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Strategic Value Chain Design for Sustainability: A Multi-Criteria Decision Support Model Integrating Life Cycle Assessments

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Abstract:

Background: Designing supply chains has become a strategic focus for companies aiming to stay economically competitive, particularly in a landscape shaped by global trade and faster industrial cycles.

Purpose: This paper presents a novel strategic decision support model that integrates Life Cycle Assessments (LCAs) with multicriteria optimization to facilitate sustainable value chain design. The goal is to identify the optimal solution(s) to a design problem while balancing multiple sustainability criterion.

Study design/methodology/approach: The study employs an integrated approach that combines Life Cycle Assessment (LCA) for environmental criteria and Life-Cycle Costing (LCC) for economic criteria within a multi-criteria optimization framework. The model considers various strategic options, including material flows and investments in new technologies, and generates Pareto fronts to depict compromise solutions between conflicting criteria. The model's key innovation lies in its ability to optimize solutions while ensuring fairness and comparability between all prospective alternatives. This is achieved through a multicriteria optimization framework that evaluates multiple objectives and determines optimal solutions. To demonstrate the model's practicality and replicability, a real-world case study is presented in the forest sector, a challenging industry characterized by complexity and convergence.

Findings/conclusions: Applying the model to a real-life case study demonstrates its potential to provide valuable information to decision-makers, and highlights its generic nature, making it applicable to a variety of industrial sectors.. The proposed model provides a novel decision support framework for companies seeking to develop a comprehensive sustainability strategy for their entire value chain, thereby enabling the identification of compromise solutions that balance minimizing environmental impacts with long-term viability. By presenting a generic and replicable approach, this paper contributes to the development of a functional strategic decision tool that can be used to support sustainable value chain design.

Limitations/future research: The current multi-criteria optimization addresses only economic and environmental factors, but integrating social aspects remains necessary for comprehensive decision support in sustainable development. Incorporating uncertainty into the solutions presents an additional challenge, which could be mitigated by using a stochastic optimization framework to better account for risks and trade-offs.

Keywords: *Multicriteria Optimization, Life-Cycle Assessment, Life-Cycle Costing, Sustainability, Strategic, Decision Support, Supply Chain*.

Introduction

Supply chain design has become a strategic priority for companies seeking to remain economically competitive. This is especially crucial in an environment marked by globalized trade and accelerated industrial cycles (Tan et al., 2002). The business press frequently reports on logistics network reconfiguration, reorganization, mergers, and outsourcing - developments driven by trends such as increased computerization, trade flow complexity, and competition concerns (Ballou, 1997; Bowersox & Calantone, 1998). Consequently, the strategic design and planning of logistics networks has emerged as a key focus for both businesses and researchers. This interdisciplinary field, encompassing management, strategy, logistics, operations research, presents significant analytical challenges (Daskin, 1985; Esmizadeh & Parast, 2020; Schmidt and Wilhelm, 2000).

Integrating sustainability considerations into strategic design of logistics networks, alongside the previously cited factors, deliver a holistic optimization solution but introduces an additional level of challenge, as it can involve potentially conflicting criteria (Biuki et al., 2020; Nagurney & Nagurney, 2010; Neto et al., 2008). This necessitates finding compromise solutions that balance the traditional economic objectives (Lu, 2010; Wang et al., 2011). Addressing this multifaceted decision problem requires careful analysis to determine the most appropriate trade-off solutions that address both the economic and environmental dimensions of the logistics network design.

The proposed model provides a novel decision support framework for companies seeking to develop a comprehensive sustainability strategy for their entire value chain, thereby enabling the identification of compromise solutions that balance minimizing environmental impacts with long-term viability. This framework is based on a multicriteria optimization model that integrates life cycle assessments, Activity-Based Life-Cycle Costing, and prospective life cycle assessments to evaluate different investment options and generate a set of Pareto-optimal solutions.

The integration of environmental considerations into the design of logistics networks, alongside economic criteria, is a relatively recent development (Biuki et al., 2020; Demir et al., 2022). Previous studies in this domain have primarily focused on reducing waste, managing wastewater discharge, or incorporating environmental elements into economic criteria, such as calculating the benefits of reducing waste generation and processing costs. More recently, the focus has been narrowly on reducing carbon emissions alone. However, this limited "carbon tunnel" perspective fails to consider the broader environmental impacts across the entire product lifecycle, overlooking other important environmental considerations (Prado et al., 2022). Emerging research suggests that a more comprehensive approach focusing on multicriteria decision-making and life cycle assessment (LCA) could be beneficial (Neto et al., 2008; Rees & Wang, 2014).

Multi-criteria optimization has been the focus of extensive research in recent years, but there are relatively few publications that document its real-world applications. This scarcity has been attributed to the complex nature of preference structures among criteria, the challenges in resolving optimization models, and the difficulties associated with implementation (Fei et al., 2017; Greco et al., 2015; Zavadskas et al., 2020).

The presented model aims to support industrial managers in choosing between investment options that maximize economic profits, minimize environmental impacts, or offer a compromise between these two criteria. This model utilizes a cradle-to-gate attributional LCA on a portfolio of products, as presented in Laurent et al. (2016), to quantify the environmental aspects of a specific product portfolio for a forestry industry. Additionally, an Activity-Based Life-Cycle Costing assessment (ABLCC), based on the methodology proposed by Emblemsvåg (2001), is used to determine the cost of each product of the same portfolio (Laurent et al., 2021). Finally, a prospective LCA (P-LCA) (Moni et al., 2019; Thonemann et al., 2020) is conducted to estimate the environmental impacts of integrating new technologies and the substitution effects of competitive materials with a consequential LCA (C-LCA) (Schaubroeck et al., 2020; Corona et al., 2020).

This application is based on primary data from a forestry company, supporting decisions on future technology investments. The forestry sector presents a major challenge due to its complex and divergent nature (Vila et al., 2006; Hurmekoski et al., 2018). The result of this analysis is a set of Pareto-optimal solutions that represent the compromises between economic and environmental objective (Wang & Rangaiah, 2017). The generated solutions will be accompanied by material flow diagrams to enhance understanding (Vaskan et al., 2014). From the 150 solution generated by the multicriteria optimization model, a marginal abatement cost curve (MAAC) of the net carbon emissions reductions is presented in the discussion section (Kesicki & Strachan, 2011) . This holistic approach is considered a decision-making support tool for the strategic design of a sustainable logistics network within the forestry industry.

Literature Review

The next paragraphs present the different methodologies used in this analysis and applied in the case study.

Attributional Life-Cycle Assessment

Attributional Life-Cycle Assessment (A-LCA), which is commonly called just LCA, is a methodology that attributes the environmental impacts associated with each activity of a product or service's lifecycle. By definition, the lifecycle encompasses all stages from the extraction of raw materials to the final disposition of the product.

This methodology, which first emerged in the 1980s, has since been the subject of international standardization (ISO 14040) and is now one of the most widely used method for determining the environmental impacts of products (Lesage & Müller, 2017; Postlethwaite, 1994). A key premise of this methodology is that all environmental interventions (e.g., resource extractions, emissions) occurring during the lifecycle of a product are attributed to that product. This allows for a comprehensive evaluation of the environmental performance of a product or service, identifying hot spots and opportunities for improvement (Curran, 2004; Jessop and Mac Donald, 2023).

Activity-Based Life-Cycle Costing

In recent decades, numerous lifecycle cost assessment methodologies have been developed. Comprehensive literature reviews provide a list of these methods along with brief descriptions (Asiedu & Gu, 1998; Durairaj & Tan, 2002; Gluch & Baumann, 2004).

Among them, the accounting method based on "Activity-Based Costing" has captured our attention due to its potential parallels with the A-LCA methodology. The Activity-Based Life-Cycle Costing (AB-LCC) method allows for guidance on the profitability of a product or a portfolio of products, as described by Emblemsvåg (2001). The basic principle is to identify the relevant activities required to produce a good or provide a service, and then allocate the costs of these activities to the final product or service.

Prospective Life-Cycle Assessment

Prospective Life Cycle Assessment (P-LCA) is a relevant approach to assess the environmental performance of future energy pathways and emerging technologies at an early stage of development, in order to guide investment and technology deployment towards a sustainable economy. By exploring potential future scenarios based on a set of assumptions and prospective data, Prospective LCA can provide valuable insights to support decision-making (Arvidsson & al., 2017; Thonemann et al., 2020).

Consequential Life-Cycle Assessment

The use and application of Consequential Life-Cycle Assessments (C-LCA) are primarily driven by the need to understand the consequences of a decision (Ekvall & Weidema, 2004). C-LCA identifies the consequences of a decision by describing the physical and socio-economic causal relationships involving the study system, and by exploring how physical flows can change, thereby anticipating the consequences of decision-making (Schaubroeck, 2023).

In contrast to A-LCA, which aims to attribute environmental impacts of a product without considering prospective impacts, C-LCA has implications for the methodology, particularly in defining system boundaries. Even minor changes can have consequences that extend beyond the product of concern. This is especially relevant for multifunctional processes, open-loop recycling, or the use of resources with potential competition, such as wood resources. Since the emergence of competing products in the industry and petroleum eras, it is necessary to extend the system boundaries to include parts of other systems affected by the decision. The system boundaries must be implicitly extended to include additional functions, such as energy substitution, or the use of materials in construction (Petersen & Solberg, 2005; Luu et al., 2020).

The integration of environmental criteria into operational research

Mounting consumer and regulatory pressures on corporate social responsibility have prompted industry to reduce the environmental impacts of their entire value chains. Numerous studies have also examined various aspects of logistics networks, including closed-loop supply chains and reverse logistics (Srivastava, 2007). Others have focused on one or more specific elements, such as inventory management, eco-design, production and recycling planning, product recovery, or greenhouse gas emissions (Azevedo et al., 2011). However, these studies have typically centered on production centers without considering the full product life cycle. Life cycle assessment, commonly used to quantify the potential environmental impacts of a product or service, seems appropriate to meet this need for a more comprehensive approach (Azapagic & Clift, 1999). The use of the life cycle approach in the field of logistics dates to 1996 (Bloemhof-Ruwaard et al., 1996), addressing the potential for reducing environmental impact using recycled paper. In 1999, Azapagic & Clift (1999) proposed a methodology for integrating LCA into a three-step optimization framework. The first step is to perform an LCA, then formulate a multi-criteria optimization problem, and finally select the solution offering the best compromise. The first real case studies were published in 2011, but they used the eco-cost approach. This approach monetizes environmental impacts, leading to the use of a single-criteria optimization model (Čuček et al., 2011). Some applications use an aggregation of environmental damage to obtain a single score, thus reducing the model to bicriteria, i.e. environmental and economic (Cerri et al., 2013; Kostin et al., 2012). Moreover, the literature on the resolution of these models has been performed either through heuristics (Bernier et al., 2013; Rivallain et al., 2012) or by the ε-constraint method (Cerri et al., 2013; Čuček et al., 2011; Kostin et al., 2012). More recently, Shekarian et al. (2022) offer a comprehensive review of sustainability in value chain design. Jayarathna et al. (2021) published a literature review on multi-objective optimization sustainable supply chain. Paul et al. (2021) discuss recent advancements in multi-criteria decision-making, highlighting how the following methodology fits into and improves upon current practices by addressing the complexities of sustainable value chain design for strategic decision support.

Methodology

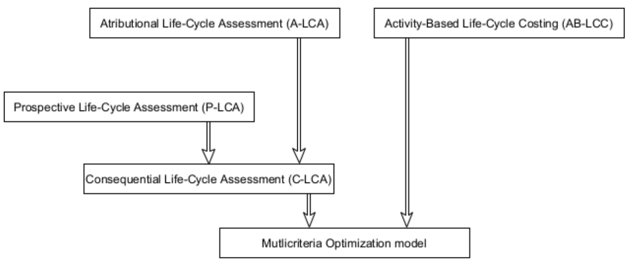

***Figure 1** Mapping of the proposed decision support model*

Source: the authors

The proposed methodology offers the benefit of incorporating economic and environmental quantifications to support industrial decision-makers in investment choices. As depicted in Figure 1, this methodology comprises four steps and is founded upon four methods that have been previously documented in the literature review. By embedding an LCA within an optimization framework, the approach ensures a holistic assessment, where environmental impacts give equal weight alongside economic factors, enabling a balanced and comprehensive evaluation of industrial systems for sustainability.

The first step is to perform an A-LCA to quantify the environmental impacts of the activities within the industrial system under study. This step establishes a baseline quantifying of the system's environmental performance, such as climate change, biodiversity, human health, resource consumption impacts. The second step involves conducting Activity-Based Life Cycle Costing (ABLCC), a contemporary accounting methodology that enables the quantification of costs across the entire product portfolio and establishes a connection between these costs and the corresponding environmental impacts. Together, these steps provide a robust foundation for integrating economic and environmental dimensions into the decision-making process.

The third step adopts a prospective and consequential approach. Consequential Life Cycle Assessment (C-LCA) is employed to determine the environmental impacts arising from substitution effects and the implementation of new technologies, as identified through the application of P-LCA (Bisinella et al., 2021). This forward-looking perspective ensures that the methodology is not limited to current conditions but also considers potential future developments, such as technological innovations and evolving regulatory environments.

Once the environmental and economic quantification is completed, including prospective solutions, all these data are integrated into a multicriteria optimization model in the fourth step. The optimization model resolution is conducted using an exact method (Halffmann et al., 2022) and an a posteriori approach by varying the set of possible weights for each criterion (Kellner et al., 2019). This enables the generation of a set of non-dominated solutions, which are presented in a graph called the Pareto front (Pereyra et al., 2013). The Pareto front represents the systematic exploration of trade-offs between criteria, offering decision-makers a transparent view of how improvements in one area (e.g., environmental performance) may compromise or complement another (e.g., economic viability). Furthermore, the methodology incorporates future-oriented decision support through scenario and sensitivity analyses. These analyses identify how solutions might perform under various future conditions, such as changes in regulatory frameworks, market dynamics, or technological advancements. By providing a prospective roadmap rather than a one-time solution, the methodology equips decision-makers with the tools to navigate the uncertainty and make resilient, long-term investment choices.

The following paragraphs present the mathematical model for generating the solutions through mathematical optimization, ensuring a rigorous and transparent approach to decision-making.

The mathematical model

The logistics network optimization problem can be represented as a directed graph model. The mathematical formulation presented here is a mixed-integer linear programming model. This model enables the consideration of opening new production facilities to generate products not currently in the company's portfolio. The MILP model we propose is a multi-criteria optimization, meaning the objective function aims to optimize multiple criteria simultaneously. Additionally, to account for temporal and dynamic aspects, the modeling approach is also the multi-period in nature.

The goal in solving a network optimization problem is to determine the optimal material flow along each connection (arc) between production units (nodes) such that the input and output quantities are balanced. An optimal solution maximizes an objective function that accounts for revenues, losses, purchases, and the costs of implementing new technologies on each of the five criteria.

The mathematical model consists of five components. First, the sets (2.1.1) are presented to aid in the presentation and comprehension of the model. Next, the decision variables (3.1.2), parameters (3.1.3), and objective function (3.1.4) - which serves to find the optimal solution based on the criteria - are described. Finally, the constraints (3.1.5) are presented. The following paragraphs provide a detailed description of each of these elements.

- **Sets**

Table 1 *Sets*

U	All production units (a unit is a site where a processing activity takes place generating one or more products).
A	Criterion set (economic, human health, ecosystem quality, climate change, resource consumption).
F	Set of arcs between the pairs of units.
T	Set of periods (5 periods of 1 year)
P	Set of products
R	Set of processes (process includes transportation process)
R_u	Set of processes available at units *u*
J	Sub-set of assembly product *P* can be used as energy input.

- **Variables of Decision**

The variables of decision are the elements on which the solver varies the values to calculate an optimum. We thus find the flow of matter and the opening of new technologies. The parameters are expressed to correspond to the functional unit defined in the environmental and economic analyses, which is the cubic meter.

Table 2 *Variable of decision*

$\alpha_{p,u,t}$	Quantity of product *p* produced at unit $u \in U$ at period *t*.
$\omega_{r,u,t}$	Number of times the process *r* is used at the unit *u* at the period *t*.
$\sigma_{u,t}$	Binary variable which indicates the initial opening (1st opening) of the unit *u* at the period *t* (0 if closed, 1 if open). This variable applies the opening cost only once in the objective function.
$\gamma_{u,t}$	Binary variable which indicates the opening condition of the unit *u* at the period *t* (0 if closed, 1 if open). This variable ensures the respected the production capacity.

- **Parameters**

$i_{a,r,u,t}$	Impacts on criterion *a* of producing recipe *r* in the unit *u* at the period *t*.
$y_{a,u,t}$	Impacts on criterion *a* of opening the unit *u* at the period *t*.
p_a	Weighting applied to the criterion $a \epsilon A$ (varying from 0 to 1; $\sum \rho_a = 1$).
$q_{p,t}$	Quantity of product p externally available at period t (can be infinite if unlimited).
$v_{r,p,u,u',t,t'}$	Volume of the product *p* used as input (negative) or generated as output (positive) at unit u' at time t' by a quantity of one process *r* executed at unit *u* at time *t*.
$q_{r,u,t}^{min}$	Minimum quantity of process *r* to execute when opening the unit *u* at the period *t*.
$q_{r,u,t}^{max}$	Maximum quantity of process *r* to execute when opening the unit *u* at the period *t*.
d_u	Delay in periods between the opening of the unit and its first production

In all generality, a process taking place at the unit *u* can have a non-zero volume $v_{r,p,u,u',t,t}$ for *u'* different of *u*, but in our experiment that happens only for transportation processes. Similarly, a process taking place at time *t* can have non-zero volume $v_{r,p,u,u,t,t'}$ for *t'* different of *t* to express delays, however in our experiments it never happens as the periods are quite long. The only links that period shares involves the persistence unit that has been open in the past. Finally, note that as a convention a transportation process is linked to unit it originates from but that it is quite arbitrary.

External products refer to all products that are not implicitly modeled by the model, or that are modeled but for which internal production may not be sufficient.

- **Objective function**

The objective function is formulated to obtain the optimized solution. In this model, the aim is to maximize a weighted combination of economic and environmental measures for a given logistics network and set of investment options. Since the model considers multiple criteria, the concept of "utility" is utilized, as it enables the incorporation of both economic and environmental factors. The model employs a utility function, which assigns weights to the profits and losses associated with each criterion. Additionally, the objective function integrates the diverse impacts stemming from external procurement and the implementation of new technologies.

Table 4 *Objective function*

$MaxZ = \sum_{a \in A} \rho_a (\sum_{p \epsilon P} \sum_{t \epsilon T} \sum_{t \epsilon T} i_{a,r,u,t} \omega_{r,u,t}$	Score for criterion *a* associated to the use of recipe *r* in unit *u* at period *t*.
$- \sum_{u \epsilon U} \sum_{t \epsilon T} y_{a,u,t} \sigma_{u,t})$	Score for criterion *a* associated with opening the unit *u* at period *t*.

- **Constraints**

Table 5 *Constraints*

$$\sum_{u \in U} -\alpha_{p,u,t} \leq q_{p,t} \forall p \in P, t \in T$$	(1)
Equation 1 limits the quantity of external product used at each period *t*	
$$\alpha_{p,u,t} = \sum_{r \in R_u} \sum_{u' \in U} \sum_{t' \in T} v_{r,p,u',u,t',t} \omega_{r,u,t}$$	(2)
Equation 2 defines the quantity of product *p* produced at unit *u* at time *t*	
$$\gamma_{u,t'} = \sum_{t \vee t \leq t' - d_u} \sigma_{u,t} \quad \forall u \in U, t \in T$$	(3)
Equation 3 assures unit u is open d_u periods after opening	
$$\gamma_{u,t+1} \geq \gamma_{u,t}, \forall u \in U, t \vee t < \lvert T \rvert - 1$$	(4)
Equation 4 ensures that opening the unit u at time *t* keeps it opens afterward	
$$\gamma_{u,t} Q_{u,t}^{min} \leq \sum_{r \epsilon R_u} \omega_{r,u,t} \leq \gamma_{u,t} Q_{u,t}^{max} \forall p \epsilon P, \forall u \epsilon U, \forall t \epsilon T$$	(5)
Equation 5 assures that a unit *u* executes the minimal and maximal quantity of the process *r* at time *t* if it opens at that time	

Case Study

The proposed decision support model was applied to a long-established forestry company, Chantiers Chibougamau Ltée (CCLtée), operating in the boreal forests of Quebec. The company's production network spans from the forest to the finished products, and it is distinguished by its diverse product portfolio, which includes not only lumber but also an array of engineered wood products.

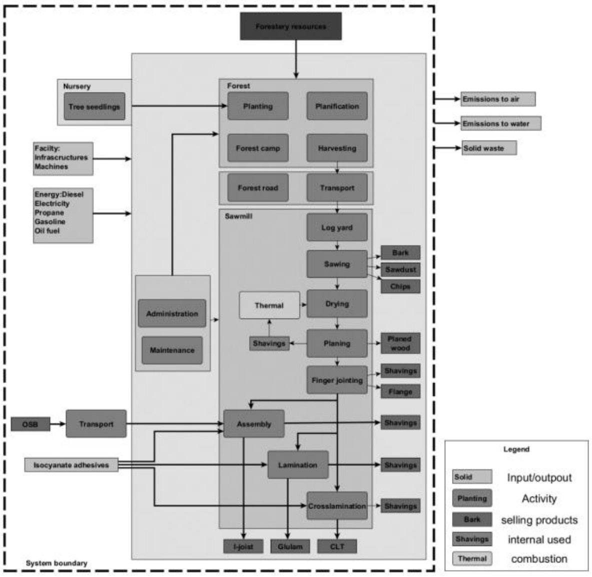

Figure 2 *Scheme of the study case activities*

As illustrated in Figure 2, the company's offerings encompass I-beams, glued laminated beams (glulam), and cross-laminated timber (CLT), in addition to the typical products and by-products of a traditional sawmill operation.

The log wood supply for the company is sourced from the public forests of Quebec. The annual allocations of log wood are determined by the forestry ministry of the Quebec province, which necessitates a constraint on the wood and biomass supply in the model. The biomass volume is calculated as a percentage of the crowns and branches from the harvested trees. The forestry activities involve harvesting and transporting the wood to the plant. After sorting at the wood yard, the logs are sawn, generating a divergent process that yields bark, chips, sawdust, and green boards. The boards that are not sold green are then dried, and the resulting planks are planned. These activities constitute the primary transformation processes in a traditional sawmill. The secondary transformation activities include joining, assembling, laminating, and cross-lamination, which produce engineered wood products such as I-beams, glulam, and CLT. These engineered wood products have a higher value-added compared to lumber and offer environmental advantages as they can substitute more energy-intensive building materials like steel and concrete.

The company's operations also generate various by-products. The bark is transported to a nearby cogeneration facility (CHP), while the wood chips are utilized by the pulp and paper industry and sold to the highest bidder. A fraction of the planed material is employed to provide the energy required for the drying process, while the remaining planed material and the sawdust are combined with the wood chips. One of the key objectives of this analysis is to propose alternative uses for these by-products to enhance the company's economic and environmental performance.

The following paragraphs present the parameters of the case study following the chronology of the methodological elements.

Attributional Life-Cycle Assessment (A-LCA)

An attributional life-cycle assessment, published in (Laurent et al., 2016), was conducted to assess the environmental impact of the industrial partner's entire product portfolio from cradle to factory gate. The system boundaries of the A-LCA were restricted to the activities under the control of the industrial partner, as the objective was to provide an environmental profile and identify potential areas for improvement. This does not preclude the subsequent addition of the "Gate-To-Grave" steps to conduct a comprehensive "Cradle-To-Grave" assessment, for instance for a building.

The environmental impacts of the product portfolio were evaluated using a functional unit of the cubic meter of solid and over-dried wood input to the system, in line with the recommendations of the forest Product Category Rules, which utilize a volumetric basis for allocation (Institut Bauen und Umwelt eV, and The Norwegian EPD Foundation). The modeling was conducted using the LCA software SimaPro v7.0 (edited by Pre consultant). Primary data was used for the initial processing activities, while secondary activities were modeled using the ecoinvent database (version 2.2) (, adapted to the Quebec context. The IMPACT 2002+ (Jolliet et al., 2003) method was employed to quantify the environmental impacts. The primary reason for using this methodology was to obtain endpoint indicators, known as damage categories, which cover all environmental impacts in just four criteria (human health, ecosystem quality, climate change and consumption of resources).

Activity-Based Life-Cycle Costing (AB-LCC)

The economic results used in this study were determined according to the principles of AB-LCC (Emblemsvåg, 2001). This method was chosen to create a parallel between the economic quantification and environmental assessment, facilitating the integration of the results from these two analyses into the optimization model. Using the same parameters as the A-LCA assessment, the costs of each activity, both in the forest and at the plant, were determined and published in (Laurent et al., 2021). These costs were allocated to the 15 products generated by the activities on a volumetric basis, the cubic meter of over-dry solid wood.

Consequential Life-Cycle Assessment (C-LCA)

The functional unit for this C-LCA assessment is the "prospective production of a forest product portfolio over a five-year horizon". This prospective production encompasses the current network of CCLtée, referred to as the baseline scenario, as well as the prospective technologies detailed in Table 1.

The main guidelines on C-LCA recognize the substitution approach between different products that serve equivalent functions (Ekvall & Weidema, 2004). Accordingly, we have adopted a consequential approach that accounts for the substitution effects of using wood products instead of the materials typically employed in construction and energy production. The identified impacts associated with these substitutions are based on the most current practices in North America. Equivalences of service were calculated using volumes, as determined by the Athena Impact Estimator software (version 5.1) published by the Athena Institute.

- I-Joint beams offer an alternative to the beams in steel structures that dominate light structure.
- Wood glulam and CLT allow the construction of' massive frame (or heavy) which come into competition with the concrete.

The environmental impacts were quantified by determining the equivalent amounts of steel and concrete required to replace the three engineered wood products. The ecoinvent database, with adaptations to the North American context, was utilized for this purpose. The IMPACT 2002+ method was employed to obtain the same four environmental damage categories as previously, namely human health, ecosystem quality, climate change, and resource consumption.

The proposed model incorporates new technologies and their corresponding substitutions. Since the company CCLtée already produces engineering products, there is limited material available to integrate additional building materials. As a result, the focus has been on energy products. The energy equivalents are incorporated into the model using the parameter Lp, which accounts for the calorific values of different energy sources adjusted by a combustion efficiency factor, as this can vary depending on the fuel. The economic and environmental impacts have been quantified using the previously described methodologies.

Table 6 *Prospectives technologies*

New technologies	Sources of environmental data	Sources of economic data	Substitution
Biomass	LCA of biomass harvested in the Matapedia Valley (Laurent & Dessureault, 2015)	(Desrochers, 2008)	
Industrial Pellet	Specific data of a wood pellet company in Quebec (Laurent, 2010) + ecoinvent (Version 2.2) (Hedemann & König, 2007) adapted to the Quebec context.	(Brodeur et al., 2008; Pellet.org 2015; Scott 2012)	Heavy fuel oil (# 6)
Domestic Pellet			Light oil
Cogeneration use	ecoinvent (Version 2.2) (Hedemann & König, 2007) adapted to Quebec context.	(FPInnovations, FPAC (Forest Products Association of Canada, and CFS (Canadian service for ETS, 2011; Hydro-Québec, 2015)	-The thermal energy is used at the sawmill for drying -Electricity is modeled to be sent to the Hydro-Québec network (Hydro-Québec, 2015)
Cellulosic ethanol	Ethanol, 95% in H_2O, from wood, at distillery / CH U (Althaus et al., 2007. Borrion, McManus, and Hammond, 2012; Murphy & Kendall 2015)	(Edenhofer Pichs-Madruga and Sokona 2012; FPInnovations, FPAC (Forest Products Association of Canada, and CFS (Canadian service for ETS), 2011; Koch 2008)	Fossil fuel (can be sold or used internally in CCltée, pickups fuel per example)
Biodiesel from pyrolytic	Ecoinvent Ethanol production	(Clark et al., 1999.	Petro diesel (may be

oil	adapted with confidential data	FPInnovations, FPAC (Forest Products Association of Canada, & Canadian Forest Service, 2011; Meier & Faix 1999; Wakker et al., 2005).	sold or be used diesel machinery harvesting or handling)

Multi-criteria optimization

The primary data used for the environmental and economic analyses were based on annual average data provided by CCLtée. To account for interannual variations in recipes and the increase in annual costs, the model was constructed with 5 one-year periods. A discount rate of 2% was applied to all costs to express that immediate gain is more certain and consequently more desirable than future gain. To enhance the model's realism, constraints were added regarding the introduction of new technologies.

To enhance the model's realism, constraints were added regarding the introduction of new technologies. A construction period was assumed for any facilities, resulting in a delay production capacity, equation 1. For example, cogeneration was estimated to have a 1-year construction timeline, while ethanol and biodiesel facilities were projected to take 2 years to build. Due to the high installation costs, hundreds of millions of dollars, for ethanol and biodiesel technologies, a constraint was added to limit the implementation to only one of these two options.

The multi-criteria optimization is conducted using the data from the consequential life-cycle assessment. The results generated directly from the CPLEX software version 12.5 (published by IBM) indicate the objective function value, as well as the material flows and technology deployment decisions. To explore the full range of potential solutions among the five criteria, an a posteriori analysis approach is adopted, wherein non-dominated solutions are generated by systematically varying the weights of the different criteria between 0 and 1 (Yalçınöz & Köksoy, 2007). This enables the creation of Pareto fronts, which are presented in the results section.

Results

The optimization model generated a substantial number of solutions, one for each scenarios (about 10^5) in a relatively short timeframe of less than 2 minutes. A scenario is a set of values of the five criterions. These experiments produced more than 150 distinct solutions. However, it would not be appropriate to provide a detailed overview of all these solutions to decision-makers. Instead, this results section focuses on the most relevant solutions, which can be categorized into three parts:

The first part graphically presents all non-dominated solutions, known as Pareto fronts;

The second graphic is a pentagon that shows the solutions for all five criteria simultaneously, allowing us to determine whether any specific criterion is being neglected;

The third part of this analysis presents the network scheme, including the flow of materials, the facility openings, and the carbon footprint and net profits.

The results are presented in graphical form to facilitate visualization and aid decision-makers' understanding. The complexity of multi-criteria optimization (Greco et al., 2015) and the life cycle approach, especially when not using a single score to aggregate environmental impacts (Hermann et al., 2007), make understanding the results challenging. Presenting the results graphically addresses these complexities. Furthermore, the methodology of solution selection is based on the principle of comparison, which makes the results easier to interpret (Horne et al., 2009). The Pareto fronts enable the visualization of the optimization model results with respect to two criteria simultaneously. After selecting a small number of relevant solutions, the analysis of results is also apparent in a comparative approach between the selected solutions (Pereyra et al., 2013).

The results presented are specific to the case study of the company CCLtée. While the scales have been preserved to demonstrate the potential gains across the different scenarios, the shape of the Pareto fronts obtained may be unique to the activities and context of CCLtée and could vary for another organization. For reasons of confidentiality, the abscissa graphs displaying the economic benefits have been removed from the presentation.

Pareto fronts

The non-dominated solutions, known as Pareto fronts, are presented to visualize the compromises between two criteria at a time, with the economic criterion as a common horizontal axis. The next four graphs show the results of future scenarios based on data from the industrial partner. The following paragraphs discuss the Pareto fronts representing the compromises between the economic criterion and climate change, human health, biodiversity, and resource consumption.

- **Compromise between the economic criterion and climate change**

The optimization model incorporates the findings of consequential life-cycle assessment, which accounts for substitution effects. Harvested wood products offer dual benefits in mitigating climate change. Timber retains approximately 50% of the sequestered carbon throughout the product's lifespan, and the processing of wood products requires less energy and generates fewer greenhouse gas emissions compared to traditional building materials like concrete and steel (Profft et al., 2009). By considering substitution effects, the avoidance of emissions makes wood products advantageous for addressing climate change. The substitution of fossil fuels with sustainably harvested biomass for energy could also be considered nearly "carbon neutral," though the greenhouse gas emissions generated during harvesting and processing of the biomass must be accounted for. Figure 3 depicts the Pareto front of non-dominated scenarios, representing the trade-off between the economic criterion and climate change. The point labeled S1 on the far left corresponds to the solution that maximizes the economic criterion, while the point denoted S4 at the bottom right represents the solution that maximizes carbon sequestration. The point S1407 is an intermediate solution that appears promising, as it can increase carbon sequestration while still maintaining a favorable economic outcome.

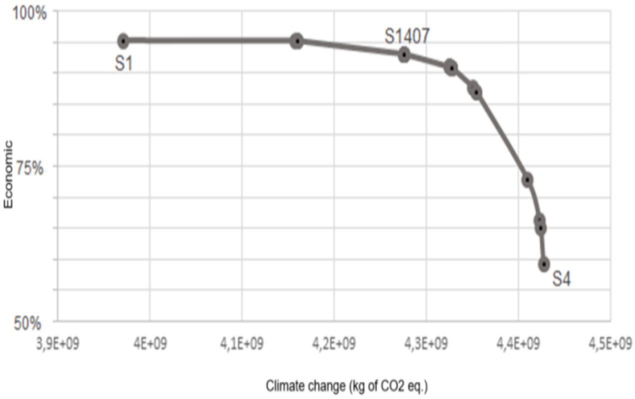

Figure 3 *Pareto's front presenting non dominated solution between economic and climate change criterion*

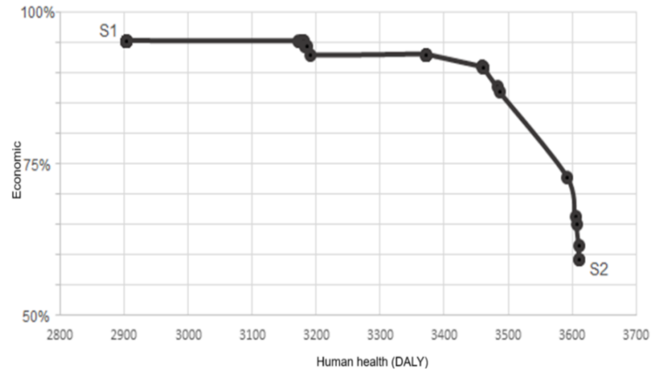

Figure 4 *Pareto's Front between economic and human health criterion*

Variations on the economic criteria are more important than climate change. Indeed, the economic gains between the scenario maximizing carbon sequestration and that maximizing profits are higher than 60%. Between the two solutions, the carbon sequestration is increased by 10%. Indicatively, the change is in the order of 0.5E09 kg of CO_2. That represents the consuming of about 150 million liters of diesel.

The optimization results indicate that variations in the economic criteria have greater significance than climate change considerations. The economic gains between the scenario that maximizes carbon sequestration and the one that maximizes profits exceed 60%. While moving from the profit-maximizing to the carbon sequestration-maximizing scenario increases carbon sequestration by approximately 10%, the corresponding economic benefits decrease substantially. Specifically, this shift in the scenario corresponds to a change in the order of 0.5 billion kg of CO2 sequestered, which is equivalent to the consumption of around 150 million liters of diesel fuel.

The optimization results indicate that future solutions are increasingly favoring bioenergy production, which enables substantial reductions in greenhouse gas emissions. However, the type of bioenergy technology implemented has a significant influence on the required investment costs, thereby explaining the variations in profitability and costs associated with the economic criterion.

- **Compromise between economic criteria and human health**

The human health impact is measured in DALYs (Disability Adjusted Life Years), a metric used by the World Health Organization to quantify the loss in life expectancy. In this case study, the primary driver of human health damage is particulate matter emissions, specifically NOx and SO2, which are byproducts of incomplete combustion of fossil fuels, such as those used in adhesives. As mentioned, the prospective scenarios favor biofuel production, which reduces climate change impacts. This explains the correlation observed between the climate change and human health criteria, as reflected in the shapes of the Pareto frontiers shown in Figures 3 and 4. The Pareto frontier in Figure 4, which presents the trade-off between economic and human health considerations, indicates that the solutions on the border are not fully optimized, representing a compromise between economic and human health objectives.

The Pareto frontier in Figure 4, which depicts the trade-off between economic and human health considerations, exhibits a characteristic bend at the top. This can be attributed to the human health impacts associated with the use of adhesives. Specifically, the scenario that aims to maximize economic revenue suggests producing I-beams at the maximum capacity, which directly leads to an increased consumption of adhesives in the OSB (oriented strand board) production process. This increased adhesive usage has a detrimental impact on human health, as reflected in the shape of the Pareto frontier.

The difference in profitability between the solution that maximizes the economic criterion (S1) and the solution that minimizes the impact on human health (S2) is comparable to the difference observed in the previous figure, amounting to approximately 60%. However, the gains in terms of reducing human health impacts are slightly more substantial, at around 20%.

- **Compromise between the economic and ecosystem quality criterion**

The ecosystem quality metric, expressed in PDF·m²·yr (Potentially Disappeared Fraction of species), quantifies the potential loss of biodiversity over a given area and time period. The primary driver of ecosystem impacts is the land use change and occupation associated with forest harvesting for wood procurement. The solution that minimizes ecosystem impacts (S3) suggests significantly reducing the harvested volume from forests. In this scenario, the biomass is utilized solely for cogeneration and industrial pellet production. The limited ecosystem impacts from the lower harvesting levels are offset by the benefits of energy substitution. However, this solution exhibits a roughly 65% shortfall in economic performance compared to the profit-maximizing scenario (S1).

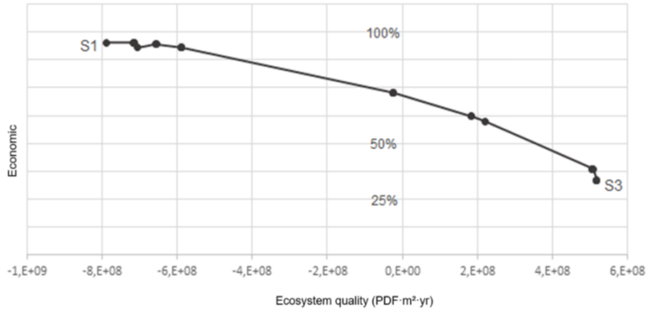

Figure 5 *Pareto's front between economic and ecosystem quality criterion*

- **Compromise between economic criteria and resource consumption**

Figure 6 depicts the trade-off between economic considerations and resource consumption, the latter measured in gigajoules, an energy unit. The difference between the solutions that maximize economic gain (S1) and minimize resource consumption (S5) is around 25% for both criteria. Furthermore, the Pareto front shows a clustering of non-dominated solutions in the region that favors resource consumption benefits. This solution consolidation can be attributed to the introduction of biofuel production technologies. The high investment costs associated with these technologies directly impact the potential profitability.

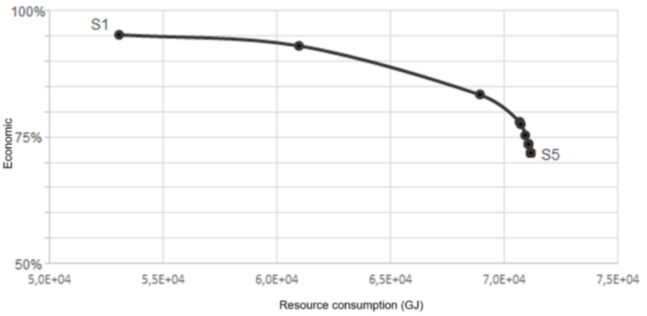

Figure 6 *Pareto's front between economic and resource consumption criterion*

Analysis of selected scenarios

The Pareto front analysis presented earlier was used to select a small number of solutions for further in-depth examination. For this discussion, we have chosen to highlight extreme solutions as well as an intermediate solution that offers an interesting result. To visualize the performance of these solutions across the five criteria, we generated pentagonal charts. When the results are weighted, this type of chart, as shown in Figure 7, provides a comprehensive overview of the analyzed solutions' performance across all criteria. A straightforward surface area calculation of the pentagon allows us to determine the scenario that achieves the best compromise among the five criteria. In the present case, the largest surface area is offered by Solution 1407, which was generated with a 93% weight of the economic criterion and a 7% weight of the climate change criterion. The solutions that minimize damage to climate change (S4) and human health (S2) were found to have very similar weighted results across the five criteria, with negligible differences between them. This led us to combine these two solutions in the chart. However, it is important to note that the material flows of these two solutions are not precisely the same.

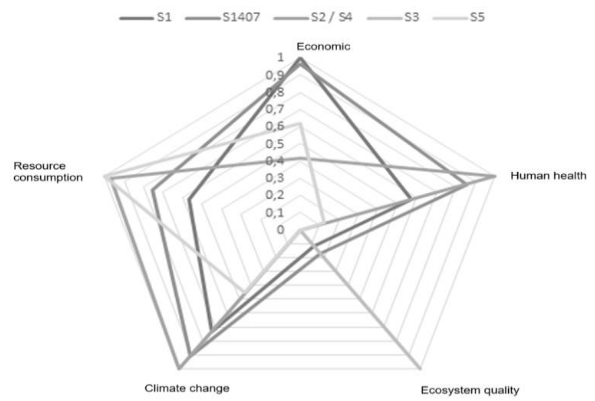

Figure 7 *Pentagon with the weighted results of the 5 criteria*

Network diagram

In addition to the pentagon chart, network diagrams were used to provide a more concrete representation of the solutions modifying the logistics network. As shown in Figure 8, these network diagrams illustrate the flow of materials (line thickness) and the technologies that were implemented. The network diagrams also include the net profit and net greenhouse gas emissions associated with each solution. Net profit is calculated by subtracting total costs from the revenue generated by selling products, while net GHG emissions represent the actual impacts of the proposed solution's activities, without considering substitution effects. Unlike the raw results of the multi-criteria optimization, which were determined using a consequential approach, these results provide an attributional perspective on the real impacts of implementing the proposed solutions. This information is considered relevant for decision-makers.

The network diagrams and calculations were generated for all scenarios using a Python script. In this section, only the solution for Scenario 1407 is presented, to avoid overloading the document. However, to illustrate the impacts of implementing new technologies, the optimized initial scenario for Scenario 1407 is also presented. Unlike the prospective scenarios, the initial scenarios only optimize the flow of materials, and do not allow the implementation of new technologies.

- **Optimized prospective solution**

The network diagram for Solution 1407, depicted in Figure 8, showcases the proposed model's incorporation of new technologies. The dotted frame surrounding the original plant layouts delineates the areas where these novel technologies have been integrated.

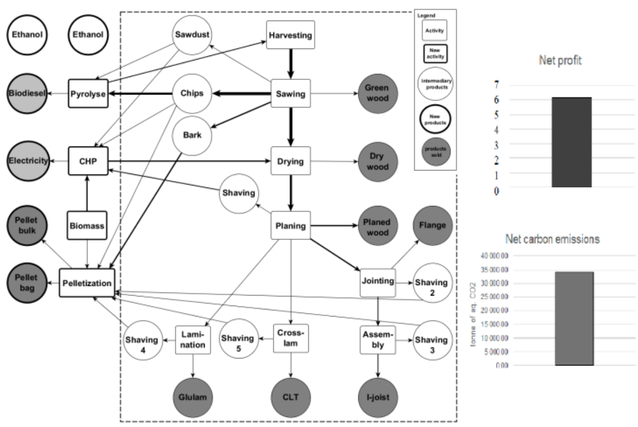

Figure 8 *Material flow network of the solution 1407*

The proposed solution involves harvesting forest biomass and utilizing it to power the cogeneration plant. The thermal output from the cogeneration plant is used for drying, while the generated electricity is sold to the national grid. The remaining biomass is used to produce industrial-grade wood pellets, which are then sold as a substitute for heavy fuel oil. Additionally, the white matter (without bark) from wood shavings is densified and bagged for sale as a higher-priced domestic wood pellet product. This scenario also includes the production of biodiesel, which is used directly in the forestry equipment and logging trucks.

- **Optimized initial scenario**

Figure 9 illustrates the outcome of the optimized initial scenario, in which the introduction of new technologies was not allowed, and the decision variable was restricted to material flow. As depicted, all products are sold directly. The energy products generated in the prospective scenario, however, increase the added value of these resources, resulting in a doubling of expected profitability for the company. This finding emphasizes the merit of the proposed implementation of new technologies presented previously.

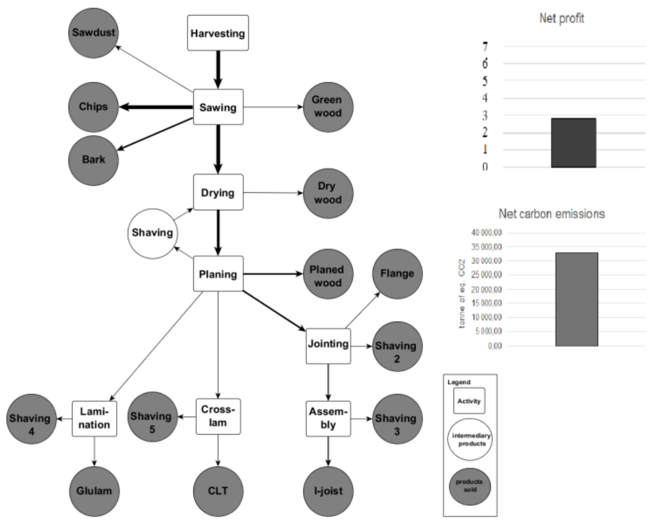

Figure 9 *Material flow network of the optimized initial scenario (without allow the model to open prospectives technologies)*

As depicted in the histograms in Figures 8 and 9, this solution enables a doubling of profits compared to the optimized baseline scenario, without significantly increasing greenhouse gas emissions. This is achieved through the implementation of biofuel production and internal utilization.

Discussion

The costs of reducing greenhouse gas emissions through the implementation of new technologies can be calculated by subtracting the gains from the initial scenarios (without new technology) from the prospective scenarios. Using these results, a marginal abatement cost curve was generated, as shown in Figure 10. The marginal abatement cost curve (MACC) is a graphical representation that explicitly displays the cost associated with the implementation of a technology for reducing GHG emissions, expressed as a percentage relative to a reference scenario (Kesicki and Strachan, 2011).

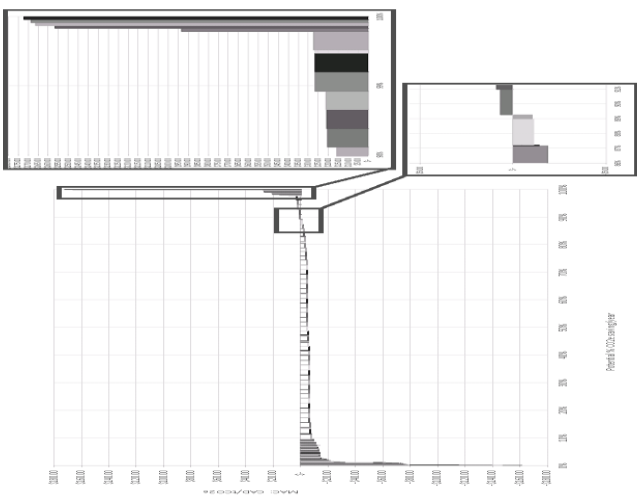

Figure 10 *Marginal Abatement Costs Curve*

The MACC indicates that 89% of the proposed scenarios reduce greenhouse gas emissions while increasing profits, as shown by the point where the curve intersects the horizontal axis. A closer examination of the MACC reveals that 99% of the scenarios have a cost of less than CAD 50 per ton of CO_2 equivalent.

The MACC presented in this study could be useful not only for industry, but also for government policy makers in the context of climate change mitigation and carbon pricing. By conducting similar analyses and generating MACCs, policymakers may be able to reduce uncertainty around the appropriate carbon price to facilitate the implementation of new emissions-reducing technologies. Based on the findings of this specific case study, a carbon price of CAD 25 per ton of CO_2 equivalent would enable the implementation of 98% of the proposed technological solutions.

Conclusion

The objective of this research project is to provide a tool for strategic decision which is distinguished by its retrospective approach and by using the result of economic and environmental analysis to anticipate changes based on specific data. The results demonstrate that the integration of environmental criteria to generate solutions that would not have been visible only looking at the economic aspects and probably also by aggregating all environmental criteria into a single score. The proposed approach presents a panel of compromises between each of the optimized criteria. This will offer decision makers a more complete picture of opportunities, which can thus allow them to make a more informed decision in the planning of future developments.

Multi-criteria optimization presented here integrates economic and environmental aspects only. As a tool for decision support covering the whole sustainable development, it would need to integrate to social aspects through a Social Life-Cycle Assessment (Kloepffer, 2008; UNEP 2020), or sustainable assessments (Sala et al, 2015). Although these are implicit in the case of this study, as in remote regions of Quebec, good corporate economic health allows benefits to the entire local community. The development of Social Life-Cycle Assessment has already been underway for a few years now, and so when it will be extended it will provide representative quantifications despite contextualization difficulties (Wulf et al., 2019). Therefore, adding criteria to the optimization model should not present difficulties, other than when interpreting the results.

Another potential improvement would be to provide a robust solution int a stochastic model by integrating uncertainty into the proposed solutions represents an additional challenge. Both Attributional Life-Cycle assessment and Activity-Based Life-Cycle Costing have yielded uncertainty estimates for the results. However, the mixed-integer linear programming approach employed makes it difficult to easily determine the shadow costs of the optimal solutions. Adopting a stochastic optimization framework could provide a more robust evaluation of the solution alternatives, accounting for the uncertainties in the input parameters and modeling assumptions. This would allow decision-makers to better comprehend the risks and trade-offs associated with the different options.

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