Industrial and Domestic Waste Management

Research Article
Volume 5(2), 2025, 97–109
https://doi.org/10.53623/idwm.v5i2.752

Optimization of Manufacturing-Remanufacturing Model in Circular Supply Chain Considering Warehouse Capacity Constraints by Using Chinese Pangolin Optimizer Algorithm

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SUBMITTED: 2 July 2025; REVISED: 14 August 2025; ACCEPTED: 19 August 2025

ABSTRACT: This research developed an optimization model within a circular supply chain framework incorporating factors such as carbon emissions, social sustainability, and warehouse capacity limitations. The model adopted a modified Economic Order Quantity (EOQ) approach, with a comprehensive cost assessment that included production cost, remanufacturing cost, storage cost, disposal cost, and penalty cost for emissions, all formulated within a Mixed Integer Nonlinear Programming (MINLP) structure. To address the complex nonlinear problem, the metaheuristic Chinese Pangolin Optimizer (CPO) algorithm was applied, as it effectively balanced solution exploration and exploitation. The simulation results indicated the optimal combination of production lot size, remanufacturing, and the share of reusable goods, achieving the minimum total system cost. The sensitivity analysis showed the significant influence of production and remanufacturing costs, emissions, and the rate of product returns on system efficiency. Overall, this research demonstrated more credible, cost-efficient, and sustainable inventory control approaches in a circular supply chain by considering warehouse constraints and applying the CPO.

KEYWORDS: EOQ; manufacturing-remanufacturing; warehouse capacity; carbon emissions; Chinese Pangolin Optimizer; circular supply chain

1. Introduction

The circular supply chain (CSC) model became a significant focus in supporting economic and environmental sustainability, particularly in developing countries. The CSC aimed to reduce waste and extend product life cycles through recycling, repair, and remanufacturing practices [1], while promoting material efficiency and reducing carbon emissions [2]. The implementation of this model proved effective in enhancing operational resilience and industrial competitiveness, as demonstrated in case studies of the paint manufacturing supply chain in Peru [3] and waste management practices in India [4]. However, CSC implementation was not entirely free of challenges, and one of the key issues was the management of new, returned, and remanufactured goods simultaneously through the inventory system. Warehouse capacity limitation [5] was among the least discussed aspects in the literature, despite its direct implications for storage space efficiency, operational cost, and logistics flexibility [6, 7]. Most

EOQ and EPQ models applied in production–remanufacturing planning continued to assume unlimited warehouse capacity, which led to optimization outcomes that were less realistic for actual conditions [8].

Although previous research addressed economic and environmental aspects such as production costs, carbon emissions, and cap-and-trade mechanisms [9–11], most studies did not explicitly integrate warehouse capacity constraints into mathematical modeling. Furthermore, social dimensions such as ergonomic considerations and worker well-being were rarely included in quantitative circular supply chain models [12, 13]. This study proposed an EOQ-based optimization model that explicitly combined warehouse capacity constraints with economic, environmental, and social costs to bridge this gap. The model was formulated within the MINLP framework, considering product return dynamics, emission constraints, and policy incentives [14, 15]. In addition, the CPO algorithm, a recent metaheuristic inspired by the adaptive behavior of pangolins, was applied for its ability to balance exploration and exploitation in nonlinear search spaces [11]. This study aimed to minimize total system costs by determining optimal lot sizes for production and remanufacturing, as well as the appropriate proportion of reusable products, under warehouse capacity constraints and emission regulations. Overall, the study contributed to expanding circular inventory modeling by offering a realistic approach that holistically considered physical constraints alongside sustainability objectives. It was hypothesized that integrating warehouse capacity constraints would enhance the feasibility and cost efficiency of lot-sizing decision-making in CSC systems, and that the CPO would effectively solve nonlinear inventory models with optimization results that were competitive with conventional approaches.

2. Methodology

2.1. Assumptions of the mathematical model.

The proposed model was developed based on several assumptions. Queries were deterministic and constant with a positive rate, and the return rate was assumed to be less than one hundred percent. Manufactured, remanufactured, and transmittable items were all available in stock, and additional items could be produced or reproduced at any time to increase the stock of returned and finished items. Goods were treated as unique, and the manufacturing or reproduction process did not consider more than one product type. When stock ran out, a new lot could be produced and shipped immediately, and the time required for production or reproduction was considered negligible. No stock-out problem was assumed. The cost per unit of product produced, remanufactured, or scrapped was considered independent of quantity. All expenditures and emissions, except for the disposal-related parameter, were assumed to be non-negative [16]. Harmful emissions could occur in discarded goods by applying carbon capture and waste-to-energy generation technologies. The social cost of the setup process was not negligible but was included in the model through the ongoing social cost component associated with manufacturing setup and remanufacturing activities. However, social costs related to the product disposal process were considered negligible and were not included in the model calculations.

2.2. Model parameters and variables.

The model parameters and variables considered various influences, and social and environmental costs were incorporated into the economic lot model. This section describes the assumptions applied in the model to assign values to social and environmental impacts. Table 1 presents the variables and parameters used for the model formulation.

Table 1. Model parameters and variables.

Economic parameters
λ: Demand (unit/time)
C_d: Disposal cost ($/unit)
C_m: Production cost ($/unit)
C_r: Remanufacturing cost ($/unit)
h_m: Variable cost of holding production stock ($/unit/time)
h_n: Variable cost of holding recoverable stock ($/unit/time)
h_r: Variable cost of holding remanufactured stock ($/unit/time)
K_m: Manufacturing setup cost ($)
K_r: Remanufacturing setup cost ($)
r: Rate of return (%)
cap_m: Production lot warehouse capacity
cap_r: Warehouse capacity of remanufacturing lot
Environmental and social parameters
α: Emission quota ($kgCO_2eq$)
C: Emission cost ($/$kgCO_2eq$)
σ: Break fee
s_m: Fixed costs associated with continued labor use in manufacturing
s_r: Fixed costs associated with continued use of labor in remanufacturing
s_{or}: Variable costs associated with the continued use of labor in remanufacturing
g_{om}: Fixed emissions from produced stock ($kgCO_2eq$/unit/time)
g_{on}: Fixed emissions from recoverable stock ($kgCO_2eq$/unit/time)
g_{or}: Fixed emissions from remanufactured stock ($kgCO_2eq$/unit/time)
X: Emissions of carbon credits to be bought or sold ($kgCO_2eq$/time)
Variables
Q_m: Production lot size (unit)
Q_r: Reproduction lot size (unit)
μ:: Proportion of recoverable goods or remanufacturing tax (%)

2.3. Math model.

The model in this study aimed to minimize the total cost of the manufacturing and remanufacturing system within a circular supply chain scenario. The system involved the production of new products, the remanufacturing of returned products, warehousing, and the disposal of non-recyclable products. It integrated three elements of sustainability: economic, environmental, and social. Total expenses were calculated as a function of the aggregate fixed and variable production, setup, storage, and disposal costs. Environmental elements were reflected in carbon emissions ($kgCO_2eq$) generated by ordering, storage, production, and remanufacturing activities. These emissions were regulated under a cap-and-trade system, with additional expenses or benefits determined by the difference between actual emissions and the allocated quota. The social dimension was represented by the cost of unemployment associated with labor during production setup and remanufacturing, following the approach of Battini et al. [17].

The model also considered the proportion of demand that could be met through remanufacturing and the storage limits for both new and remanufactured products. Returned products were classified as either remanufacturable or non-remanufacturable, with the latter incurring disposal costs. System-wide costs depended on the direction of product flow and economic, environmental, and social influences. The mathematical model used in the numerical analysis was developed to calculate the total cost of the entire system, including production, remanufacturing, storage, and disposal of non-reprocessable products. The resulting total cost was derived from manufactured, remanufactured, recoverable, or disposed products, depending on the direction of product flow. Costs in this model were categorized as fixed or variable, according to the number of items processed. The process flow of the manufacturing and remanufacturing system is illustrated in Figure 1. The diagram depicted the relationships between procurement, storage, distribution to end users, and product returns for inspection and repair. This flow formed a closed cycle that supported product reuse, reduced waste, and lowered carbon emissions.

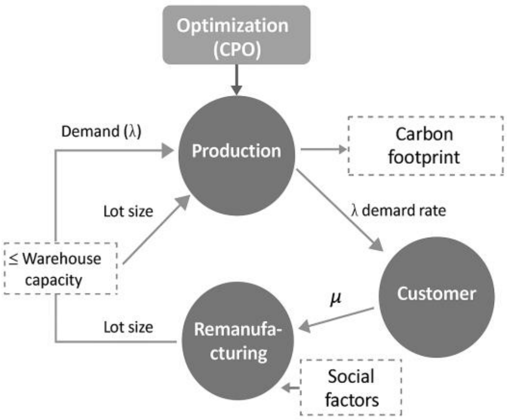

Figure 1. Manufacturing-remanufacturing system process flows in a circular supply chain.

The system's total cost (TC) was formulated using a Mixed Integer Nonlinear Programming model, as presented in Equation (1).

Minimize:

$$TC = \frac{(K_m+\sigma S_m)\lambda(1-\mu)}{Q_m} + \frac{(K_r+\sigma S_r)\lambda\mu}{Q_r} + \frac{K_m(1+\mu)Q_m}{2} + \frac{h_r\mu Q_r}{2} + \frac{h_n}{2}\left(\mu Q_r + \left(\mu - \frac{r-\mu}{1-\mu}\,\frac{\mu}{r}\right)\right) + \lambda\big((1-\mu)c_m + \mu(c_r+\sigma S_r) + (r-\mu)c_d\big) - CX \tag{1}$$

The objective of the mathematical model was to minimize the total cost in a supply chain system involving manufacturing and remanufacturing while incorporating social and environmental aspects. Equation (1) represented the total cost function per cycle, which consisted of various cost components related to production activities, remanufacturing processes, inventory management, and emissions. In this model, the variable X was not explicitly formulated as a decision variable but was implicitly obtained as the difference between the total fixed emissions from manufacturing and remanufacturing activities $g_{om} + g_{on} + g_{or}$ and the allocated emissions quota α. This difference was then multiplied by the carbon price per unit emission C and included as either a penalty or an incentive in the total system cost. With this formulation, the model conceptually reflected the cap-and-trade principle, although the value of X was not directly optimized as an independent variable.

To ensure that the solution generated by the objective function remained within operational and policy boundaries, the model was constrained by several functions. These constraints represented the technical and structural limitations of the system, such as demand fulfillment and warehouse capacity restrictions. The formulation of the constraint functions is presented in the following section:

Constraint

$$Q_m, Q_r < \lambda \tag{2}$$

$$Q_m, Q_r > 0 \tag{3}$$

$$Q_m \leq cap_m \tag{4}$$

$$Q_r \leq cap_r \tag{5}$$

$$0 \leq \mu \leq 1 \tag{6}$$

The mathematical model proposed in this scientific article is to minimize the total cost (TC), so that Equation (2) limits the amount of production of new goods (Q_m) and remanufactured products (Q_r) so as not to exceed the total demand (λ), this is done to avoid overproduction so as not to increase costs. Furthermore, Equation (3) ensures that both variables are positive to ensure validity and operational feasibility in the system. In addition to that, storage capacity is also a critical problem in this model. Equations (4) and (5) limit the number of productions lots based on the warehouse's maximum capacity, cap_m for new products and cap_r for remanufactured products, respectively. Finally, Equation (6) imposes a constraint on the variable μ, i.e., the proportion of demand fulfilled by remanufacturing, which is limited to the range (0,1) or according to the maximum allowed value in the system.

2.4. CPO algorithm implementation.

To address complex nonlinear inventory optimization problems in circular manufacturing and remanufacturing systems, this study applied the CPO, a metaheuristic algorithm inspired by the natural behavior of pangolins in searching for food. The algorithm mimicked pangolins' scent detection, digging, and adaptive movement strategies to balance global exploration and local exploitation, thereby avoiding premature convergence and expanding the scope of the solution search. The optimization process began with the initialization of a population of search agents, or virtual pangolins, which were randomly distributed within the solution space, where each agent position represented a candidate solution vector evaluated through the objective function consisting of total system costs, including production costs, remanufacturing costs, carbon emissions, and social factors. In each iteration, agent behavior was governed by several mechanisms: scent-based navigation guided by scent concentration, wind dispersion, and olfactory direction; energy and fatigue management, in which energy levels decreased gradually to encourage broad exploration in the early stages and intensive local exploitation in later stages; and Levy random steps with position disturbances, which enhanced solution diversity and prevented entrapment in local optima. Depending on the strength of scent signals and stochastic influences, agents displayed adaptive behavioral phases such as luring behavior when a scent was detected, search and localization under weak scent conditions, quick approach when scent was moderate, and digging and predation when scent was strong. During the search process, agent positions were continuously updated based on scent information and their distance to the current best solution, which was dynamically stored and refined until the maximum iteration limit was reached. At the conclusion of the optimization process, the algorithm produced the optimal solution in terms of production lot size, remanufacturing lot size, and the proportion of returned items that could be reused. For clarity, the pseudocode of the CPO is presented in Algorithm 1, which summarizes the computational steps and position update rules based on the relevant control parameters.

Algorithm 1
Pseudocode Chinese Pangolin Optimizer

```
    Initialize a population of N search agents with random positions in the search space.
Inputs: The population size n, maximum number of iterations T, and variable dimension d
Outputs: The location of the Chinese pangolin X_best and its fitness value
Initialize the random population X_i (i = 1,2,...,n)
while t < T do
  Calculate the fitness values of the Chinese pangolin
  Update the aroma concentration C_M
  Update the rapid decrease factor C_1
  Update the aroma trajectory factor a
  Update the levy's flight step length L_levy
  X_M  = best position (Chinese pangolin)
  X_A  = second best position (Ant)
  for (each Chinese pangolin position (X_i )) do
    Update the energy fluctuation factor A_i
    Update the energy consumption factor E
    Update the fatigue index Fatigue
    Update the Generate random r_1
    /*Luring Behavior*/
    if (C_m ≥ 0.2 && r_1 ≤ 0.5) then
      Update the location vector //Attraction and Capture Stage
      Update the location vector //Movement and Feeding Stage
      Update the best position X*
    /*Predation Behavior*/
    else if (C_m ≤ 0.7 || r_1 > 0.5) then
      if (0 ≤ C_M < 0.3) then
        Update the location vector using) //Search and Localization Stage
        Update best position X*
      Else if (0.3 ≤ C_M < 0.6):
        Update location vector //Rapid Approach Stage
        update best position X*
      else if (C_M ≥ 0.6) then
        Update the location vector using //Digging and Feeding Stage
        update best position X*
  end if
 end if
end for
  t = t + 1
return the best position X*and its fitness value
```

This study implemented the CPO to determine the optimal combination of decision variables to minimize the total system cost. The algorithm parameters were carefully configured, with 750 search agents, a maximum of 1000 iterations, and a three-dimensional search space defined by the manufacturing lot size (Q_m), remanufacturing lot size (Q_r), and the proportion of products eligible for reprocessing (μ). To illustrate the optimization process, pseudocode was developed to conceptually represent the main steps of the algorithm without being tied to the syntax of a specific programming language, thereby facilitating a clearer understanding of its working mechanism. This pseudocode was adapted from the original MATLAB implementation to suit the structure of optimization problems in the proposed model. Through this approach, the CPO was expected to provide more efficient and effective solutions for manufacturing–remanufacturing model optimization and to make a meaningful contribution to the advancement of optimization methods in this field.

2.5. Numerical data.

Numerical values used to solve and simulate the developed mathematical model are presented in this section. These values fall into three general categories of parameters: economic, environmental, and social. Optimization and simulation were performed based on the values listed in Table 2, ensuring realistic and industrially applicable results for the case under study. MATLAB software was employed to implement the CPO algorithm to solve the optimization of the proposed complex model. CPO was selected for its ability to explore a wide solution space and avoid premature convergence, thereby achieving more efficient and effective optimal solutions. The algorithm was used to determine optimal values of key decision variables, namely manufacturing lot size (Q_m), remanufacturing lot size (Q_r), and the remanufacturing rate (μ). These values minimize the total cost within a circular supply chain while considering carbon emissions, warehouse capacity constraints, and social aspects.

Table 2. Parameter values.

Economic Parameters	Environmental parameters	Social parameters
λ:100	α: 300	σ: 2
C_d: -10	C: 1	s_m: -0,1
C_m: 62	g_{om}: 0	s_r: -0,245
C_r: 50	g_{on}: 0	s_{or}: 0,153
h_m: 10	g_{or}: 0	σ: 2
h_n: 5		
h_r: 9		
K_m:100		
K_r: 100		
r: 0,8		

To reflect the physical constraints of the real system, the model imposes an upper limit on warehouse storage capacity. Specifically, the production lot size (Q_m) is restricted to a maximum of 100 units, while the remanufacturing lot size (Q_r) is capped at 110 units. These limits ensure that production decisions do not result in overstocks that exceed available warehouse capacity. To solve this optimization problem and determine the set of variables that minimize the total system cost, the CPO metaheuristic algorithm is employed. Inspired by the prey-hunting behavior of Chinese pangolins, CPO was developed to solve large-scale nonlinear optimization problems by effectively balancing exploration and exploitation in the solution space. In this study, the objective function is based on the previously formulated mathematical model with four key decision variables: production lot size (Q_m), remanufacturing lot size (Q_r), and the proportion of remanufactured products (μ). The optimization process yields optimal parameters that balance economic, environmental, and operational constraints while minimizing the total system cost. These findings can support companies in adopting more sustainable, ethical, and worker-oriented policies, enhancing corporate image and employee loyalty.

In addition, sensitivity analysis was conducted on several critical parameters that could influence the total cost and decision variables. This analysis examines how variations in these parameters affect the optimization outcomes and provides insights into the robustness of the proposed model. Six parameters were tested under different data scenarios: demand, manufacturing cost, remanufacturing cost, emission cost, rate of return, and warehouse capacity. Demand (λ) was varied to evaluate how fluctuations impact optimization decisions and total costs. Manufacturing cost (C_m) was analyzed to assess its influence on the optimal solution; while remanufacturing cost (C_r) was tested to determine its effect on total costs and operational strategies. Similarly, changes in emission cost (C) were examined to evaluate their implications for decision-making and cost outcomes. The rate of return (r) of used products was varied to identify its impact on total cost and system efficiency. Finally, the influence of warehouse capacity, represented by $Q_m$and Q_r, was analyzed to determine its effect on total system cost and the feasibility of inventory management strategies.

3. Results and Discussion

3.1. Results.

This study develops an EOQ optimization model for a remanufacturing–manufacturing system within a circular supply chain framework, incorporating warehouse capacity constraints, carbon footprint considerations, and social dimensions. The proposed model is designed to achieve an optimal balance between operational costs and sustainability requirements. The optimization results demonstrate efficient lot sizes for production and remanufacturing while minimizing overall system costs. A summary of the optimization outcomes is presented in Table 3.

Table 3. Model optimization results.

Parameter	Nilai Optimal
Production lot size (Q_m)	100 unit
Reproduction lot size (Q_r)	37,1 unit
Total cost (TC)	Rp4.053,45
Fixed costs associated with continued labor use in manufacturing (S_m)	–0,1
Fixed costs associated with continued use of labor in remanufacturing (S_r)	–0,245
Disposal Cost (C_d)	–10

In addition to being cost-effective, the model demonstrates that certain components with negative values can, in fact, contribute positively to the overall system. This outcome reflects the influence of external incentives or long-term benefits driven by existing social and environmental policies. For example, waste disposal mechanisms that possess economic value while reducing social costs highlight the beneficial role of improved worker well-being [17], [18]. By integrating economic, environmental, and social dimensions, this approach offers a more comprehensive and realistic framework for decision-making in inventory management, which is particularly relevant in circular supply chains where efficiency must be achieved without compromising sustainability [8, 19]. The sensitivity analysis conducted on critical parameters such as demand, production cost, remanufacturing cost, carbon emission cost, product return rate, and storage capacity further reinforces the robustness of the model. Results reveal that even minor changes in some of these parameters can significantly influence optimization outcomes, especially regarding total system costs and determining optimal lot sizes. Compared to previous research, the present study is notable for explicitly incorporating social considerations into the modeling process. While prior works by Govindan et al. [8] and Ghasemi et al. [20] addressed economic and environmental metrics without accounting for social dimensions, this study extends the scope by including ergonomics and worker well-being as cost factors. Additionally, the model provides a pragmatic solution by accounting for storage capacity dynamics and product return flows, consistent with the findings of Utama et al. [21] and Jauhari et al. [22]. Integrating a cap-and-trade scheme for carbon emissions further adds flexibility and aligns with contemporary environmental policymaking. Overall, the results indicate that adopting an integrated, multidimensional EOQ approach enhances operational performance and supports sustainability objectives within modern circular supply chain systems.

4.2.Sensitivity analysis.

The sensitivity analysis aims to examine the robustness of the model against variations in several critical parameters, including rate of return, emission cost, remanufacturing cost, and demand. This analysis enhances the understanding of how changes in these parameters influence the optimal decision variables (Q_m, Q_r, and μ_{opt}) as well as the total system cost. The sensitivity analysis of demand, production cost, remanufacturing cost, emission cost, return rate, and warehouse capacity constraints, as presented in Table 4, provides an overview of how these parameters influence the total cost (TC). Demand plays a critical role, as an increase raises production quantities and intensifies operational activities. Higher demand forces firms to expand production capacity, elevating costs due to greater resource and labor requirements. Understanding this dynamic is essential for firms to design strategies that effectively manage fluctuating demand. Production and remanufacturing costs are also significant determinants of TC. An increase in production cost makes each additional unit more expensive, reducing profit margins, while a higher remanufacturing cost diminishes the economic advantage of remanufacturing as a cost-saving alternative. To remain competitive, firms must continuously improve production and remanufacturing efficiency to lower these costs.

Emission costs, which directly reflect the environmental impact of production processes, further contribute to rising TC. Companies are compelled to adopt sustainable practices in an era of increasing environmental awareness and regulatory pressure. Investing in green technologies and emission-reduction strategies can mitigate these costs while enhancing corporate reputation. By contrast, an increase in the return rate (%) reduces TC significantly. Returned products can be remanufactured at a lower cost than new units, reducing overall expenses and lowering waste and environmental impact. Firms should prioritize strategies to maximize product returns, such as customer incentive programs.

Finally, warehouse capacity constraints also affect TC, though their impact is comparatively smaller. Expanding warehouse capacity enhances production and storage efficiency, reducing the need for repeated operations and stabilizing overall costs. Thus, warehouse infrastructure investment is an important long-term strategy to support operational growth and sustainability.

Table 4. Sensitivity analysis results.

Parameters	Parameter Change	Total Cost	Q_m	Q_r	μ opt
Demand	-50%	$ 875,10	100	26,37	0,9
	-25%	$ 2.470,28	100	33,44	0,9
	-10%	$ 3.853,82	100	32,25	0,9
	10%	$ 5.219,81	100	39,49	0,9
	20%	$ 5.629,04	100	42,19	0,9
	50%	$ 7.199,37	100	45,52	0,9
Production Costs (C_m)	-50%	$ 3.723,55	43,81	43,33	0,1
	-25%	$ 3.898,39	100	37,69	0,9
	-10%	$ 3.991,39	100	37,54	0,9
	10%	$ 4.115,40	100	37,99	0,9
	20%	$ 4.208,39	100	37,64	0,9
	50%	$ 4.363,39	100	37,94	0,9
Remanufacturing Cost (C_r)	-50%	$ 1.803,47	100	38,42	0,9
	-25%	$ 2.928,39	100	37,61	0,9
	-10%	$ 3.603,39	100	37,74	0,9
	10%	$ 4.503,43	100	38,22	0,9
	20%	$ 5.178,39	100	37,84	0,9
	50%	$ 6.303,39	100	37,76	0,9
Emission Cost C	-50%	$ 3.793,39	100	37,68	0,9
	-25%	$ 3.923,40	100	37,38	0,9
	-10%	$ 4.001,39	100	37,71	0,9
	10%	$ 4.105,39	100	37,79	0,9
	20%	$ 4.157,39	100	37,35	0,9
	50%	$ 4.313,39	100	37,7	0,9
Rate of Return (%) r	-50%	$ 4.453,42	100	38,18	0,9
	-25%	$ 4.253,41	100	37,36	0,9
	-10%	$ 4.133,39	100	37,76	0,9
	10%	$ 3.973,39	100	37,69	0,9
	20%	$ 3.853,39	100	37,64	0,9
	50%	$ 3.653,50	100	38,55	0,9
Warehouse Capacity (Q_m and Q_r)	-25%	$ 4.650,84	74,89	57,16	0,9
	-50%	$ 5.174,42	49,97	46,46	0,9
	-75%	$ 5.774,08	25	25	0,9
	25%	$ 4.053,47	100	38,41	0,9
	50%	$ 4.053,43	100	38,22	0,9
	75%	$ 4.053,40	100	37,93	0,9

5. Result Implications

This research significantly contributes to four key areas: managerial, environmental, social, and theoretical implications. From a managerial perspective, the developed model enables companies to determine the optimal lot sizes for new production (Q_m) and remanufacturing (Q_r), as well as the proportion of recoverable products (μ), to minimize total operating costs. Given the model's sensitivity to product recovery rates, managers should pay greater attention to improving the efficiency of remanufacturing processes and reverse logistics. Moreover, the potential savings from negative disposal costs and negative fixed labor costs highlight that effective waste management strategies and enhanced employee welfare generate positive social outcomes and yield financial benefits. Thus, the model helps companies control costs while encouraging a holistic approach to sustainability.

From an environmental perspective, the model supports reductions in carbon footprints and dependency on virgin raw materials by increasing remanufacturing utilization. The optimization results demonstrate that companies can achieve environmental sustainability targets without compromising profitability, proving that operational efficiency and environmental responsibility can be mutually reinforced. Socially, integrating sustainable employment aspects into the model provides valuable insights, showing that improved worker welfare such as reduced risk of injury and sufficient rest time contributes to long-term efficiency. These findings suggest that adopting ethical and worker-friendly practices strengthens corporate reputation and fosters greater employee loyalty.

Finally, from a theoretical standpoint, this research advances the EOQ and closed-loop supply chain literature by developing a model that simultaneously integrates economic, environmental, and social dimensions while explicitly accounting for warehouse capacity constraints. Applying the CPO algorithm effectively solves complex optimization problems and opens new avenues for exploration. The framework presented here can be extended in future studies to address uncertain demand, multi-product systems, or specific industrial contexts characterized by more complex circular logistics structures.

6. Conclusion

This research develops a manufacturing–remanufacturing optimization model for circular supply chain systems by integrating carbon emissions, warehouse capacity, and sustainable social factors. The model minimizes overall logistics and operational costs while ensuring emission limits and employee welfare compliance. It employs an EOQ-based approach combined with the CPO algorithm to achieve optimal results. The simulation results demonstrate that under realistic economic, environmental, and social parameters, considering warehouse capacity constraints enhances total cost (TC) efficiency through optimal production and remanufacturing strategies. Sensitivity analysis reveals that demand, production, remanufacturing, and emission costs are the four most influential parameters affecting TC. Increases in these parameters lead to significant cost escalation: higher demand raises production frequency; higher production costs increase the expense of producing new units; and higher remanufacturing costs erode the cost advantages of remanufacturing. Thus, increases in either production or remanufacturing costs directly elevate TC. In contrast, the return rate of used products plays a crucial role in reducing TC, as returned items can be remanufactured at lower costs than producing new goods. Similarly, increasing warehouse capacity contributes to cost reduction, albeit less significantly. Larger capacity improves production flexibility, reduces repetitive operations, and allows higher production volumes, stabilizing TC. Despite its contributions, this study has several limitations. The model assumes deterministic values for demand, costs, and return rates, which may not fully capture real-world uncertainty. Furthermore, it focuses on a single-product system, limiting its applicability to more complex multi-product supply chains. While warehouse capacity is considered, it is treated as a static constraint without accounting for flexible or multiple warehouse configurations. Additionally, although the model integrates ergonomics and carbon emissions, future research could expand on these aspects by incorporating more granular factors and diverse environmental policy scenarios.

Acknowledgments

The author gratefully acknowledges the Industrial Engineering Laboratory of Muhammadiyah University Malang for providing the facilities and support to conduct this research.

Author Contribution

Dana Marsetiya conceptualized and designed the research and verified and edited the manuscript. Hanum Salsabila Djirimu drafted the manuscript and developed the mathematical model formulation. All authors reviewed the research findings and approved the final version of the manuscript.

Competing Interest

The authors declare that there is no conflict of interest

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