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Aotearoa-New Zealand's Energy Future: A Model for Industrial Electrification through Renewable Integration

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ABSTRACT

This work explores Aotearoa-New Zealand's potential to fully electrify and source industrial process heat demands from renewable energy for 286 industrial sites while exploring the feasibility of green methanol production using excess electricity. Most energy models rely on spatially aggregated supply and demand, which limits the accurate representation of energy value chains. To address this limitation, the model incorporates industrial sites with varied temperature profiles, enabling the use of diverse heating technologies such as heat pumps, electrode boilers, bubbling fluidised bed reactors and biomass boilers. The proposed Mixed-Integer Linear Programming energy model uses the Accelerated Branch-and-Bound (ABB) algorithm, which is implemented within the P-graph framework to optimise the system. The model considers different energy transportation modes, including road transport for biomass and grid infrastructure for electricity. The multi-period design determines optimal heating technology capacities for each unique industrial site while accounting for renewable energy variability, spot electricity prices, and sectoral energy demand fluctuations. The optimisation results reveal the most effective configurations of heat technologies for industrial sites and projected 1.03 Mt/y of green methanol production in New Zealand when the selling price exceeds NZD1050 /ton (EUR 569 /ton). The findings demonstrate a 41.3% reduction in total process energy supply from 25.9 TWh/year to 18.8 TWh/year, driven by the higher coefficients of performance (COP) and efficiencies of electrification.

Keywords: Energy Systems, Optimization, Energy Management, Hydrogen, Modelling and Simulations

INTRODUCTION

Aotearoa-New Zealand is transitioning toward a net zero, climate resilient future where total energy supply is generated by renewable resources. The government has set aims to eliminate greenhouse gas emissions before the year 2050, with the exception of biogenic methane from agriculture and waste. The Climate Change Commission's demonstration pathway envisions a large-scale transition away from coal and fossil fuels. Under the current plans, the use of coal will be phased out by 2037 and similarly fossil gasses by 2050 [1].

In terms of direct renewable energy use in New Zealand, only 30% of primary energy consumption is supplied by renewables [2]. The hard to abate sectors namely industrial processes are primarily reliant on fossil fuels such as natural gas and coal. Industries such as dairy, meat, chemical, pulp, wood and paper sectors require larger amounts of high temperature heating where it might be prohibitively expensive or infrastructure lacking to be supplied by electrification.

Electricity consumption in New Zealand's industrial sector holds a significant share of the country's total usage. In 2022, New Zealand's industrial sector accounted for approximately 13.7 TWh or 34% of the nation's total electricity consumption. Industrial process heat which encompasses systems such as hot water, direct heat, process steam is responsible for 8.3 Mt of carbon dioxide equivalent emissions annually, where 35% of the nation's total energy use is consumed for process heat [3]. Energy efficiency and switching to low-carbon fuels help reduce the energy needed to provide useful heating. This, in turn, lowers the carbon footprint associated with meeting the heating demand.

A utility system delivers the heating, cooling, and power essential for industrial processes. Renewable energy resources have the potential for the generation of process heat namely direct combustion (e.g. bioenergy) and indirect heating via electrification. Wood energy industrial symbiosis is particularly important to create a circular economy in the forestry and wood processing sector and potentially solving energy problems in industries. Wood processing regions have substantial forestry resources which could potentially alleviate the infrastructure cost of full electrification reducing the need for capacity upgrades and grid reliance [4].

Optimisation models have been generally accepted as the most applied methodology for energy system analysis since 2010 [5]. It is also a robust method due to the inclusion of techno-economic structure and the capability to simulate numerous scenario-based projections which would inherently be important for policy makers to undergo decision making processes. These energy system optimization models (ESOMs) determine the cost-optimal mix of fuels and conversion technologies required to meet energy demand efficiently. Among them, the most prominent ESOMs frameworks are Long-range Energy Alternatives Planning (LEAP), MARKet and Allocation (MARKAL), The Integrated MARKAL-EFOM System (TIMES), Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGEix) [5].

Geographic information system (GIS) has been partially addressed in studies to deal with spatial-related difficulties [6]. Spatial tools are often used to conduct analysis and geographic data processing. GIS is combined with energy system modelling tools such as The Integrated MARKAL-EFOM System [7]. The integration effort demands a variety of parameters and datasets, and increased analytical effort which amplifies the model's complexity, resulting in longer computational run-time.

An alternative approach is to build an energy systems model from a generic modelling framework, such as P-graph connected with ArcPy. The P-graph framework is introduced along with the systematic creation of defined mathematical optimisation models for process synthesis [8]. P-graph has been employed as an energy modelling tool. For example, Aviso et al. have extended the scope of P-graph into macroscale energy systems modelling [9]. Xu et al. investigated the technoeconomic feasibility of converting electricity generated from renewable sources into hydrogen using P-graph [10]. P-graph framework has been popularised in solving large models with low computational power which leads to many hybrid uses of P-graph being carried out. The efficiency of P-graph solvers has encouraged the development of an open-sourced Python library which allows P-graph models to be scaled more seamlessly to build and solve large scale problems more efficiently [11].

The implementation of ArcPy automates the analysis for one or a series of spatial tools for each row of the dataset [12]. For example, Wang has applied ArcPy within the Python environment to process qualitative and quantitative descriptions in the urban building energy model [13]. ArcPy is also used to assess solar generation output for the electrification of transportation [14]. The benefit of ArcPy lies in its extensive range of spatial tools. As such, ArcPy is used to estimate distances across various levels or layers in each successive step. Additionally, ArcPy is used to identify the points of connection assigned to specific generation and factory sites by defining electricity transmission and distribution lines as barrier boundaries.

As noted, existing energy models tend to aggregate industrial heat loads without distinguishing temperature demand profiles resulting in poor resolution and the selection of non-optimal solutions (e.g. boilers instead of heat pumps) [15]. Separating temperature profiles by sector would provide better resolution for evaluating different heating technologies or implementing heat cascading in energy models [16]. However, this also elicits the need to build a new model using a generic framework and packages.

The aim of this research is to develop a national energy transition model, applying the P-graph approach, to assess Aotearoa-New Zealand's potential to achieve net zero in the industrial sector in the future. This includes exploring opportunities to produce high-value, hydrogen-rich compounds, all within the country's resource constraints.

The content of the paper is structured as follows. The context and the scope of the model introduce the extent of the research. In the methods section, it outlines the software implementation and model structure which introduce the application of modelling tools and the approaches which are used to design the structure. The results section presents the configurations of heat technologies in the optimisation model while the conclusions summarise the key findings.

SCOPE OF THE MODEL

The purpose of this model is to identify the most suitable heating technologies which run on renewables resources for every industrial site nationwide using more than 1 GWh/y. These include various classes of industrial heat pumps (HPs) designed for specific thermal profiles, electrode boilers for high-temperature applications, and biomass boilers for using biomass fuels.

Given the research aim involves heat cascading across different plants in Aotearoa-New Zealand, a high level of detail in spatial resolution is essential. Temporal dynamics of industry energy demand is accessed in a monthly time series. The time period is important to take account the intermittent renewable generation which affects the capacity factor of electricity output, monthly average electricity spot price for each point of connection, heat and power demand profiles for industrial, residential and commercial consumption. The analysis covers one year to capture seasonal changes in heating capacity and green methanol production capacity.

METHODS

Software Implementation and Tools

The national energy transition model (NET-Mod) is implemented as Python. Python is a high-level programming language equipped with an extensive range of libraries which is suitable for data analysis and mathematical optimisation. The Python-based model utilised the following libraries: Pgraph, ArcPy and RenewablesNinja.

P-graph Optimisation Model

P-graph is a directed bi-partite graph which consists of two types of vertices: operating units, (O) and material nodes (M^*). The P-graph superstructural model, S comprises three main sets, expressed as $S = (P, R, O)$ where P and R are the subset of set of materials M^*, representing the products and raw materials respectively [8]. Additionally, operating units (O) generate subgraphs (M^*, O) and (O, M^*) to represent the interconnections between two material nodes, incorporating transformation coefficients that define the flow conversion between the connected nodes [9]. The sets and indices in the model are stated in **Table 1**.

Table 1. Sets and indices in the model.

$i, u \in I$: Point of Connections	$t \in T$: Monthly Periods
$j \in J$: Electricity Generation Sites	$(i, u) \in V$: Edges between POCs
$k \in K$: Biomass Supply Sites	$n \in N$: Heating Technologies
$q \in Q$: Temperature Profiles	$l \in L$: Factory Sites
$p \in P$: Electricity Generation Technologies	

In the model, the "raw material" nodes represent the resources supplied to the energy system. These include the electricity generated using technology p at site j at time t, denoted as $E_{j,p,t}$ and biomass resource available at site k at time t, represented by $B_{k,t}$. The "product" nodes define the targets for the energy model, which must be fulfilled for a feasible process network synthesis problem (PNS) solution. The product set includes the temperature profile demand q at site l at time t $(D^{in}_{l,q,t})$, green methanol production at site j (G_j), residential and commercial demand at POC i at time t $(D^{re}_{i,t})$ and electricity curtailment at site j at time t $(H_{j,t})$. The "operating unit" nodes are critical components of the model, influencing costs as well as endogenous and exogenous flows within the system. The elements include electricity generation capacity using technology p at site j $(Cap^e_{j,p})$, methanol plant capacity at site j (Cap^g_j), and heat technology capacity n at industrial site l $(Cap^{ht}_{l,n})$. Additionally, transmission and distribution charges in POC i at time t ,$(T^e_{i,t})$, biomass transport costs from site k to industrial site l at time $t(T^b_{k,l,t})$ and biomass transport costs from site k to electricity generation site j at time t, $(T^b_{k,j,t})$ are included within the set of "operating unit" nodes. The equations defining the sets are:

$$R = \{E_{j,p,t}, B_{k,t}\} \tag{1}$$

$$P = \{D^{in}_{l,q,t}, G_{j,t}, D^{re}_{i,t}, H_{j,t}\} \tag{2}$$

$$O = \{Cap^e_{j,p}, Cap^g_j, Cap^{ht}_{l,n}, T^e_{i,t}, T^b_{k,l,t}, T^b_{k,j,t}\} \cup O' \tag{3}$$

In this work, time step is a crucial factor in the optimisation model, as it determines the sizing of operations.
The optimisation model is formulated in **Equation 4**:

$$\min CC_R + CC_O - CC_P \tag{4}$$

where the total annualised cost is the sum of resource costs (CC_R) and operating units costs (CC_O), subtracting the total revenue or product costs (CC_P).
The detailed cost formulation for CC_R, CC_O and CC_P are outlined in **Equation 5-7**. The symbol C represents a cost function, where the respective subscript and superscript specify costs for different components.
The resource cost is formulated as:

$$CC_R = \sum_{j\in J}\sum_{t\in T}\sum_{p\in P} C^e_{j,p,t} \cdot E_{j,p,t} + \sum_{t\in T}\sum_{k\in K} C^b_k \cdot B_{k,t} \tag{5}$$

The operating cost is outlined as:

$$CC_O = \sum_{j\in J}\sum_{p\in P} C^{cap^e}_{j,p}\, Cap^e_{j,p} + \sum_{j\in J} C^{cap^g}_j\, Cap^g_j + \sum_{l\in L}\sum_{n\in N} C^{ht}_n\, Cap^{ht}_{l,n} + \sum_{t\in T}\sum_{i\in I} C^e\, T^e_{i,t} + \sum_{t\in T}\sum_{k\in K}\sum_{l\in L} C^b\, T^b_{k,l,t} + \sum_{t\in T}\sum_{k\in K}\sum_{j\in J} C^b\, T^b_{k,j,t} \tag{6}$$

The product cost is given by:

$$CC_P = \sum_{t\in T}\sum_{l\in L}\sum_{q\in Q} C^{in}_q D^{in}_{l,q,t} + \sum_{t\in T}\sum_{j\in J} C^g G_{j,t} + \sum_{t\in T}\sum_{i\in I} C^{re} D^{re}_{i,t} + \sum_{t\in T}\sum_{j\in J} C^H H_{j,t} \tag{7}$$

Model Structure

The model comprises five parts: utility generation, transmission, local generation, biomass resources, factory sites, and green methanol plants. **Figure 1** provides a simplified model structure, showing utility-scale generation and green methanol production for a single time step. For local generation, the structure is similar, but the electricity node bypasses transmission and connects directly after distribution charges.

Electricity is generated either at the utility scale or local scale, with the capacity and utilisation factor (or capacity factor) specified. Electricity generated from utility power stations can be delivered to the National Grid by injecting it into the designated points of connection.

Additionally, both utility-scale and local-scale electricity have the option to convert excess electricity into green hydrogen, which serves as a raw ingredient to produce green methanol.

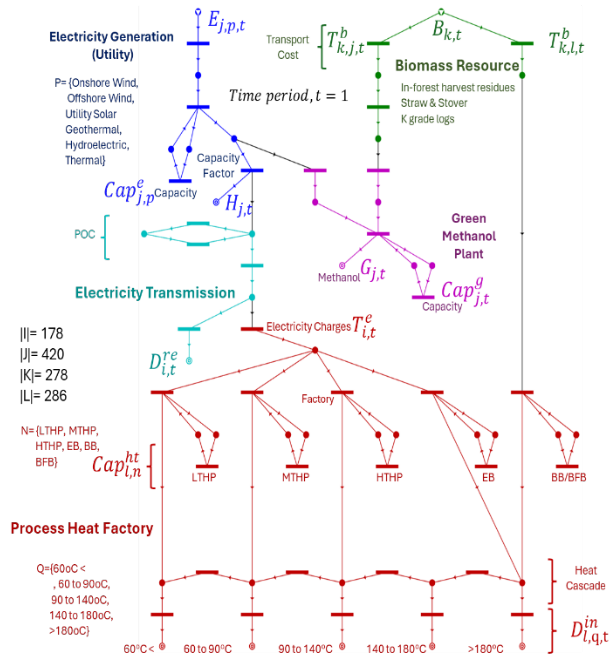

Figure 1. Example of the P-graph structure for the energy model for a single time period, t=1, for one generic industrial site, existing electricity demand at the POC, and one new green methanol plant, all supplied by renewable electricity generation and/or biomass.

Note. POC=point of connection, LTHP=low temperature heat pump, MTHP=medium temperature heat pump, HTHP=high temperature heat pump, EB=electrode boiler, BFB=bubbling fluidised bed reactor, BB=biomass boiler.

The National Grid is interconnected through a network of transmission infrastructure, primarily a series of points of connection. Electricity can flow in two directions but only one direction at a time, necessitating the application of mutual exclusion for each connection. The electricity is then supplied to meet the residual demand of industrial, commercial, and residential consumers. The aggregate electricity demand includes the current industrial electricity demand behind POC nodes, which distinguishes electricity demand from energy demand met by non-renewable fuels. Subsequently, the electrical flow is directed to the respective factories and distributed among four operating units, each representing a different heating technology tailored to specific temperature profiles. Consequently, there will be multiple configurations for each factory across New Zealand.

On the biomass side, three different biomass types are specified, none of which exhibit intermittent characteristics or serve as intermediate commodities for further processing. The biomass resources used in this study are k-grade log wood, in-forest harvest residues as well as straw and stover. Biomass can be directly supplied to factories for high-temperature heating or delivered to prospective green methanol plants as a source of carbon and hydrogen. Since biomass is transported by trailers, there is a direct relationship between transport distance and associated transportation costs. The transport cost is estimated at 0.3 NZD per ton-km.

The NET-Mod comprises 420 electricity generation power stations, which include commissioned, consented, proposed, or under appeal facilities (342 utility-scale and 78 local-scale); 286 industrial sites with an annual process heat demand exceeding 1 GWh; 178 points of connection; 278 biomass sites; 14,956 connections between factories and biomass sites; and 18,980 connections between biomass sites and generation facilities. In total, there are 202031 variables (117021 material nodes and 85010 operating units) and 104210 equations.

Table 2 presents the efficiencies or coefficient of performance (COP) of each heating technology and its respective specifications. It is particularly important for the introduction of heat pumps in industries as it has a higher COP and efficiency when operating in lower temperature, meaning useful energy is supplied to fulfil the load demand in the processes.

Table 2. Specifications of proposed industrial heating technologies.

Tech	Fuel	Temperature (°C)	COP	Cost (NZD /MW·y)
LTHP	Electricity	60<	4.57	342,933
MTHP	Electricity	60-90	2.69	201,399
HTHP	Electricity	90-140	1.73	129,983
EB	Electricity	>180	0.99	7,920
BB	K-log wood, In-forest residue	>140	0.80	83,333
BFB	Straw and Stover	>140	0.70	53,333

RESULTS

The Accelerated Branch and Bound (ABB) solver was executed on an Intel CPU 2.30 GHz i7-12700H processor with 32 GB of RAM. The solver required 60 mins to find the optimal solution. In the solution, 15.9% of process heat energy is sourced from biomass, as indicated by the energy model. This significant share highlights the diverse dependence on various energy sources. The reliance on biomass varies significantly across regions, reflecting disparities in energy resource availability and industrial demand (**Figure 2**). For example, industrial sites in the central and southern part of the South Island heavily rely on bioenergy for process heat, with 55% of the process heat met locally by abundant biomass resources. **Figure 2** illustrates that the Central North Island regions such as Waikato and the Bay of Plenty region also benefit from biomass resource due to their high concentrations of forest plantation-based pulp and paper mills. In contrast, regions such as Northland, Auckland, Taranaki and Wellington region face limited biomass mass availability, resulting in a high dependence on electricity for industrial heat demands, exceeding 95%.

In process heat sectors, **Figure 3** illustrates the heat technologies used in different types of industrial sectors. High-temperature heating technologies not only supply heat to their intended temperature profiles but cascade residual heat to lower-temperature processes, maximising energy utilisation. Although highly efficient heat pumps offer notable benefits, the economic feasibility of biomass boilers, especially in regions with abundant biomass resources, makes them a more practical choice for industrial heating. For instance, the high utilisation of electrode boilers in the Taranaki Region is largely attributed to Methanex, a grey methanol plant. According to the model, a proposed scenario for its future operation involves replacing all heating with electricity while retaining natural gas as a raw material for chemical processes.

Table 3. The energy requirements for industrial process heat by proposed heating technologies.

Heating Technologies	Energy required (TWh/y)
Electricity Total	**15.85**
- LTHP	0.36
- MTHP	1.12
- HTHP	3.29
- EB	11.01
Biomass Total	**2.99**
- BB	2.97
- BFB	0.02

Table 4. Projected green methanol production by region and power generation type (at NZD 1050/tonne).

Zone	Region	Type	Production (kt/y)
UNI	Northland	Geothermal, Wind	839.29
CNI	Waikato	Geothermal, Wind	36.34
LNI	Manawatu-Wanganui	Wind	6.66
CSI	Canterbury	Hydroelectric	152.09
Total Production			**1034.37**

The shift towards combined electrification and increased biomass utilisation has reduced the total process heat demand across industrial sites in New Zealand. Advanced energy technologies, such as heat pumps and electrode boilers, have significantly enhanced energy efficiency. These technologies operate with much higher efficiency, requiring lower input power to deliver the same amount of process heating compared to conventional systems. **Table 3** illustrates the end-user demand fulfilled by each heating technologies. The transition has contributed to a 41.3% reduction in total end-use heating demand, from 25.9 TWh/year to 18.8 TWh/year.

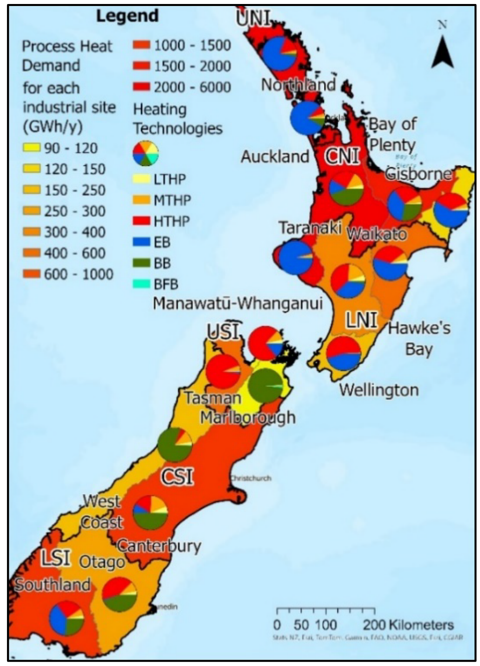

Figure 2. Process heat demand and its respective heating technologies across New Zealand.

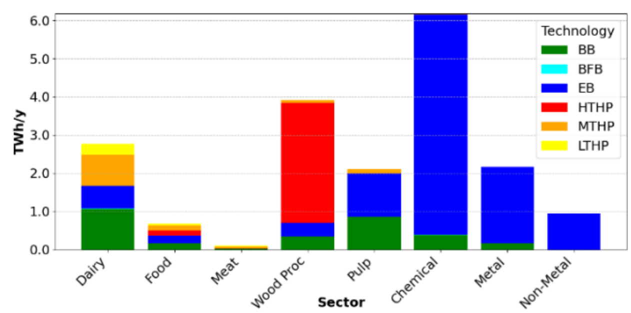

Figure 3. The amount of energy required from heating technologies across industrial sections in New Zealand.

As the model incorporates a new green methanol industry to showcase the potential for sustainable industrial practices in New Zealand, the economic feasibility of this production is influenced by the total capital and fixed operating cost of 180 NZD/tonne whereas the variable operating cost such as electricity and biomass are based on their respective distances and locations [17]. According to the modelling simulation, green methanol becomes profitable when the selling price exceeds NZD 1050/ton. **Table 4** outlines the potential off-grid production of green methanol and its respective power generation type. To produce one tonne of green methanol, the process requires 3.44 MWh of electricity for electrolysis and 4.38 MWh of biomass as carbon and hydrogen sources.

Given the promising path of power-to-fuel technologies, it is vital to access other green hydrogen-based chemical compounds, such as ammonia, urea and sustainable aviation fuel, to meet New Zealand goals to achieve net-zero carbon emissions by 2050.

CONCLUSIONS

The nationwide modelling approach offers an outlook on decarbonising industrial process heat demand with a good firming capacity from biomass and electricity supply. The results indicate a reduction in industrial energy supply from 25.9 TWh/year to 18.8 TWh/year within national resource constraints. Additionally, a green methanol economy is feasible in specific regions of New Zealand where surplus electricity and biomass resources are available, provided the selling price exceeds NZD1050/tonne. The utilisation of the open-source P-graph framework enables users to conduct custom analysis on site specific modelling studies by modifying and customising key parameters.

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