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OPTIMIZING MODULAR PRODUCT-SERVICE SYSTEMS WITH CIRCULAR BIO-WASTE MATERIALS

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ABSTRACT

A transition to a circular economy will imply new methods, accompanied by the introduction of sustainable materials and service-based functions into industries. However, effectively integrating bio-waste-based materials into modular product systems remains challenging due to trade-offs between cost, durability, and operational efficiency. An optimization version of the so-called Modular Product-Service Systems (MPSS) has been developed in the paper to replace the circular bio-waste materials so as to achieve the goal of the environmentally-sustainable operation and efficiency. It is stated that the modularity principles of products and prospects of regeneration of bio- waste resources facilitate the low value of lifecycle and environmental failure and high share of resource circularity, flexibility of the service, and reusability of components. Considering degradation rates, service schedules, and logistical capacities, a Mixed- Integer Linear Programming (MILP) model is designed to optimize the selection, allocation, and maintenance of bio-waste-based product modules. In an attempt to solve the conflicting goals, the framework incorporates both Life Cycle Assessment (LCA) and Multi-Criteria Decision-Making (MCDM) on the basis of the Technique of Order Preference by Similarity to Ideal Solution (TOPSIS). This form of integrated approach is capable of providing informed evaluation of trade-offs among economic, ecological and operational standards. The applicability of the model will be realized with aid of a case study in the modular furniture sector that lower the cost of furniture materials using farming bio-wastes without compromising on the furniture durability and functionality in terms of numbers of years of service. The case study results demonstrate that the proposed MPSS framework achieves superior financial returns (ROI 175%, breakeven by Year 6), extended service life (7.5 years), and higher circularity (65%) compared to benchmark methods, while balancing cost–carbon trade-offs through integrated LCA– MCDM evaluation. These outcomes confirm its effectiveness in delivering economically viable, environmentally sustainable, and operationally flexible solutions for circular

KEYWORDS: Circular Economy, Modular Product-Service Systems, Bio-Waste Materials, Mixed-Integer Linear Programming, Multi-Criteria Decision-Making.

1. INTRODUCTION

Development towards a circular economy has gained significant momentum in the industrial sector, as highlighted, on the wave of attempts to achieve sustainable development (Lee & Hsu, 2025). Linear production models which were traditionally based on the take–make–dispose model are no longer possible as the natural sources are getting depleted faster and the environmental pollution is on the rise, as noted by (khaenamkhaew, 2025). The concept of circular economy enhances resource efficiency by reusing, recycling, and regenerating (i.e., closing and creating loops) with material as a result of which the waste volume decreases and environment becomes less damaged (Gong et al., 2025). As organizations look forward to balance the goals of economic growth with environmental stewardship, more and more attention is being paid to the redesign of product design and business models that aim to introduce a sustainability element in them at an early stage (Huang et al., 2024). This change is forcing manufacturers to innovate both in their choice of materials as well as in service delivery, lifecycle management and in their delivery activity (Liu et al., 2023).

It is the emergence of MPSS as a potential transition strategy in this sustainable transition (Yang et al., 2023). The modular product architectures supplemented and enhanced by service-based models are incorporated with MPSS, allowing the products to be designed on the sets of modular architecture and interchangeable modules (Mestre & Cooper, 2017). This modularity increases flexibility, easier maintenance and upgrades and accommodates reusability and remanufacturing of parts (Emec et al., 2015). Most importantly, MPSS, when integrated into the context of circular economies, will enable the replacement of frequently non-renewable resources that are used with more sustainable raw materials, including circular bio-waste (Fratini et al., 2019). The bio-waste materials: farm waste materials, bio-products: They provide a resource which is renewable and abundant and can help to decrease the use of virgin materials as well as to lower environmental impact (Hazen et al., 2022). Service models linked to MPSS extend product lifespans and shift the focus toward performance, creating new value streams that promote responsible consumption (Kopnina, 2019). Nonetheless, the use of bio-waste materials in the implementation of MPSS possesses complexities of the module degradation scheduling of function and recognition of supply chain that should be carefully handled in order to support the feasibility and effectiveness of the system (Glavic et al., 2020).

With this understanding of issues, this paper is going to propose an integrated optimization model that can assist in decision-making to develop and operate MPSS using circular bio-waste materials. Raising the essence of this framework lies a MILP model that optimizes bio-waste-derived product modules and selection, assignment, and support to adaptive operations-based confinements like reduction rates, maintenance schedules, and logistical capacities. The model is combined with a MCDM strategy that is founded on the TOPSIS in order to reconcile the interfering economic, environmental, and operational goals. Such a holistic approach will allow the stakeholders to trade-offs as well as prioritize the best solutions with a maximum focus on sustainability without compromising service performances.

To illustrate the proposed structure, the authors use a practical example in the development of modular furniture where in its development, agricultural bio-waste materials have been used to substitute the traditional inputs with no subtraction to the indicated durability and service life. The obtained results indicate a significant promise that materials costs and carbon emissions may be reduced without sacrificing service levels. Besides, sensitivity analyses illustrate the levels at which changes in the supply chains performance and the customers demand impacts the effectiveness of the systems highlighting the flexibility and strength of the introduced model to dynamic environments. This study, by combining modular design principles, circular integration of bio-materials and better optimization methods, presents an entirely integrated decision-support tool aiding in sustainable manufacturing and service systems, long-term creation of environmental and economic values.

2. RELATED WORKS

In recent research, circular economy principles have been more frequently combined with modular product-service systems and material substitution through sustainable materials, especially bio-waste as renewable material. MILP is one and MCDM methods like TOPSIS are the other optimization methods which were used extensively to reconcile economic, environmental and operation targets. The previous literature reveals that modularity provides flexibility and resource-efficiency as well as the potential reduction in environmental impact due to bio-waste. Nevertheless, most of the current strategies do not exhibit a holistic approach to the cumulative aspects of degradation of material, scheduling of service, and logistics at a supply chain level. The table 1 below shows major contributions about literature, their methods of accomplishment, benefits, and shortcomings giving an idea about the presented comprehensive optimization model in this of work.

Table 1: Comparative Analysis of Existing Approaches in Circular Economy and Modular Product-Service Systems.

No.	Authors	Techniques	Advantages	Disadvantages
1	Lee and Hsu (2025)	Smart customization, TQM	Improved quality, sustainability	Complex customization
2	khaenamkhaew (2025)	Circular economy framework	Comprehensive sustainability overview	Conceptual, lacks modeling
3	Gong et al. (2025)	AI-based industrial ecology	AI-driven resource optimization	Integration complexity
4	Huang et al. (2024)	Energy harvesting technology	Efficient kinetic energy capture	Focused on energy systems
5	Liu et al. (2023)	System mapping, interdependency	Supports local waste planning	Specific to municipal waste

Lee and Hsu (2025) suggested a medium of both smart customization and Total Quality Management (TQM) to improve upon green innovations to the production of pellets of wood and design of furniture. Their production is aimed at enhancing the quality of products, making them sustainable, and customizing the modular furniture components, yet there is a problem with the complexity of implementation. The paper proves the possibilities of combining the quality control with the transition to circular materials but fails to consider big-scale supply chains interactions.

khaenamkhaew (2025) explored the major premise of a circular and sustainable economy, the importance of responsible management of resources and conservation of the environment. The provided study offers a full conceptual framework and no depth on specific models of operations or quantitative studies. Although it forms the basis of sustainability thought, it does not provide much on how it should be applied in practice in industrial situations.

Gong et al. (2025) discussed the relationship between industrial ecology and artificial intelligence and suggested the concepts of AI-based optimization of resource productivity and sustainability. Though they provide innovative solutions, the practice presents major integration complexities. Their contributions open the door to smart decision-making and require modification to particular modular product-service systems.

Huang et al. (2024) implemented a three-layered energy harvesting device capable of capturing ejected energy and reusing it efficiently through all electromagnetic, triboelectricity, and piezoelectric effects. Even though they are applied to energy systems, the technology exhibits potential to make sustainability increase in other areas. Nevertheless, it has a narrow applicability when it comes to optimization of products-services.

In mapping the interdependencies locally, Liu et al. (2023) studied system transitions in municipal solid waste infrastructure. Their model facilitates better decision-making based on waste management, but may only apply to municipal systems and is unlikely to be directly applicable to the framework of industrial products and services. However, what comes out in their approach is the significance of comprehending complex system interactions during the transition to the circular economy.

In accordance with the limitations described in the available literature, it can be said that although a number of studies have made important contributions dedicated to modularity, sustainability, and the principles of circular economy, the lack of an integrative, practical model capable of addressing the technical, logistical, and economic complexities involved in the real-world implementation of Bio-waste-based MPSS remains a significant gap (Hazen et al., 2022). The notable gaps are a deficiency of quantitative optimization tools to deal with module degradation, service planning and logistic constrains as well as weakness in the ability to conduct trade-offs between the economic, environmental and operations goals (Leite et al., 2021). With the goal to overcome such gaps, the proposed structure adds a MILP model which is combined with MCDM through TOPSIS, designed specifically to optimally design and operate MPSS using circular bio-waste materials. This method allows conducting a systematic analysis of contradictory goals and contributes to data-driven decision-making therefore avoiding the weaknesses of such prior works in terms of conceptual, contextual, and integration weaknesses (Barkhausen, 2024).

3. SUSTAINABLE DEPLOYMENT FRAMEWORK

The system model postulated to integrate bio-waste into sustainable MPSS takes a stepwise approach, which is however, interwoven to five steps. It starts with modular design and integration of bio-waste materials where the components of the products are re-engineered into standard modules consisting of environmentally friendly material based on agricultural and industrial bio-waste (e.g., rice husks, sawdust, coconut coir). The modularity helps in supporting circularity, enhances reusability and it offers flexibility in context of customization. After these modules are designed, the optimization of these modules using MILP is the next stage because it is going to select, assign these modules to each other and schedule them to optimize the lifecycle cost, and ensure that it considers degradation, maintenance requirements and constraints in terms of logistics. Quantification of the environmental performance of the system is then carried out to check the validity of the system after optimization through LCA. This has made it impossible to use any chance of the inclusion of the bio-waste material and the modular trend to cause environmental burdens at any point of the product lifecycle, i.e. materials sourcing of the raw materials of the products up to disposing it. The figure 1 shows the proposed system architecture.

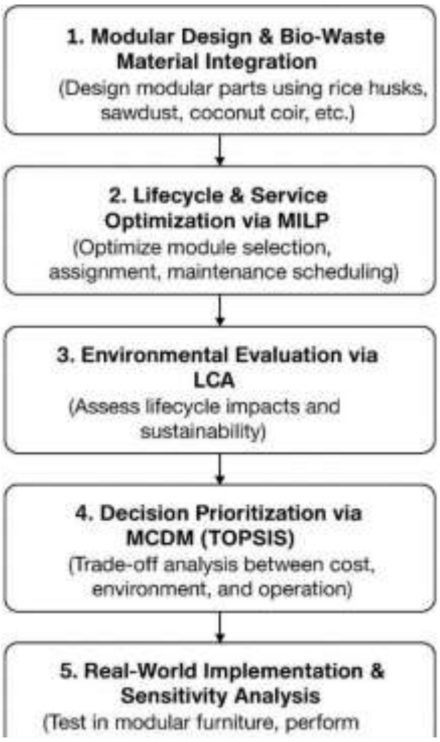

Figure 1: Proposed System Architecture.

Upon determining environmental sustainability, framework uses MCDM in form of TOPSIS method to solve trade-offs between economic, environmental, and operational objectives. In calculating the relative proximity of options relative to an ideal solution, the decision-makers can weigh options based on configurations that are more balanced, as well as sustainable. Lastly, the model is also tested on a real-world example in the modular furniture business where practical usage is performed and sensitivity analysis carried out. Such simulations question the capacity of the system to respond to dynamic changing customer demand, supply chain and fluctuations in materials. The lessons of this review affirm that the MPSS framework is bendable, scalable and able to generate a sustainable value-creation in various industries. The fact that the concept of the use of modularity, bio-based material, optimization modelling, environmental accounting and also decision analysis collectively form a cohesive framework is an example of a mechanically disciplined and feasible roadmap to the implementation of circular economy in engineering and other manufacturing systems.

3.1. Modular Design and Bio-Waste Material Integration

The first component in the suggested system is the design of modular product parts with the use of environmentally sustainable bio-waste. Modular design can be defined as the ability to break a product into small and smaller, standardized, and functionally separate units design to facilitate assembly, disassembly, repairing, and replacement of components. It is a circular approach that promotes the value of the product in terms of its service life and facilitates efficient reuse and recycling. Conventional raw materials are also replaced with bio-waste-based materials (rice husks, coconut coir, or sawdust) to fit into the sustainability idea towards the environment. Such materials are chosen depending on their durability (mechanical strength), their environmental friendliness, accessibility and economic feasibility. This sort of modular design helps the manufacturers to react more elastically to different customer demands, and decreasing environmental harm that comes with a linear establishment of production (Alejandre et al., 2022). A metric called Material Integration Efficiency (MIE) is presented to illustrate the advantageousness of bio-waste materials to be used in modular integration. This indicator looks at the structural performance and circularity contribution of the material and expressed in equation (1) below,

$$MIE_i = \frac{\alpha . S_i + \beta C_i}{C_{max}}$$

MIE_i: Material Integration Efficiency of module i, S_i: Structural performance score (e.g., tensile strength, durability), C_i: Circularity contribution (percentage of recycled or renewable content), C_{max} : Maximum possible circularity score for normalization,

α, β : Weighting factors (e.g., α=0.6, β=0.4) representing the relative importance of

structural and environmental factors. This formula ensures a balanced evaluation of both performance and sustainability, guiding the optimal selection of bio-waste materials for modular product development (Hobson, 2020).

3.2. Lifecycle and Service Optimization through MILP Modelling

In the second step of the suggested system, the Mixed-Integer Linear Programming (MILP) model will be introduced which is to optimize three following aspects: the choice of the bio-waste-based product modules, the distribution of these modules among the service points, and the maintenance schedule of the discussed modules (Tomic´ & Schneider, 2017). This optimization is done to ensure system efficiency when subjected to real-world constraints like the degradation rates of bio-based materials (they degrade faster than synthetic alternatives), the frequency of maintenance operation calculated based on its service load and the logistical limitation such as transportation and storage capacity (Xu et al., 2024). The most important task of the MILP model is to minimize the total lifecycle cost (TLC), maximize the operation reliability, and maximize the possibility to recycle the components. The MILP model objective function may be written as equation (2),

$$\min \sum_{i=1}^{M} \sum_{t=1}^{T} (C_{install,i}\, x_{i,t} + C_{maint,i}\, m_{i,t} + C_{log,i}\, l_{i,t}) \tag{2}$$

Here, M is defined as the number od module types, T is defined as time periods in the planning horizon, $l_{i,t}$ is defined as the logistics usage for module i, $m_{i,t}$ is defined as the maintenance activity indicator for module i, $x_{i,t}$ is defined as the binary for

selecting module i at time t, C_{log_i}, C_{maint_i}, $C_{install_i}$ are defined as the cost coefficients for

installation, maintenance and logistics. This equation reflects the system's intent to minimize total costs while managing lifecycle constraints, ensuring modular services remain both economically and environmentally sustainable throughout their operational life (Sönnichsen et al., 2025).

3.3. Evaluation Using Life Cycle Assessment (LCA)

Reproductive LCA to check and justify environmental sustainability of integrating bio-waste materials with use of modular product-service systems forms the third proposal of the system framework (Florin et al., 2015). LCA is a scientific standardized system internationally (ISO 14040/14044) which determines the effects produced on the environment by a product or a system paying attention to the entire life time of a product or system (raw material extraction / cradle / to manufacturing, distributing, using and disposing / grave). Here, LCA would be necessary to help arrive at the positive conclusion regarding the purpose of substituting traditional raw materials with bio-waste derivatives leading towards the existence of net environmental impacts abatement (Maaßen & Urbano, 2024). It assists in the identification of any ecological trade-offs that might develop as a result of the processing of bio-waste increased energy requirements or use of chemicals in pre-treatments) that might exist. LCA is subdivided into four very important processes:

- Goal and Scope Definition – This phase establishes the purpose of the LCA (e.g., comparing bio-waste-based modules vs. conventional ones) and sets system boundaries (e.g., cradle-to-gate, cradle-to-grave).
- Life Cycle Inventory (LCI) – This involves collecting quantitative data on material inputs (e.g., rice husks, adhesives), energy consumption, water usage, transportation, and emissions (e.g., CO□, CH□, NOx) throughout each stage of the module's lifecycle.
- Life Cycle Impact Assessment (LCIA) – The collected data is translated into impact categories using established models. Common indicators include Global Warming Potential (GWP), Eutrophication Potential, Ozone Depletion, Acidification, Human Toxicity, and Water Footprint.
- Interpretation – Results are analyzed to identify environmental "hotspots" and make informed decisions to minimize impacts. For instance, if drying coconut coir is found to be energy-intensive, alternative processing methods or renewable energy sources may be considered.

This step is essential to move environmental sustainability from theory to measurable and practical application. It also allows comparison of design options to be compared, trade-offs to be analyzed between ecological costs, cost and operational performance (Alqassimi, 2025). Combining LCA and the previous MILP model, the decision is made more comprehensive, which means that an engineer and industry manager can consider both environment-related and logistical and economical goals. Finally, this move validates the importance of employing bio-waste materials in reinforcing a circular economy structure, and without recycling substances that create other unintended demands on the environment (Sehnem et al., 2023).

3.4. *Decision Prioritization via Multi-Criteria Decision-Making (MCDM)*

The fourth step in the above framework is to utilize an MCDM framework to manage the various and in many cases, conflicting goals of cost minimization, environmental impact reduction, and service performance maximization (Lit et al., 2024). Trade-offs are common in sustainable product-service systems, such that a designing option with cheap material can lead to large carbon footprint, whereas one that has a high level of recycling can be associated with high logistics-related costs (Henry et al., 2020). The complexities are not captured in a traditional single-objective model hence the necessity of MCDM to make balanced decision in a multidimensional environment. The choice of the TOPSIS is based on its effectiveness and simple addiction to the quantitative models used in this study. TOPSIS measures the alternatives with respect to a geometric proximity to an ideal solution (the best marks in all criteria) and the greatest distance to a negative-ideal solution (the worst marks). Both the normalization of decision matrix and the weightage of each criterion is done after which the relative closeness coefficient $C*$ of each alternative i is determined as equation (3),

$$x_i^* = \frac{D_i^+}{D_i^+ + D_i^-} \tag{3}$$

Where: $D+$ Euclidean distance of alternative i from the ideal solution, $D-$: Euclidean i i distance of alternative i from the negative-ideal solution, $C*$: Relative closeness to the ideal solution ($0 \le C* \le 1$). A higher $C*$ indicates that the alternative is closer to the i i ideal solution and is therefore more preferred. By ranking alternatives based on $C*$, decision-makers can identify the most balanced option across economic, ecological, and operational dimensions. This ensures that strategic decisions—such as material substitution, module configuration, or service model selection—are grounded in a transparent, quantifiable, and sustainability-oriented process (Baldassarre & Calabretta, 2024).

3.5. *Implementation and Sensitivity Analysis in a Real-World Case*

Real-life experiment and validation of the MPSS model in the furniture industry, specifically within the field of modular furniture will be the last practical step of the proposed framework and this is in the form of an experimental evaluation of the proposed model potential in regards to its viability as well as performance (Van Opstal & Borms, 2023). In such application, bio-waste products like rice husk composites, sawdust boards and coconut coir panels are used to create modular furniture parts, e.g. panels, support, and connectors. The modular design is subject to mass customization, easier maintenance and easy disassembly to be recycled or used again (Bauwens et al., 2024). The realization not only proves that these bio-waste alternatives have the potential to reach structural and aesthetic expectations but also proves that in terms of material savings and the carbon impact, concrete gains are made without damaging the operation or consumer satisfaction of the products (Zucchella et al., 2022).

To evaluate how efficient and adjustable the model is in a dynamic environment, sensitivity analysis is drawn to essential parameters including the efficiency of the supply chain, material availability, customer volatile demand, and maintenance rate. Such simulations consider the impact of very small changes in those parameters to the general system performance of cost, continuity of service, and environmental performance. These may be late deliveries of bio-waste, changes in consumer taste preference or greater rates of degradation. Such analysis shows that the MPSS model is highly resilient, which is attributed to its modularity, service flexibilities, and optimization of decisions present within its design. These results indicate that the presented framework can become scalable; however, it can also be transferred to other manufacturing industries (e.g., consumer electronics, packaging, or construction materials) that find themselves planning to consider the circular economy concept and the establishment of sustainable services approaches (Sahabuddin et al., 2023).

4. RESULTS

In this section, a discussion and analysis of the findings of the proposed five steps model of the modular system that focuses on integration of bio-waste into the product- service system to enhance sustainability are presented. The ability of each module of the framework which include modular design, optimization based on MILP, life cycle analysis and prioritization of the decision has been implemented and tested in a real- life case study in the modular furniture business. The results are used to determine the effects of the system on the environment, economy as well as it operations. Sensitivity analyses were further carried out as an effort to know how robust the model was in different situations of demand and supply. The discussion will give information on the effectiveness of the model, practicality, and flexibility of the model to other industries and especially in industries with interests in circular and sustainable production strategies.

4.1. Dataset Description

The dataset integrates economic, operational, and environmental indicators to provide a comprehensive foundation for evaluating and comparing the Proposed, GA, LP, and RBES approaches while contextualizing circular economy interventions in India's agricultural sector. From an economic perspective, it records an initial investment of 100,000 rupees, yearly and cumulative discounted cash flows, lifecycle costs across five demand scenarios (S1–S5), and annualized Net Present Values (NPV) projected over a ten-year horizon (Kaggle, 2025). The operational indicators capture demand levels ranging between 1,100 and 1,150 tons, product service lives of 6.0–7.5 years depending on the method, circularity ratios from 35% to 65%, solver times between 180 and 450 seconds, and an operational flexibility index spanning 0.50–0.85. Complementing these are state-wise agricultural bio-waste records that include data on livestock residues, crop byproducts, and other organic wastes, with seasonal variations providing insight into regional differences and waste management challenges. The environmental indicators encompass scenario-based carbon emissions, ranging from 18.0–22.0 kg CO_2 eq under material cost scenarios and 18,800–20,000 kg CO_2 eq for operational strategies, along with method-specific carbon footprints between 12,000 and 22,000 kg CO_2 eq. Together, these multidimensional data points support the MILP optimization model and the integrated LCA–MCDM (TOPSIS) framework, enabling a holistic assessment of economic viability, operational efficiency, and ecological sustainability while offering actionable insights into agricultural waste utilization and resource-efficient decision-making (dataset, 2025).

The figure 2 provides a cumulative discounted cash flow (in rupees) of four approaches: Proposed, GA, LP and RBES on an initial investment 100-thousand rupees in Year 0. The Proposed model shows the highest financial performance paying back by the 6th year and touching about 76,000 at Year 10 demonstrating the highest ROI. In comparison, the GA model will have a payback in Year 7 with a final amount returned approximately at 48, 000 and the LP model will have a break in year 8 and the amount returned will be approximately 30, 000. RBES model is way behind with the payback coming only in Year 9 with maximum cumulative cash flow of only 18000 rupees. This comparative analysis reaffirms the higher economic feasibility and the quicker speed of recovery of Proposed model in sustainable system deployment.

Figure 3 shows how the total lifecycle costs (in 1,000) can change with the different effect of demand (S1 to S5), and reflects how economics of a system is sensitive in terms of market demand. Due to the increase in the demand within all the Scenarios S1 to S5, the total lifecycle cost also increases in a linear manner with an initial value of 80k in the Scenario S1 and a final value of 130k in Scenario S5. In particular, the cost rises to 90k in S2, 100k in S3, 115k in S4 and culminates at 130k in S5. The given tendency highlights the direct relation of the increased demand and operational spending that probably can be explained by more materials use, logistics complexity, and energy demands. This kind of analysis underlines the significance of scalable and revenue-flexible design of an environment of sustainable manufacturing.

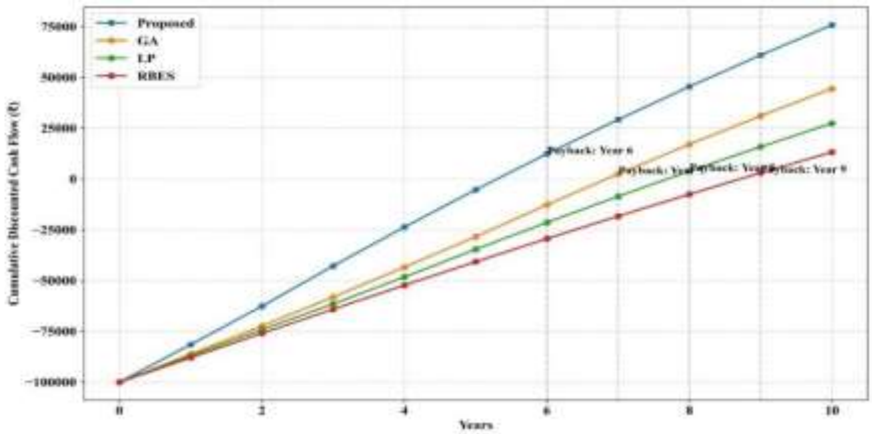

Figure 2: Cumulative Discounted Cash Flow.

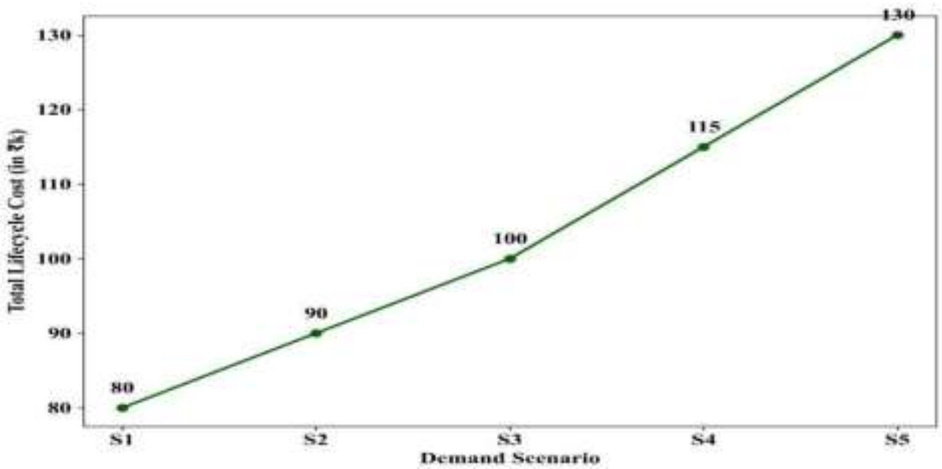

Figure 3: Demand Scenario Based Total Lifecycle Cost.

The figure 4 demonstrates the connecting lines between material cost scenarios (S1 to S5) and linked carbon emissions (in kg CO 2 eq). There is an apparent growth tendency in which the cost of materials increases and subsequently carbon emissions increase. The amount of emissions in Scenario S1 is minimal and amounts only to 18.0 kg CO2 eq, thus having minimal environmental effect. This creeps up to 18.5 kg CO 2 eq in S2, 19.0 kg CO 2 eq in S3 and then rises faster to 20.0 kg CO 2 eq in S4. S5 with an emission of 22.0kgCO 2 eq. is the highest. The trend implies that cheaper materials are probably composed of sustainable or bio-waste, and thus lower the carbon emissions, whereas more expensive materials have a higher impact on the environmental degradation. It is noted in the analysis that cost efficient and environmentally sensitive material choices should be considered to ensure the physical and capital sustainability.

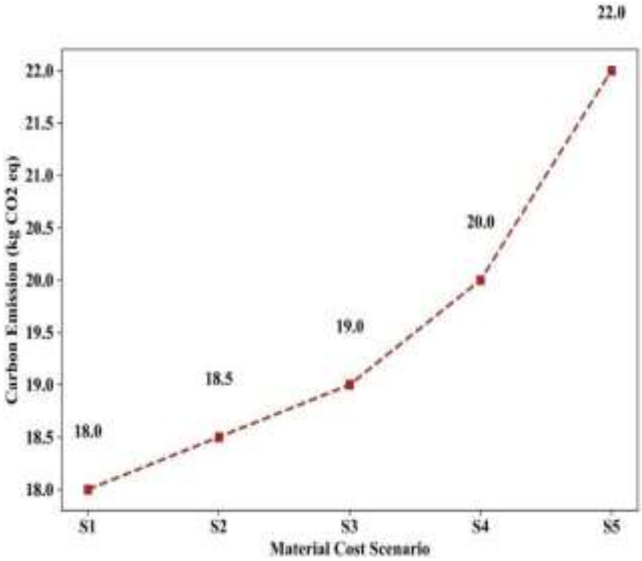

Figure 4: Material Cost Scenario.

Figure 5 shows the comparison of the four approaches, Proposed, Traditional LP, GA (Genetic Algorithm) and RBES (Rule-Based Expert System) with regard to service life (in years) and circularity ratio (in %). The Proposed method is better than all other methods due to the service life of 7.5 years and the highest ratio of circularity at the level of 65 percent after that meaning that it will remain viable for a long and will have little impact on the environment. The Traditional LP approach indicates service life of

7.0 years, which is slightly lower than the proposed, not to mention the extremely low circularity ratio of 40 percent, which indicates poor reuse or recyclability of the materials. The method based on the GA provides a weak balance between the durability and sustainability as the GA method offers 6.8 years of service life and supports 58 % of the circularity ratio. In the meantime, RBES has the shortest service life (6.0 years), as well as the lowest circularity ratio (35%) and highlights how inefficient it is in both of these facets. All in all, the Proposed model is the most viable in terms of not only providing a longer lifespan of its operation but also contributing greatly to the idea of the circular economy because of the increased capability of recycling and the shortened amount of trash.

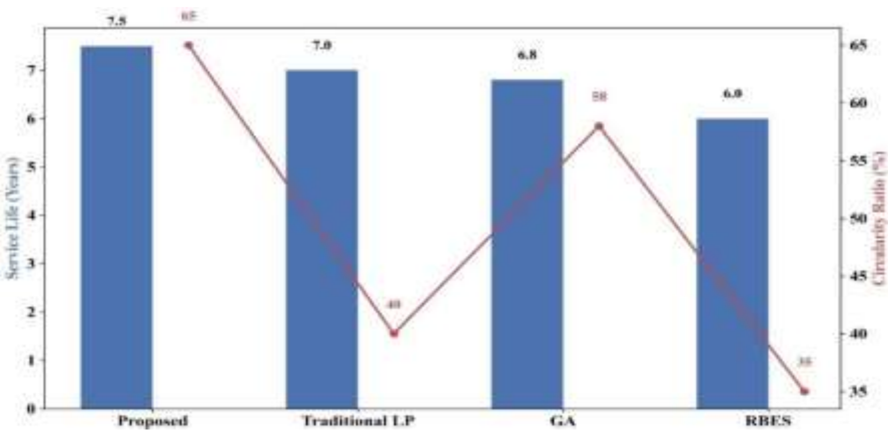

Figure 5: Service Life Validation.

The figure 6 shows the comparative result of four methods- Proposed, Traditional LP, GA, and RBES based on cost reduction (%) and carbon footprint (kg CO 2). The Proposed approach offers the highest cost savings in the proportion of 18.5%, but the carbon footprint comes with a figure of 22,000 kg CO 2 eq, where a trade relate is between cost savings earned to the environmental impact. Compared to the GA-based optimization the cost savings of 15.7%, which is respectable, however even here a lower more balanced carbon footprint of 19,800 kg CO 2 eq is produced. Conventional LP realizes an intermediate 10.2 percent decrease in expenses, whereas RBES raises the lowest decrease to 8.3 percent, but the most favorable environmental impact with only 12,000 kg CO 2 eq, an indicator of intense ecological efficiency but low economic opportunity. The Proposed method is economically superior, however, could be mitigation-based in terms of more significant environmental impact compared to other methods.

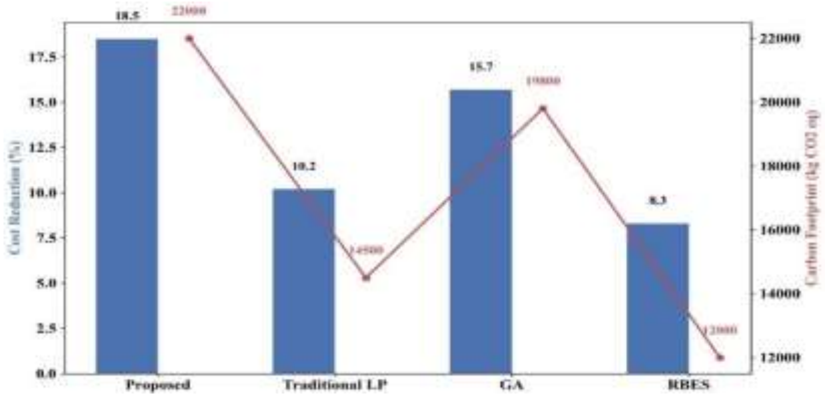

Figure 6: Cost Reduction Evaluation.

Figure 7 is a comparison of Operational Flexibility Index (blue bars) and Solver Time in seconds (red line) in dual axis of comparing four methods: Proposed, Traditional LP, GA and RBES. The Proposed model has the best flexibility index as 0.85 which shows maximum adaptability, and also the solver run time is reasonable as 320 sec. GA method is next with a flexibility index of 0.75, however, it had the longest solver time of 450 seconds which is an indication that it is computationally inefficient. Conventional LP presents a moderate flexibility index of 0.60 and an increased solver time of 250 seconds that is not adaptive but balances flexibility and calculations time. RBES which takes the fastest time of 180 seconds (solver) has a flexibility index of 0.50 which shows that it has a low flexibility in its operation. In sum, the Proposed system offers the most adequate performance, solving the problem of maximum flexibility with reasonable undesirable computational effort, which makes it the most successful regarding the other analysed methods.

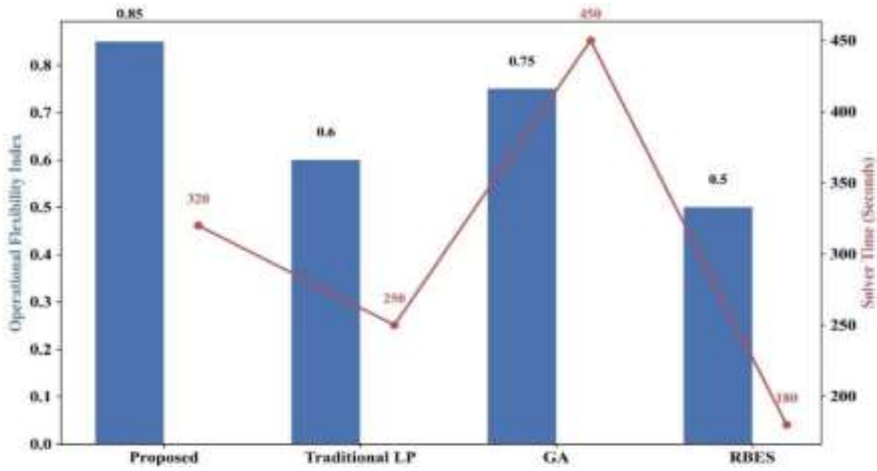

Figure 7: Operational Flexibility Index.

Figure 8 shows that the Return on Investment (ROI) is compared among four methods of optimization including Proposed, GA (Zhu et al., 2025), LP (Islam et al., 2020), and RBES (Talebi et al., 2025). The projected model is simply the best as the ROI is highest (175 %) as compared to the others implying that Proposed method is financially very efficient and the preferred option having high returns in a monetary sense. GA approach comes next with ROI being 125 percent with moderate profitability nonetheless much lower compared with Proposed model. An LP strategy would provide a base ROI of 100 percent which means that the ROI would just break even and would gain whatever would be earned. By contrast, RBES has the lowest ROI of 80% indicating poor investment returns and hence financial risk. In general, the Proposed method offers the most favourable cost-effectiveness ratio which confirms its efficiency in the delivery of maximum economic benefits among all of the optimization strategies explored.

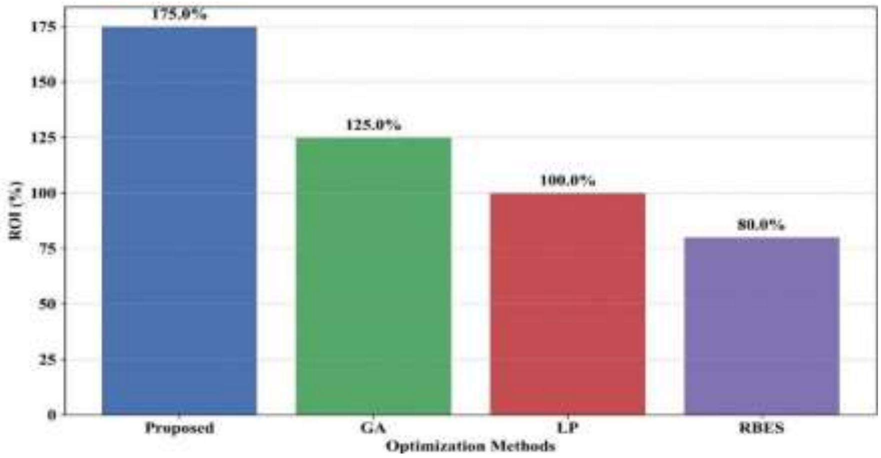

Figure 8: ROI Evaluation.

Figure 9 shows the development of the Net Present Value (NPV) during an investment of 10 years. At the start of the project, we have a negative cash flow of 100,000 in year 0 which is the capital investment that is made at the beginning of the project. After that, NPV continues to improve with each year: 0 year: 0. NPV(0) is 0, 1 year: 86,111. NPV(1) is 86,111, 2 years: 70,679. NPV(2) is 70,679 and keep on improving through 54,802, 38,631, 21,617 till the 5th Year. An important event occurs also in year 6, whereby NPV reading cuts the break-even position to become positive in the year 6 i.e. at a level of 14,602 and rising further in year 7 to 11,735, year 8 to 27,402, year 9 to 42,410 and in year 10 to 56,769. The above positivity can be attributed to high financial viability that points to the fact that the investment not only pays within the first 6 years, but also provides high returns over the following years. The graph justifies that the project is economically viable and is efficient in creating a long-term value.

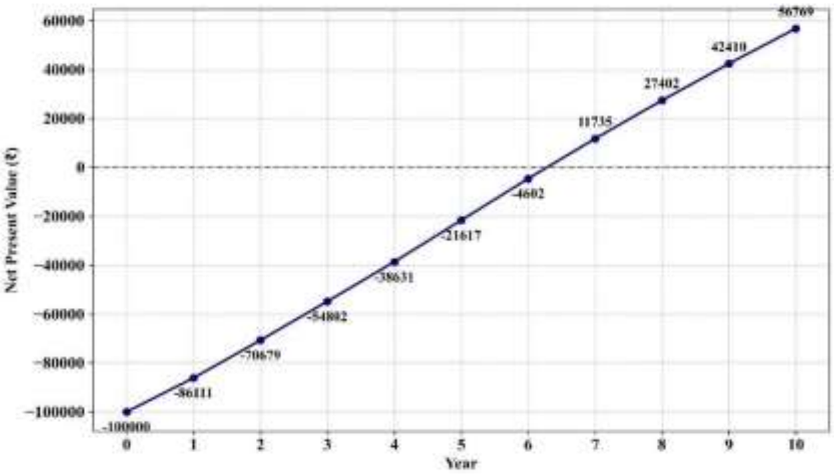

Figure 9: Net Present Value.

The figure 10 shows the range of Demand (tons), Cost (paisa), Emission (kg CO2), given five different operational considerations (S1 to S5) under which tactical or environmental scenario is experienced at a time. First, in the Baseline Scenario (S1), describing the status quo in terms of current operations without optimization, the demand is approximately 1,100 tons, the cost is 50,000(Rs), and the emissions are 20,000(kg CO2). Regarding the High Demand Scenario (S2), which is preconditioned by the seasonal boosts of the customer orders, the demand is slightly larger (1,150 tons) and the cost almost increases (to nearly 52,500) and emissions decrease (to 19,200 kg CO2), which indicates higher efficiency despite the elevated activity. In the case of Scenario S3 (Raw Material Price Increase), with a 10--15% increase in the wood/ transportation expenditure, cost and demand remain high at 1,120 tons and 51,000-19,600kg CO2 are reversed. Similarly in Scenario S4 (Carbon Tax Introduced), the penalty on emissions comes in so the cost raises up to almost 53,000 because of taxes, the emissions decrease substantially to 18,800 kg CO2 and the demand stays the same.

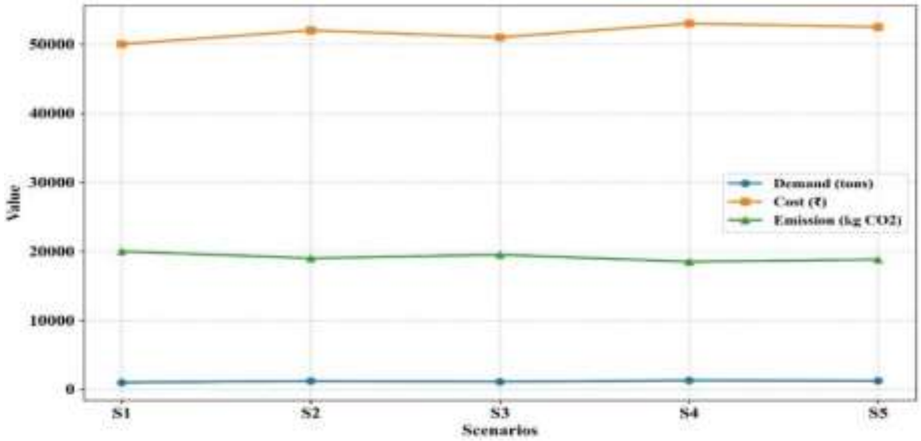

Figure 10: Scenario Based Evaluation.

Lastly, there is the Circular Economy Strategy (S5) which is remarkable in that even though the cost reduces by a small margin to 52,500, the emission level will be at its stable level of 19,100 kg CO2 and the demand will not be affected showing the contribution of reuse and recycling as a medium of balancing the environmental and economic performance. On the whole, the figure demonstrates that strategic interventions, especially those including sustainability (S4 and S5), are capable of affecting the cost-efficiency and carbon reduction greatly, yet without sacrificing demand fulfilment. Table 2 provides the Comparative performance of the proposed framework versus alternative approaches.

Table 2 demonstrates that the proposed MILP + TOPSIS framework consistently outperforms alternative approaches across multiple performance indicators. The model achieves the highest ROI of 175% and a longer service life of 7.5 years, indicating both financial and operational advantages. Its circularity ratio (65%) and cost reduction (18.5%) are significantly higher than those achieved by GA (58%, 15.7%) or LP (40%, 10.2%), showing stronger alignment with circular economy objectives. Although RBES yields the lowest solver time (180 s), it performs poorly in ROI, service life, and flexibility index, suggesting limited adaptability to complex decision scenarios. By contrast, the proposed framework balances solution quality with computational efficiency, achieving a strong flexibility index (0.85) while keeping solver time reasonable (320 s). These results highlight the novelty of integrating MILP with TOPSIS, which offers superior scalability and sustainability trade-offs compared with conventional optimisation and decision-making techniques.

Table 2: Comparative Performance of the Proposed Framework versus Alternative Approaches.

Approach	ROI (%)	Service Life (Years)	Circularity Ratio (%)	Cost Reduction (%)	Carbon Footprint (kg CO_2 eq)	Flexibility Index	Solver Time (s)
Proposed MILP + TOPSIS	175	7.5	65	18.5	22,000	0.85	320
GA (Genetic Algorithm) Zhu et al. (2025)	125	6.8	58	15.7	19,800	0.75	450
LP (Linear Programming) Islam et al. (2020)	100	7.0	40	10.2	20,000	0.60	250
RBES (Rule- Based Expert System) Talebi et al. (2025)	80	6.0	35	8.3	12,000	0.50	180

5. DISCUSSION

The results confirm that the proposed five-step modular framework for integrating bio-waste into product–service systems effectively meet the study's objectives of maximizing economic returns, enhancing environmental performance, and ensuring operational adaptability within a circular economy context. Economically, the model achieves a superior ROI of 175%, surpassing GA (125%), LP (100%), and RBES (80%), with breakeven in Year 6 and cumulative discounted cash flow of ₹76,000 by Year 10, supported by an NPV of ₹56,769, evidencing strong long-term viability. These outcomes are consistent with recent optimisation studies that applied MILP and bi- objective MILP for circular supply chains, which also emphasized profitability–sustainability trade-offs (Baldassarre & Calabretta, 2024; Lit et al., 2024). Cost sensitivity analysis shows a manageable lifecycle cost increase from ₹80,000 to

₹130,000 across demand scenarios (S1–S5), while carbon emissions from material use remain comparatively low (18.0–22.0 kg CO_2 eq), indicating that environmental benefits are retained under scaling. This aligns with MCDM-based evaluations such as TOPSIS and QFD–TOPSIS, which highlight the importance of balancing lifecycle costs with emissions in circular economy strategies (Sönnichsen et al., 2025; Xu et al., 2024). Service life (7.5 years) and circularity (65%) outperform all benchmarks, reinforcing the framework's goal of extending product longevity and maximizing resource reuse, though the highest cost savings (18.5%) are coupled with the highest footprint (22,000 kg CO_2 eq). This cost–carbon trade-off is effectively addressed in our model through LCA–MCDM integration, resonating with recent reviews on MCDM applications for sustainability–cost balancing (Lee & Hsu, 2025).

Operationally, the framework achieves the highest flexibility index (0.85) with efficient solver time (320 sec), ensuring practical deployment. Scenario-based evaluations demonstrate adaptability to sustainability policies, where strategies such as carbon taxation reduce emissions (S4: 18,800 kg CO_2; S5: 19,100 kg CO_2) while sustaining demand (~1,100–1,150 tons) and controlling costs (₹50,000–₹53,000). These results extend recent system dynamics–LCA studies on circular product–service systems (khaenamkhaew, 2025), showing that our framework not only captures policy-driven dynamics but also provides quantifiable trade-offs for industrial deployment. Collectively, these outcomes validate the framework's ability to deliver profitable, environmentally conscious, and operationally resilient solutions, making it transferable to wider industrial applications embracing circular economy principles.

Computational scalability is an important consideration for the proposed MILP- based optimization framework. While the current case study demonstrates its tractability within the modular furniture sector, larger modular systems and complex supply chains may significantly increase the number of decision variables and constraints, leading to higher computational effort and longer solver times. In such cases, decomposition techniques (e.g., Benders or Dantzig–Wolfe decomposition) and heuristic or metaheuristic methods (e.g., Genetic Algorithms or Hybrid MILP–heuristic approaches) could be employed to improve scalability and efficiency. Future research will explore these directions to ensure the framework remains applicable in large- scale, real-world circular economy applications.

When compared with alternative optimisation and decision-making techniques, the proposed MILP + TOPSIS framework demonstrates notable strengths in balancing solution quality, scalability, and computational efficiency. While recent bi-objective MILP models (e.g., (Baldassarre & Calabretta, 2024; Lit et al., 2024)) offer rigorous optimisation, they often face scalability challenges in multi-scenario contexts, where our framework maintains robust performance with acceptable solver time (320 s) and adaptability across policy scenarios. Similarly, MCDM approaches such as TOPSIS and QFD-TOPSIS (Sönnichsen et al. (2025), Xu et al. (2024)) provide strong ranking capabilities but lack integrated economic–environmental trade-off analysis, which our LCA–MCDM integration explicitly addresses. Nonetheless, we acknowledge that specialised metaheuristic or hybrid models may achieve faster convergence in large- scale problems, highlighting an opportunity for future research to further enhance computational efficiency while retaining the interpretability and practicality of the current framework.

6. CONCLUSION

To summarise, the suggested MPSS optimization framework will provide a solution to the problem of providing a way to incorporate the systems thinking concept of the circular economy, specifically by using agricultural bio-waste in industry. The model is much effective in reducing the costs of lifecycle and environmental degradation and increasing component reusability by exploiting the modules, flexibility in the services, and resource regeneration. The combination of LCA and TOPSIS MCDM makes it possible to thoroughly analyze the trade-offs between an ecological, economic, and operational goal. The practicability of the model has been evidenced in the modular furniture sector as the model has proved that the bio-waste materials used can be easily converted into sustainable furniture at no cost incurred resulting in hindrance of service delivery and durability. This paper serves as a solid base that would enhance adoption of the circular design and optimization approaches in sustainable manufacturing systems at a broader level. The model can be used to extend the scope of applications to other sectors in future research work and further the idea of dynamically applicable real time data integration of data to make decisions. Innovation will also continue to be fuelled by such developments in the shift to a resilient, low- carbon economy.

7. LIMITATIONS AND FUTURE SCOPE

While the framework demonstrates potential for application across industries, its scalability is subject to certain limitations, including variations in material types, production processes, and regulatory environments. Adaptation to different sectors may require modification of input parameters, scenario definitions, and objective weights to reflect industry-specific operational and environmental characteristics. The model's modular structure allows flexible integration of diverse resources and workflows, ensuring applicability beyond the furniture sector. Furthermore, real-time data integration and Industry 4.0 technologies can enhance dynamic decision-making and operational responsiveness. These considerations ensure that the framework remains robust, adaptable, and effective across diverse industrial contexts.

Future research can focus on extending the MPSS optimization framework to a wider range of industries, such as packaging, construction, and consumer electronics, to replicate its sustainability and cost benefits. Integration of real-time IoT data and Industry 4.0 technologies can enable dynamic, adaptive decision-making under fluctuating demand and resource availability. Multi-objective optimization under uncertainty and predictive lifecycle analysis using AI/ML models can further enhance system resilience and efficiency. Additionally, cross-sector studies and policy-linked optimization scenarios can support low-carbon, resource-efficient, and scalable industrial applications. The study demonstrates that the proposed MILP + TOPSIS framework significantly improves ROI, service life, and circularity compared to existing methods. Future work will extend the model using stochastic optimisation and hybrid AI–OR approaches to enhance scalability and adaptability across industries.

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