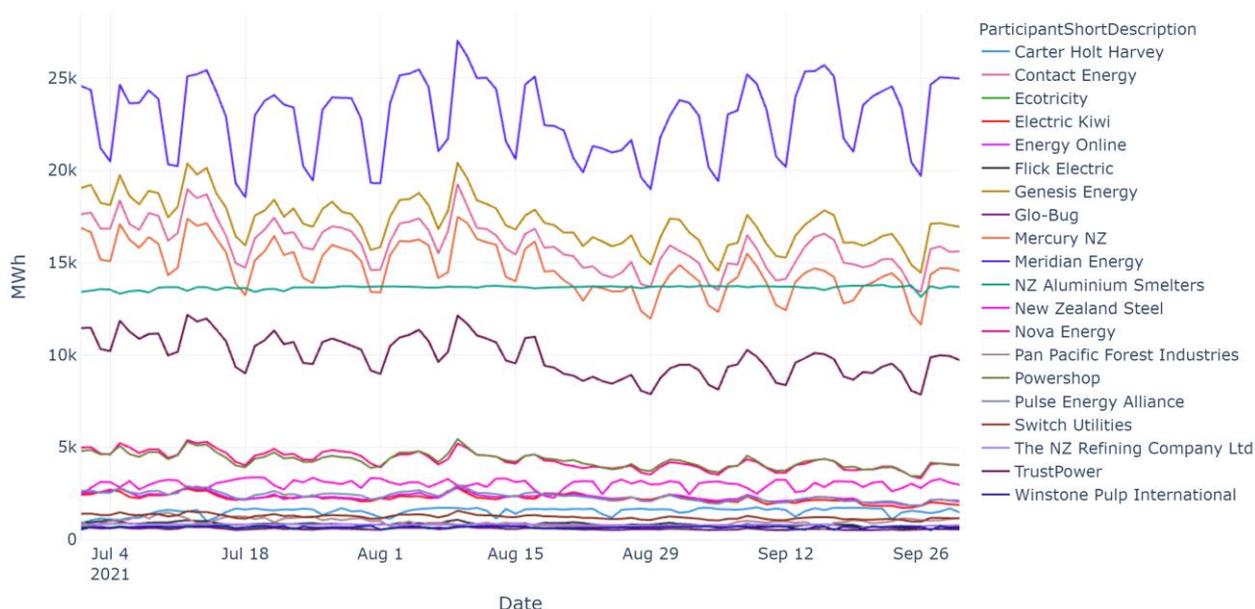
1.10   Peak half hourly demand for the quarter was 7,034 MW and occurred at 6pm on 9 August 2021. Blackout events that occurred as a result of the spike in demand are the subject of a separate investigation.

2   Retail

2.1   Participant market share and participant numbers remain similar to the previous quarter. Collective market share of the five largest retailers Contact, Genesis, Mercury, Meridian and TrustPower was 83.8 per cent at the beginning of the quarter, increasing to 84.1 per cent by the end of the quarter. Collective market share of small and medium sized retailers fell by a corresponding amount from 16.2 per cent at the beginning of the quarter to 15.9 per cent by the end of the quarter.

2.2   On 30 September 2021 the five largest retailers held 1,867,234 ICPs between them while remaining retailers held 353,751 ICPs. Over the quarter the total number of ICPs grew by 7,694 from 2,213,291 ICPs to 2,220,985 ICPs.

2.3   At the time of writing this report, two of the three conditions of sale of Trustpower's retail business to Mercury have been met with the Commerce Commission clearing the sale in September. The sale will be finalised following the restructure the Tauranga Energy Consumer Trust (TECT) which is subject to a High Court hearing in November. When

the sale is complete Mercury would gain approximately 234,000 customers from Trustpower. At the end of the quarter Trustpower was the fifth largest retailer with 11.9 per cent market share.

2.4   Figure 4 shows the changes in market share of each participant from 1 July 2021 to 30 September 2021. Meridian has exhibited the greatest growth with an increase of 7,684 ICPs with Contact a close second with an increase of 7,376 ICPs. Other participants either gained up to 676 ICPs or lost up to 2,168 ICPs.

Figure 4: Changes in Trader Market Share
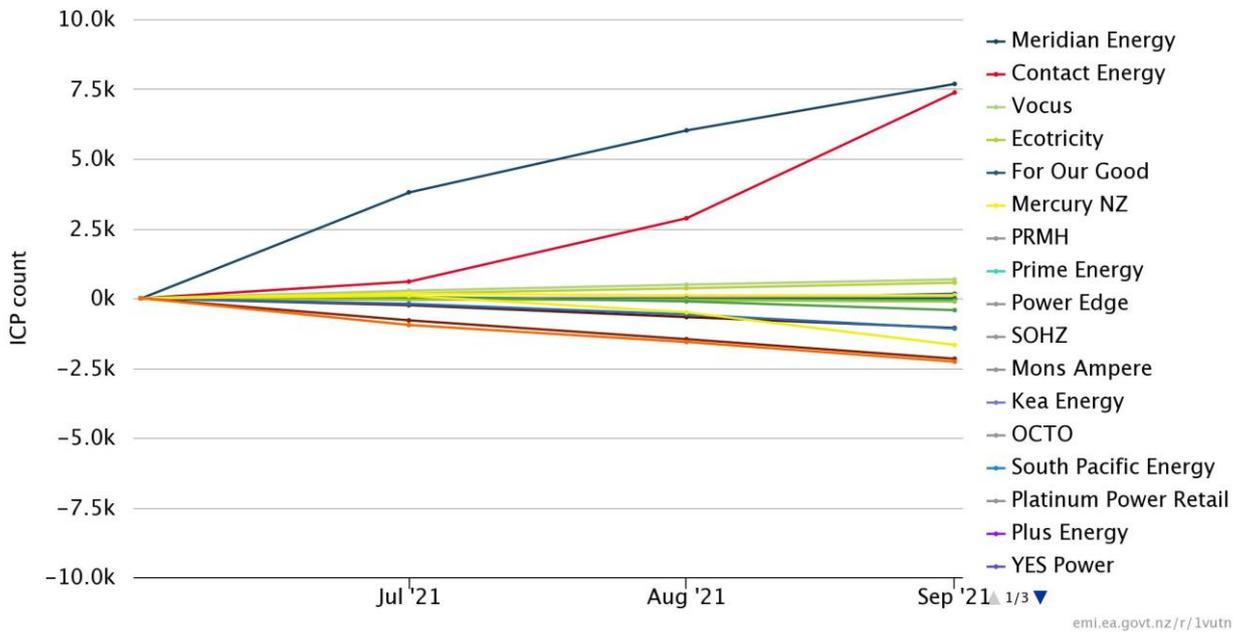
2.5   Figure 5 shows the number of electricity connections (ICPs) that have changed electricity suppliers from 1 July 2020 to 30 September 2021 categorised by type 'move in', 'trader' or 'half hour'. Move in switches are switches where the customer does not have a contract with the losing trader whereas trader switches are switches where the customer has an existing contract with the losing trader. Both move in and trader switches declined over the quarter with move in type switches showing the greatest drop, declining from 25,978 ICPs in July to 17,792 ICPs in August. This change can be directly associated with Covid lockdown, with numbers far below the number of switches for the same quarter last year.

2.6   Overall, total switches declined from 38,196 ICPs in July to 28,758 ICPs in September, a decline of almost 25 per cent.

Figure 5: ICP Switches by Type, Jul 2020 – Sep 2021

emi.ea.govt.nz/r/ma14x
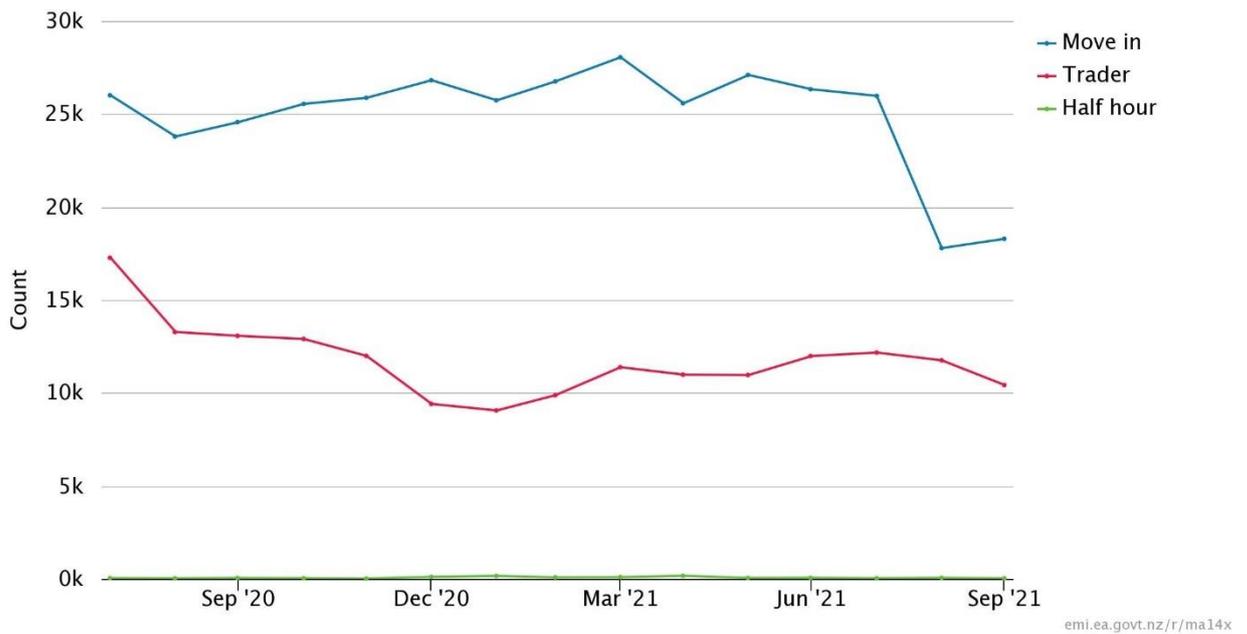
3 Wholesale

3.1   Figure 6 shows total national controlled hydro storage up to 30 September 2021. Between 1 July 2021 and 30 September 2021 total controlled hydro storage rose by 729 GWh. On 1 July 2021 hydro storage was 2,801 GWh, 90 per cent of historical mean (3,099 GWh) and 61 per cent of nominal full (4,562 GWh). By 30 September 2021 hydro storage had risen to 3,520 GWh, 134 per cent of historical mean (2,627 GWh) and 80 per cent of nominal full (4,412 GWh).

Figure 6: Controlled Hydro Storage, Jul 2020 - Sep 2021

emi.ea.govt.nz/r/tqghq
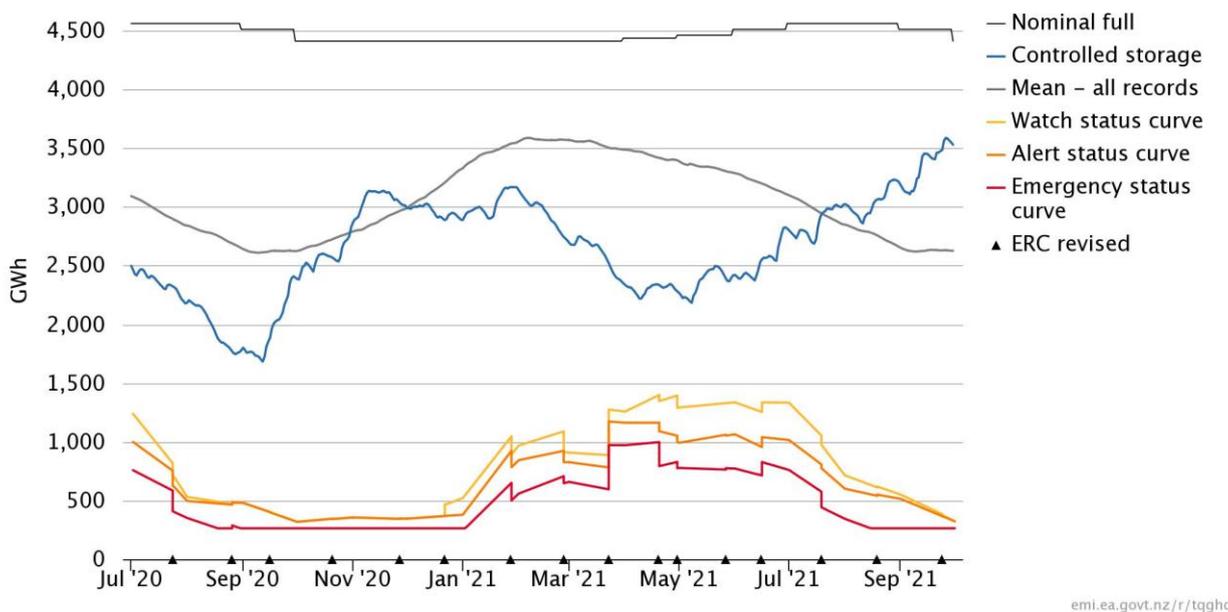
3.2   The increase in storage came from high inflows despite a small increase in average hydro generation. Figure 7 shows total daily national hydro generation, inflows and storage as a percentage difference against their respective 1926-2020 historical means. Daily hydro inflows were on average 23.2 per cent higher than their historical means

while daily hydro generation was on average 4.8 per cent higher than its historical means. Daily hydro inflows averaged 83.5 GWh for a total of 7,678.1 GWh over the quarter while daily hydro generation averaged 71.6 GWh for a total of 6,586.9 GWh over the quarter.

Figure 7: Daily Hydro Generation, Inflow and Storage
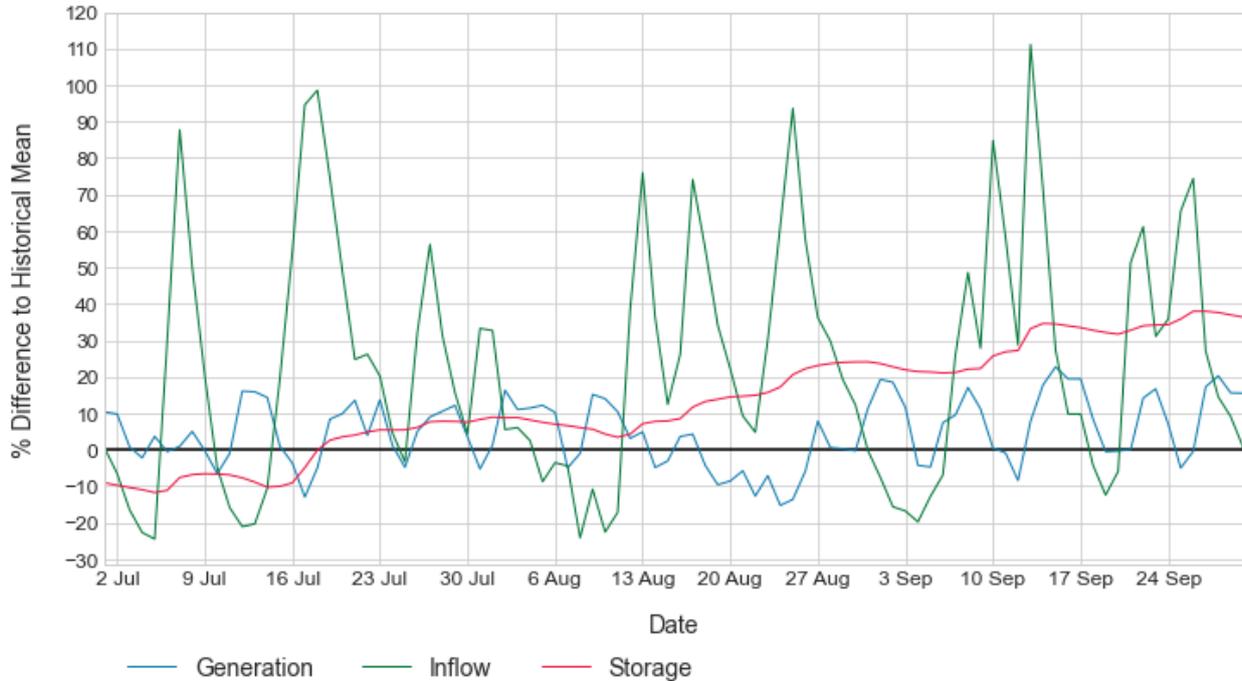
3.3   Figure 8 shows the storage of major catchments Pukaki, Taupo, Tekapo, Manapouri and Hawea in the 2021 September quarter as well as their historical 25th-75th percentiles based on data from 1926-2020. Over the quarter storage of all lakes with the exception of Lake Manapouri increased from below or close to below their 25th percentile to above or close to above their 75th percentile.

Figure 8: Major Lake Storage, 25th-75th percentile
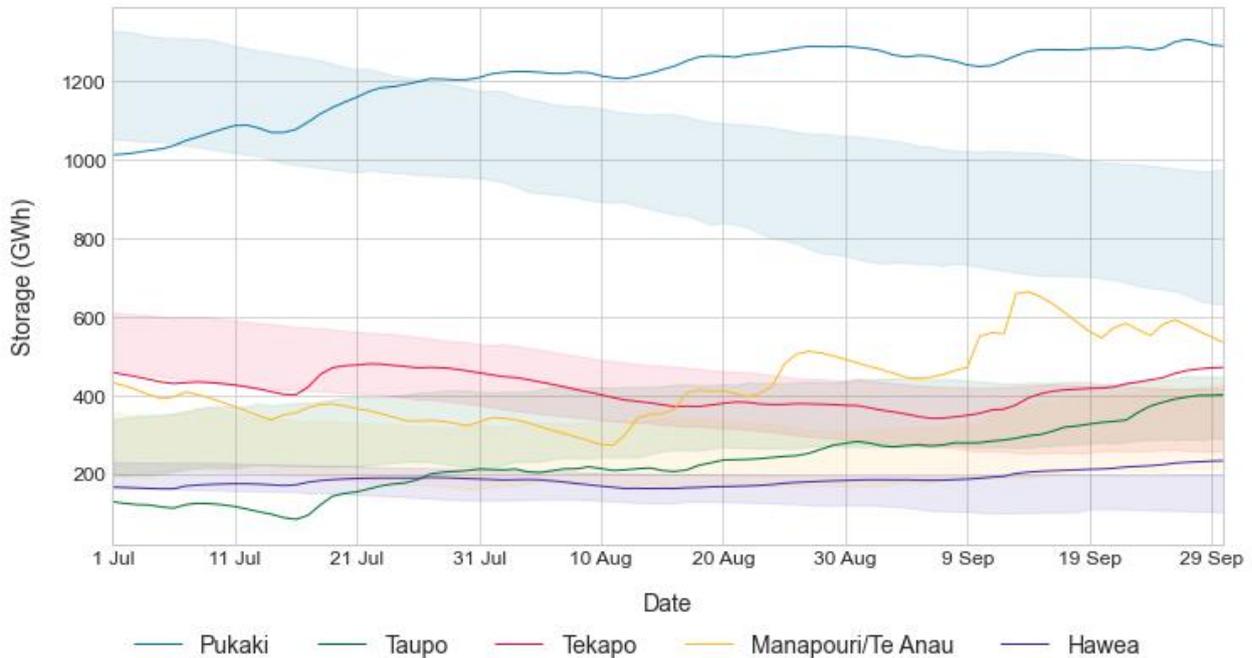
3.4   Figure 9 shows gas production by major gas fields as well as gas consumption by major gas users from the beginning of the 2020 September quarter to the end of the 2021 September quarter. Overall gas production at the beginning and end of the 2021 quarter remained steady with gas production from major fields totalling 385.77 TJ/day on 1 July 2021 and 384.02 TJ/day on 30 September 2021. In comparison gas production from major fields totalled 463.08 TJ/day on 1 July 2020 and 446.33 TJ/day on 30 September 2020 giving a difference of around ~70 TJ/day (~16 per cent difference) in daily gas production between 2020 and 2021 September quarters.

3.5   Production at Pohokura has continued to steadily decay, with the root of its issues, scaling in offshore wells, unlikely to be resolved until 2023. In the 2020 September quarter production at Pohokura was between 170.52 TJ/day and 164.55 TJ/day. At the end of the 2021 September quarter production at Pohokura was 86.72 TJ/day – almost halved.

3.6   On 3 September 2021 Pohokura proceeded with a scheduled maintenance outage that reduced gas supply by 20 TJ/day, which was extended to 21 September 2021. Prior to the outage production at Pohokura averaged ~100 TJ/day, following the outage production failed to recover to its pre-production levels, averaging around 87 TJ/day. The loss of gas was made up by an increase in production at the Turangi Mixing Station whose output increased from 47.21 TJ/day on 1 July 2021 to 60.89 TJ/day on 30 September 2021.

3.7   Demand for gas was at its greatest over July and August. Low hydro storage and high winter demand increased the need for thermal generation and subsequently gas. Restricted gas production meant the Genesis Methanex gas swap was still in effect with Methanex continuing to cut gas at its Motunui plant (Genesis and Methanex reached an agreement in May where Methanex would free up between 3.4 PJ and 4.4 PJ of gas by throttling its Motunui plant to help increase the amount of gas available for thermal generation for Genesis over winter). Consumption at Motonui was around ~95 TJ/day while consumption at Huntly was around ~70 TJ/day for all of June up to 24 August

2021. As weather warmed and the country exited winter demand for thermal eased and Huntly demand fell, totalling 46.16 TJ/day on 30 September 2021. Consumption at Methanex rose at the same time to 170.65 TJ/day signalling the swap was over.

Figure 9: Daily Gas Production and Consumption[1]
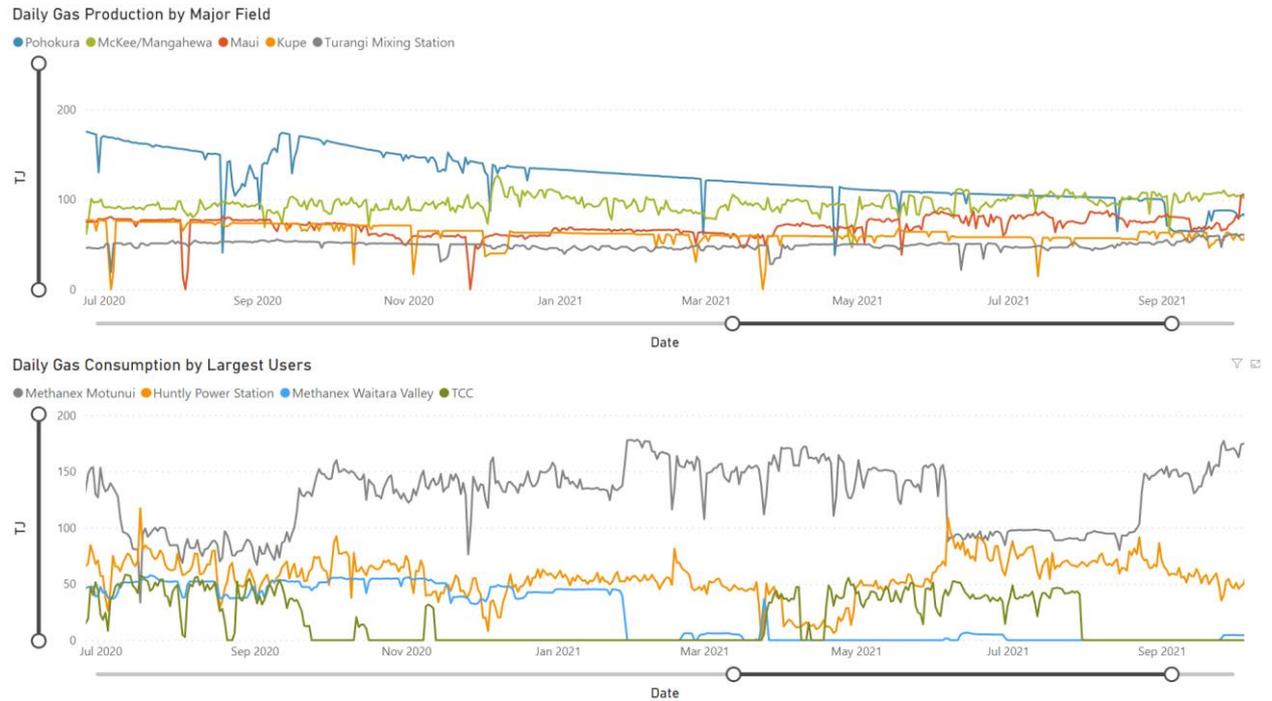
3.8 Figure 10 shows the Maui pipeline average marginal price (AMP) from 1 July 2020 to 30 September 2021. Pricing data was taken from BGIX (Balancing Gas Information Exchange) and used as a proxy for gas wholesale spot prices. Over winter gas prices reached record highs, exceeding $50/GJ and frequently fluctuating between $10/GJ and $60/GJ reflecting the high demand for gas as generators competed with organisations with expiring gas contracts for available gas. Gas prices finally settled to around $10/GJ in September when demand for thermal generation dropped. Gas trades began to increase once prices dropped with September gas trading volumes on emsTradepoint double that of August while the gas VWAP halved.

Figure 10: Gas Prices (Maui Pipeline)
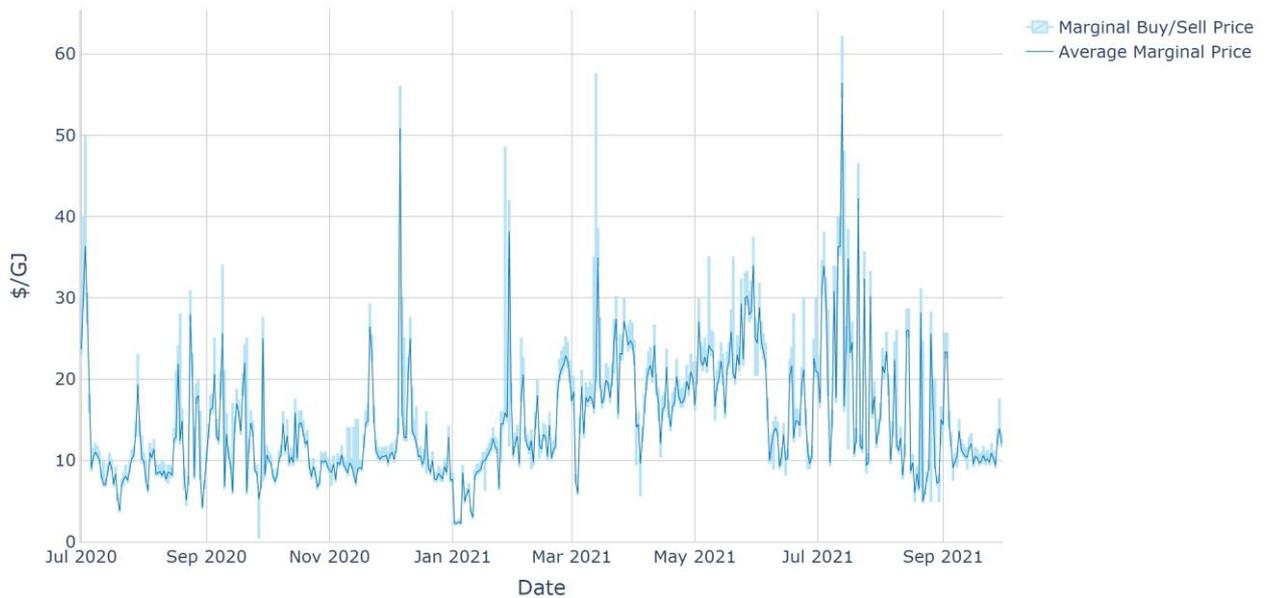
3.9 Restricted gas production was substituted by coal with coal fuelled generation reaching record levels over winter.

3.10 Figure 11 shows weekly generation by type from 28 June 2021 to 3 October 2021 as a percentage of total weekly generation. At the beginning of the quarter thermal generation made up for 21.8 per cent of total weekly generation which only fell to below 10 per cent in September. An increase in geothermal generation along with increased hydro generation, increased wind generation and decreasing summer demand all contributed to the drop in thermal generation.

3.11 Weekly geothermal generation increased from 13.1 per cent at the beginning of the quarter to 16 per cent by the end of the quarter due to Kawerau geothermal plant returning from outage on the week of 19 July 2021 after a mechanical fault put it out of service on 7 June 2021.

3.12 Weekly hydro generation increased from 60.8 per cent at the beginning of the quarter to 68.5 per cent by the end of the quarter largely due to above average inflows and increasing hydro storage.

3.13 Weekly wind generation increased over August and September, reaching up to 10.2 per cent of total generation. Wind generation averaged 334 MW over the quarter and totalled 747 GWh.

Figure 11: Generation by Fuel Type

Date	Hydro	Geothermal	Thermal	Wind
28 Jun	60.8%	13.1%	21.8%	4.2%
05 Jul	60.1%	13.3%	19.8%	6.7%
12 Jul	61.8%	13.3%	17.5%	7.3%
19 Jul	64.2%	15.6%	15.9%	4.0%
26 Jul	64.5%	16.5%	14.6%	4.2%
02 Aug	64.6%	15.8%	14.2%	5.2%
09 Aug	64.0%	15.4%	12.5%	7.9%
16 Aug	62.3%	16.4%	12.2%	8.8%
23 Aug	64.0%	17.8%	10.0%	7.8%
30 Aug	67.5%	15.5%	8.9%	7.7%
06 Sep	65.5%	16.4%	7.5%	10.2%
13 Sep	67.9%	16.0%	8.1%	7.8%
20 Sep	66.1%	17.8%	6.7%	9.2%
27 Sep	68.5%	16.0%	9.4%	5.9%

Legend: Hydro · Geothermal · Thermal · Wind · Co-generation
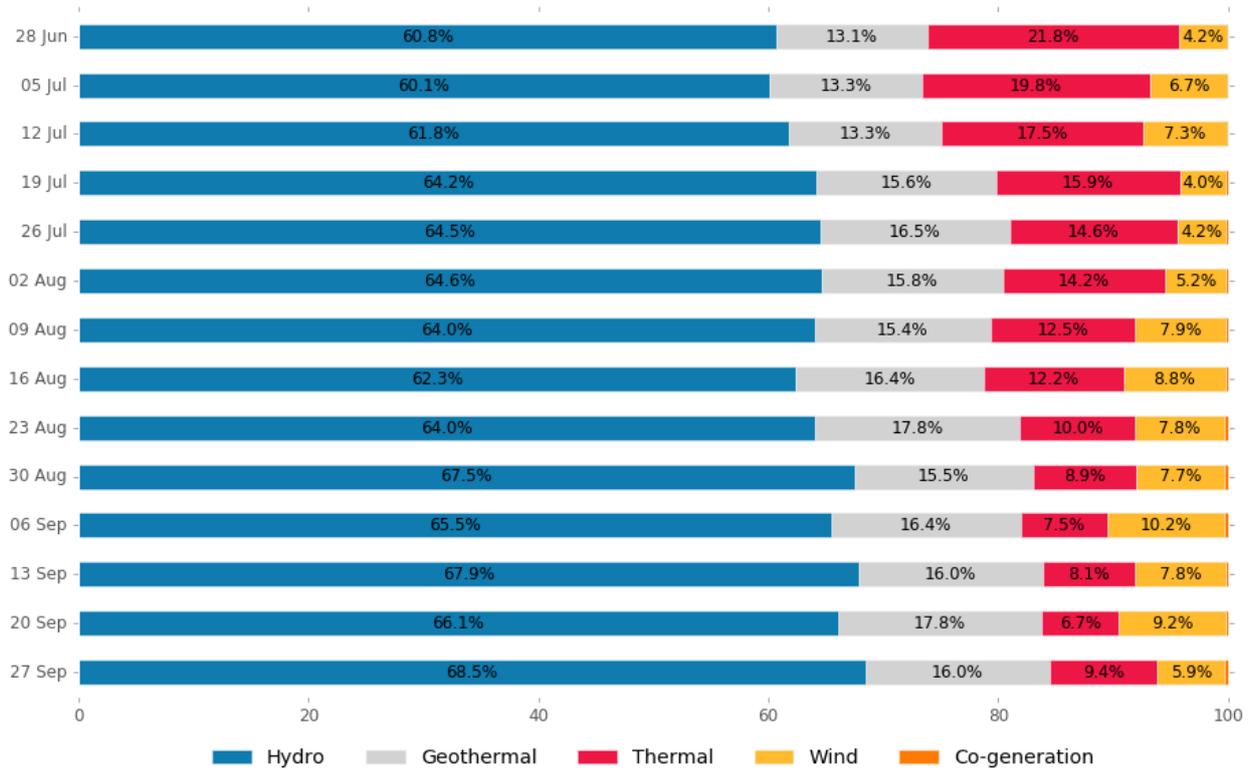
3.14 Figure 12 shows average daily wholesale electricity spot prices at nodes Benmore and Haywards from 1 July 2021 to 30 September 2021. Wholesale spot prices across all nodes averaged $136.42/MWh over this period with 95 per cent of prices between $24.52/MWh and $307.73/MWh.

3.15 Due to unusually high evening demand the daily average spot price on 9 August 2021 peaked to above $1,000/MWh. Outside of this outlier prices have been primarily influenced by restricted gas production, hydro storage quantities and demand.

3.16 High winter demand at the beginning of the quarter combined with below average hydro storage and below average gas production drove wholesale prices up, with prices decreasing over the quarter as demand decreased and hydro storage and the percentage of renewable generation increased.

Figure 12: Average Daily Wholesale Spot Price BEN v HAY
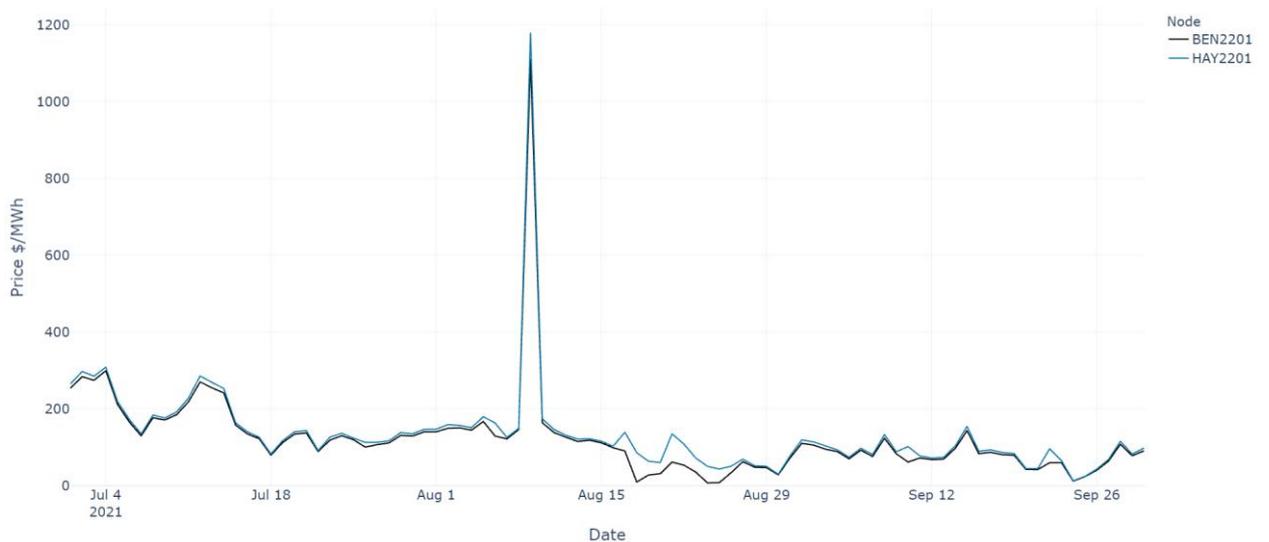
3.17   Figure 13 compares the distribution of electricity wholesale spot prices of every node and every trading period in the September quarter from 2011 to 2021. While the September quarter for 2021 has had lower outlying prices compared to the last five years the range of prices is the largest and maximum price the highest over the last 10 years. Compared to 2011-2020 wholesale spot prices this quarter have shown the most volatility reflecting a steep offer curve and the difference between conditions (high thermal generation, low renewable generation and high demand) at the start of the quarter and fuel conditions (low thermal generation, high renewable generation and low demand) at the end of the quarter.

**Figure 13: Spot Prices September Quarter 2011-2021**
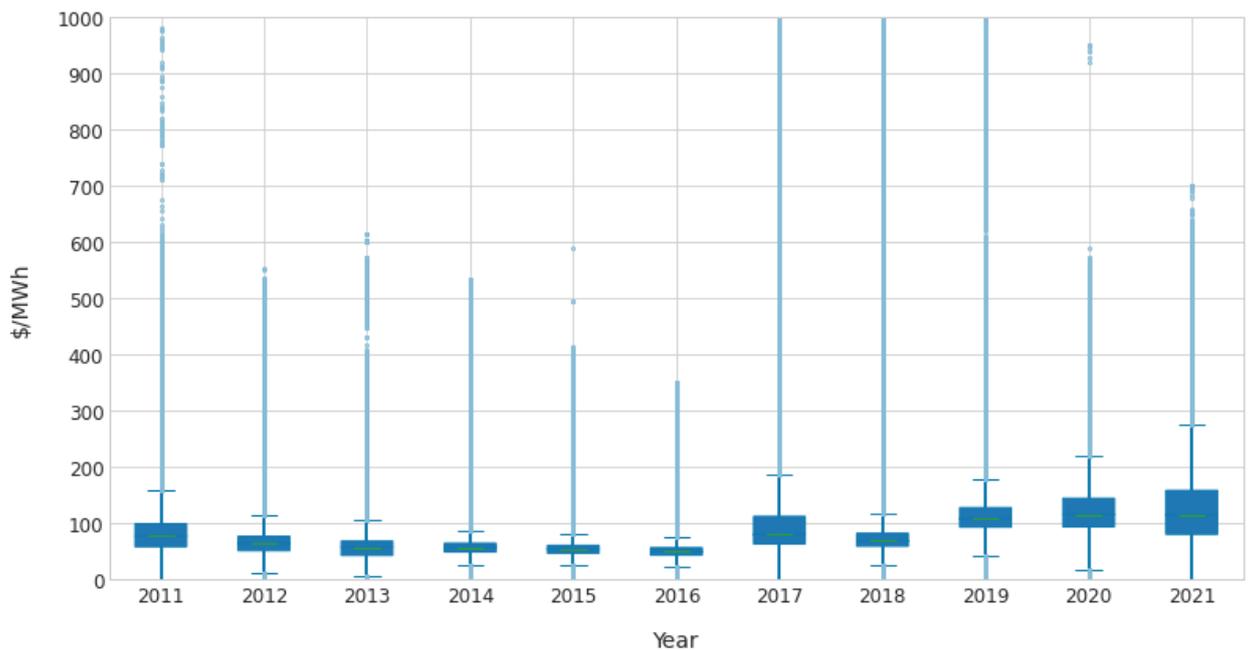
4   Forward Market

4.1   On average short term forward prices have decreased over the quarter while long term forward prices have seen minimal change.

4.2   Figure 14 shows the settlement price trends of short-dated (expiring up to September 2022) base futures at Otahuhu. Increased hydro storage levels decreasing the price of hydro generation has been one of the main drivers behind short term forward prices dropping throughout the quarter. Short term prices at the end of the quarter sat between $100/MWh and $160/MWh.

Figure 14: Short-Dated (< Sep 2022) Futures at Otahuhu
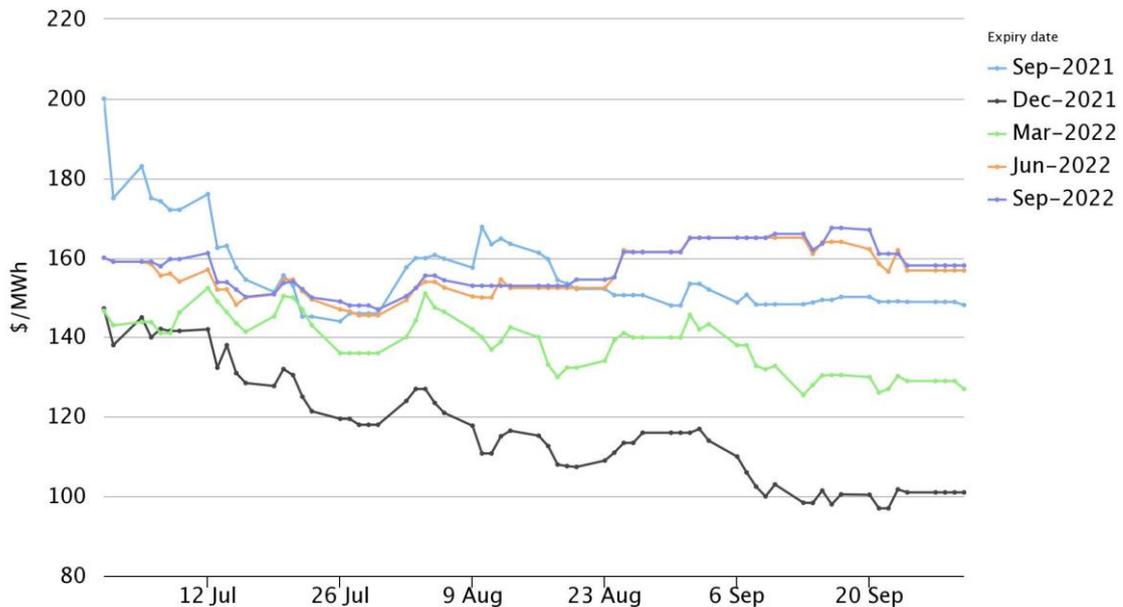
4.3   Figure 15 shows the settlement price trends of long-dated (expiring after September 2022 and before December 2024) base futures at Otahuhu over the quarter. Long term forward prices by the end of the quarter were similar to long term forward prices at the beginning of the quarter, remaining within a $5/MWh range. Long term prices at the end of the quarter sat between $110/MWh and $145/MWh. Fluctuations in prices during the quarter likely came from a combination of factors including carbon price increases.

Figure 15: Long-Dated (> Sep 2022) Futures at Otahuhu
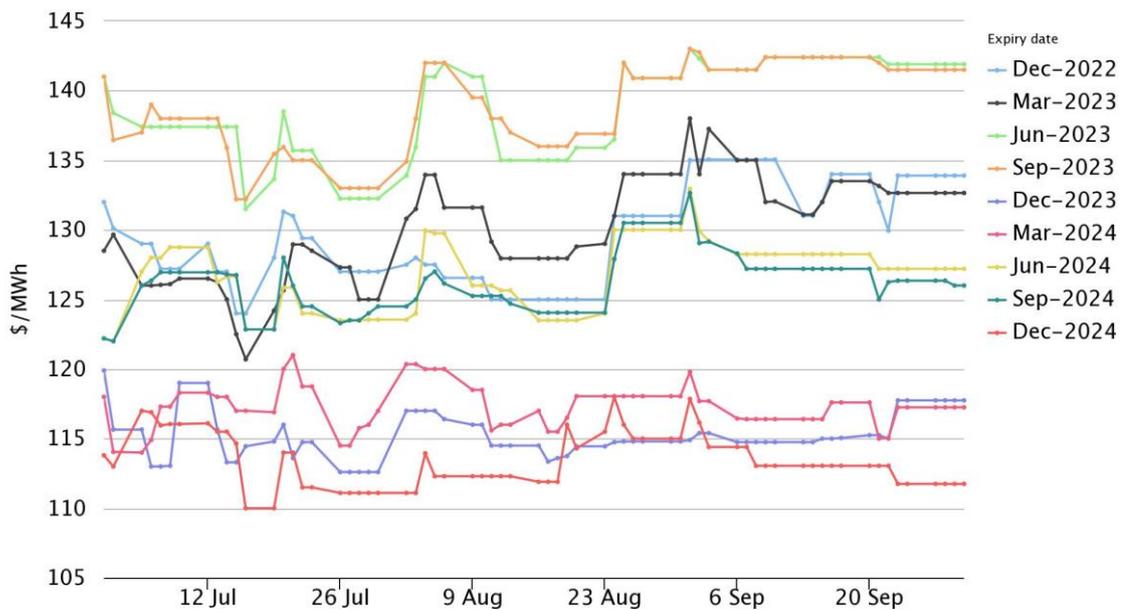
4.4 Although short term forward prices decreased over the quarter prices were still above average when compared to historical forward prices. Compared to forward prices in September 2020 forward prices expiring from June the following year onwards for September 2021 were approximately ~$35/MWh higher.

4.5 The costs and risks associated with thermal generation has had a large impact on above average forward prices. Below average gas production, primarily from problems at the Pohokura gas field, has increased the price of gas as well as increased the reliance on the Indonesian coal used by Huntly which has become more expensive due to Covid disrupting supply chains and increased demand from China. Increases in thermal fuel prices tend to translate into $1 for $1 increases in Rankine short-run marginal costs. Decarbonisation efforts will likely limit investment into thermal assets therefore the costs associated with thermal generation are unlikely to drop in the future.

4.6 Increased carbon credit prices have also likely contributed to increases in long term forward prices. The third ETS carbon credit auction for 2021, meant for companies who need the credits to meet their carbon liabilities but also open to companies without any carbon liabilities, took place on 1 September 2021 with a price floor of $20/tCO2e and cap of $50/tCO2e. During ETS auctions if bids are below the floor then credits remain unsold, if they look to go above the cap then extra units known as 'cost containment reserve' (CCR) units are released.

4.7 At the September 2021 auction 4.75 million scheduled units were sold as well as all available 7 million Cost Containment Reserve (CCR) units leaving no CCRs for the final auction for 2021 on 1 December 2021. All 11.75 million units settled at $53.85/tCO2e. Prices in the secondary market immediately spiked to $51.5/tCO2e after the auction, finishing at over $60/tCO2e by the end the week marking the first time prices have passed $50/tCO2e.

4.8 It was apparent the sale of almost all the reserve units were to investors using the units as a financial hedge. With the floor set to rise to $39.32/tCO2e and cap to $110.15/tCO2e by 2026 investors likely saw the auction as an opportunity for low-risk

profit with companies needing the units likely being forced to turn to the secondary market at some point.

5 Deep Dive: machine learning application to demand

5.1 We built a model that considers any number of explanatory variables to calculate the national demand in each trading period. We use the Gluon Time-Series Toolkit[2] (GluonTS), a Python library for deep learning time series modelling, to forecast national demand.

5.2 The evening of 29 Jun 2021 was especially cold and national demand peaked at 3.4 GWh. This provides an excellent opportunity to test our machine learning approach. We find that weather observations in major population centres are the greatest factors that determine demand. Temporal factors are also important, such as time of day (half hourly increments), month of year (Jan to Dec), week of year (1 to 52), weekends (True/False), and public holidays (True/False).

5.3 We explore how to build models in situations where data for some explanatory variables are unavailable. To calculate demand one or two days into the future, the best method is to use weather forecasts. The predicted demand is accurate as long as forecast temperatures and observed temperatures follow the same trends as each other.

Method

5.4 GluonTS is the first ever dedicated toolkit for building time series models based on deep learning and probabilistic modelling techniques. It bundles components, models and tools for time series applications like forecasting and anomaly detection. Well-established open-source packages like TensorFlow and PyTorch can perform time-series forecasting, but they require a comparatively large amount of coding and therefore great proficiency in the area of machine learning.

5.5 GluonTS can parse sequences of large collections of time series. Given a probabilistic model, the goal of forecasting is to predict the probability distribution of future values given the past values, covariates (features), and the model's hyperparameters.

5.6 The package provides a wide variety of pre-built neural network-based models. For example the DeepAR[3] function uses a recurrent neural network (RNN) with long short-term memory (LSTM) or gated recurrent unit (GRU) cells, and estimates parameters of a parametric distribution or uses a parameterisation of the quantile function.

5.7 The next section is a short overview of the mechanisms behind neural networks[4].

Neural networks in a nutshell

5.8 Artificial neural networks (ANNs) comprise a web of computing units (artificial neurons) organised in homogeneous layers. There is one (passthrough) input layer, one or more hidden layers, and one final output layer. Each layer is connected to the next so that information flows between the layers (Figure 16). Each connection between layers mimics the behaviour of synapses in the brain.

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[2] (i) A. Alexandrov *et al.*, GluonTS: Probabilistic and Neural Time Series Modeling in Python, *J. Mach. Learn. Res.* **21**(116), 2020. (ii) A. Alexandrov *et al.*, arXiv:1906.05264, 2019.

[3] D. Salinas *et al.*, DeepAR: Probabilistic forecasting with autoregressive recurrent networks, *Int. J. Forecast.* **36**(3):1181-1191, 2020.

[4] A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*, O'Reilly (2nd ed.), 2019.

5.9   Abstractly speaking, artificial neurons are considered as functions that take some input values and returns a real number. They have two key roles:

(a)   Neurons multiply each input value with a corresponding *weight* coefficient and calculates the sum of all products. This operation is a scalar product of two vectors: input data and weights.

(b)   Neurons weigh each input value using an activation function (e.g. logistic sigmoid, tanh) and assigns a quasiprobability value to it.

5.10   The backpropagation algorithm trains the ANN. It is an implementation of the gradient descent method which finds the minimum of a function by exploring values in the direction of the steepest descent. The algorithm makes a prediction at each neuron during the forward pass (going from input layer to output) and measures the error.

5.11   The gradient is calculated on the weights on the output layer, and the error information is pushed backward to the previous layer where the calculation is repeated on the local weights. This recursive process continues until the error reaches the input layer. The aim is to minimise the error of the outputs.

Figure 16:   Simplest model is the feed-forward neural network with backpropagation algorithm. The network can have any number of nodes and layers.
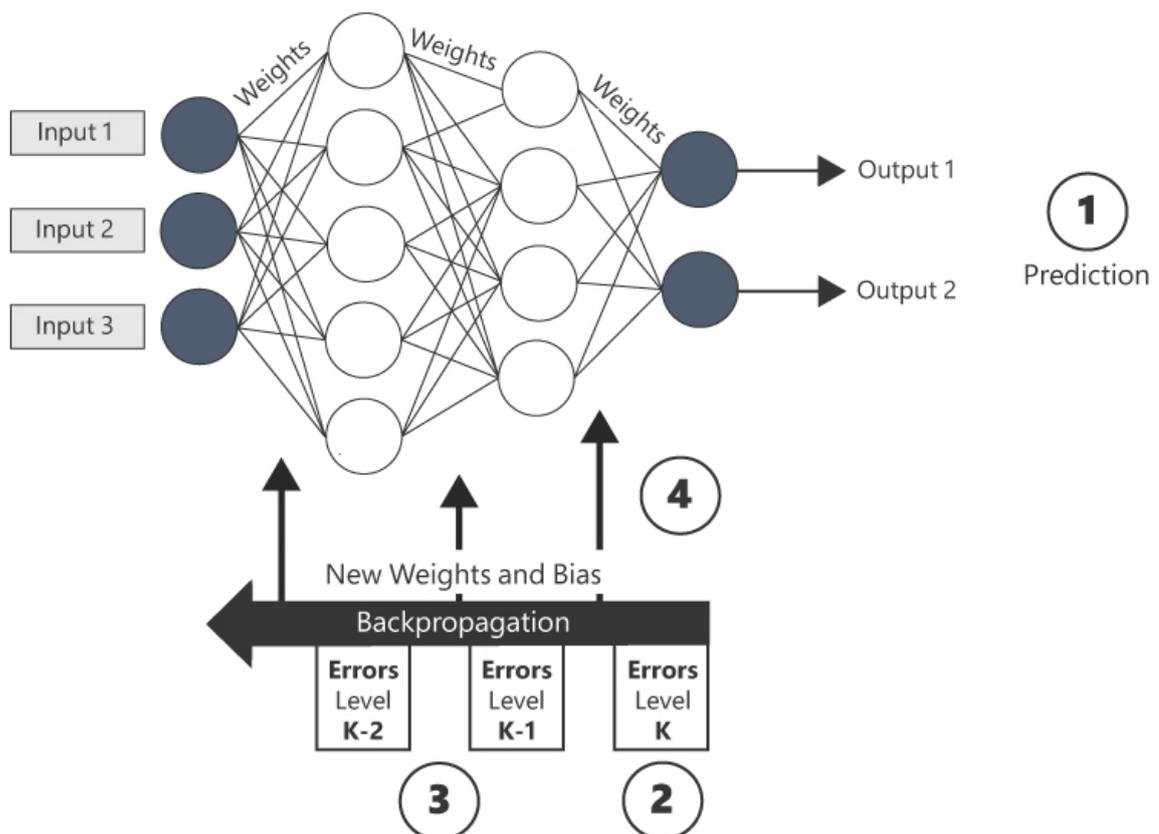
Source: Adapted from D. Esposito and F. Esposito, *Introducing Machine Learning*, Microsoft Press, 2020.

5.12 Time series analysis requires the concept of state to be built inside the ANN itself to make it possible to extrapolate based on historical information. The anatomy of a stateful ANN allows the information to leave tracks as it flows forward from the input layer to the output.

5.13 For this purpose, RNNs contain hidden states and loops, allowing information to persist over time. Connections between neurons form a directed cycle which creates an internal state and allows the network to exhibit dynamic temporal behaviour. It follows the same concepts as the ANN and uses the same back propagation algorithm.

5.14 RNNs use the idea of hidden state (or internal memory) by updating each neuron so that it remembers what it has seen before (Figure 17: Back propagation process in RNNs to compute gradient values.). The memory is preserved so that when the neuron reads an input X_n at time step n, it also processes the content of the memory H_n (i.e. outputs of the previous time step $n-1$) and combines the information to generate an output for the current time step Y_n.

Figure 17: Back propagation process in RNNs to compute gradient values.
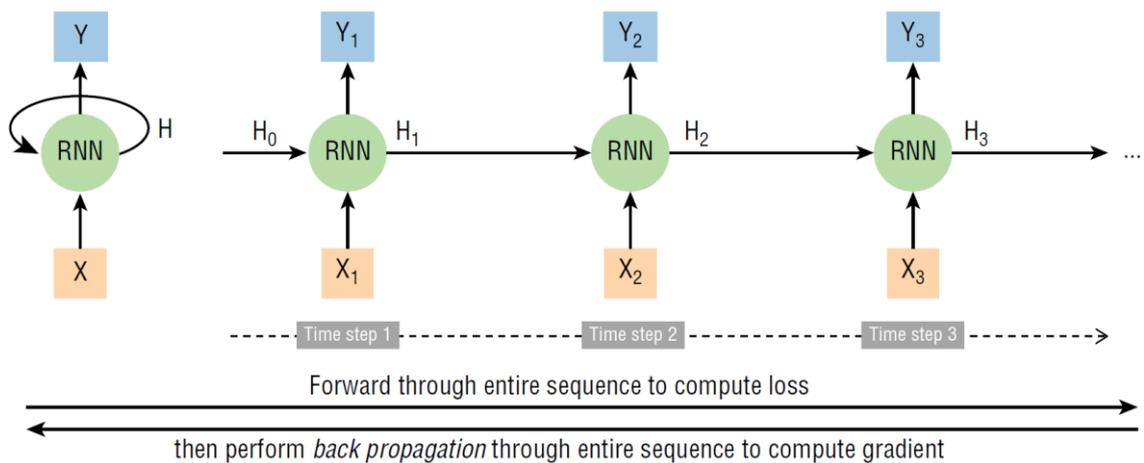
Source: F. Lazzeri, *Machine Learning for Time-Series Forecasting with Python*, Wiley, 2020.

5.15 In order for the cells to remember information from the distant past and not just the previous timestep, the RNN can be built using LSTM or cells (Figure 18). The internal mechanisms in both cells involve learning to recognise an important input (input gate); storing it in the long-term state; preserving it for as long as needed (forget gate); and extract it when needed. Both LSTM and GRU are useful for capturing long-term patterns in time series, long texts, audio recordings, and other applications.

**Figure 18:   LSTM and GRU cells to replace green RNN cells in Figure 17.**
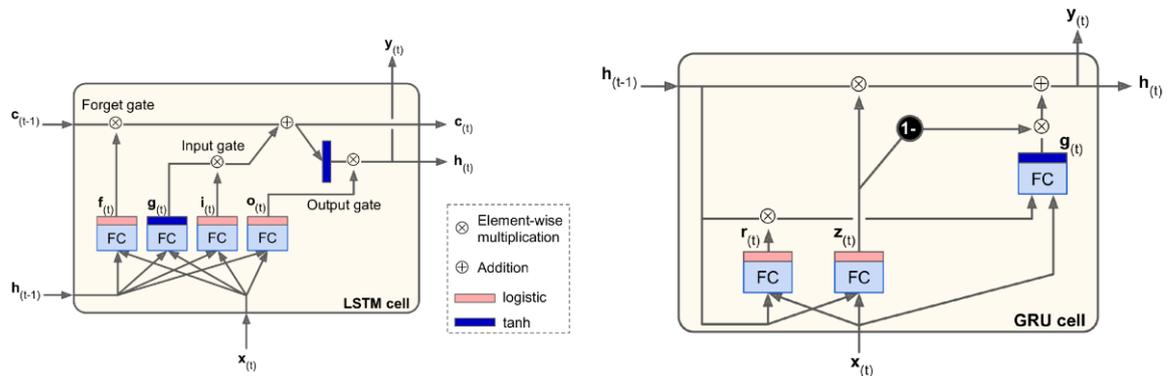
Source: A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*, O'Reilly (2nd ed.), 2019.

Deep AR model

5.16   In this report, we use a more sophisticated RNN based on Salinas *et al.*'s DeepAR model[5]. It is a forecasting method based on autoregressive RNNs, which learns a global model from historical data of all time series in the dataset (Figure 19).

5.17   In the forecasting community, ANNs are typically applied to individual time series, i.e., a different model is fitted to each time series independently. In comparison, DeepAR tailors a LSTM-based RNN architecture to the probabilistic forecasting problem.

Figure 19:   Schematics of DeepAR method used by gluonts.model.deepar.DeepAREstimator function.

Method follows the same structure as in Figure 17. The important addition is p, which is used to calculate the predicted distribution. Further technical details in paper.
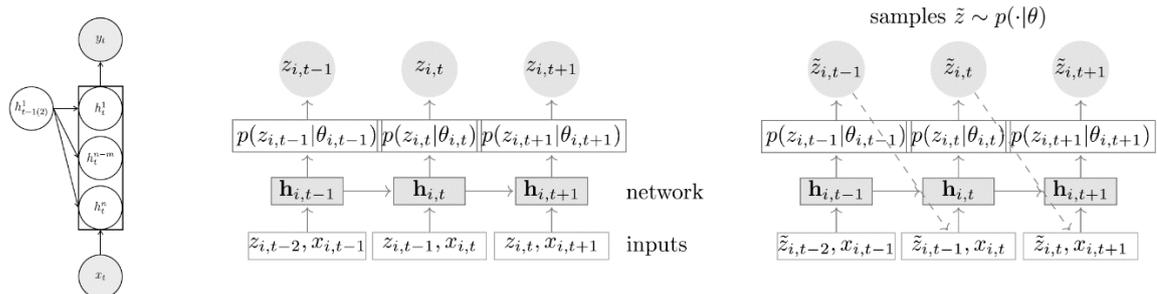
Source: Salinas *et al.*

5.18   As well as having greater forecasting accuracy than classical approaches, DeepAR has several important advantages:

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5   D. Salinas *et al.*, DeepAR: Probabilistic forecasting with autoregressive recurrent networks, *Int. J. Forecast.* **36**(3):1181-1191, 2020.

(a)   The model learns seasonal behaviours and dependencies on given covariates across time series. Minimal manual intervention in providing covariates is needed in order to capture complex, group dependent behaviour.

(b)   DeepAR makes probabilistic forecasts by taking Monte Carlo samples that can be used to compute consistent quantile estimates for all sub-ranges in the prediction horizon.

(c)   By learning from similar items, DeepAR can provide forecasts for items that have little or no history available, a case where traditional single item forecasting methods fail.

(d)   Our approach does not assume Gaussian noise, but can incorporate a wide range of distribution functions, so we can choose one appropriate for the statistical properties of the data.

5.19   Points (a) and (c) set DeepAR apart from classical forecasting approaches. Points (b) and (d) are important to produce accurate forecast distributions that are learned from historical behaviour of all time series. This has not been addressed by previous methods.

Data inputs and output

5.20   The idea is to feed inputs into the GluonTS algorithms to see how they affect the national demand.

5.21   Inputs are the apparent temperature[6] in major population centres (Auckland and Wellington, °C). Other inputs were also considered, such as the COVID-19 alert levels taken from government records of key events[7]. However we found that the model had the most accurate results when only given temperature data.

5.22   The output is national demand (GWh)[8].

5.23   We use equally-spaced timesteps of 30 minutes, starting from 1 Mar 2014 00:00:00 which was the first day that half hourly weather data was available (and without any missing or corrupted data). We choose 2 Jul 2021 23:59:59 as the end date, which gives us roughly 130,000 consecutive timesteps (i.e. trading periods) to train and test the model.

Weather data

5.24   Apparent temperature T_A measures what an observer feels[9]. It considers four environmental factors: wind, temperature, humidity, and radiation from the sun:

$$T_A = T_M + 0.348E - 0.70 \left(w_s - \frac{Q}{w_s + 10} \right) - 4.25 \qquad (1)$$

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6   Source: Weather Underground.

7   Source: History of the COVID-19 Alert System, https://covid19.govt.nz/alert-levels-and-updates/history-of-the-covid-19-alert-system/

8   Source: Electricity Authority.

9   R. G. Steadman, A Universal Scale of Apparent Temperature, *J. Clim. Appl. Meteorol.* **23**(12):1674-1687, 1984.

with dry bulb (measured) temperature T_M (°C); wind speed w_s (m/s) at an elevation of 10m; net radiation absorbed per unit area of body surface Q (W/m²); and water vapour pressure (humidity),

$$E = \frac{\text{RH}}{100} 6.105 \, e^{17.27 \, T_M / (237.7 + T_M)} \tag{2}$$

in hPa where RH is relative humidity (%).

5.25   For simplicity, we assume that the observer is outdoors in the shade so $Q = 0$.

5.26   Instead of considering three environmental factors separately, the apparent temperature is a more compact way to estimate how hot or cold it feels in major population centres (Auckland, Wellington) and therefore the likelihood that many people will switch on air conditioners and heaters.

Results

5.27   Here are some examples showing how GluonTS models demand. We build different models that predict demand, based on what data is available.

(a)   **Many-to-one** forecast models take more than one input and gives one output. This can be used when we know the weather in Auckland and Wellington. It is best suited for checking historical demand since we would have weather and demand data.

(b)   **Many-to-many** forecast models take more than one input and gives more than one output. This is used when we do not know the weather and need to predict the demand. We must therefore train the model and ask it to forecast both weather and demand. In other words, this method is used for predicting future trends.

(c)   **One-to-one** forecast models take one input and gives one output. Here we would only consider demand.

Many-to-one model

5.28   Figure 20 shows the results of a many-to-one model. Predictions are shown in orange, and actual demand is in brown. The orange line is the median of the model prediction. Probabilistic forecasting requires that we learn the distribution of future values so we need to specify the type of distribution of future values.

5.29   GluonTS comes with many different distributions like Gaussian, Student-t, and Uniform. By default, the model assumes a Student-t distribution and LSTM cells.

Figure 20:   Many-to-one model.
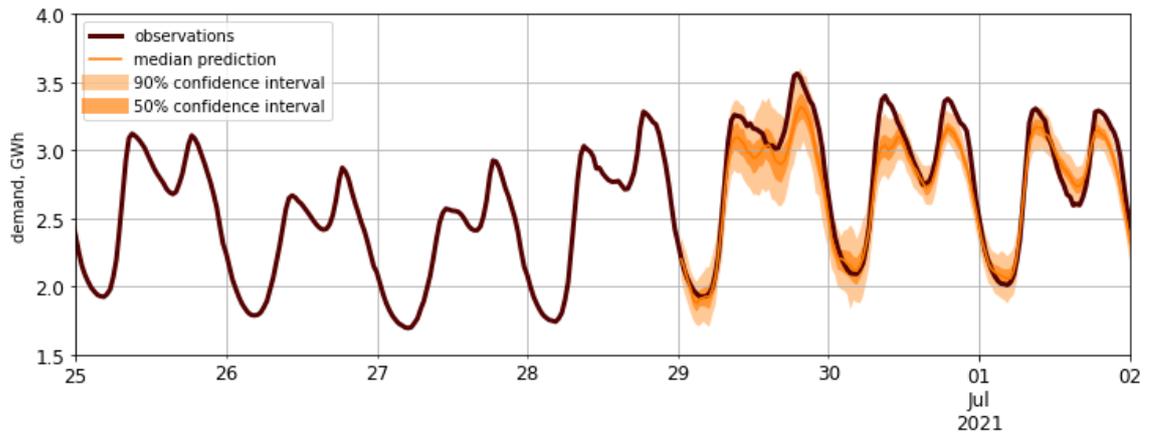
Source: Electricity Authority

5.30   The shaded areas are the confidence intervals surrounding each prediction, in which 90% and 50% of predictions are expected to fall. Smaller intervals imply greater confidence in the prediction.

Many-to-many model

5.31   Figure 21 shows the results of a many-to-many model. Observed values in orange. Model predictions in brown, blue and green. Since we do not know the weather inputs and have to predict demand, the model must calculate forecasts for all three variables.

5.32   As expected, the predictions are poorer than for the many-to-one model. It is caused by the inaccurate temperature predictions for Auckland and Wellington. Because the forecast temperatures are higher than actual temperatures, demand is expected to be lower. This will be a problem if we use this method to predict future demand.

Figure 21:   Many-to-many model.
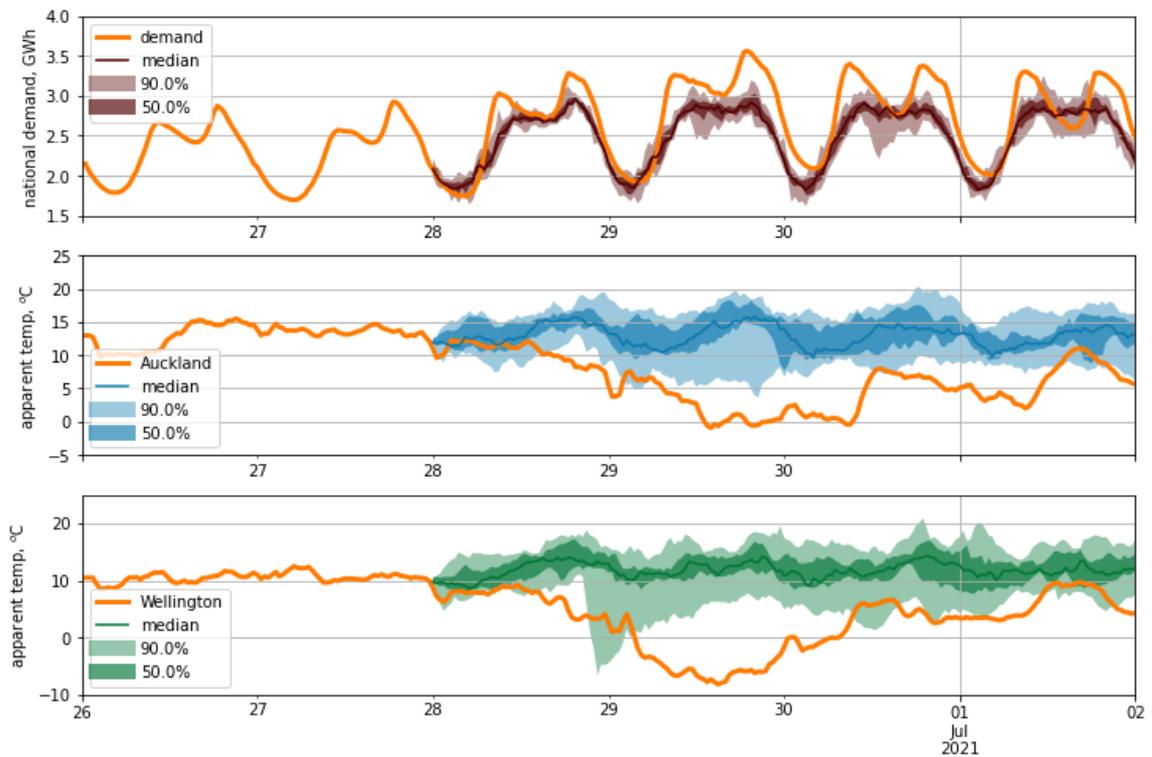
Source: Electricity Authority

One-to-one model

**Figure 22:   One-to-one model.**
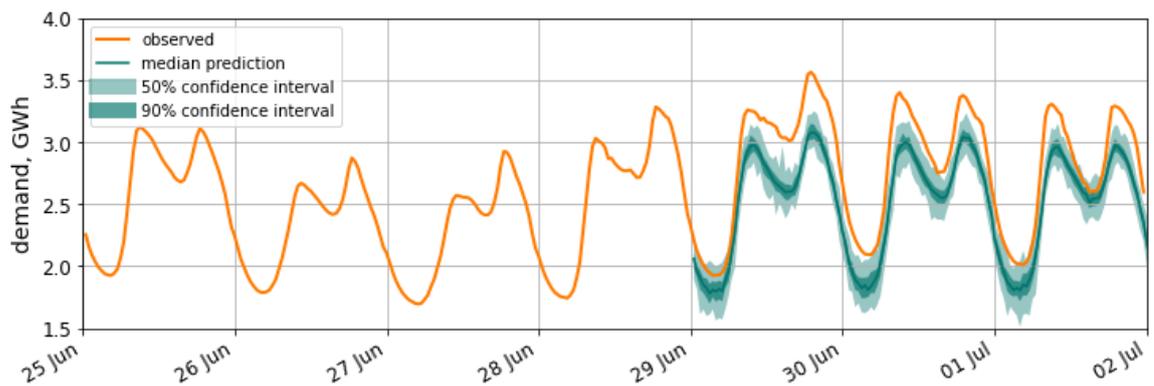
Source: Electricity Authority

5.33   The one-to-one model (Figure 22) only considers demand. The model clearly captures the M-shaped trend over the 48 trading periods, which correspond to the morning and evening demand peaks. The predictions are slightly off since the model does not consider the cold weather.

Many-to-one model, revisited

5.34 In order to work around the issues shown in the many-to-many and one-to-one models, we can consider hourly or half-hourly weather forecasts for some future day. Because it was not possible to obtain the 29 Jun 2021 weather forecasts, we try another set of dates.

5.35 Here we consider the end of Oct 2021. We want to predict future demand for 28-29 Oct 2021. We define 'future demand' as a point in the future when we do not have historical weather data. This means we need to use weather forecasts.

Figure 23: **Apparent temperature data for Auckland and Wellington.**

Solid lines are observations, dashed lines are forecasts.
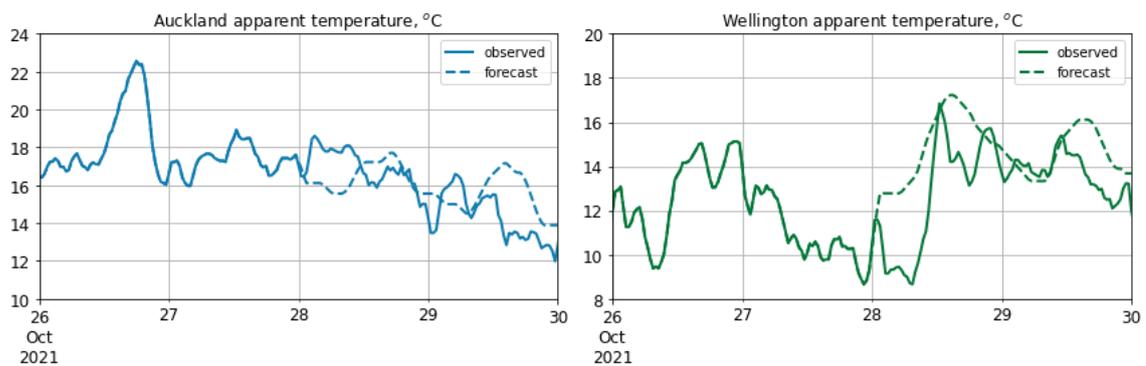
Source: Weather Underground

5.36 Figure 23 shows temperature forecasts (dashed lines) for Auckland and Wellington over 28-29 Oct 2021. The data was acquired on 27 Oct 2021 at roughly 15:00. For comparison, we also plot observed temperatures over these two days (solid lines). This data was acquired after 29 Oct.

5.37 Figure 24 shows the results of our model which is trained using a combination of historical (1 Mar 2014 - 27 Oct 2021) and forecast (28-29 Oct 2021) weather data. The model accurately predicts demand, as there is significant overlap between the confidence intervals and observed demand.

5.38 Even though the weather forecasts do not precisely match the observations, they provide a decent prediction of the overall trend across 28-29 Oct 2021: decrease in Auckland temperature, and steep increase in Wellington temperature followed by gradual decrease.

Figure 24: **Many-to-one model.**

Uses observed weather data over 1 Mar 2014 to 27 Oct 2021 period to train model. Then uses weather forecasts for 28-29 Oct 2021 to predict demand.
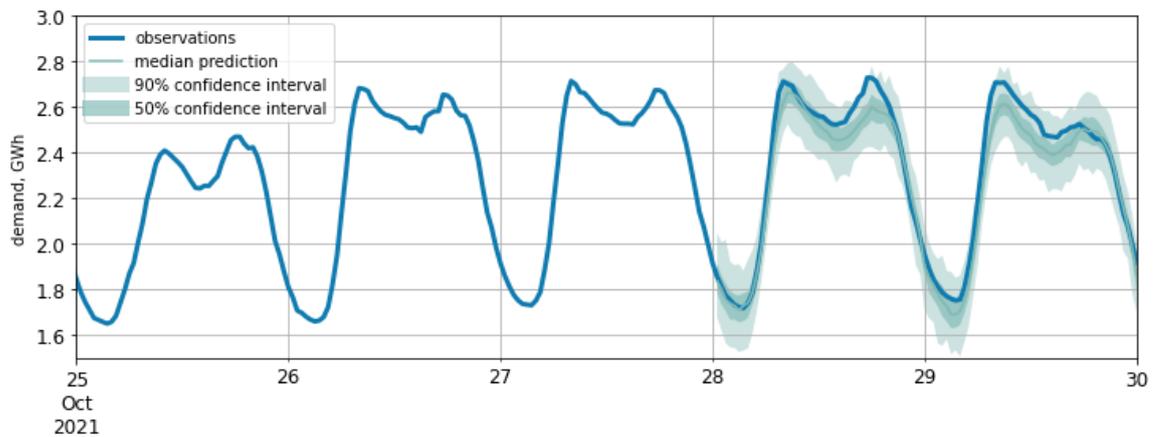

Source: Electricity Authority

5.39   To compare, we now train the model using only historical weather data that covers the 1 Mar 2014 - 29 Oct 2021 period Figure 25. From inspection, both sets of model predictions are highly accurate.

5.40   These results show the importance of using weather data to predict national demand. Compared to the many-to-many model in the above section, training the model to predict only demand is better than asking it to also predict the weather.

5.41   Clearly there can be unpredictable behaviour and large variations in hourly temperature. Hence it is much better to train the model with a combination of historical and forecast weather and use this to predict future demand.

Figure 25: **Many-to-one model.**

Uses observed weather data for entire 1 Mar 2014 to 29 Oct 2021 period.
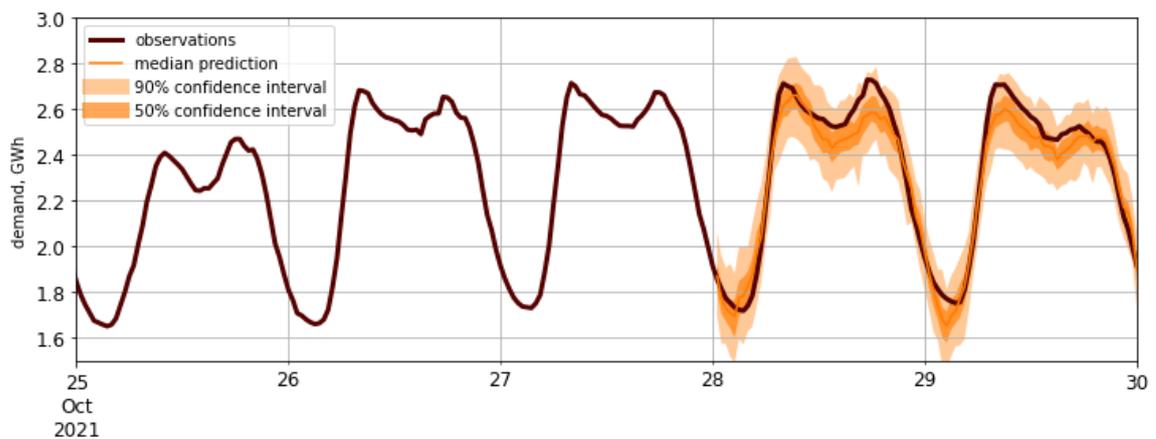
Source: Electricity Authority

5.42   It is possible to numerically evaluate the quality of our forecasts. In GluonTS, we can compute many aggregate performance metrics[10], such as coverage

$$C[\text{quantile}] = \text{mean}(Y < \hat{Y}), \qquad (3)$$

mean absolute percentage error

$$\text{MAPE} = \text{mean}\left(\frac{|Y - \hat{Y}|}{|Y|}\right), \qquad (4)$$

mean absolute scaled error

$$\text{MASE} = \frac{\text{mean}|Y - \hat{Y}|}{\text{SE}} \qquad (5)$$

with scaled error $\text{SE} = |Y_t - Y_{t-m}|$, and symmetric mean absolute percentage error

$$\text{sMAPE} = 2\,\text{mean}\left(\frac{|Y - \hat{Y}|}{|Y| + |\hat{Y}|}\right) \qquad (6)$$

5.43   The metrics are summarised in Table 1:   Metrics.

Table 1: Metrics

Metric	Figure 24	Figure 25
Coverage[0.9]	0.9062	0.8541
MAPE	0.0256	0.0235
MASE	0.5891	0.5553
sMAPE	0.0259	0.0239
Seasonal error	0.1019	0.1019

Source: Electricity Authority

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[10]   R. J. Hyndman and G. Athanasopoulos, *Forecasting: principles and practice*, OTexts (3rd ed.), 2021.