Decarbonisation using nuclear power generation in New Zealand.

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***Abstract*—To examine the use of nuclear power for decarbonisation, a Python model was made, projecting New Zealand's power generation data to 2050, using historical data from 1974-2023. High and low power generation scenarios with high and low emissions values were simulated and compared, showing an averaged emission of 8.160 Mt CO_2-e in 2050. Using an 11% nuclear power supply, replacing fossil fuels, yielded 4.59 Mt CO_2-e, a 43% reduction. A single 4000MW Nuclear reactor could meet the necessary supply. However, implementation is met with difficulty due to New Zealand's anti-nuclear stance and the risks of nuclear energy.**

I. Introduction

As of August 2024, New Zealand has 82% renewably sourced electricity. However, only around 30-40% of New Zealand's total energy consumption comes from renewable sources [23]. The two main problems with renewable energy sources are its low energy density per unit cost and irregular supply times, often referred to as a lack of scaleability and intermittency respectively [3].

For domestic energy policy, New Zealand signed up to the Paris Agreement in 2016 [25] with 2050 targets being a stepped reduction in biogenic (produced by living organisms) methane and net zero for all other gases [1]. While this goal is firmly aligned with carbon reduction, it leaves a large demand for energy needed by industry and for further decarbonisation.

An often overlooked solution to on-demand, high density power generation is nuclear energy, both because of societal stigma around its safe use and being considered a non-renewable resource. However, recent advances in Uranium extraction from sea water provides a possible sustainable source of fuel [28]. This is important as 'Without nuclear, it will be almost impossible to decarbonize by 2050', UN atomic energy chief, Rafael Grossi [26]. In this study, the renewable use of nuclear energy for power generation in New Zealand is evaluated, for reducing carbon emissions in a future of growing power demand.

We evaluate the benefits and costs of nuclear power generation with a focus on the future state of New Zealand. Using monte carlo analysis in Python, we project historical data on New Zealand power usage and compare the cost of using nuclear power generation against other power generation methods and their associated carbon emissions. The forecasting period is set to be 25 years. To inform our model, we will review existing literature on power generation methods, their costs, methods of quantifying their carbon emissions and historic uses of nuclear power and its effects. Finally, a set of scenarios will be constructed, with nuclear replacing existing fossil fuel-based energy generation methods, or only replacing additional future energy demand.

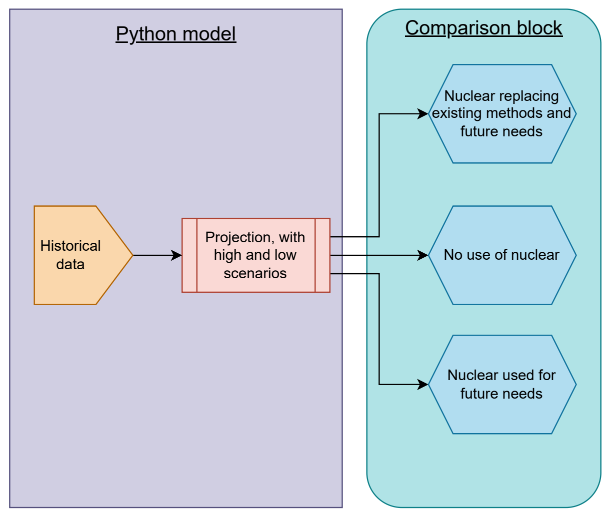


Fig. 1: Model design, historical data refers to national power consumption.

Here, the comparison block will evaluate the carbon emissions of each scenario, for the high and low power consumption cases. The block designations will be elaborated on in the Method section, but may not form separate parts of the final model. The baseline case is included to verify that decarbonisation is indeed achieved. This is composed of the current governmental plans for future power generation, at the time of writing.

II. Literature Review

We construct our review of current literature to best inform our model and provide an informed approach to assumptions and likelihoods chosen for the scenarios outlined in Figure 1.

A. Historical data

New Zealand's Ministry for the Environment provides an annual Greenhouse Gas Inventory (GGI) report [11] outlining all anthropogenic emissions from 1990-2022. Between 2021&2022, gross emissions fell by 4%, with reductions across all sectors. However, the Energy sector had the largest percentage change of 8.1%, or 2.5 Mt CO_2-e. Here, CO_2-e refers to carbon dioxide equivalent, a normalising metric used to compare different greenhouse gas emissions using the same units. The Ministry for the Environment also releases an annual report on measuring emissions [12], within which the CO_2-e calculation method is outlined. The **ISO 14064-1:2018** standard and the GHG Protocol [16] are required to be adhered to for businesses and for the aforementioned Greenhouse Gas Inventory report. The detailed version of this report outlines a calculation method for CO_2-e as:

CALCULATION METHODOLOGY

E = Q × F

Where:

E	=	emissions from the emissions source in kg CO_2-e per year
Q	=	activity data, eg, quantity of fuel used
F	=	emission factor for emissions source

This formula applies to the calculation of both CO_2-e emissions and individual carbon dioxide, methane and nitrous oxide emissions, with the appropriate emission factors applied for F.

The preferred form of data is in the units expressed in the emission factor tables, which results in the most accurate emission calculation. If the data cannot be collected in this unit, use the appropriate conversion factors.

Fig. 2: Calculating CO_2-e using relevant standards (Ministry for the Environment, 2024 [13]).

This report provides a sound basis for historical emissions data for our model, however, it should be noted that this year the change to conform to Paris Agreement reporting standards, has led to a difference in the calculation of CO_2-e emissions. Particularly for the warming effects of the agricultural industry. ”Agriculture now represents a higher percentage of Aotearoa New Zealand’s total emissions, due to methane having a higher carbon dioxide equivalence under AR5 than under AR4.” (Ministry for the Environment, 2024 [11]). Practically, this means that for our scenarios, we should only use the current GGI report. Both for input values and for comparison, as that keeps emission definitions consistent.

B. Projections

The Ministry of Business, Innovation and Employment releases an annual report on Electricity Demand and Generation (EDG) [24]. This report estimates New Zealand’s power consumption and therefore generation needs until 2050. Also included is the change in power generation methods over this projection period. For their scenarios, they define:

”Each of the five scenarios illustrate a possible future based on several high-level assumptions (which will differ from scenario to scenario). The scenarios are:

- Reference: Current trends continue with anticipated changes
- Growth: Higher economic growth drives immigration while policy and investment focus on priorities other than the energy sector
- Innovation: Current economic trends continue, alongside accelerated technological uptake and learning rates
- Constraint: International trends leave little room for domestic growth or innovation
- Environmental: New Zealand targets more ambitious reductions in emissions ”

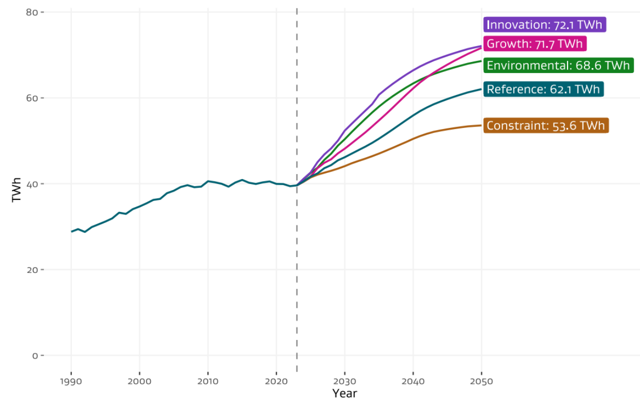


Fig. 3: Various scenarios for New Zealand’s future power consumption (Ministry for Business, Innovation and Employment, 2024 [24]).

These scenarios align closely with our own forecasting. Additional to the low and high scenario in Figure 1, we will use the reference scenario as outlined in this report for our baseline case, then vary this scenario to low and high power consumption levels. The EDG report estimates an average renewable energy production of 96.88% by 2050. This seems very optimistic based off of New Zealand’s current 82% renewable status, considering the report shows an 80.9% increase in demand for electricity under the Innovation scenario.

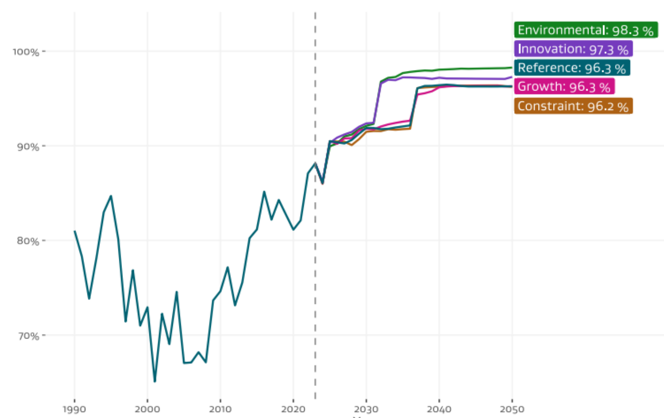


Fig. 4: Renewable energy share for New Zealand’s future power consumption (Ministry for Business, Innovation and Employment, 2024 [24]).

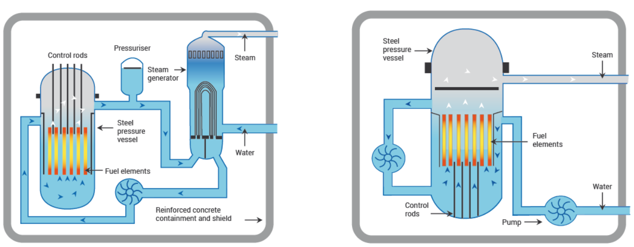
The law of diminishing returns alone should be indicative that nearing 100% of any goal generally follows an asymptotic, slow trend towards that goal. While Figure 4 appears asymptotic due to the step change from introduced new renewable plants, drawing a line from 2024 to 2050’s forecasted values is nearly linear.

A large assumption in this report is that gas and coal plants such as the Huntly Rankine units and the Taranaki Combined

Cycle plant will close, being replaced by solar or wind power generation, but cites no strategy or plans for how this would be funded, when it would be achieved, or where these plants would be set up. The well known Mount Cass Wind Farm is a good example of just how long the planning and consenting period is, having been in planning since 2006. This so far 18 year period of planning stasis is a strong argument against the feasibility of fully implemented future systems that have not currently been planned yet. The caveat here is that the same argument can and should be made against nuclear power generation. Our assumption here, is that the use of nuclear power generation is successful and the details of planning, consenting, construction and implementation are investigated in the next section.

C. *Nuclear power generation methods*

The two main kinds of nuclear reactors are pressurized water reactors (PWR) and boiling water reactors (BWR). The PWR reactor is by far the most commonly used, with 310 reactors in USA, France, Japan, Russia, China and South Korea [5].



(a) Pressurized water reactor design.

(b) Boiling water reactor design.

Fig. 5: Most common nuclear reactor types (World Nuclear Association, 2024 [5])

The functional principle behind nuclear power generation is the transfer of heat to an evaporative coolant, such as water or deuterium (heavy water), from the fission process. The fission process is caused by a chain reaction of emitted radiation, by absorbing and emitting neutrons. To control the fission process, neutron absorbing material called control rods or blades are inserted into the nuclear core containing uranium. These control the rate of the reaction, or halt it by absorbing the emitted neutrons, limiting or stopping the chain reaction process. At the phase change of the coolant to a gas, the resulting steam drives a turbine to generate electricity. Heavy water is used as it is has more mass (^2H_2O) at a similar boiling point of 101.4 $^\circ C$ to "light" water at standard pressure and temperature. The primary difference between PWR and BWR reactors is that the latter only has one fluidic circuit, which is also at lower pressure [5].

D. *Cost*

Assessing the monetary cost is useful, but the environmental and societal cost of any new technology should be well understood before its integration.

1) Environmental, societal costs: The most recent nuclear power accident was at Fukushima, Japan in 2011. "Following a major earthquake, a 15-metre tsunami disabled the power supply and cooling of three Fukushima Daiichi reactors, causing a nuclear accident beginning on 11 March 2011. All three cores largely melted in the first three days." (World Nuclear Association, "Fukushima Daiichi Accident", 2024 [4]). Thankfully, no deaths were directly attributed to this disaster, but over 100,000 people were relocated as a precaution. This caused severe mental stress and fatigue for those affected. As an event catalysed by seismic activity, it is especially relevant to New Zealand and the public perception of nuclear energy generation and its dangers. A survey by Younghwan, et. al, 2013 [19] over 42 countries and 24,556 respondents showed that 52.7% favoured the use of nuclear energy before the accident and only 45.4% after. Though this survey is now 11 years old, Government and regulatory bodies should ensure public opinion and consent is granted for the use of nuclear power and its risks.

2) Financing: Plant construction: A comprehensive study on the overnight construction cost (OCC) of nuclear power plants is presented by Lovering et. al, 2016 [20]. The OCC includes the cost of engineering, procurement and construction services of the plant. Indirect costs are also included, such as land, site preparation, project management and other overheads. The trend in construction costs vary significantly between countries, with more recent construction around the 2010's in South Korea showing sustained cost escalation, while the U.S. shows very high cost escalation and no new plants being constructed after 1978. The largest impact on OCC is "How costs evolve over time appears to be dependent on different regional, historical, and institutional factors at play" [20]. As such, to be most representative of New Zealand's economic climate, South Korea is examined. South Korea via their Kepco government energy company has won several contracts to construct nuclear power plants in other countries. Due to the technical difficulty and high development costs of developing this capability in NZ, we use the cost basis of contracting Kepco for constructing power plants. The construction cost is around USD $3,500 per kW or NZD $5,844.00 per kW [30] [17]. This is for their APR1400 PWR reactor, which is a 4,000 MW reactor [27].

3) Financing: Uranium, fuel: A novel approach to a sustainable source of uranium fuel is from the extraction of sea water. This may be considered sourcing Uranium renewably, though more expensive at around USD$600/kg [29] compared to traditionally mined Uranium at around USD$180/kg [32]. This costing is subject to the time of writing, where future technological improvements may allow this source to be used in parallel with decarbonisation objectives. We assume that by 2050 harvesting Uranium from sea water is not yet commercially viable and proceed with traditional costing.

Nuclear power plants generally utilise long-term contracts to provision their fuel needs. At the time of writing, the long term price of uranium is $81 [USD/lb U_3O_8] by the (World Nuclear Association, 2024 [8]), using their reference firm's

[9] price estimates. This is subject to independent reporting, as "Uranium does not trade on an open market like other commodities. Buyers and sellers negotiate contracts privately." [9].

E. Decarbonisation

Using nuclear power generation as a method of decarbonisation is relevant to the comparison block of our software model. Both of our scenarios in our model have provided power generation needs per year, so we can perform our decarbonisation calculation by taking each scenario in the comparison block and attributing the appropriate amount of power generation to nuclear and examining the difference. From Figure 1, these were:

- No nuclear used
- Nuclear used for all future needs
- Nuclear used for future needs and replacing fossil fuels

From the GWh of nuclear power needed, we can then calculate the CO_2-e produced and perform our comparisons. To perform these, we first need to calculate the CO_2-e of the no-nuclear scenario, then we can take the difference from this case for the respective nuclear scenarios. The reference scenario is expected to reach 62.1 TWh by 2050 in the EDG report [23]. The same report states an estimated 2.526 Mt CO_2-e emissions electricity generation.

We can examine the energy mix as outlined in the Energy in New Zealand report [23], in 2024:

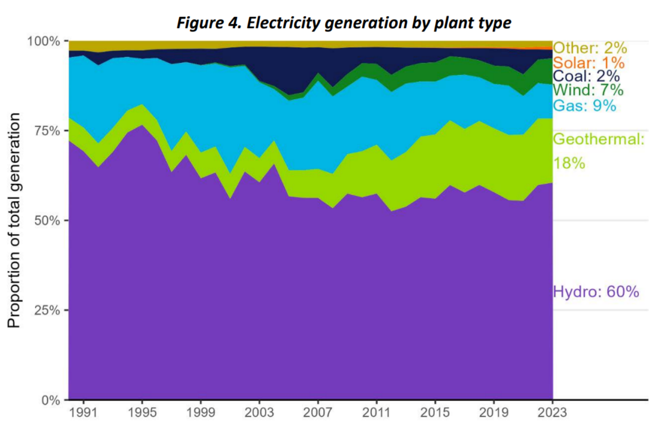


Fig. 6: Electricity generation by plant type (MBIE, Energy in New Zealand, page 11, 2024 [23])

For GHG emissions, we refer from page 71 of the United Nations Economic Commission for Europe (UNECE)'s Life Cycle Assessment of Electricity Generation Options report [10]. For geothermal emissions, we refer to Table 2 in (McLean, 2019 [18]).

Energy production method	Net generation 2023 [GWh]	Percentage of total electricity (%)	Minimum [g CO_2-e/kWh]	Maximum [g CO_2-e/kWh]
Hydro	26,309	60	6	147
Geothermal	7,758	18	21	304
Biogas	275	<1	-	-
Wood	408	<1	-	-
Wind	3,206	7	7.8	16
Solar	367	1	27	122
Oil	4	<1	-	-
Coal	1,031	2	751	1095
Gas	4,097	9	430	513
Waste Heat	33	<1	-	-
TOTAL	43,488	100	-	-
Nuclear	-	0	5.1	6.4

TABLE I: Emissions per power generation type in New Zealand

Greyed-out entries are omitted due to being less than 1% of overall power generation, or in the case of nuclear, not being part of the energy mix currently.

III. Method

A. Overview and methodology

We investigate the difference in carbon emissions between scenarios where nuclear power generation meets projected increased power demand and where nuclear meets this demand while also replacing fossil fuel based power generation methods. We use Python to construct the model outlined in Figure 1. We use the projected values from the EDG report in Section II-B. Our data is retrieved from the "Data tables for electricity" Excel file from MBIE [22], which contains the annual net power generation and usage from 1974-2023 for New Zealand.

B. Framework, tools used.

The foundational language we use is Python and we version control our work in GitHub [21].

1) Data processing: We use the Pandas library to load the excel sheet's data and perform data wrangling to extract the data section from the workbook that we are interested in: annual net power generation and usage.

2) Trend analysis: The Python library Prophet [31] is a utility for forecasting time-series data, ideal for our application of trend analysis and variation. We specifically use the so-called logistic growth model, an S-shaped growth model, which is given by:

$$f(x) = \frac{L}{1 + \exp^{-k(x-x_0)}} \tag{1}$$

Where:

- L is the carrying capacity, set to the desired scenario value from the EDG report.
- k is the logistic growth rate, this is set by the Prophet library.
- x_0 is the value of the function's midpoint, also set by the Prophet library.

3) Monte Carlo: Monte Carlo analysis is a stochastic method, meaning it involves a random variable, used for scenario modeling. It is based on the central limit theorem in statistics, which states that the distribution of a sample will approximate a normal distribution, as the sample size becomes larger. As this is based on the principle of random sampling, this can be implemented using the NumPy [14] package's random normal method like so:

```
import numpy as np

target_growth_rate = 0.05 # some growth rate
std_growth_rate = 0.02 # some standard deviation

sample_value = np.random.normal(
loc=target_growth_rate,
scale=std_dev_growth_rate
)
```

Where:

- "loc": Mean ("centre") of the distribution.
- "scale": Standard deviation (spread or "width") of the distribution. Must be non-negative.

We can then formulate a range of growth rates and outputs based off of how we select the mean and standard deviation of this distribution and applying it to a yearly forecasting method.

Due to the simplicity of this method, often inspection is a commonly used method to tune models of this sort.

4) Data visualisation: The matplotlib library [15] is used to create various plots for our simulations and examine the output of our data. We created a custom file to make the output of these plots look more consistent and legible, called `matplotlib_rc.py`, which changes some font and styling settings.

IV. Results and Discussion

A. Python model

We used the Prophet framework to create a projection purely based off of historical data, to examine what trend the model would predict without any hyper-parameter tuning. Refer to the `power_forecasting.py` file in the GitHub project repository [21].

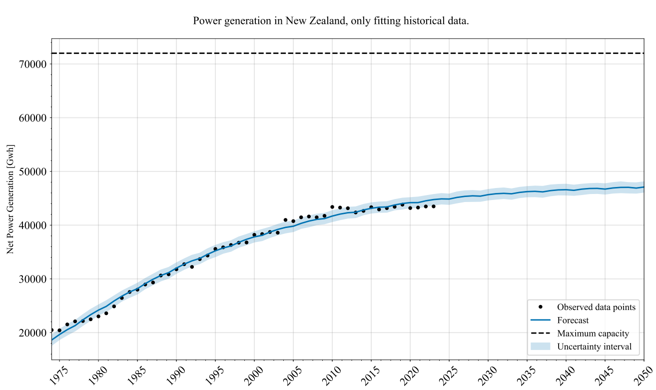


Fig. 7: Power generation trend purely off of historical data.

We can see that the model is clearly well-fitted to the data and here a carrying capacity (L) of 72,000 was used, setting the upper limit to the Innovation case of 72.1 TWh in 2050 from Figure 3. This outcome was close to the Constraint trend, which had a 2050 power consumption of 53.6 TWh. Where this unmodified Prophet scenario had a predicted power consumption of 47 TWh.

We then performed a Monte Carlo analysis to find what parameters and variance would result in the Innovation case of 72.1 TWh. For the standard deviation input or the "scale" argument for the numpy random normal distribution, we used the coefficient of variation [2] of the historical data:

$$CV = \frac{\sigma}{\mu} \tag{2}$$

This is because we wanted the projected values to be representative of historical data. This worked well, however we see how wide the confidence intervals are in Figure 8 as a result. We used the 68–95–99.7 rule to estimate the confidence intervals in our visualisation, for indicating the 1, 2 and 3 sigma variance in our Monte Carlo simulation respectively.

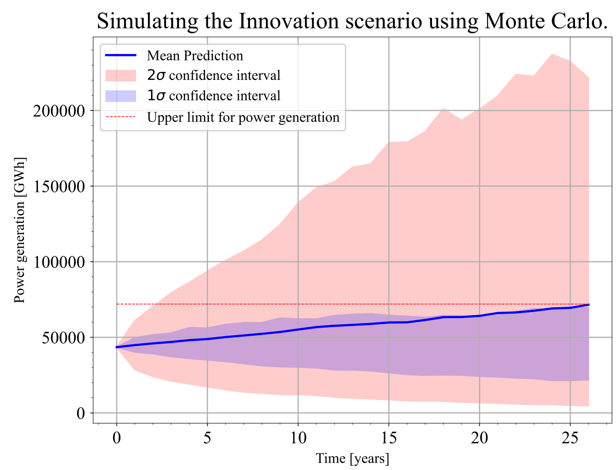


Fig. 8: Choosing an annual growth rate of 2% yielded the Innovation case from EDG report.

The large variance at 2 sigma is not unexpected, as the trend shown in Figure 7 shows that a large increase in future power consumption is not obvious from historical data and trends. We have now constructed our high and low scenarios using the Python model and may proceed with the Comparison block as outlined in Figure 1.

B. Comparison

We outlined our values to be used for GHG emissions in Section II-E. Since the projections we generated start at our last data point of 2023, we make a simplifying assumption and project the energy mix in Table I forward as-is. To achieve our comparison objective, we use the high and low projections given by our Monte Carlo analysis in Figure 8 and our Prophet forecast in Figure 7.

1) No nuclear used: In `power_forecasting.py` Table I was used to find the CO_2-e of GHG emissions, per energy source, for each year in kilotonnes. The data sourced from the MBIE Energy statistics Excel workbook [22] was in GWh. As our CO_2-e ratios were in g/kWh, we converted power to kWh by multiplying by 1e6. Then the power value was multiplied by the CO_2-e ratio, yielding grammes of CO_2-e. This was divided by 1e9 to yield kilotonnes. This was applied to both the Monte Carlo and Prophet simulations, for minimum and maximum CO_2-e, satisfying our comparison.

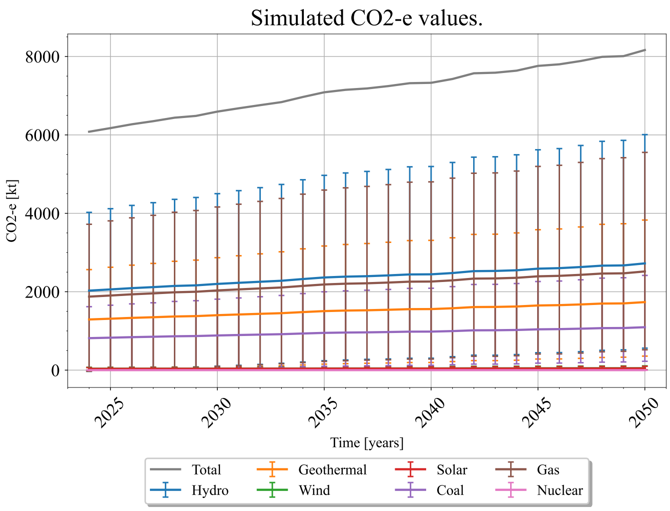


Fig. 9: Kilotonnes of CO_2-e as simulated with Prophet and Monte Carlo.

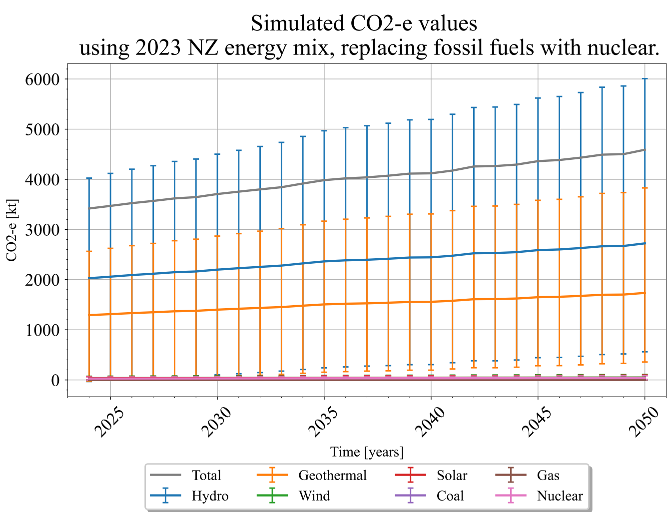


Fig. 10: Kilotonnes of CO_2-e as simulated with Prophet and Monte Carlo, with nuclear energy.

The error bars indicate the minimum and maximum CO_2-e values for each type of power generated. Then the energy proportions of coal and gas (a combined 11% of the energy mix) were set to zero, replaced by nuclear energy generation, using the `apply_energy_mix()` function.

In Figure 10 the total CO_2-e is significantly lower, with a 2050 value of 4.59 Mt. See Section VII-B for all code used to construct the python model and data visualisations. The model's outputs are also provided for the forward simulation period in Section VII-A. These are the y-values of the data points for the "Total" line shown in Figures 9 and 10.

V. Discussion, Conclusion

Nuclear power generation was investigated to aid with New Zealand's decarbonisation goals. A common misconception is that the New Zealand Nuclear Free Zone, Disarmament, and Arms Control Act has a ban on nuclear power generation, but this explicitly allows land-based nuclear power plants.

A. Model outputs

The model in Figure 1 was fully implemented. To evaluate the use of nuclear power under high and low power consumption and consequently CO_2-e, historical data was used. For the low power consumption scenario, the Prophet model by Facebook was used to fit a trend to historical data and project this to 2050. For the high power consumption scenario, the energy mix in 2023 was used as a basis and projected forward using Monte Carlo analysis with a fixed annual growth rate of 2%. The average of these two scenarios resulted in a 2050 CO_2-e emission of 8.160 Mt. This is much higher than the 2.526 Mt estimate of the EDG report, however this assumed a nearly complete renewable generation of 96.88%, whereas our estimate was used for New Zealand's current energy mix.

From the higher emissions scenario using the Monte Carlo approach, we showed that the power production value was close to the target set by the EDG report, which is what was used to find an appropriate growth rate for the simulation. The two simulation methods performed well, given a very basic approach and an oversimplification of the domain. The CO_2-e values used in Table I were wide estimates, so that the analysis for our scenarios are conservative. This also contributed to the much higher 2050 CO_2-e value.

Figure 10 shows the nearly halving of GHG emissions by replacing fossil fuel electricity generation plants, in this scenario coal and gas, with nuclear power generation. This is a very strong result and a clear indication of the merits of nuclear power generation for decarbonisation. This scenario assumed that nuclear power would used from 2024 onwards, which is not realistic, but this was chosen as a visualisation to show that irrespective of when nuclear power could be added to New Zealand's energy grid, it would result in a halving of GHG emissions, as the "Total" line clearly indicates. The 2050 value for GHG emissions was 4.59 Mt CO_2-e, which is a 43% reduction in CO_2-e emissions. It should be re-iterated that this is a very simplified model, however this result should be compelling for decarbonisation.

B. Nuclear power output

We can use the capacity factor (CF) to find the amount of energy produced by one plant, annually. The relation is given by:

$$\text{CF} = \frac{\text{Annual generation [MWh]}}{(365[\text{days}]) \times (24[\text{hours/day}]) \times (\text{Capacity [MW]})} \quad (3)$$

The global average capacity factor was 81.5% in 2023 [6]. For the South Korean APR1400 reactor, this has a 4000MW output. As such, a single reactor's yearly power output is:

$$\begin{aligned} &\text{Annual generation [MWh]} = \\ &\text{CF} \times (365[\text{days}]) \times (24[\text{hours/day}]) \times (\text{Capacity [MW]}) \\ &= 0.815 \times 365 \times 24 \times 4000 = 28.56[\text{TWh}] \end{aligned}$$

C. Implementation

If nuclear power were to be considered, the reference scenario in the EDG report estimates a 2050 power production rate of around 60 TWh per year. The current power production rate is around 40 TWh, seen in Figure 3, which means a need of around 20 TWh. A single South Korean APR1400 PWR reactor can output 28.56 [TWh]. This is an overshoot of New Zealand's future power generation needs, which could also cover replacing fossil fuel power generation. From our Monte Carlo scenario, 72.1 TWh multiplied by the fossil fuel mix of 11%, yields 7.9 TWh by 2050. The decarbonisation and solution of future power supply needs are strong arguments for the adoption of nuclear power generation. The cost basis is high, at NZD \$58440 per kW, or NZD \$5.8 million/MW. For the APR1400, this amounts to an estimated NZD \$23.2 billion.

D. Difficulties in adoption

New Zealand has had a very strong anti-nuclear stance, with a strong history of ruling against nuclear power of any form entering New Zealand's territory. Most of this policy was set in the 1980's and as such there may be convincing arguments made to reconsider this stance going forward.

New Zealand's electricity grid is challenging both because 60% of its power comes from hydro, with the most capacity in the South Island. However, population centres such as Wellington and Auckland are high in power consumption, adding difficulties such as line losses, which have not been considered here. Placement of future nuclear power plants may have a positive effect of these phenomena, if constructed in the North Island.

Nuclear power's history of disaster as a result of seismic events, such as the Fukushima tragedy is also a strong argument against nuclear power use in New Zealand. This provides challenges for construction, though it should be noted that the Fukushima disaster was not cause by the earthquake itself, but by the tsunami afterwards.

A large issue with nuclear power is nuclear waste. New Zealand has a strong focus on re-usability and minimising waste where possible. The most common method of disposal is burying the waste in underground storage locations [7]. This would likely be met with strong opposition from indigenous Māori, who have strong cultural and religious ties with the land. A strong focus on New Zealand's cultural values should be maintained and preserved and it is important that these considerations are made by consulting indigenous leaders.

VI. AI Declaration

This report used ChatGPT for initial summary and ideas for the research topic and checking for grammatical and spelling errors in my own writing. As the author I certify the factual accuracy and reliability of all aspects of the AI generated content, and acknowledge my personal accountability therefore.

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VII. Appendix

A. Model output

Yearly emissions data without nuclear power generation:

```
[6081.30787014 6173.70764261 6271.17878364
↪ 6350.01877364 6439.19534267
 6484.56114993 6594.32701771 6678.86647549
 ↪ 6758.91146513 6836.56300767
 6967.22749898 7086.96793447 7150.29767022
 ↪ 7184.98527344 7245.42712407
 7318.88422134 7328.88646962 7426.40028161
 ↪ 7571.76545474 7586.56858227
 7638.58172746 7760.35928874 7800.64916199
 ↪ 7884.88651824 7990.87260704
 8009.09589988 8164.68161277]
```

Yearly emissions data with nuclear power generation replacing fossil fuels:

```
[3418.41856004 3470.35822563 3525.14860373
↪ 3569.46605828 3619.59390005
 3645.09488123 3706.79635856 3754.31759209
 ↪ 3799.3123998  3842.96180547
 3916.41079569 3983.71916682 4019.3180131
 ↪ 4038.81657315 4072.7920844
 4114.08371279 4119.70616636 4174.52053062
 ↪ 4256.23305306 4264.55417197
 4293.79174794 4362.24522614 4384.89292848
 ↪ 4432.24434502 4491.82113685
 4502.06479558 4589.52247738]
```

B. Code

Please see the project's GitHub repository [21] for the source code.

power_forecasting.py

```
"""
Written by J.M. (Shaun) Lowis, for ENME618: Future
↪ Project Assignment.

electricity.xlsx was retrieved from:
https://www.mbie.govt.nz/building-and-energy/energy-and-natural

Please see the attached report for further
↪ information regarding model parameters.

In VS Code, you can go: Ctrl+SHIFT+P --> Select
↪ Interpreter --> + Create Virtual Environment for
↪ setup.

You can then install the needed packages with:
python -m pip install -r requirements.txt
"""

# File I/O
import os

# Data analysis
import pandas as pd
import numpy as np

# Curve fitting
import prophet

from model_visualisation import plot_monte_carlo,
↪ plot_prophet, plot_min_max_df
import matplotlib.pyplot as plt


def prophet_forecast(cleaned_df):
    """Worked really well."""

    # Make sure this column is recognised as dates.
```

```python
    cleaned_df["ds"] =
    ↪ pd.to_datetime(cleaned_df["ds"],
    ↪ errors="coerce", format="%Y")

    cleaned_df["cap"] = (
        72000
    )

    m = prophet.Prophet(growth="logistic")
    # m = prophet.Prophet()
    m.fit(cleaned_df)

    future = m.make_future_dataframe(periods=27,
    ↪ freq="YS")
    future["cap"] = 72000
    fcst = m.predict(future)

    return m, fcst


def monte_carlo_growth(cleaned_df):
    # We want our output to be reproducible for data
    ↪ analysis
    np.random.seed(42)
    # use our historical data
    base_value = cleaned_df["y"].values[-1]
    years = 26
    num_simulations = 1000
    # These should be taken from the dataset maybe
    target_growth_rate = 0.02  # 5% target annual
    ↪ growth rate
    # std_growth_rate = 0.02  # get std from data.
    std_growth_rate = cleaned_df["y"].std() /
    ↪ cleaned_df["y"].mean()
    predictions = []

    # This is a very basic approach, but good enough
    ↪ for our case.
    for _ in range(num_simulations):
        future_values = [base_value]

        # We iterate through the number of years for
        ↪ each simulatio
        # so we can generate a large enough sample
        ↪ size to conformt to the central limit
        ↪ theorem.
        for __ in range(years):
            sampled_growth_rate = np.random.normal(
                loc=target_growth_rate,
                ↪ scale=std_growth_rate
            )
            # growth projection comes in here.
            next_value = future_values[-1] * (1 +
            ↪ sampled_growth_rate)
            future_values.append(next_value)

        predictions.append(future_values)

    return pd.DataFrame(predictions)


def apply_energy_mix(emissions_array: np.ndarray,
↪ add_nuclear=False):
    if add_nuclear:
        energy_df = pd.DataFrame(
            {
                "energy_type": [
                    "Hydro",
                    "Geothermal",
                    "Wind",
                    "Solar",
                    "Coal",
                    "Gas",
                    "Nuclear",
                ],
                "energy_proportion": [0.6, 0.18,
                ↪ 0.07, 0.01, 0, 0, 0.11],
                "min_co2e": [6, 21, 7.8, 27, 751,
                ↪ 430, 5.1],
                "max_co2e": [147, 304, 16, 122,
                ↪ 1095, 513, 6.4],
            }
        )
    else:
        energy_df = pd.DataFrame(
            {
                "energy_type": [
                    "Hydro",
                    "Geothermal",
                    "Wind",
                    "Solar",
                    "Coal",
                    "Gas",
                    "Nuclear",
                ],
                "energy_proportion": [0.6, 0.18,
                ↪ 0.07, 0.01, 0.02, 0.09, 0],
                "min_co2e": [6, 21, 7.8, 27, 751,
                ↪ 430, 5.1],
                "max_co2e": [147, 304, 16, 122,
                ↪ 1095, 513, 6.4],
            }
        )

    power_types = energy_df["energy_type"].to_list()

    output_df_min =
    ↪ pd.DataFrame(columns=power_types)
    output_df_max =
    ↪ pd.DataFrame(columns=power_types)

    # Initially, power units from electricity.xlsx
    ↪ is net generation in GWh.
    # The value for CO2-e is g/kWh.
    # 1 GWh = 1e6 kWh, so multiply power value by
    ↪ 1e6
    # Then multiply electricity value by CO2-e
    ↪ equivalent, for g.
    # 1g = 1e-9 kt. Then final units are CO2-e [kt]

    for i, power_type in enumerate(power_types):
        output_df_min[power_type] = (
            emissions_array
            * energy_df["energy_proportion"].iloc[i]
            * energy_df["min_co2e"].iloc[i]
            * 1e6
            * 1e-9
        )
        output_df_max[power_type] = (
            emissions_array
            * energy_df["energy_proportion"].iloc[i]
            * energy_df["max_co2e"].iloc[i]
            * 1e6
            * 1e-9
        )

    return output_df_min, output_df_max


def main():
    fp = os.path.join(os.getcwd(),
    ↪ "data/electricity.xlsx")
    # Retrieve annual power generation:
    df = pd.read_excel(fp, sheet_name=2, skiprows=8)

    # Data wrangling, retrieve the calendar year,Net
    ↪ Generation in GWh and Renewable share:
    reduced_df = pd.DataFrame(
```

```python
        {
            "ds": np.array(df.iloc[1,
            ↪  0:-1].index[1:]),  # Calendar year
            "y": df.iloc[1, 0:-1].values[1:],  # Net
            ↪  Generation (Gwh)
            # "Renewable share (%)": df.iloc[12,
            ↪  0:-1].values[1:],
        }
    )

    prophet_obj, df_fcst =
    ↪  prophet_forecast(reduced_df)
    plot_prophet(prophet_obj, df_fcst,
    ↪  "report_plots/projection_historical.pdf")
    df_carlo = monte_carlo_growth(reduced_df)
    plot_monte_carlo(df_carlo,
    ↪  "report_plots/first_monte_carlo.pdf")

    df_carlo_min, df_carlo_max =
    ↪  apply_energy_mix(df_carlo.mean(axis=0).values)
    df_prophet_min, df_prophet_max =
    ↪  apply_energy_mix(df_fcst.yhat.iloc[-27:].values)

    plot_min_max_df(
        prophet_dfs=[df_prophet_min,
        ↪  df_prophet_max],
        monte_carlo_dfs=[df_carlo_min,
        ↪  df_carlo_max],
        filename="report_plots/sim_co2e.pdf",
        title="Simulated CO2-e values \n using 2023
        ↪  NZ energy mix.",
    )

    # Now with nuclear replacing fossil fuels
    df_carlo_min, df_carlo_max = apply_energy_mix(
        df_carlo.mean(axis=0).values,
        ↪  add_nuclear=True
    )
    df_prophet_min, df_prophet_max =
    ↪  apply_energy_mix(
        df_fcst.yhat.iloc[-27:].values,
        ↪  add_nuclear=True
    )

    plot_min_max_df(
        prophet_dfs=[df_prophet_min,
        ↪  df_prophet_max],
        monte_carlo_dfs=[df_carlo_min,
        ↪  df_carlo_max],

        ↪  filename="report_plots/sim_co2e_nuclear.pdf",
        title="Simulated CO2-e values \n using 2023
        ↪  NZ energy mix, replacing fossil fuels
        ↪  with nuclear.",
    )


if __name__ == main():
    main()
```

model_visualisation.py

```python
import pandas as pd
import numpy as np

# Plotting
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

# Styling so output looks nice
import matplotlib_rc


def plot_prophet(prophet_obj, df_fcst, filename):
    fig = prophet_obj.plot(df_fcst)
    ax = fig.gca()

    print("Terminal predicted values:\n")
    print(f"{df_fcst.ds.iloc[-1]}:
    ↪  {df_fcst.yhat.iloc[-1]}")

    ax.set_ylabel("Net Power Generation [Gwh]")
    ax.set_xlabel("Time [years]")
    fig.suptitle("Power generation in New Zealand,
    ↪  only fitting historical data.")

    # Make x axis more legible.
    ax.set_xlim([pd.Timestamp("1974-01-01"),
    ↪  pd.Timestamp("2050-01-01")])

    ↪  ax.xaxis.set_major_locator(mdates.YearLocator(5))

    ↪  ax.xaxis.set_major_formatter(mdates.DateFormatter("%Y")
    plt.xticks(rotation=45)

    fig.tight_layout()
    ax.legend()

    fig.savefig(filename)


def plot_monte_carlo(df, filename):
    mean_prediction = df.mean(axis=0)

    sigma1_lower = df.quantile(0.32, axis=0)
    sigma1_upper = df.quantile(0.68, axis=0)

    sigma2_lower = df.quantile(0.05, axis=0)
    sigma2_upper = df.quantile(0.95, axis=0)

    fig, ax = plt.subplots()

    ax.plot(mean_prediction, label="Mean
    ↪  Prediction", color="blue")

    ax.fill_between(
        range(26 + 1),
        sigma2_lower,
        sigma2_upper,
        color="red",
        alpha=0.2,
        label=r"$2 \sigma$" + " confidence
        ↪  interval",
    )

    ax.fill_between(
        range(26 + 1),
        sigma1_lower,
        sigma1_upper,
        color="blue",
        alpha=0.2,
        label=r"$1 \sigma$" + " confidence
        ↪  interval",
    )

    ax.hlines(
        y=72000,
        xmin=0,
        xmax=26,
        linewidth=0.5,
        linestyle="--",
        label="Upper limit for power generation",
        color="r",
    )

    ax.set_title("Simulating the Innovation scenario
    ↪  using Monte Carlo.")
    ax.set_xlabel("Time [years]")
    ax.set_ylabel("Power generation [GWh]")
```

```
    ax.legend()
    ax.grid()

    plt.savefig(filename)


def plot_min_max_df(
    prophet_dfs: list, monte_carlo_dfs: list,
    ↪  filename: str, title: str
):
    fig, ax = plt.subplots(constrained_layout=True)

    x =
    ↪  prophet_dfs[0][prophet_dfs[0].columns[0]].index
    ↪  + 2024

    co2e_vals = []

    for energy_type in prophet_dfs[0].columns:
        prophet_min = prophet_dfs[0][energy_type]
        prophet_max = prophet_dfs[1][energy_type]
        prophet_y = pd.concat([prophet_min,
        ↪  prophet_max],
        ↪  axis=1).mean(axis=1).values

        monte_carlo_min =
        ↪  monte_carlo_dfs[0][energy_type]
        monte_carlo_max =
        ↪  monte_carlo_dfs[1][energy_type]
        monte_carlo_y = (
            pd.concat([monte_carlo_min,
            ↪  monte_carlo_max],
            ↪  axis=1).mean(axis=1).values
        )

        combined_y = np.mean([prophet_y,
        ↪  monte_carlo_y], axis=0)
        co2e_vals.append(combined_y)

        ax.errorbar(
            x,
            combined_y,
            yerr=[prophet_y, monte_carlo_y],
            label=f"{energy_type}",
            linewidth=1.5,
            elinewidth=1,
            capsize=2,
        )

    co2e_vals = np.array(co2e_vals).sum(axis=0)
    ax.plot(x, co2e_vals, label="Total")

    print(co2e_vals)

    ax.legend(
        loc="upper center",
        bbox_to_anchor=(0.5, -0.18),
        fancybox=True,
        shadow=True,
        ncol=4,
    )
    ax.set_title(title)
    ax.set_ylabel("CO2-e [kt]")
    ax.set_xlabel("Time [years]")
    ax.grid(linewidth=0.5)

    # Make x axis more legible.
    ax.set_xlim([2023, 2051])
    plt.xticks(rotation=45)

    plt.savefig(filename)
```