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Identifying and evaluating symbiotic opportunities for wood processing through techno-economic superstructure optimisation – A methodology and case study for the Kawerau industrial cluster in New Zealand

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ABSTRACT

In this paper we present a generalised and systematic decision support methodology and tool to identify and evaluate options for facilitated symbiotic development of industrial clusters. Our approach is developed with insight and feedback from industry, community and Government stakeholders of the Kawerau industrial site in New Zealand to support early stage engagement of diverse stakeholders. The methodology integrates cluster design by superstructure optimisation, the WoodScape techno-economic analysis methodology and Monte Carlo simulation to provide a range of metrics for investment profitability, macroeconomics and environmental impact to suit diverse stakeholder needs. The novelty of the methodology lies in the flexibility of its modular formulation using demand driven models for industrial plants at an appropriately reduced complexity and using recent advances in optimisation technology. Impact of key uncertainties are assessed through post optimisation Monte Carlo simulations. The methodology is applied to three case studies to identify and evaluate new wood processing opportunities for the Kawerau site. The methodology is formulated to be general and can be applied to other industrial clusters.

1. Introduction

1.1. Industrial symbiosis

Industrial Symbiosis (IS) is a useful concept that draws analogies from symbiotic interactions among organisms in natural ecosystems to develop industrial ecosystems, whereby business-to-business relationships mimic nature to shift from a linear, to a less wasteful more circular economy (Baldassarre et al., 2019; Ehrenfeld, 2004; Marchi et al., 2017). The principle ideas of IS are to take a systems approach to (i) integrate firms as a synergistic network of interacting and more sustainable industrial systems; (ii) optimise energy and material cycles to minimise waste and to provide business opportunities for underutilised resources (materials, energy, capacity, expertise, infrastructure, services, etc); and (iii) drive innovation and economic development, enabled by cross-sectoral knowledge transfer (Baldassarre et al., 2019; Lombardi and Laybourn, 2012). Firms in such an industrial system can achieve competitive advantages through greater economies of scale, reduced costs and being able to achieve optimisations that are not realisable as individual firms (Marchi et al., 2017). Further opportunities to increase competitiveness include diversification of product portfolios, process innovations and risk management (Kuznetsova et al., 2016; Lombardi and Laybourn, 2012).

The scope for industrial symbiosis become technically more feasible when diverse firms are co-located within proximity. This is partly because transport cost scales with transport distance, but also by exchanging by-products and sharing infrastructure and utilities such as energy and waste treatment. A prominent example of successful IS within geographic proximity is that of Kalundborg (Denmark), where a diverse group of companies collaborated to reduce costs and improve efficiency in waste management and freshwater use. The spontaneous (self-organised) emergence and successful symbiosis at Kalundborg was mainly driven by rational business interests (Ehrenfeld and Chertow, 2002).

1.2. Identifying and quantifying new symbiosis opportunities

Natural evolution through rational business transactions is not the only route to successful IS. The Ulsan Eco-Industrial Park (Korea)

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List of abbreviations

CAPEX	Capital expenditure
CDF	Cumulative probability density function
CF	Cashflow
CFBT	Cashflow before tax
CHP	Combined heat and power
CTR	Commercial tax rate
DC	Depreciation costs
DCFA	Discounted cashflow analysis
DVA	Direct value added
DE	Direct employment
MVA	Multiplier for value added
MDE	Multiplier for direct employment
EBITDA	Earnings before interest, tax, depreciation and amortisation
EBIT	Earnings before interest and tax
FC	Fixed costs
FCI	Fixed capital investments
FTE	Fulltime equivalent employment
GDP	Gross domestic product
GHG	Greenhouse gas
GTPP	Geothermal power plant
HP	High pressure
IRR	Internal rate of return
IS	Industrial symbiosis
ISM	Industrial sawmill
ITR	Income tax rate
ITREV	Income tax revenue
KPM	Kraft pulp mill
LC	Labour costs
LY	Log yard
LP	Low pressure
MC	Maintenance costs
MADS	Mesh adaptive direct search
MCS	Monte Carlo simulation
MDF	Medium density fibre board
MILP	Mixed integer linear programming
MIND	Method for analysis of industrial energy systems
MINLP	Mixed integer non-linear programming
MP	Medium pressure
NOMAD	Non-linear optimisation with the MADS algorithm
NPM	Newsprint mill
NPV	Net present value
NZ	New Zealand
odt	Oven-dry tonne
OEL™	Optimised engineered lumber
OFC	Other fixed costs
OPEX	Operating expenditure
OPTI	Optimisation inteface
PDF	Probability density function
PI	Profitability index
REV	Revenue (gross)
RFR	Risk-free rate of return
ROCE	Return on capital employed
SR	Sharpe ratio
SSM	Structural sawmill
TEA	Techno-economic analysis
TPM	Tissue paper mill
UP	Unit price
US	United States
VC	Variable costs
WC	Working capital costs

(Behera et al., 2012) developed through top-down strategic planning. At Kwinana, Australia (Van Beers et al., 2007) synergies in the mineral industry developed through a facilitated deployment approach that is a combination of self-organised and planned approaches (Chertow and Ehrenfeld, 2012).

In all of these approaches, the economic driver remains prominent and universal (Kastner et al., 2015). The ability to identify symbiotic opportunities, quantify their economic and environmental benefits and express them as sound business cases that can be effectively communicated to decision makers, is therefore critically important to catalyse and facilitate IS investment (Behera et al., 2012). Model based decision support tools can play a key role in achieving this. Several studies have reviewed recent developments in quantitative tools and methods for designing and facilitating symbiosis in industrial clusters (e.g. Baldassarre et al., 2019; Boix et al., 2015; Kastner et al., 2015; Lawal et al., 2020).

Among the practical challenges that still remain for rapid identification and techno-economic assessment (TEA) of IS opportunities is the hierarchy of scales involved, ranging from unit-processes, to multi-unit-process plants, through to the interconnected network of plants and utility systems that make up a complex industrial system-of-systems (Duflou et al., 2012; Pan et al., 2016). At the unit-process and plant levels, process simulators (e.g. Aspen Plus®) can be used in solving process design, retrofit and process optimisation problems (Karlsson and Wolf, 2008). However, such process simulation models are expensive, time-consuming to develop and add to the complexity of the full system model. In developing decision support tools to identify and evaluate IS options, emphasis on process simulation is only expected to have marginal benefit. This is mainly because process simulation predicts only the behaviour of a given plant or system configuration once it is implemented and is one of the last steps in decision-making (Diwekar and Shastri, 2010; Karlsson and Wolf, 2008). In this case, simplified models combining heuristic methods, thermodynamic principles, mass and energy balances at the plant level could be used for the purposes of input-output matching as well as thermo-economic assessments such as valuing utility heat streams of different quality (Valero et al., 2013). Such models can then be used in conjunction with well-established methods for systems analysis such as simulation or optimisation. Mathematical programming optimisation is particularly suited to problems of structural optimisation. One example is the MIND (Method for analysis of INDustrial energy systems) decision support tool based on a MILP (Mixed Integer Linear Programming) formulation. The MIND method has been used to study cost optimal system configurations in the Swedish forest industry, among other applications (Karlsson, 2011; Karlsson and Wolf, 2008).

Further challenges to model development can stem from the diversity of stakeholders such as Government or a regional Council acting as an IS facilitator, incumbent industrial firms and potential new entrants to the industrial cluster. Decision making can then be driven by more diverse objectives beyond just cost optimal resource matching. For example, reduction in greenhouse gas (GHG) emission, regional impact (e.g. job creation), security of feedstock supply for incumbent firms or risks inherent to the investment case such as price volatility.

Addressing these challenges using a MILP formulation would pose difficulties due to non-linearities inherent to such systems (e.g. plant cost scaling with production capacity), or to allow flexibility to incorporate non-linear constraints. A MINLP (Mixed Integer Non-linear Programming) formulation (Grossmann, 1990) that combine MILP and nonlinear programming can circumvent some of these difficulties. This would provide improved accuracy, but at the expense of computational complexity and concerns around globality of solutions (Kantor et al., 2015). However, recent advances in the field of MINLP and constrained derivative-free optimisation has made formulating mathematical models suitable for MINLP optimisation realistic for real-world applications (Boukouvala et al., 2016).

The WoodScape methodology is widely used in the New Zealand forestry industry to analyse the potential of traditional and emerging wood processing technologies (Hall, 2016). It can provide a basis for both the formulation of plant models at reduced computational complexity suited to an optimisation formulation for IS as well as TEA, including macroeconomic impact (Barry and Hall, 2014).

The purpose of this paper is twofold: (1) To present a flexible and systematic decision support framework to quickly identify and evaluate IS opportunities in clusters. The framework will address, to varying degrees, key issues such as techno-economics, GHG emissions, macroeconomic impacts, resource constraints, operational constraints and risk to profitability through post optimisation Monte Carlo simulation (Peters, 2007). (2) To demonstrate a proof-of-concept for the presented methodology by applying it to a case study to identify and evaluate new wood processing opportunities at New Zealand's only major IS cluster, a wood processing cluster located in the district of Kawerau. A brief description of the Kawarau industrial cluster is provided for context in the following section.

The novelty of this work lies in the flexibility of its modular formulation using demand driven models for industrial plants at an appropriately reduced complexity and applying recent advances in optimisation technology for structural optimisation. This is useful for stakeholder engaged planning by identifying new configurations for different objectives. Impact of key uncertainties are assessed through post optimisation Monte Carlo simulations.

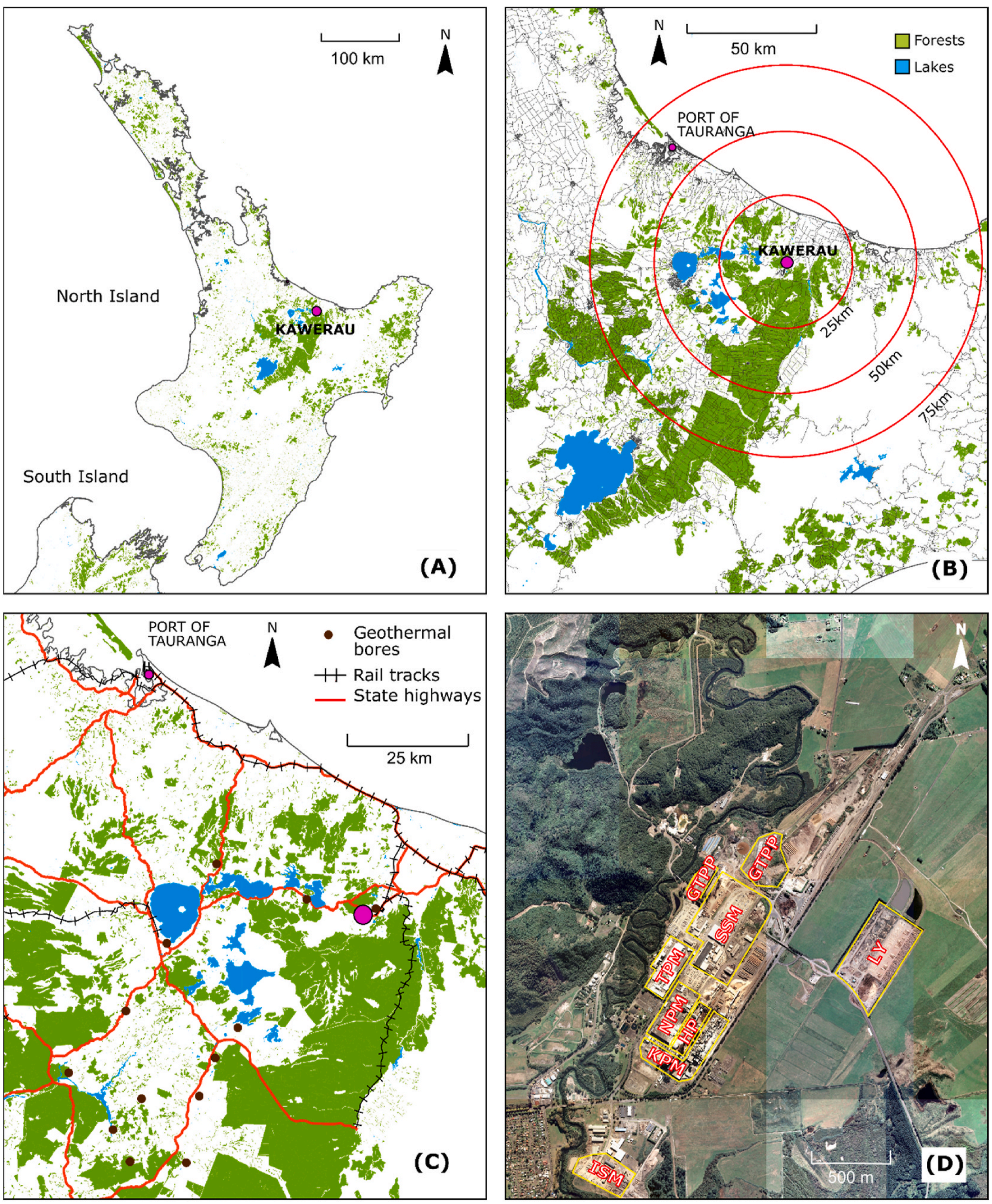

Fig. 1. The Kawerau Industrial cluster: (A) Location in New Zealand's North Island; (B) Plantation forest resource; (C) Rail and state highway network and geothermal wells; (D) Layout of major plants within the cluster (background aerial images are used under a Creative Commons Attribution 4.0 International licence (Land Information New Zealand., 2017)).

2. Kawerau wood processing cluster

2.1. Major existing plants

Kawerau, located in the Bay of Plenty region of New Zealand's North Island, is the site of the world's largest geothermal-fuelled wood processing cluster (Fig. 1(A)). The main industrial processing units within this cluster are: (1) a log yard (LY) with stem to log processing of ~1 Mm^3 per annum producing 40k green tonnes of residue per annum; (2) an industrial sawmill (ISM) nominally producing ~54k odt/y (oven-dry tonnes per year) of packaging lumber (3) a structural sawmill (SSM) nominally producing 134k odt/y of structural lumber; (4) a market kraft pulp mill (KPM) nominally producing 243k odt/y of pulp; (5) a newsprint mill (NPM) producing 121k odt/y of newsprint paper; (6) a tissue paper mill (TPM) nominally producing 44k odt/y of tissue paper; and (7) a number of geothermal power plants (GTPP) with a combined installed capacity of ~130 MW electricity. These figures are from data gathered in 2016. It should be noted that this cluster is continually evolving as the different plants in the cluster make changes to their operations. The general layout of these major plants at the site is shown in Fig. 1(D).

There is already significant industrial symbiosis within the cluster. Key material and energy exchange links are illustrated schematically in Fig. 2. Wood chip produced by the two sawmills within the cluster contribute to the total feedstock supply to both pulp mills with total demand being met by additional chip derived from pulp logs imported into the cluster from nearby plantation forests and associated log yards. The two pulp mills share a common combined heat and power (CHP) utility system that provides clean steam generated through a combination geothermal heat and biomass fired boilers. Electricity generated by the CHP plant and other geothermal power plants within and near the cluster feeds into the electric power grid at the site. Residues from the sawmills also contribute to the total heat demand of the KPM.

2.2. Wood, residue and geothermal resources

Fig. 1(B) shows a map of forests in proximity to the Kawerau and Fig. 1(C) shows state highways and railway infrastructure available for transport of wood and residue resources. The forests provide a variable wood supply over time. There are also significant log and post-harvest in-forest residues adjacent to Kawerau that are currently either exported unprocessed (logs) or left in the forest unused (post-harvest residues) that could be processed in Kawerau. In the case of the logs they pass through Kawerau on their way to the Port of Tauranga for export. There is significant wood supply potentially available above that already consumed by the cluster.

Kawerau also has significant geothermal energy resources (see Fig. 1 (C)). The current geothermal energy production is estimated at ~1000 GWh/year as electricity and ~1500 GWh/y as direct heat use (White, 2006). There is additional geothermal heat available from the geothermal field that could be exploited (estimated at up to 3000 GWh/y).

2.3. New wood processing opportunities

Given the considerable forestry and geothermal resources, there is a real opportunity for further industrial symbiosis in such an integrated site by combining primary (e.g. logs to lumber etc) and secondary (e.g. sawdust to wood pellets) wood processing in innovative ways to make better use of biomass within the existing infrastructure and to create new business opportunities. Wood processing is typically energy-intensive and wood residue are normally burnt to provide the process energy needed. Cheaper geothermal energy which is available at Kawerau can be used to free up wood residues for conversion into other more profitable products or reduce embodied GHG emission from products.

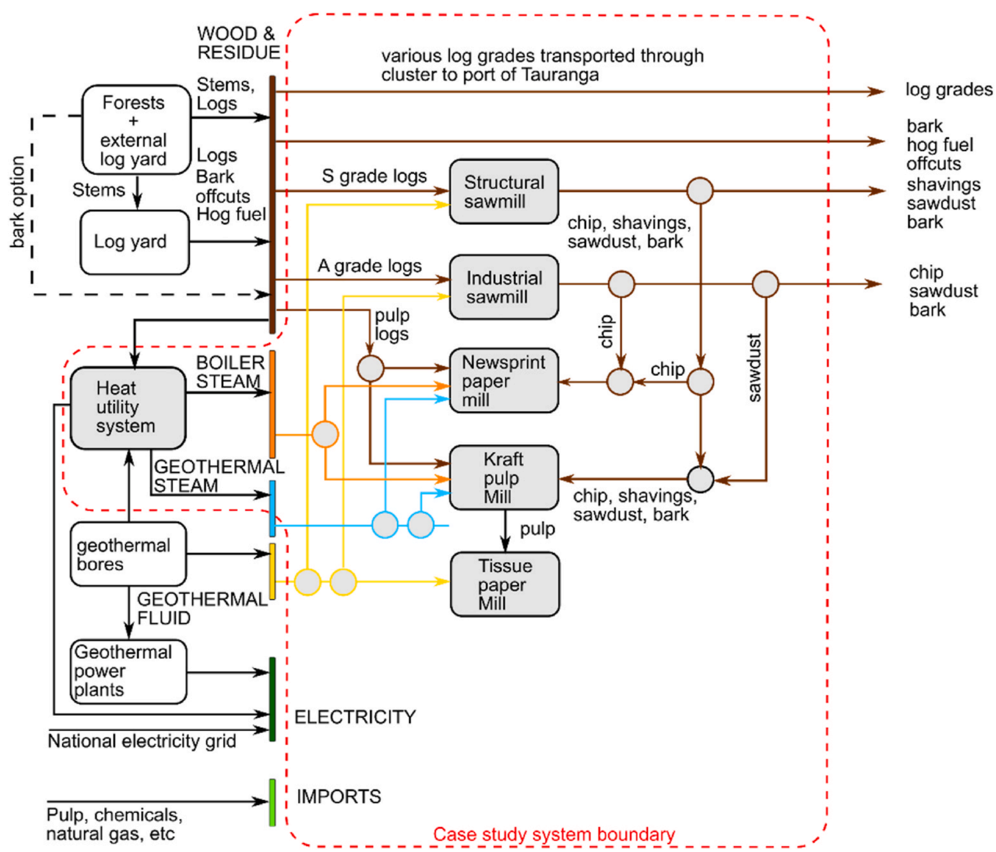

Fig. 2. Key material and energy transfer links within the Kawerau wood processing cluster.

3. Methodology

3.1. Overview of decision support framework

One of the key contributions of this work is to provide a generalised decision support methodology that is flexible enough to address diverse assessment needs and strike a balance between model complexity, accuracy and rapid deployment for "what if?" analysis. The approach centres around a demand driven modular formulation of techno-economic models for individual plants, simplified through a fit for purpose combination of unit process level and heuristic models based on key plant data. This is illustrated schematically in Fig. 3(A).

The methodology proceeds through several steps as illustrated schematically in Fig. 3(B). Details of these steps are given in the following subsections.

3.2. Plant models

Each plant model is standardised in terms of input and output streams as shown in Fig. 4. Here $\overline{\mathbf{X}} = [\mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_i, \cdots, \mathbf{X}_N]$ are a collection of N input material flow streams entering the plant, with each flow stream of material i denoted by $\mathbf{X}_i$ consisting of J sub-streams such that $\mathbf{X}_i = [X_{i,1}, X_{i,2}, \cdots, X_{i,j}, \cdots, X_{i,J}]$. Here sub-stream $j = 1$ is reserved to represent mass flow of material i. Similarly, $\overline{\mathbf{Y}}$ are a collection of plant output (product) material flow streams $\mathbf{Y}_i$ each consisting of sub-streams $Y_{i,j}$.

The material flow for each input material i is split into import streams and local streams. The left superscripts I denotes import streams which are material flows sourced from outside the boundaries of the cluster. The left superscript L denotes local streams which are sourced from within the cluster boundary. Thus, the total material flow of the j^{th} sub-stream of a material i into a plant is given by $X_{i,j} = {}^{I}X_{i,j} + {}^{L}X_{i,j}$, and the special case of mass flow of material i is given by $X_{i,1} = {}^{I}X_{i,1} + {}^{L}X_{i,1}$. Similarly, the material flow of each output material i is split into local streams and export streams. In this case the left superscript E denotes export streams which exits the cluster boundary. The left superscript L denotes products or by-products that are deposited within the cluster boundaries for access by other plants within the cluster. The total mass of product material i is given by $Y_{i,1} = {}^{L}Y_{i,1} + {}^{E}Y_{i,1}$.

In Fig. 4, $\overline{\mathbf{W}}$ denotes work streams. In this paper, this represents net electrical power consumption, with the convention that a negative value represents surplus power generation. Other energy streams such as natural gas for heat or geothermal steam are treated as material streams for which demand is calculated within the process model based on the quality (temperature) of the heat stream required for the given process. The thermodynamic properties such as enthalpy of these material streams are estimated using equations of states from the CoolProp thermodynamic properties package (Bell et al., 2014) and used to estimate any heating and cooling utility demands for the plant process.

The plant models and subsequent optimisation and Monte Carlo analyses are implemented in the MATLAB® numerical computing environment. The plant models are formulated as demand driven models of the form

$$\left[{}^{E}\overline{\mathbf{Y}}, {}^{L}\overline{\mathbf{Y}}, {}^{I}\overline{\mathbf{X}}, {}^{L}\overline{\mathbf{X}}, \overline{\mathbf{W}}\right] = \mathbf{f}_p(\mathbf{d}) \tag{1}$$

Where $\mathbf{f}_p$ denotes a vector-valued function encapsulating the process model of the p^{th} plant in the cluster, and the input argument $\mathbf{d} = [d_1, d_2, \cdots, d_K]$ is a vector of decision variables. The first 4 decision variables d_1 through d_4 are standardised as follows.

The decision variable d_1 is a binary variable such that if $d_1 = 0$, then $\mathbf{f}_p(\mathbf{d}) = 0$ but has no effect on $\mathbf{f}_p(\mathbf{d})$ when $d_1 = 1$. This represents the possibility that a plant operation can be introduced into or removed from the cluster. d_2 is a continuous variable defined to be equal to the total required rate of production of the primary product from the plant. Adopting the convention that $\overline{Y}_1$ represents the primary product, this means $Y_{1,1} \equiv d_2$. In Fig. 4, $\alpha_i \equiv d_3$ is the mass fraction of resource material i used by the plant that is imported into the cluster. Then the remaining fraction $(1 - \alpha_i)$ is the amount that is sourced locally from the cluster. Similarly, $\beta_i \equiv d_4$ is the mass fraction of product material i that is exported out of the cluster. The remaining fraction $(1 - \beta_i)$ is deposited within the cluster for local use by other plants.

An exemplar of the level of aggregation and detail expressed by the flexible demand-driven plant process model is shown in Fig. 5 which represents a kraft pulp mill.

The exemplar in Fig. 5 shows eight input material streams $\mathbf{X}_1$ through $\mathbf{X}_8$, three product streams $\mathbf{Y}_1$ through $\mathbf{Y}_3$ and one work stream $\mathbf{W}_1$. For the purposes of techno-economic analysis, the complex kraft

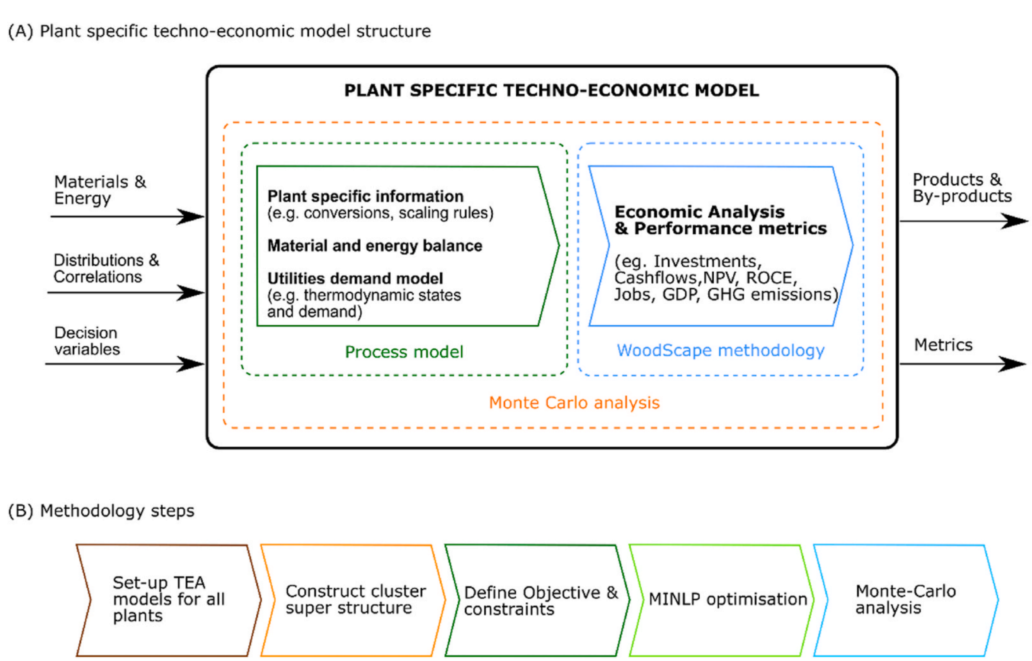

Fig. 3. (A) Model structure. (B) Methodology steps.

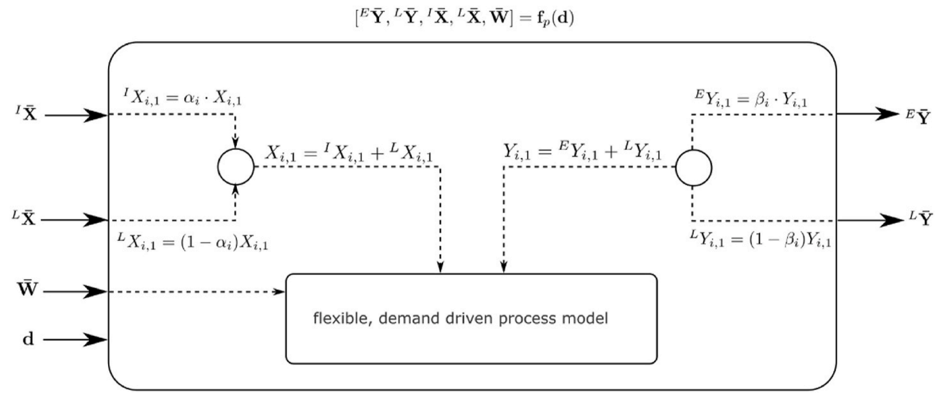

Fig. 4. Input and output standardisation for plant process models.

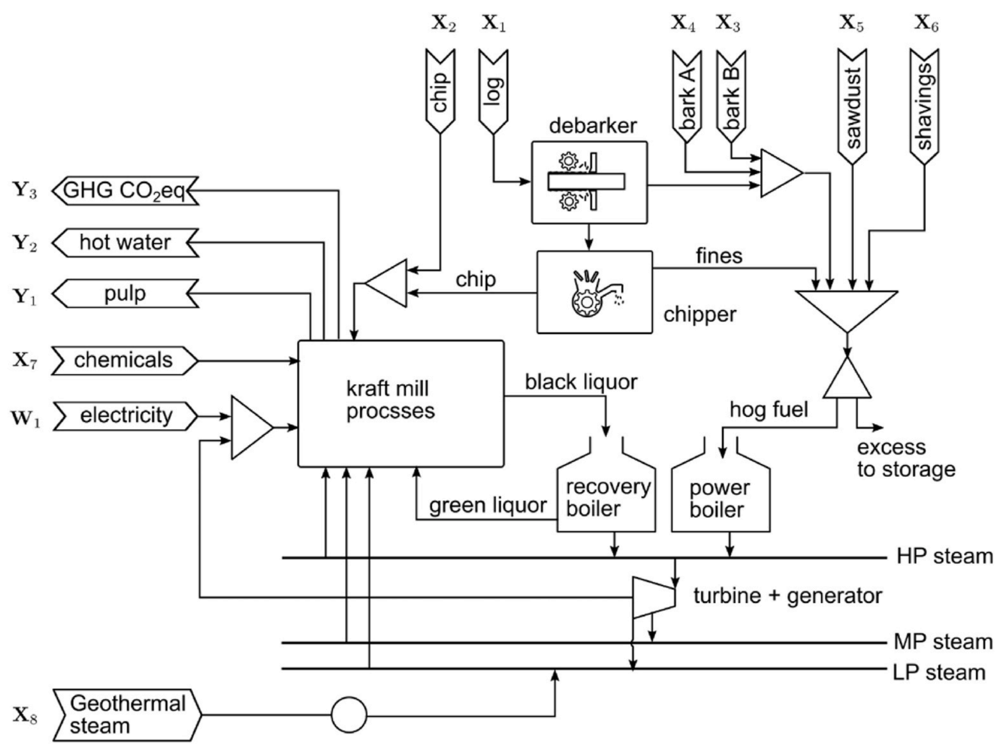

Fig. 5. Exemplar process.

processes are represented by a simplified block with yield conversion factors using pulp production rate as a basis. This allows simple and rapid back calculation of the resource requirements $\mathbf{X}_1$ to $\mathbf{X}_8$ and $\mathbf{W}_1$, as well as secondary products $\mathbf{Y}_2$ and $\mathbf{Y}_3$ for any specified demand on the primary product $\mathbf{Y}_1$. The utility system is treated with more detail based on the requirement of the temperature and pressure of high pressure (HP), medium pressure (MP) and low pressure (LP) steam in order to provide enough granularity to distinguish between the cost of steam of different qualities. Expressing the plant function $\mathbf{f}_p(\mathbf{d})$ procedurally in a programming language provides the flexibility to easily include heuristics specific to a given plant operation based on expert knowledge.

3.3. Techno-economics and performance metrics

The TEA is based on a combination of WoodScape methodology (Hall, 2016; Jack et al., 2013) and discounted cashflow analysis (DCFA) (Bejan and Moran, 1996). Once the plant function $\mathbf{f}_p(\mathbf{d})$ is evaluated for a given production rate, all the necessary material and energy flow streams become available for the DCFA. These flow streams are standardised as annual flow rates, and cash flows determined using unit prices for the flow streams. The following performance metrics are then determined from a TEA (Details are provided in Appendix A.1).

- *EBITDA* – Earnings before interest, tax, depreciation and amortisation, which is a measure of operational profits.
- *EBIT* – Earnings before interest and tax, is useful for high capital investments, and is estimated by adopting the straight-line depreciation method and assuming no salvage value or amortisation costs.
- *NPV* – Net present value, is a projection of earnings that will be generated by the investment over its lifetime.
- *IRR* – Internal rate of return for the investment, is often a useful metric that assesses the desirability of an investment by comparison against a company's required rate of return.
- *ROCE* – Return on capital employed, is a useful measure of profitability and capital use efficiency.
- *PI* – Profitability index, which is a measure of the value created per unit of investment. $PI = 1$ represents a breakeven scenario, $PI < 1$ a loss, and $PI > 1$ a profitable investment.

The Authors' experience with Kawerau stakeholders, including business, district council and Government stakeholders, has been that there is variation in the preferred metrics for assessing IS opportunities. The project financial metrics listed above were motivated by these needs. Further to these, business stakeholders required metrics that account for risks posed by price and currency exchange rate volatilities, whereas district council and Government stakeholders were also keen to understand macroeconomic as well as environmental impacts.

The environmental impact metric in this work is GHG emission on a CO_2 equivalent basis. These are embedded in the plant models as an emissions flow stream, calculated using emission factors corresponding to energy use specific to each plant. This is considered as a variable cost stream in the DCFA. Details are given in Appendix A.1.

The WoodScape methodology provides for the estimation of three macroeconomic impact metrics that would result from investment projects:

- ΔGDP – contribution to gross domestic product (*GDP*),
- ΔFTE – additional full-time-equivalent employment (*FTE*), and
- $\Delta ITREV$ – additional income tax revenue (*ITREV*).

This methodology is based on economic multipliers. These are industrial sector-specific numbers derived from economic data or statistical models of a national or regional economy, that estimate wider impacts of local economic changes. These multipliers arise from linkages and interactions of the local export sector, businesses and households in the community. They include multipliers for direct effects to firms that export additional goods and services, indirect effects to firms that supply the exporting firm, and induced effects from household spending in the community (Dixon et al., 2012; Miller, 2017). Details are given in Appendix A.2.

To facilitate decision making under uncertainty, a Monte Carlo simulation (MCS) approach (Harrison, 2010) is adopted. The approach involves: (1) an input-output representation of the deterministic model system whereby uncertain variables are designated as inputs and decision metrics are designated as outputs; (2) representing the uncertain variables as probability density functions (*PDF*) which may be correlated; and (3) repeatedly evaluating the model function using random sampling from these distributions to generate output distributions. This approach is superior to a traditional sensitivity analysis over a limited range of parameters since the output distributions provide a complete picture of the range of possible outputs and their probability of occurrence. The deterministic input-output relation for the techno-economics of candidate plants can be constructed as a parametric function by a composition of the metrics defined above with the plant function $\mathbf{f}_p(\mathbf{d})$ as follows,

$$Z_i = \mathbf{g}_p\left(\mathbf{f}_p(\mathbf{d}), p_j\right), \tag{2}$$

Where $\mathbf{g}_p$ defines the TEA model function for plant p, Z_i are the set of scalar decision metrics that require risk assessment, and p_j is the set of uncertain parameters (e.g. currency exchange rate) that influence the metrics Z_i. The MCS scheme is then as illustrated schematically in Fig. 6.

The correlated *PDF*s of uncertain parameters are obtained by fitting an appropriate distribution to historical data and determining the Spearman ranked correlation coefficients between the parameters. When sufficient data is not available, a reasonable distribution is estimated based on industry knowledge of nominal and extreme values. The distributions are sampled using the latin hypercube method which converges faster than normal random sampling (McKay et al., 2000).

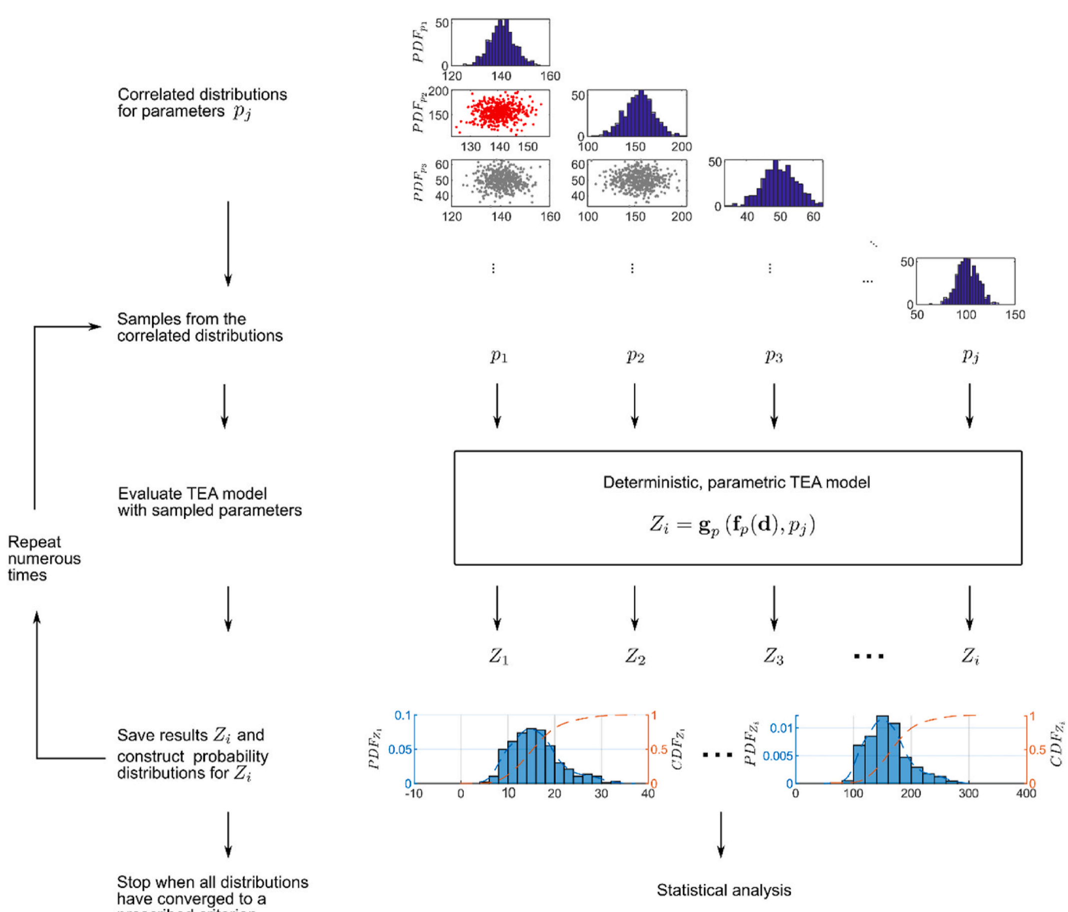

Fig. 6. Monte Carlo simulation scheme.

The convergence criterion is that the changes in mean values, the standard deviations and average percentiles are all below 1% for all computed distributions over three consecutive iterations. The sample size is variable and determined by iteratively increasing the number of samples until this convergence criterion is met. Summary statistics for the decision metrics such as the expectation values, standard deviations, or confidence intervals can be determined from the converged *PDF*s and *CDF*s (cumulative probability density function).

An important reason for the Kawerau stakeholder's interest in MCS is the volatility of currency exchange rate, as many export prices are priced in US$. In this case the best investment opportunity may not be those with the highest returns. A better metric of favourability for investment is the Sharpe ratio (*SR*). This is a measure of the returns on investment to volatility ratio (Lo, 2002). This ratio can be deduced from MCS results, and is defined as follows,

$$SR = \frac{\langle ROCE \rangle - RFR}{\text{standard deviation of } ROCE} \tag{3}$$

Where $\langle \cdot \rangle$ denotes expectation value and *RFR* is the risk-free rate of return, which is assumed to be the New Zealand Government treasury bond yield rate (2.48% pa, in October 2016).

3.4. Cluster superstructure

The approach taken for conceptual cluster design is that of synthesis by superstructure optimisation (Chen and Grossmann, 2017; Umeda et al., 1972). This is considered superior to the alternative hierarchical decision approach (Douglas, 1985) for synthesis which involve sequential stages of design and evaluation, in two important ways: (1) The superstructure approach systematically evaluates a large number of alternative structures; (2) The hierarchical approach cannot readily capture the interactions between decision criteria during various stages of design and evaluation, whereas the supercluster approach can do so because it solves the simultaneous design problem as a mathematical optimisation problem (Mencarelli et al., 2020).

Fig. 7 illustrates how the formulation of the TEA models can be used to generate a superstructure.

The method proceeds by starting with TEA models for the collection of plants that already exists within the cluster. This collection is then expanded by adding models for several plausible plant opportunities to construct a superstructure of alternatives in a network that is linked by mass and energy balance at a collection of nodes. Two main type of nodes are distinguished: (1) import nodes ${}^{I}N_i$ for each resource *i* which are received at the node from sources external to the boundary of the cluster. (2) local nodes ${}^{L}N_i$, each of which receives resource *i* from all plants that produce the resource and supplies it to all plants that require it. Either of these node types can be further distinguished based on whether the resource exchanged is a material resource that is required as a feedstock (e.g. wood chip) or whether it is a resource that serves as an energy carrier (e.g. electricity or geothermal steam). Denoting these distinctions by a left subscript *M* or *E* to represent material and energy resources respectively, the supercluster is established by the following set of nodal balance equations.

For local nodes, mass balance for a material resource *i* is expressed as the difference between all the supplies of mass to the node and all demands from that node, which gives the excess supply at the node as,

$${}^{L}_{M}e_i = \sum_{\substack{\forall \text{ local} \\ \text{suppliers } j}} {}^{L}_{M}s_{i,j} - \sum_{\substack{\forall \text{ local} \\ \text{demands } k}} {}^{L}_{M}d_{i,k} \tag{4}$$

For local nodes, energy balance for an energy resource *i* is expressed as the difference between all the supplies of energy to the node and all demands from that node, which gives the excess supply at the node as,

$${}^{L}_{E}e_i = \sum_{\substack{\forall \text{ local} \\ \text{suppliers } j}} {}^{L}_{E}s_{i,j} - \sum_{\substack{\forall \text{ local} \\ \text{demands } k}} {}^{L}_{E}d_{i,k} \tag{5}$$

Similarly, for import nodes the excess supply of material resource *i* is given by,

$${}^{I}_{M}e_i = \sum_{\substack{\forall \text{ external} \\ \text{suppliers } j}} {}^{I}_{M}s_{i,j} - \sum_{\substack{\forall \text{ local} \\ \text{demands } k}} {}^{I}_{M}d_{i,k} \tag{6}$$

and for import nodes, the excess supply of energy balances,

$${}^{I}_{E}e_i = \sum_{\substack{\forall \text{ external} \\ \text{suppliers } j}} {}^{I}_{E}s_{i,j} - \sum_{\substack{\forall \text{ local} \\ \text{demands } k}} {}^{I}_{E}d_{i,k} \tag{7}$$

In equations (4)–(7), the quantity $s_{i,j}$ denotes a supply of resource *i to* a node ${}^{I}N_i$ or ${}^{L}N_i$ unique to that resource type *from* a source *j* (local plant or import) and the quantity $d_{i,j}$ denotes a demand for the resource from a sink *j* (plant). The quantity e_i therefore represents the excess supply at nodes (see Fig. 7). All three quantities have units of either mass or energy depending on whether the resource is a material feedstock or an energy resource, respectively.

3.5. MINLP optimisation

The final step in identifying an optimal configuration that incorporates new opportunities is to specify an objective function and hence formulate the optimisation problem with appropriate constraints

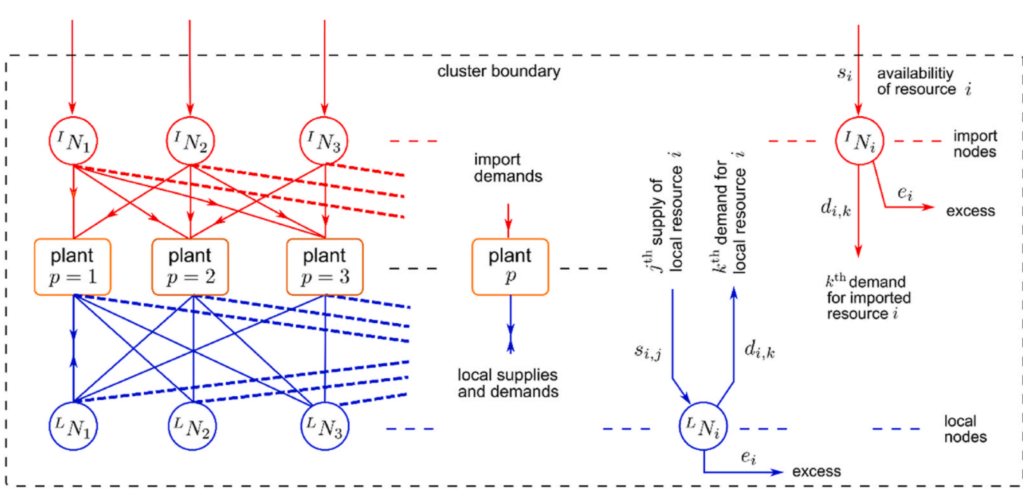

Fig. 7. Schematic of generalised superstructure network.

that is amenable to optimisation algorithms. An important insight from multi-stakeholder engagement is that there is diversity in what may be considered optimal. Such diversity may arise for purely business economic reasons or concern for broader social and environmental impacts, purely technical constraints such as risk associated with process modification for symbiotic exchanges or general aversion to risk. The modular approach taken in this work using demand-driven process and TEA models provides the flexibility to swap different objective functions with relative ease and allow assessments from different perspectives. The objective function takes the form

$$Z_{obj} = F_{\mathrm{obj}}(\mathbf{x}) \equiv F_{obj}\left(\mathbf{g}_p\left(\mathbf{f}_p(\mathbf{d}), p_j\right)\right) \tag{8}$$

Where F_{obj} is a scalar function and Z_{obj} is the performance metric to be minimised or maximised. For example, Z_{obj} could be total GHG emissions that need to be minimised or total GDP contribution that needs to be maximised. It is clear that F_{obj} will be non-linear (e.g. see equation (A.6)). Furthermore, the decision variables $\mathbf{x}$ include both continuous variables such as plant production rates and binary integer variables that effect the inclusion or exclusion of a plant option in the cluster. Therefore, mixed integer non-linear programming becomes the appropriate formulation of the optimisation problem, and has the form,

$$\min_{\mathbf{x}} F_{obj}(\mathbf{x})$$

Such that

$$\mathbf{L}_{\mathrm{b}} \leq \mathbf{x} \leq \mathbf{U}_{\mathrm{b}}$$

$$\mathbf{c}(\mathbf{x}) \leq \mathbf{b}$$

$$\mathbf{c}_{\mathrm{eq}}(\mathbf{x}) = \mathbf{b}_{\mathrm{eq}}$$

$$x_i \in \mathbb{R},\ x_j \in \{1, 0\} \tag{9}$$

Where the inequality constraints $\mathbf{c}(\mathbf{x}) \leq \mathbf{b}$ at a minimum includes the non-negativity constraints ${}^{L}_{M}e_i \geq 0$, ${}^{L}_{E}e_i \geq 0$, ${}^{I}_{M}e_i \geq 0$, and ${}^{I}_{E}e_i \geq 0$ that enforces the physical requirement that no node can supply resources in excess of what it receives. The lower bounds $\mathbf{L}_{\mathrm{b}}$ and upper bounds $\mathbf{U}_{\mathrm{b}}$ constraints enforce resource supply limits. The equality constraints enforce physical relations such as mass balances. The optimisation problem is solved using the NOMAD algorithm (Le Digabel, 2011) in MATLAB® using the OPTI (OPTimisation Interface) toolbox (Currie et al., 2012). The name NOMAD stands for "non-linear optimisation with the MADS algorithm" wherein the acronym MADS stands for mesh adaptive direct search. The fact that NOMAD is a derivative-free direct search algorithm that can solve non-differentiable global non-linear programmes, including non-convex MINLPs, adds to the flexibility of the overall methodology since any arbitrary "black box" plant function can be implemented without being overly concerned about MINLP solvability. In principle it is possible to perform MINLP optimisation on MCS-derived metrics. However, in this work, MCS is post optimisation (See Fig. 3) to circumvent potential convergence issues due to randomness introduced by the MCS.

4. Kawerau case study

4.1. Case study system

The case study, demonstrating the methodology presented, looks at identifying profitable symbiotic opportunities by introducing new processing plants into the cluster for better utilisation of existing resources. This includes looking at options of utilising some of the logs that currently pass through the cluster and bringing additional residues from nearby forests into the cluster.

Existing and new plant options and their key resource exchanges are summarised in Table 1 and the corresponding superstructure is illustrated in Fig. 8. These options were chosen based on, a qualitative consideration of the existing cluster as it stands and, consultations with industry stakeholders.

Table 1
Inputs and outputs for existing and prospective processing options for Kawerau.[a]

Plant	Resource	Products or by-products
Kraft pulp mill (KPM)	Pulp log, chip, bark A, bark B, shavings, chemicals, geothermal LP steam, electricity	Pulp, hot water, GHG
Newsprint mill (NPM)	Pulp log, chip, chemicals, geothermal LP steam, geothermal HP steam, electricity	Newsprint, bark B, GHG
Structural sawmill (SSM)	S grade log, geothermal LP steam	Lumber, chip, offcuts, shavings, sawdust, bark A
Industrial sawmill (ISM)	A grade log, geothermal LP steam, electricity	Lumber, sawdust, chip, offcuts, bark A, bark C, GHG
Tissue paper mill (TPM)	Pulp, chemicals, freshwater, geothermal MP steam, natural gas, electricity	Tissue paper, wastewater, GHG
Optimised Engineered Lumber (OEL™)	*K grade log, geothermal LP steam, electricity*	*OEL™, chip, shavings, sawdust, bark A, bark C, offcuts, GHG*
Medium density fibre board (MDF)	*Pulp log, sawdust, chip, natural gas, electricity*	*MDF, bark B, bark C, fines, GHG*
Plywood	*K grade log, A grade log, geothermal LP steam*	*Plywood, cores, hog, bark A, bark C, GHG*
Wood pellets	*Sawdust, geothermal LP steam*	*Pellets, GHG*
Terpenes and wood pellets	*Chip, shavings, sawdust, offcuts, chemicals, geothermal LP steam*	*Terpenes, pellets, GHG*
Tannins and bark briquettes	*Bark A, bark D, process water, geothermal steam*	*Tannin, bark briquette, wastewater, GHG*

[a] Rows in italic denote new processing options.

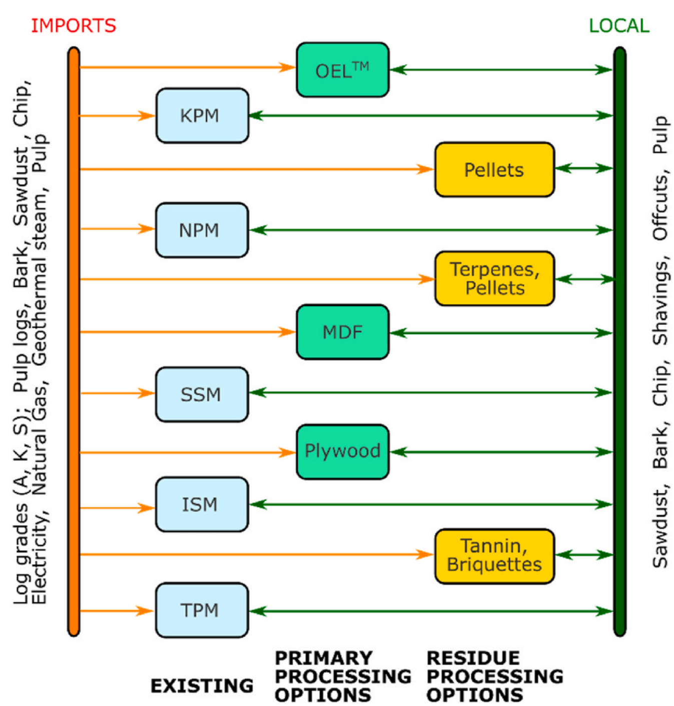

Fig. 8. Simplified schematic of superstructure for Kawerau case studies.

In Table 1, bark has been separated into four different grades depending how they are sourced and to what purpose they can be usefully applied. Bark A is from thick lower stem logs that are supplied from sawmills. Bark B is the thinner upper stem bark sourced from pulp mill debarking operations. Bark C is sourced from log yards which can contain significant amounts of dirt and Bark D is whole stem bark that can be sourced externally from forests and log yards (see Fig. 2). Similarly, different log grades are used depending on their suitability to the target product and price. Residues from outside the cluster are priced at the site as a purchase price plus a transport cost for a nominal distance of ~85 km. Locally produced residue is assumed accessible to all plants with a $5/odt transport cost.

The material consumption and production for the existing plants (the base case) and assumptions on the upper bound (U_b) on resource availability are summarised in the Sankey diagram shown in Fig. 9 which also shows existing symbiotic material exchange within the cluster (2016 data).

In Fig. 9 all mass flows are indicated on an annual oven-dry basis (i.e. excluding moisture). The flow units are kilo-odt/y, indicated as kt for brevity. In interpreting the figure, any arrows out of an import or local node represent potentially available material in excess to the requirement of the current plants in the cluster. For example, the flows in and out of the "Pulp logs import" node show that the upper limit on available pulp logs is 588,000 odt/y, of which 417 kt is used by KPM and 21 kt used by NPM leaving an excess of 150 kt for other activity. The figure shows that the biggest additional log volumes are of A and K grade logs. Use and price assumptions for resources indicated in Fig. 9 are given in Appendix A.3.

Fig. 10 shows the base case annual energy flows. The energy resources are assumed to be available in large excesses such that current plant operations as well additional plant opportunities considered in this study will not be limited by these energy supplies. Hence there are no free arrows out of energy nodes.

Case 1. adding new plants to maximise resource utilisation

This case addresses the question, what new plants(s) could be added to the cluster to make better use of potentially accessible resources? That is, what scenario (or plant configuration) will maximise the amount of biomass used that is imported into the cluster. The equivalent optimisation objective is to minimise the sum of excess biomass for all material resource import nodes. This is subject to the constraints that all existing plants maintain their current nominal production rate and their *EBITDA* must not fall below their current values, and any new plants added must achieve *ROCE* > 0. These constraints ensure that the resulting configurations will not diminish the earnings of the existing plants. The resulting configuration along with key decision metrics are summarised in Table 2. The corresponding material flows are illustrated in Fig. 11.

The key financial assumptions for all cases are: 100% debt finance, 7% interest rate, 28% tax rate and 100% annual sales rate.

The configuration in Fig. 11 can be understood by comparison with the base case (Fig. 9) where 562 kt of A grade and 315 kt of K grade logs are potentially available, in excess of existing demand. OEL™ requires K grade logs while Plywood can take a combination of K and A. The reason only 155 kt of A grade log is used for plywood production while still leaving 407 kt unused in this configuration, is a heuristic constraint within the Plywood model that the fraction of K grade log must not

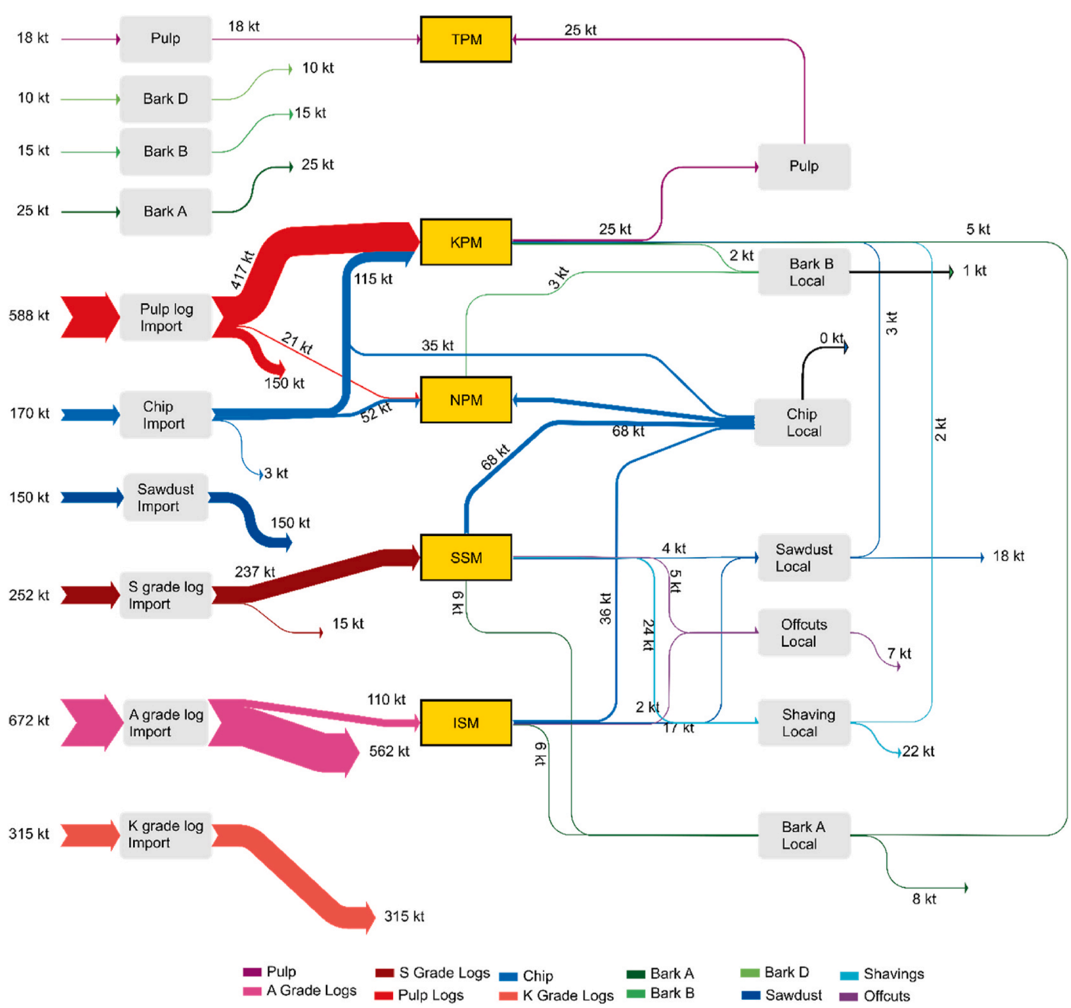

Fig. 9. Base case annual material flows and resource availability assumptions.

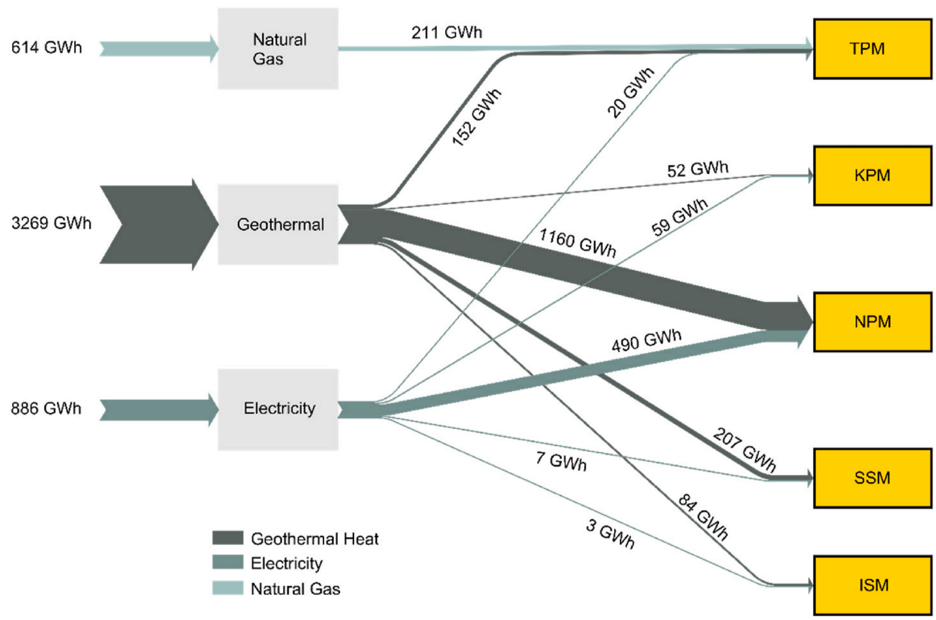

Fig. 10. Base case annual energy flows.

Table 2
Performance metrics for optimal configuration to maximise resource use.[a].

Plant	Production (odt/y)	Investment (M $)	*EBITDA*/odt ($/odt/y)	*NPV*(M $)	*ROCE*(%)	*SR*(-)	Δ*GDP*(M $/y)	Δ*FTE*(-)	Tax rev. (M $/y)	GHG (kt CO_2eq)
TPM	44k									
SSM	134k									
NPM	122k									
KPM	244k									
ISM	54k									
MDF	–	–	–	–	–	–	–	–	–	–
OEL™	*252k*	*51*	*206*	*174*	*42*	*2.0*	*261*	*320*	*4*	*6*
Plywood	*348k*	*170*	*152*	*139*	*19*	*1.1*	*396*	*631*	*7*	*33*
Pellets	–	–	–	–	–	–	–	–	–	–
Terpenes, pellets	–	–	–	–	–	–	–	–	–	–
Tannins, briquettes	*2k, 31k*	*27*	*204*	*10*	*13*	*1.4*	*24*	*108*	*1*	*2*
Cluster[b]	–	258	71	323	–	–	681	1157	12	41

[a] Rows in italic indicate new plants or changes to existing plants selected by the optimisation.
[b] The Cluster row shows an aggregate of a selection of metrics by treating the new configuration a result of a single investment.

exceed 50% to achieve desired product quality. This coupled with the competition for the lower priced K grade logs between OEL™ and Plywood means that the supply of K grade logs limits how much A grade logs that Plywood can accept. It is not surprising that Tannin & Briquette appears in the configuration, being the only new plant option that can accept imported bark (see Table 1).

The TEA results in Table 2 gives an idea of how a proposal for this configuration might be received by various stakeholders. The expected *ROCE* for Tannin & Briquettes is well below 20%. This is a threshold that the authors' have gauged through stakeholder engagement, that would need to be cleared in order to motivate stakeholder interest. Relative to the base case, this scenario has increased GHG emission by 44 tonnes CO_2 eq./y. The regional impact through *GDP*, employment and income tax revenues are found to be relatively low. Both the OEL™ and Plywood options are favourable from a *ROCE* perspective. However, the low Sharpe ratio suggests that a plywood plant would not be an attractive investment due to price volatility. Both options provide favourable regional economic impact prospects, although Plywood production will have a significant GHG emission impact. The latter is because plywood production is an energy-intensive process and the plant is large. While geothermal steam used for this process is a renewable resource, it typically contains significant CO_2 and therefore has a GHG emission (0.1024 tonne CO_2-e/tonne steam at Kawerau) (see Fig. 12 and compare with Fig. 10).

Case 2. adding new plants to Maximise GDP contribution

This case seeks a configuration that maximises the aggregate increase in *GDP* contribution by the cluster and hence regional impact. This is primarily an economic objective aimed at a positive overall regional impact. The addition of new plants should not result in a loss of revenue for existing plants, for example, through competition for resources. This is enforced with constraints to maintain the nominal pro-

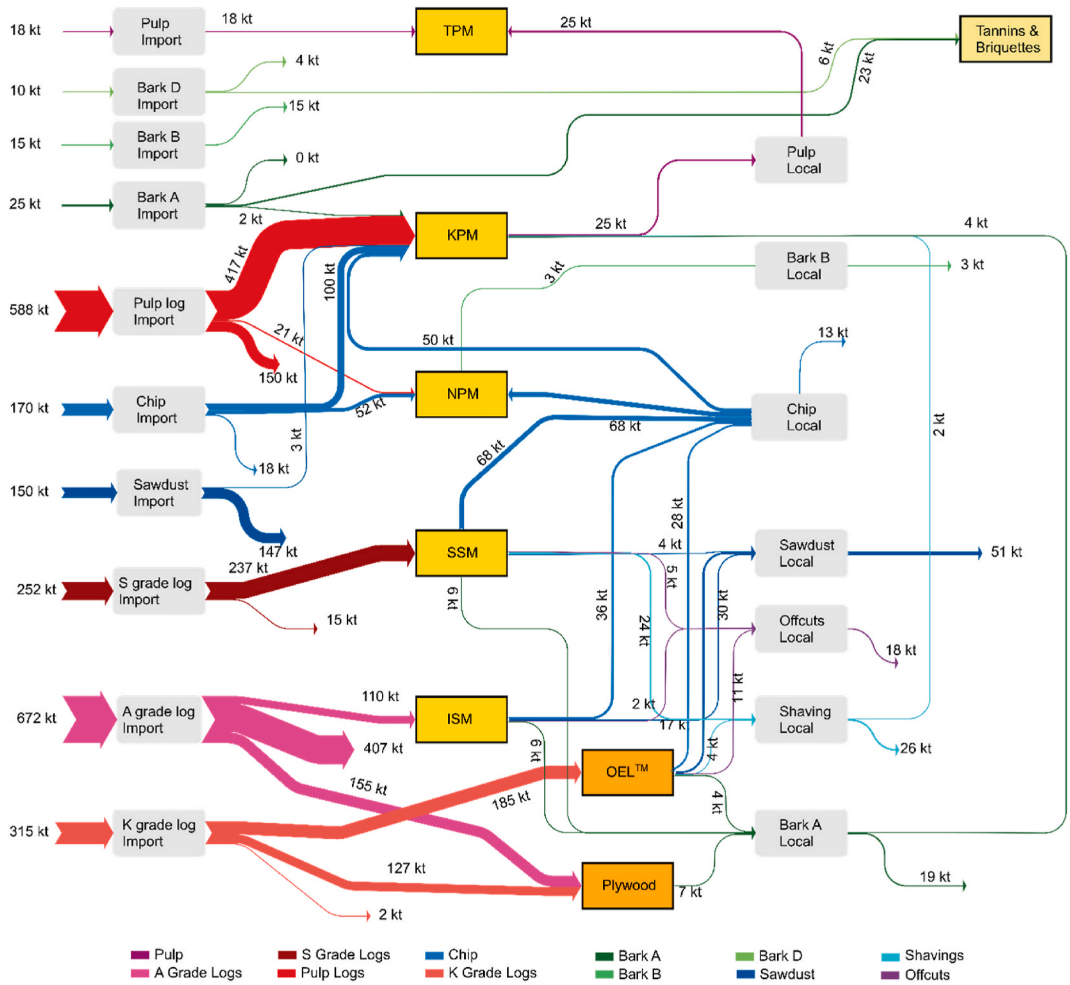

Fig. 11. Material flows of optimal configuration and scales to maximise resource use.

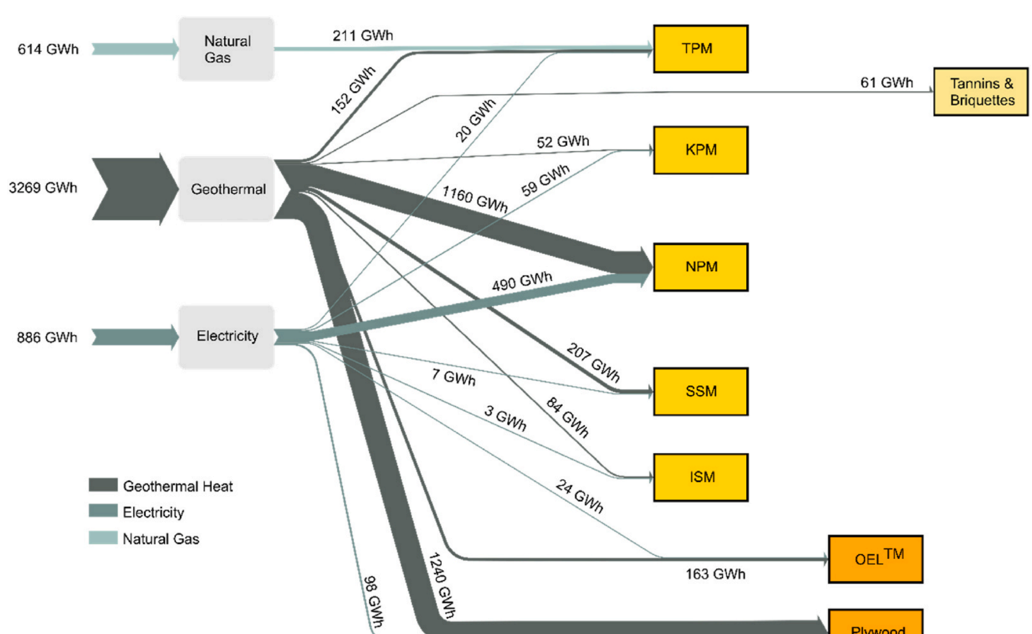

Fig. 12. Energy flows of optimal configuration and scales to maximise resource use.

Table 3
Performance metric for optimal configuration to maximise GDP contribution.[a].

Plant	Production (odt/y)	Investment (M $)	$\frac{EBITDA}{odt}$($/odt/y)	*NPV*(M $)	*ROCE*(%)	*SR*(-)	Δ*GDP*(M $/y)	Δ*FTE*(-)	Tax rev. (M $/y)	GHG (kt CO_2eq)
TPM	44k									
SSM	134k									
NPM	122k									
KPM	244k									
ISM	54k									
MDF										
OEL™	*394k*	*70*	*209*	*288*	*46*	*2.0*	*409*	*491*	*6*	*9*
Plywood	*350k*	*170*	*180*	*131*	*18*	*1.1*	*381*	*631*	*7*	*33*
Pellets										
Terpenes, pellets										
Tannins, briquettes	*2k, 35k*		*199*	*16*	*16*	*1.8*	*30*	*117*	*1*	*2*
Cluster[b]	–	267	77	435	–	–	819	1,229	13	44

[a] Rows in italic indicate new plants or changes to existing plants selected by the optimisation.
[b] The Cluster row shows an aggregate of a selection of metrics by treating the new configuration a result of a single investment.

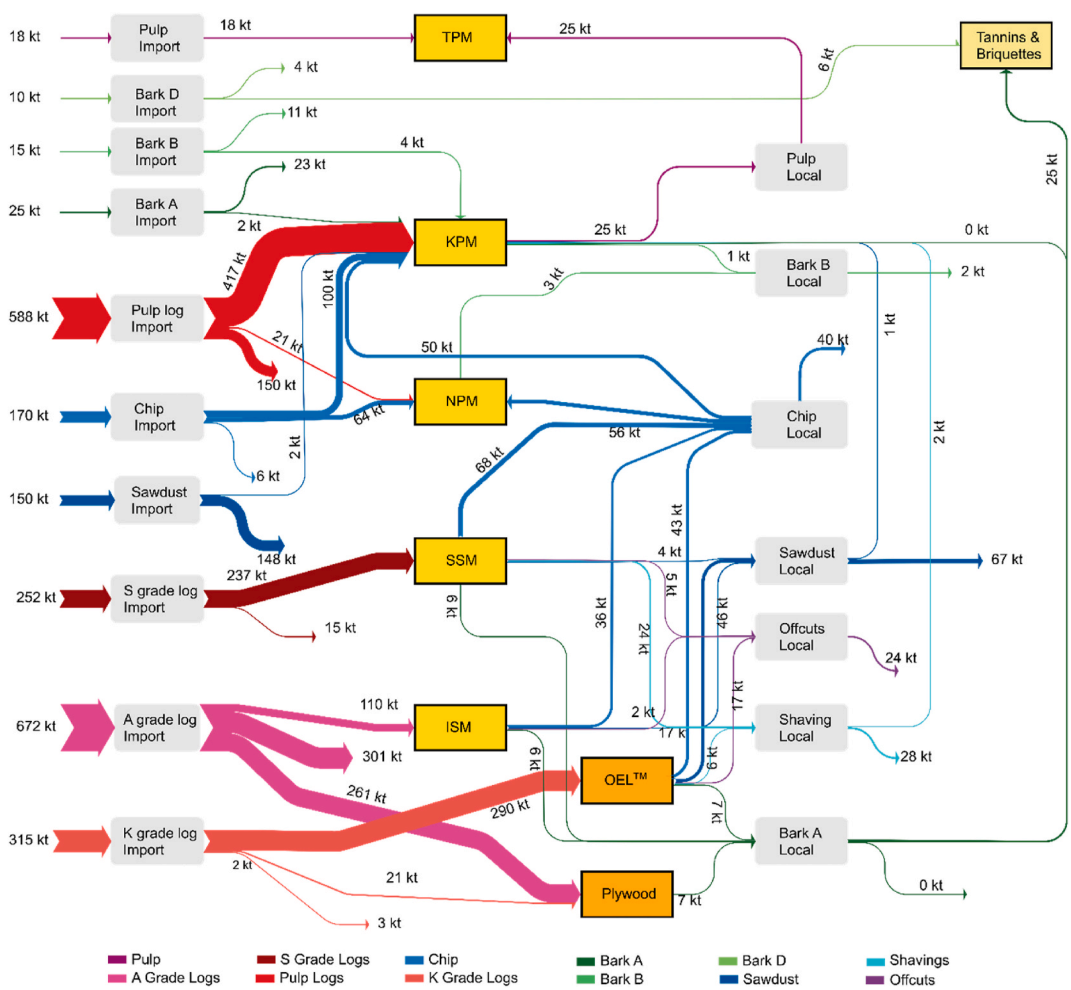

Fig. 13. Material flows of optimal configuration and scales to maximise *GDP* contribution.

duction rate and EBITDA of existing plants at least at their current level while requiring $ROCE > 0$ as in Case 1. The resulting configuration and key decision metrics are summarised in Table 3 and material flows are in Fig. 13.

The new configuration has the same new plants selected as in Case 1, but at different scales such that Case 2 provides an increase in cluster aggregate *GDP* contribution by \$136M/y relative to Case 1. This can be sub-optimal from the perspective of individual plants. For example, this proposal asks for more of the more expensive A grade logs to be taken up by Plywood in order to free up K grade logs to allow scaling up of the OEL™ operation which has a higher *EBITDA*/odt and *GDP*/ odt. However, this has not impacted the attractiveness for investment in OEL™ or Plywood as gauged through *ROCE* and *SR*. This significantly improves the profitability of a potential Tannin & Briquette operation within the cluster. This is because the new scales of operation produce local residues of Bark A feedstock in excess of what was available for import and at lower cost, from debarking of K grade logs in the OEL™ and Plywood production.

The energy flow distribution from sources to processing plants for the Case 2 optimal configuration is given in Appendix A.4 Fig A.1.

Case 3. maximising revenue per unit mass of feedstock while allowing an existing plant to expand

Rather than building new plants, a further option to grow the cluster could be for one or more of the existing plants to expand. This case explores this option by allowing the existing ISM to expand. This mill is the only existing plant capable of using further volumes of underutilised A grade logs. The optimisation objective is to minimise the cluster aggregate *EBITDA*/odt of biomass resource consumed. The key constraints are that all existing plants except for ISM maintain their current nominal production rate and their *EBITDA* must not fall below their current values and that new plants added must have $ROCE > 0$. ISM on the other hand can scale up production, with the constraint that new investment for the scale up must achieve a positive *ROCE*. The resulting optimal configuration and key decision metrics are summarised Table 4 and Fig. 14.

These results show that a scale-up of ISM can locally produce significant amounts of chip and sawdust. This in conjunction with the inclusion of an OEL™ plant that produces additional chip and sawdust, is then able to support an MDF plant by importing some additional pulp log. This however places the MDF plant and the existing KPM in competition for pulp log, which will impact future growth options for both plants. It is also observed that while the *EBITDA*/odt improved for the cluster relative to Case 1, other financial metrics becomes worse.

Whilst the cluster configuration conforms to the optimisation constraint $ROCE > 0$ for all new investments, both ISM and MDF have negative NPVs for these investments (Table 4). This is consistent with the high threshold requirement for *ROCE* expressed by industry stakeholders. The configuration is also consistent with industry experience that MDF typically need large scale operations to be profitable. Another important observation is that both investments show unprofitable Sharpe ratios. Some insight into these observations can be obtained from the post-optimisation MCS. As an exemplar, Fig. 15(A) shows a tornado plot that ranks cost parameters that have the most influence on *ROCE*. The horizontal span of the bars represents the range of variation in *ROCE* due to variations of the influence parameters over the 95-percentile extent of their probability distributions. ROCE values outside these bars are highly improbable.

Fig. 15(B) and (C) shows the sensitivity of *ROCE* to the two most influential cost parameters, the price of A grade logs and the foreign exchange rate. The reason for the large influence of the foreign exchange rate is that the product is exported out of New Zealand and priced in US \$, and the foreign exchange rate between US\$ and NZ\$ happens to be quite volatile.

To understand the aggregate impact of all such sensitivities on *ROCE*, the correlations amongst the influence parameters must be considered. Fig. 16, shows the MCS-derived distributions for ROCE considering the correlation between cost parameters. The figure shows that whilst the expected value of *ROCE* is positive (+4% corresponding to $CDF = 0.5$) there is potential for considerable variation, that would result in a low Sharpe ratio. Furthermore, $CDF = 0.4$ for $ROCE = 0$ indicates that there is a 40% chance that the investment will have negative returns and corresponds to the negative *NPV* despite a positive *ROCE*.

The energy flow distribution from sources to processing plants for the Case 3 optimal configuration is given in Appendix A.4 Fig A.2.

5. Conclusions

This paper has presented a generalised and systematic decision support methodology and tool to quickly identify and evaluate symbiosis opportunities in industrial clusters. The methodology centres around cluster design by superstructure optimisation using mixed integer non-linear programming. Individual plant models that form the superstructure are demand-driven and have a standardised yet flexible modular formulation that seeks a balance between high-level process models that may be too optimistic in their predictions, and rigorous process models that can become too complex and intractable. This was achieved using a combination of heuristics methods and thermodynamics principles and is reliant on recent advancements in derivative-free optimisation algorithms that can robustly solve arbitrarily defined MINLP problems.

Table 4
Performance metric for optimal configuration to maximise revenue per unit resource allowing ISM to scale up.[a]

Plant	Production (odt/y)	Investment (M\$)	$\frac{EBITDA}{odt}$(\$/odt/y)	*NPV*(M\$)	*ROCE*(%)	*SR*(-)	Δ*GDP*(M\$/y)	Δ*FTE*(-)	Tax rev. (M\$/y)	GHG (kt CO_2eq)
TPM	44k									
SSM	134k									
NPM	122k									
KPM	244k									
ISM	*176k*	*85*	*22*	*−34*	*4*	*0.1*	*88*	*339*	*2*	*4*
MDF	*414k*	*438*	*208*	*−8*	*8*	*0.7*	*410*	*550*	*5*	*114*
OEL™	*239k*	*49*	*204*	*160*	*41*	*1.9*	*243*	*291*	*4*	*6*
Plywood	*347k*	*169*	*191*	*151*	*19*	*1.2*	*393*	*631*	*7*	*33*
Pellets										
Terpenes, pellets										
Tannins, briquettes	*1k, 22k*	*19*	*213*	*10*	*15*	*1.9*	*18*	*66*	*<1*	*18*
Cluster[b]	–	761	92	278	–	–	1149	1877	18	157

[a] Rows in italic indicate new plants or changes to existing plants selected by the optimisation.
[b] The Cluster row shows an aggregate of a selection of metrics by treating the new configuration a result of a single investment.

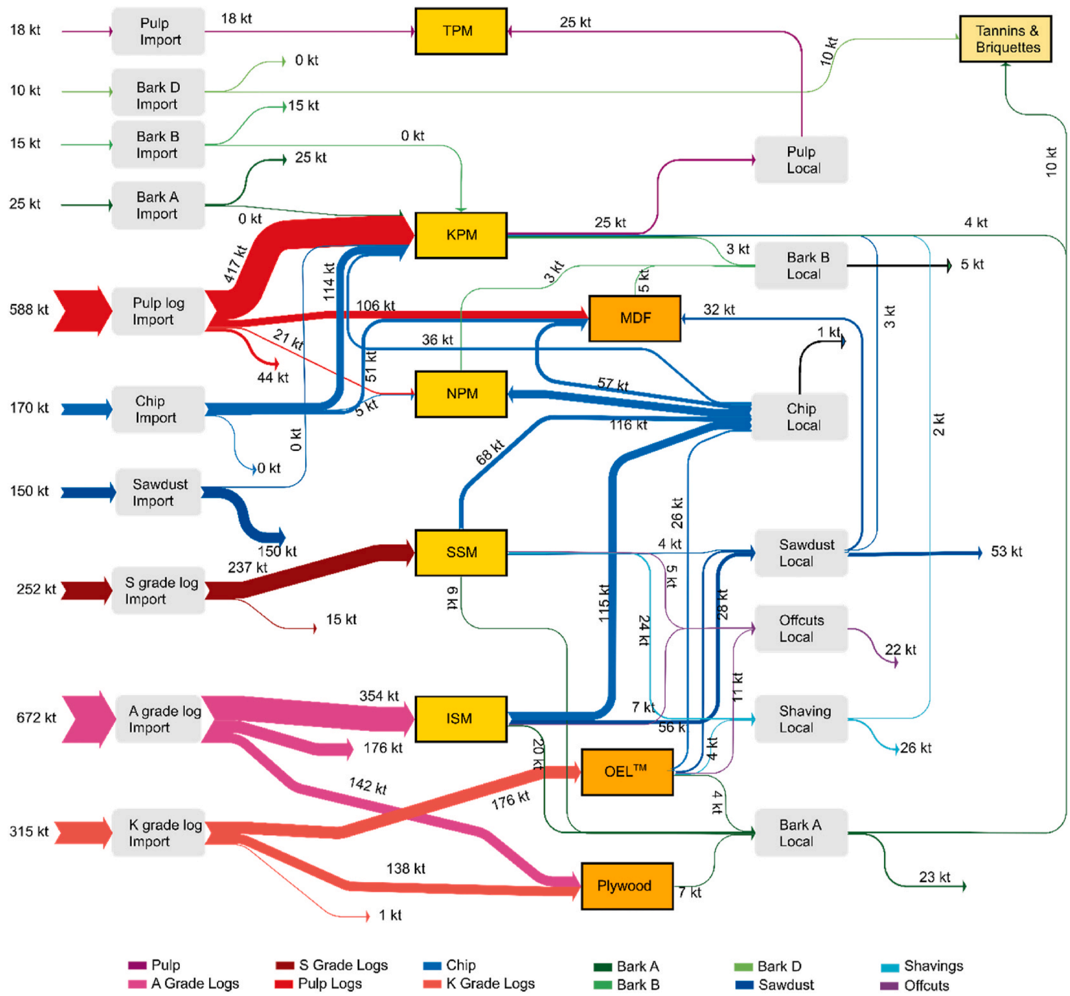

Fig. 14. Material flows of optimal configuration and scales to maximise revenue per unit resource allowing ISM to scale up.

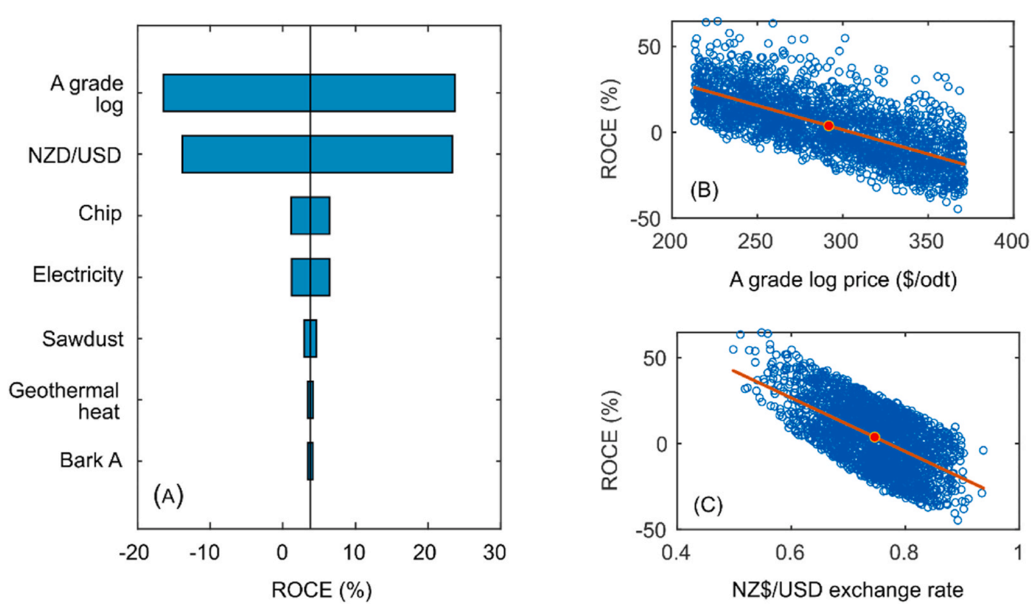

Fig. 15. (A) Influential costs for *ROCE*. (B) & (C) Sensitivity of *ROCE* to the two most influential costs.

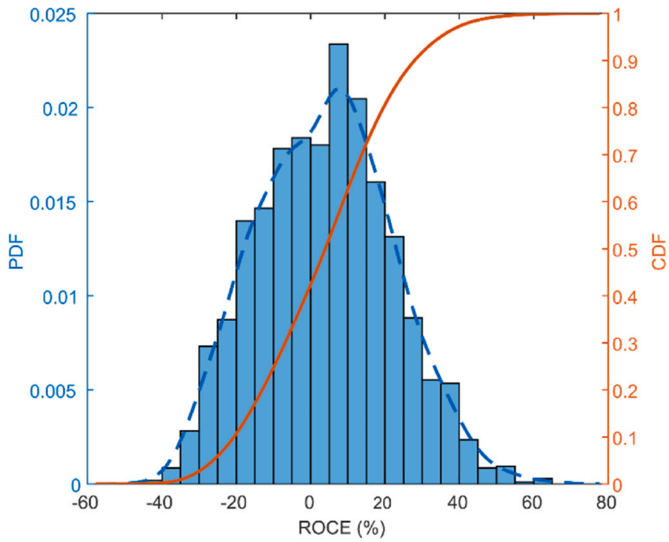

Fig. 16. The probability distribution of the ROCE function.

The model includes both flexible cluster design objectives and decision metrics for investment profitability, macroeconomics and environmental impact. This makes it a powerful tool for evaluating symbiosis opportunities in industrial clusters and addressing the diverse needs of the stakeholders involved in a cluster. The flexibility of the tool offers potential for application in other integrated planning with stakeholder engagement such as integrated farm planning.

The methodology has been demonstrated by applying it to three case studies to identify and evaluate new wood processing opportunities at Kawerau, New Zealand. These looked for profitable symbiotic opportunities by introducing a small selection of plausible new primary processing and/or residue processing plants into the cluster. The case studies using several optimisation objectives, suggest that some combination of the production of Optimised Engineered Lumber™, tannins and bark briquettes and plywood are promising new opportunities for the Kawerau cluster and that the optimal configuration depends on the criteria used to optimise the cluster. The case studies also highlight the importance of considering the impact of price volatility in industrial cluster design or expansion. Notably, the Monte Carlo analysis provides plausible explanations for the rather high threshold requirements for returns on capital employed that were expressed by industry stakeholders at Kawerau. While these case studies are for a single site, the methodology is formulated to be quite general and based on fundamental principles of mass and energy balances, which makes it applicable to other clusters.

An important limitation of the proposed model framework is that it does not explicitly incorporate a spatial dimension and relies on an average transport cost for local use of resources by all processing plants within the cluster. Whilst this may not be significant for clusters of limited geographical extent such as Kawerau, the model framework would be significantly improved by incorporating an explicitly location-based transport model to estimate the cost of transport within the industrial cluster.

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CRediT authorship contribution statement

Muthasim Fahmy: Conceptualization, Methodology, Writing – original draft, Software, Formal analysis. **Peter W. Hall:** Writing – original draft, Investigation, Writing – review & editing. **Ian D. Suckling:** Writing – original draft, Writing – review & editing. **Paul Bennett:** Supervision, Writing – review & editing. **Suren Wijeyekoon:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.129494.

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