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An Integrative Model for Remanufacturing Operations through Two-Stage Data Envelopment Analysis: Insights using Game Theory Perspective

Sahil Nasa
Department of Operational Research,
Faculty of Mathematical Sciences, University of Delhi, Delhi, India.
E-mail: nasa.12.sahil@gmail.com

Chanchal
Department of Operational Research,
Faculty of Mathematical Sciences, University of Delhi, Delhi, India.
E-mail: chanchaljatran94@gmail.com, chanchal@or.du.ac.in

Adarsh Anand
Department of Operational Research,
Faculty of Mathematical Sciences, University of Delhi, Delhi, India.
Corresponding author: adarsh.anand86@gmail.com

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Abstract
Manufacturing operations that emphasize environmental responsibility, product quality and end-of-life (EOL) management are increasingly adopted by firms. These steps are necessary due to increasing environmental legislation and a growing consumer demand for sustainable products. An advantageous approach to effectively addressing returned items within this framework is remanufacturing. The findings of this research explore the dynamic processes involved in the remanufacturing stages, namely the collection, sorting, and testing phase, as well as the development phase, which remanufactures the product, and how they affect the entire supply chain (SC) performance. The current research offers a unified strategy to thoroughly evaluate model responses across a wide range of variables by analysing the impact of key variables within these phases and employing various distribution functions to model their behaviour. A two-stage Data Envelopment Analysis (DEA), an efficient analytical method in Multi-Criteria Decision Making (MCDM), is employed to evaluate the efficiency of the developed models. Research findings indicate that the initial phases of collection, sorting and testing are more efficient than the development phase. Furthermore, the findings show that the cooperative method yields more efficient outcomes than the leader-follower approach in the non-cooperative setting.

Keywords- Closed loop supply chain, Game theory, Non-cooperative/Cooperative method, Remanufacturing process, Two-stage data envelopment analysis.

1. Introduction

Sustainability has evolved into a shared responsibility in the modern world, requiring cooperation from individuals, particularly firms. In the face of escalating consumer demand and dwindling resources, sustainable practices are no longer an option but a prerequisite for business survival (Mangla et al., 2020). To navigate this reality effectively, businesses must prioritize optimizing their SCs by meticulously evaluating the efficiency of each stage. Therefore, a well-structured, well-defined closed-loop supply chain (CLSC) is required to maximize product sustainability.

A CLSC operates like a circular system. On one side, you have the traditional flow: getting materials, manufacturing products, and delivering them to customers. This is the forward chain. On the other side, you have the return journey. Once a product reaches the EOL, it is returned. These returned items are then sorted and processed. They might be fixed up (refurbished, remanufactured), recycled, or properly disposed of. This reverse chain completes the loop. Fundamentally, CLSC aims to establish a model that ensures efficient resource utilization, minimal waste production and an extended product lifecycle. It promotes more sustainable and eco-conscious business practices. Central to this idea is the circular economy (CE), which entails a closed-loop system designed to minimise waste, thereby reducing its environmental impact, while optimising the use of both natural and technical resources (Chokshi et al., 2023). A reverse logistics network links the used-return products market to the new-product market. The integration of both results in a closed-loop network. Within this context, reverse logistics is increasingly regarded as a structured approach through which industries can mitigate their environmental impact while supporting broader sustainability objectives (Mangla et al., 2016; Rouhani et al., 2025). In reverse logistics, there are usually six types of returns (De Brito and de Koster, 2004):

i. *By-products & Scrap* are the leftover components or products from production. These are unavoidable during cutting or blending and below the quality standards.
ii. *Commercial Returns* are returns after sales due to dissatisfaction, testing, overstock, or promotions.
iii. *Warranty, Repairs & Recalls* are the returned defective items. These are often replaced with similar or the same products.
iv. *Reusable Items* are returned after consumption or use, for instance, reusable refillable cartilage, bottles or 'one-way' cameras.
v. *End-of-Use Returns are* returned after lease/trade-in. These returned products or components may be refurbished, resold or remanufactured.
vi. *EOL Returns* are products that are worn out and no longer usable.

Following a return, there are various recovery options available to maximize the product's value: product recovery, which includes fabricating the product; component recovery, which involves breaking down products into their component parts to obtain reusable parts; and material recovery, which includes recycling. To implement these recovery options, businesses should integrate the various 'Rs' of reverse logistics into their product take-back programs: Repair, Remarket, Remanufacture, Recycle, Refurbish, and Reuse (**Figure 1**).

Among the methods for handling items nearing EOL, such as reusing, repairing or rebuilding them entirely, remanufacturing is among the most prevalent. Because it minimizes waste and recovers "value" from discarded items, remanufacturing offers both economic and environmental benefits as well (Domínguez et al., 2021; Zhou et al., 2021). As defined by Wilton and Owen (2010), “For business, remanufacturing is about retaining both the value of the product and a client base”.

A CLSCN is shown in **Figure 2**, demonstrating the reverse logistics activities within the remanufacturing strategy framework. In other words, rather than purchasing new or fresh resources the focus shifts towards reusing existing ones. The collected products are either used as raw materials, recycled, or remanufactured. Obsolete items or equipment are disposed of responsibly. Returned products may take the form of manufacturing returns, commercial returns, warranty returns, service returns, end-of-use returns, EOL returns, and others (Anand et al., 2017).

Remanufacturing is a cornerstone of the CE. It differs from other EOL management methods, such as refurbishment, repair, reconditioning and reuse. Each has its particular definition and scope. According to the Centre for Remanufacturing and Reuse (CRR), remanufacturing can be defined as ‘a process of returning a used product to at least its original performance with a warranty that is equivalent to that of the newly manufactured product’. The practice of remanufacturing offers a strategic pathway for organizations to achieve their sustainable development objectives. Furthermore, this approach yields benefits by positively impacting both the environment and society, while concurrently fostering principles of sound governance (Zhou and Li, 2024).

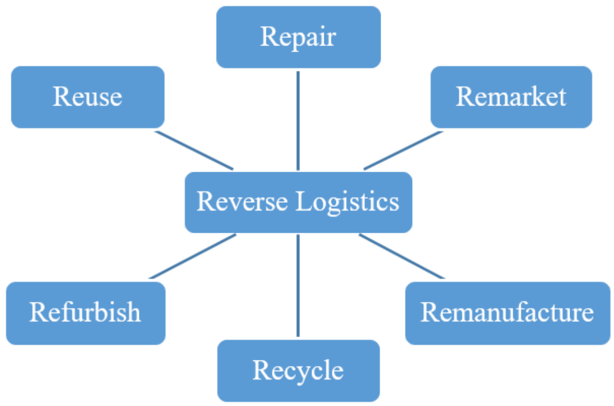

Figure 1. 7 R's of Reverse logistics; Source: Author's own creation.

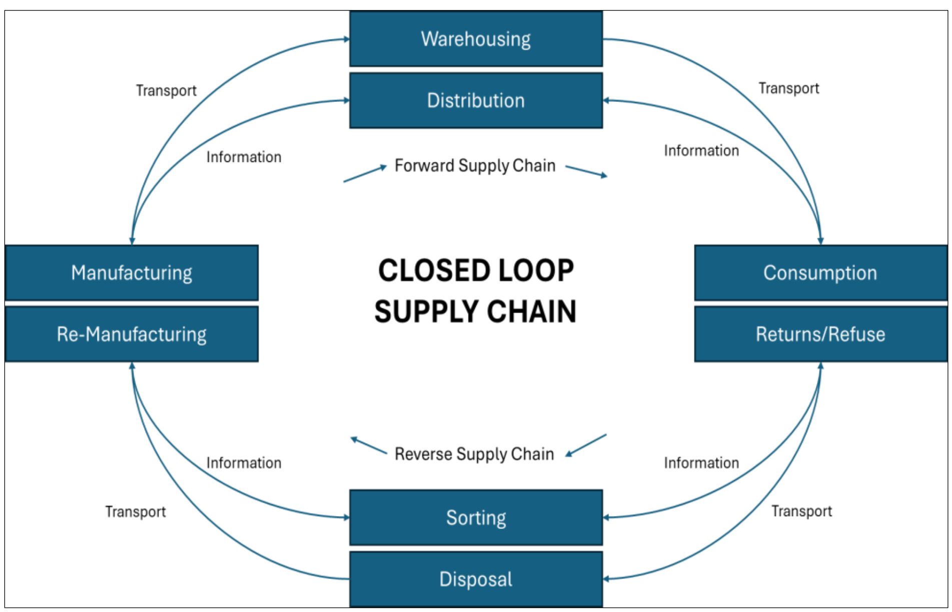

Figure 2. CLSC integrating remanufacturing strategy framework; Source: Author's own creation.

Based on the discussion and the need to systematically evaluate efficiency across remanufacturing stages within a CLSC, the present study aims to address the following research questions:

- **RQ1:** What is the appropriate quantitative approach for evaluating the efficiency of a two-stage remanufacturing process comprising the inspection phase (collection, sorting and testing) and the development phase within a CLSC framework?
- **RQ2:** What is the impact of cooperative and non-cooperative (leader-follower) decision-making structures on stage-wise and overall efficiency of remanufacturing operations when analyzed using a two-stage DEA framework?

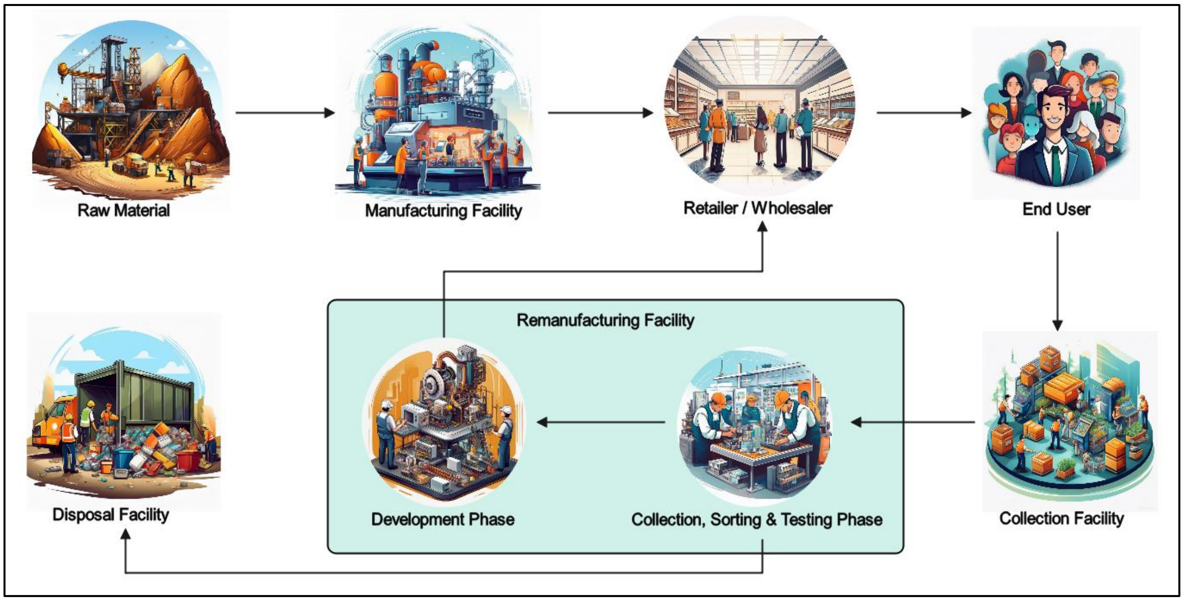

Figure 3. Generalised CLSC; Source: Author's own creation.

Figure 3 presents a schematic representation of a CLSC that integrates remanufacturing as a core process. This model represents a cyclical material flow, beginning with raw material acquisition, followed by product manufacturing, distribution, and consumer use. In the post-consumer phase, products are retrieved at a collection centre and sent to the remanufacturing centre, which undergoes rigorous quality evaluation. Products that meet predefined quality criteria are routed to the development phase in the remanufacturing facility, while non-compliant items are directed to disposal. Remanufactured products are then reintroduced into the distribution network, thereby fulfilling customer demand. The efficiency of the closed-loop system depends on how well the remanufacturing facility is optimized, with particular emphasis on the efficiency of both the initial collection, testing, and sorting phase and the subsequent development stage. This optimization is crucial for achieving a sustainable and economically viable CLSC (Huang et al., 2024).

The novelty of the proposed study that differentiates it from the current research is outlined below:

- The study presents a generalized mathematical model that represents the dynamics of CLSC, with a particular emphasis on capturing the complete remanufacturing process, from the initial collection of used products to the final delivery of remanufactured items
- The study centres on two stages of remanufacturing operations within the reverse SC framework.
- Efficiency evaluation has been conducted to compare the different scenarios using the generalized model.
- Two-stage DEA has been implemented incorporating both non-cooperative and cooperative methods of game theory.

This study presents a two-stage DEA approach to evaluate the efficiency of the remanufacturing process. The paper is structured as follows: Section 2 provides a brief literature review of two-stage DEA in the context of remanufacturing. The building block of the proposed generalized modelling is outlined in Section 3. Model development is discussed thoroughly in Section 4. Section 5 demonstrates the numerical illustration. Outcomes of the proposed study are discussed in Section 6. Managerial implications of the finding are highlighted in section 7. Finally, Section 8 concludes the study, followed by references.

2. Literature Review

A comprehensive literature review on CLSC is provided in this section. The main emphasis is on the remanufacturing process and stage-based modelling approaches within the CLSC framework. The application of two-stage DEA for their performance evaluation is the primary focus.

The concept of a CLSC extends the traditional SC model by incorporating reverse logistics operations for the recovery and reprocessing of used products, ultimately reintegrating them into the forward flow (Stindt and Sahamie, 2014). This conceptualization builds on foundational work by Wells and Seitz (2005), who first highlighted the need to integrate reverse flows. CLSC management, therefore, encompasses the strategic design, operational control, and execution of a system aimed at maximizing value extraction across the product lifecycle, dynamically adapting to the variability in volume and type of returned goods (Guide & van Wassenhove, 2009). Given its inherent focus on resource recovery and cyclical material flows, the CLSC emerges as a critical operational implementation of CE principles, particularly significant for meeting sustainability requirements. Therefore, scholarly attention is shifting towards the optimization of robust CLSC frameworks. A comprehensive analysis by Shekarian (2020) identifies twelve principal factors that exert influence on CLSC efficacy: economic considerations, sharing mechanisms, environmental impacts, incentive structures, financial implications, three-dimensional (3D) printing integration, inventory management systems, information technology infrastructure, quality assurance protocols, cannibalization effects, e-tailing dynamics, and international trade considerations. These factors collectively constitute a multi-dimensional framework for evaluating and optimizing CLSC performance.

Remanufacturing, as defined by the American National Standards Institute (ANSI, 2017), involves the restoration of end-of-use products to a state conforming to original or newly established quality specifications. Inherent to reverse logistics, remanufacturing occupies a pivotal position within CLSC operations. Consequently, the strategic integration of remanufacturing processes within diverse CLSC configurations warrants rigorous examination (Guide & Van Wassenhove, 2009; Naz et al., 2022). Abbey and Guide Jr (2018) proposed a typology of remanufacturing strategies and categorized them along two axes: profit versus cost focus, and robust versus single-use design. The identified remanufacturing approaches include strategies addressing multiple lifecycle products, commercial returns, reparability & durability, and involvement of third-party manufacturers.

In recent years, the utility of stage-based modelling within the CLSC research domain has attracted considerable academic interest. For instance, Amin and Zhang (2013) developed a three-stage closed-loop supply chain network (CLSCN) model incorporating uncertainty, proposing a multi-objective approach for integrated CLSC configuration and supplier selection. Bozdoğan et al. (2023) employed agent-based modelling to simulate the design of a dynamic CLSCN. Wang and Huang (2013) utilized a two-stage robust programming methodology to address demand-driven disassembly planning within a CLSC system. Shankar et al. (2018) formulated a decision model for strategic CLSC management, specifically focusing on the reclamation of EOL vehicles. Similarly, As'ad et al. (2019) presented two-stage CLSC models analyzing consignment stock agreements and diverse procurement strategies.

DEA is a linear programming method used to assess the efficiency and productivity of decision-making units (DMUs). Recently, researchers have turned to the two-stage extension of DEA for studying multi-phase systems. This methodological extension has proven valuable as a managerial tool for organizational performance assessment, including within CLSCNs. For instance, Azadeh et al. (2016) proposed an integrated simulation-Taguchi-DEA approach for supplier selection in a CLSC. In their study, Zarbakhshnia and jaghdani (2018) developed a two-stage DEA model integrating undesirable outputs and uncontrollable inputs. The model was demonstrated through sustainable supplier selection in the plastic industry. Another robust two-stage DEA model was introduced by Fathi et al. (2022) for sustainability assessment in SCs. Shafiee (2017) employed a rough two-stage DEA model, formulated as a non-cooperative Stackelberg game, to evaluate SC performance. Kahi et al. (2017) presented a CLSC framework leveraging DEA to assess the circularity of SCs. In the context of reverse logistics and remanufacturing, Wang et al. (2021) proposed a two-stage fuzzy optimization model tailored to e-commerce retailers. Li et al. (2020) proposed a two-stage model to monitor the performance of green suppliers, accounting for both dual-role characteristics and undesirable factors. In the context of remanufacturing reverse logistics, Zhang et al. (2021) developed an integrated MCDM framework for selecting collection models. A two-stage fuzzy interactive multi-objective method was proposed by Zhou et al. (2022) in an interval type-2 fuzzy environment, with application to remanufacturing old clothes. A fuzzy DEA model was introduced by Yang et al. (2022) for a parallel two-stage structure of a complex product system. The proposal focuses on evaluating manufacturing service efficiency and ranking. Their study was illustrated using a solid waste management system as an example. Yuan et al. (2020) developed a multi-objective ecological strategy optimization model. It is designed for a two-stage disassembly line balancing under constrained-resource conditions.

Despite the extensive body of literature on CLSC, remanufacturing and efficiency evaluation, several critical gaps remain unaddressed:

- Lack of integrated stage-wise efficiency assessment: Existing studies predominantly evaluate remanufacturing performance either at an aggregate level or focus on isolated stages, without explicitly modelling and comparing the efficiency of the inspection and development phases within a unified analytical framework.
- Limited use of dynamic modelling in the DEA-based remanufacturing studies: most DEA applications in CLSC and remanufacturing rely on static input-output representations. The dynamic nature of return, inspection throughput, and remanufacturing rates (which are inherently time-dependent) has received limited attention.
- Insufficient integration of game-theoretic structures with two-stage DEA: While cooperative and non-cooperative decision-making structures have studied independently, their integration with two-stage DEA for evaluating remanufacturing efficiency across sequential stages remains sparse.
- Inadequate representation of uncertainty and behavioural variations in remanufacturing flows: Previous studies often assume deterministic behaviour of returns and processing rates. The influence of different growth and learning patterns across remanufacturing stages is underexplored in efficiency evaluation models.

2.1 Our Contribution

Table 1 presents a comprehensive list of previous studies that have considered all aspects of efficiency and the remanufacturing process. While numerous studies in the literature address only a few aspects of efficiency and remanufacturing, this study makes a distinct contribution by incorporating multiple scenarios across two stages of the remanufacturing process. Additionally, it models these scenarios using ordinary differential equations, providing a more comprehensive analytical framework.

The present study contributes to the existing literature on CLSC and remanufacturing by directly addressing the key research gaps identified in the earlier section. This research develops a two-stage remanufacturing framework that explicitly distinguishes between the inspection, collection, sorting, and testing phases and the development-phase remanufacturing. By integrating this structure within a two-stage DEA model, the study enables stage-wise as well as overall efficiency assessment. It provides insights into performance bottlenecks across the remanufacturing process. Additionally, the proposed framework incorporates dynamic behaviour through differential-equation-based modelling. The evolution of returned products, inspection items, and remanufactured outputs is captured using various functional forms. This dynamic representation enables the model to capture realistic time-dependent remanufacturing operations, which are largely absent from existing efficiency valuation studies. Additionally, this study embeds game-theoretic decision structure within the two-stage DEA framework. Both non-cooperative and cooperative approaches are examined to assess how strategic coordination across stages affects overall remanufacturing efficiency. This integration provides novel analytical evidence on the role of collaboration and decentralisation in CLSC performance assessment. Furthermore, the proposed model evaluates multiple scenarios by varying key parameters related to inspection rates, remanufacturing rates, return proportions, and learning effects. By analysing these scenarios within a unified modelling and DEA framework, the study offers a comprehensive understanding of how uncertainty and growth dynamics affect efficiency across the manufacturing stages. This research contributes to the scientific literature by presenting a generalised dynamic and integrative evaluation of efficiency. The proposed approach not only advances methodological rigour by combining differential equations, two-stage DEA and game theory but also provides actionable insights for designing more efficient and sustainable remanufacturing systems.

Table 1. Literature review and author's contribution.

Articles	DE	RSC	R	EE	Two-Stage DEA	DEA technique: CO & NCO
Amirteimoori (2013)				✓	✓	
Ansari et al. (2022)			✓	✓		
de Arquer et al. (2022)				✓		
Bansal et al. (2020)	✓		✓			
Delavar et al. (2022)		✓	✓	✓		
Fathi et al. (2022)				✓	✓	
Ghadami et al. (2021)				✓		
Kahi et al. (2017)				✓		
Ke et al. (2021)		✓	✓	✓		
Li et al. (2020)				✓	✓	
Nishizaki et al. (2022)				✓	✓	
Noveiri et al. (2020)		✓		✓		
Shafiee (2017)				✓	✓	✓
Wang et al. (2021)			✓	✓	✓	
Wang et al. (2023)		✓		✓	✓	
Yang et al. (2022)				✓	✓	
Yuan et al. (2020)		✓	✓	✓	✓	
Zhang et al. (2021)			✓	✓		
Zhou et al. (2022)			✓	✓	✓	
This Paper	✓	✓	✓	✓	✓	✓

CO and NCO: Cooperative and Non-Cooperative, DE: Differential Equation-based Modelling, DEA: Data Envelopment Analysis, EE: Efficiency Evaluation, R: Remanufacturing, RSC: Reverse supply chain

In the next section, the authors discuss the research methodology employed in the study.

3. Building Blocks of the Proposed Modelling Framework

This section outlines the methodological approach utilized to evaluate the efficiency of the two-stage remanufacturing operation. The first step involves collecting, sorting, and testing items, which constitutes the inspection phase; the second stage focuses on remanufacturing processes, which constitute the development phase, required to satisfy demand. The fundamental assumption on which the proposal is based and the notation used throughout the paper are specified in the preceding subsections.

3.1 Assumptions
The proposed modelling framework is based on certain assumptions. The following are the assumptions:
1) All tested products that pass the quality check in the inspection phase will be used for remanufacturing.
2) No stock-outs are allowed, and demand is always satisfied.

In the present study, it is assumed that all products that successfully pass the inspection phase are sent for remanufacturing, so that the output of the inspection stage can be treated as a clear and measurable input to the development stage. This is essential for building a well-defined two-stage DEA structure. Allowing inspected items to be diverted elsewhere would introduce additional decision layers beyond the scope of efficiency evaluation. It also reflects a remanufacturing-oriented operational policy in which firms prioritize value recovery from all quality-approved returns. This minimises waste and maximises resource utilisation within the CLSC. Furthermore, the assumption that demand is always satisfied, so that no stockouts occur helps avoid complications that are related to shortages, backorders or unmet demand. This implies that the remanufacturing system is sufficiently responsive and capacity adequate to meet market demand at all times. This also enables the model to focus on evaluating operational efficiency rather than on inventory or service-level trade-offs.

3.2 Notations

Symbols	Definition
$a(t)$	Total products returned by the time 't'
$D_1(t)$	The cumulative count of returned products collected, sorted and tested by time 't'
$D_2(t)$	The cumulative count of remanufactured products used to meet the demand by time 't'
$r_1(t)$	Rate of collection, sorting, and testing of products
$r_2(t)$	Rate of remanufacturing products
α	Proportion of returned product
η	Learning parameter for remanufacturing

4. Model Development
A thorough analysis of the two-stage remanufacturing operations must first include a thorough explanation of the operations themselves. The efficiency evaluation methodology will then be explained, comprising both the inspection phase (collection, sorting, and testing) and the development phase of remanufacturing operations.

4.1 Remanufacturing-based Proposed Modelling Framework
Remanufactured products are ones whose constituent components may be recovered and reused to produce either the original product (perhaps at a later period, depending on demand and/or the emergence of a next-generation variety) or a comparable product. Such products can consist entirely of new components, consist entirely of recovered components, or comprise a combination of the two. Additive manufacturing, specifically Fused Deposition Modelling (FDM), facilitates remanufacturing production and is gaining popularity. Furthermore, product categories such as mobile communications devices, cars, paper products, wood remanufacturing, and electrical appliances are routinely subjected to redesign and remanufacturing procedures that use recovered components (Kam et al., 2017; Kam et al., 2018; Şengül and Kam, 2019; Rafiei et al., 2021).

The remanufacturing operation initiates with the collection of obsolete goods. Following collection, these goods undergo rigorous screening and testing. During this stage, predefined quality-control procedures are performed to assess each product's suitability for remanufacturing. Products that fail these inspections are directed to a designated disposal facility. Those that pass inspection move forward to the development stage. Finally, remanufactured products are used to meet end-user demand. In this way, remanufacturing operations can be described as a two-stage process. Let us examine this using a systematic diagram of the entire remanufacturing process.

Figure 4 outlines the complete framework considered in this study. The diagram represents a two-stage process. It highlights the bifurcation between stages which is further used to develop the corresponding mathematical modelling framework discussed in the following section:

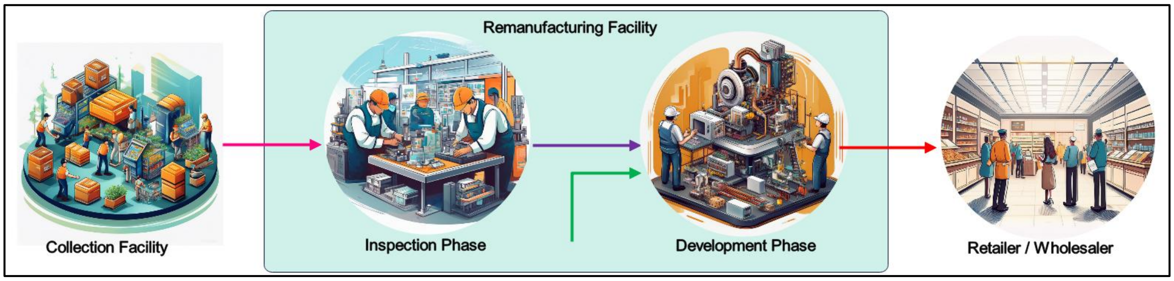

Figure 4. Two-stage process of remanufacturing operations; Source: Author's own creation.

Stage 1 (S1): The remanufacturing operations commence with the inspection phase. This stage involves the acquisition of products from designated collection centres, followed by rigorous sorting and testing to evaluate their suitability for subsequent remanufacturing. Companies adopt various strategies to achieve this objective. In line with what Bansal et al. (2020) have proposed, it has been assumed that the rate of collection, sorting and testing of the returned product in the remanufacturing facility is directly proportional to the number of returned products that are collected from the collection centre (Anand et al., 2019).

$$\frac{d}{dt}D_1(t) = r_1(t)\left[a(t) - D_1(t)\right] \tag{1}$$

Stage 2 (S2): Following the inspection phase, products that meet established quality criteria are channelled into the development phase. The remanufacturing rate governs the throughput of this stage. The quantity of remanufactured products can be determined using the following equation:

$$\frac{d}{dt}D_2(t) = r_2(t)\left[D_1(t) - D_2(t)\right] \tag{2}$$

Following the standard approach given in the two equations above, the current study varies the number of parameters for $D_1(t)$, $D_2(t)$, $a(t)$, $r_1(t)$, and $r_2(t)$. Building on the initial multi-stage framework depicted in **Figure 4**, a more comprehensive representation is needed to account for the intricate relationships among the input and output parameters in the proposed modelling work. Consequently, **Figure 5** provides a further refined conceptualization of this modelling study, offering more thorough consideration of the parameters. These parameter variations have led to the development of multiple distinct models. Each model illustrates a distinct scenario regarding inspection and remanufacturing. Thus, within this modelling framework, eight models have been examined incorporated in $D_1(t)$, $D_2(t)$, $a(t)$, $r_1(t)$, and $r_2(t)$. **Tables 2** to **9** show the values of these input and output parameters.

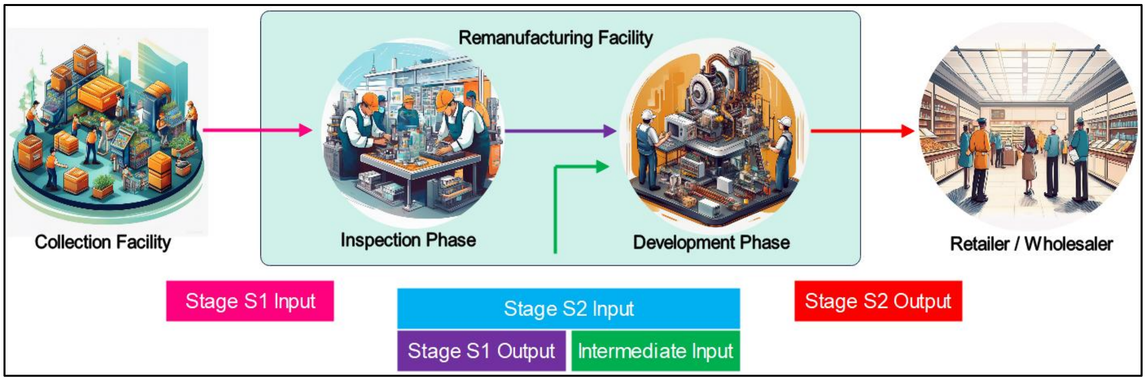

Figure 5. Input and Output parameters of two stages of remanufacturing operation; Source: Author's own creation.

- **Scenario I:** When the inspection and remanufacturing phases follow the exponential behaviour with the same rate of r, it represents a rapid and continuous growth pattern, indicative of escalating return products. Exponential behaviour in returned products suggests a compounding effect; the rate of increase is directly proportional to the existing returns, often denoting changes in customer preferences or seasonal returns. Hence the differential equations of both the stages will be:

$$\frac{d}{dt}D_1(t) = r\left[a - D_1(t)\right];\ \frac{d}{dt}D_2(t) = r\left[D_1(t) - D_2(t)\right] \tag{3}$$

Table 2. Input and output parameters of scenario I.

S1 Inputs	S2 Inputs		S2 Output
	S1 Outputs	Intermediate Inputs	
a	$D_1(t)$	-	$D_2(t)$
r		-	

- **Scenario II:** When the inspection phase and remanufacturing phase follow the exponential behaviour with different rates of r_1 and r_2. It signifies rapid and continuous growth pattern but with different rate of inspection and remanufacture. Hence the differential equations of both the stages will be:

$$\frac{d}{dt}D_1(t) = r_1\left[a - D_1(t)\right];\ \frac{d}{dt}D_2(t) = r_2\left[D_1(t) - D_2(t)\right] \tag{4}$$

Table 3. Input and output parameters of scenario II.

S1 Inputs	S2 Inputs		S2 Output
	S1 Outputs	Intermediate Inputs	
a	$D_1(t)$	r_2	$D_2(t)$
r_1			

- **Scenario III:** When the inspection phase of returned products follows the exponential behaviour with the rate of r and the remanufacturing of the inspected products follows the logistics distribution by the remanufacturing rate and a learning parameter of r and η, respectively. This implies a growth pattern that eventually reaches a saturation point.

$$\frac{d}{dt}D_1(t) = r\left[a - D_1(t)\right];\ \frac{d}{dt}D_2(t) = \frac{r}{1+\eta e^{-rt}}\left[D_1(t) - D_2(t)\right] \tag{5}$$

Table 4. Input and output parameters of scenario III.

S1 Inputs	S2 Inputs		S2 Output
	S1 Outputs	Intermediate Inputs	
a	$D_1(t)$	η	$D_2(t)$
r			

- **Scenario IV:** When the inspection phase of returned products follows the exponential behaviour with the rate of r_1 and the remanufacturing of the inspected products follows the logistics distribution by the remanufacturing rate of r_2 and a learning parameter η.

$$\frac{d}{dt}D_1(t)=r_1\left[a-D_1(t)\right];\ \frac{d}{dt}D_2(t)=\frac{r_2}{1+\eta e^{-r_2 t}}\left[D_1(t)-D_2(t)\right] \tag{6}$$

Table 5. Input and output parameters of scenario IV.

S1 Inputs	S2 Inputs		S2 Output
	S1 Outputs	Intermediate Inputs	
a	$D_1(t)$	r_2	$D_2(t)$
r_1		η	

- **Scenario V:** When the inspection phase of returned products follows the exponential behaviour with the rate r and the total number of return products increases with the time with scale parameter α, and the remanufacturing of the inspected products follows the exponential distribution by the remanufacturing rate of r.

$$\frac{d}{dt}D_1(t)=r\left[ae^{\alpha t}-D_1(t)\right];\ \frac{d}{dt}D_2(t)=r\left[D_1(t)-D_2(t)\right] \tag{7}$$

Table 6. Input and output parameters of scenario V.

S1 Inputs	S2 Inputs		S2 Output
	S1 Output	Intermediate Inputs	
a	$D_1(t)$	-	$D_2(t)$
r		-	
α		-	

- **Scenario VI:** When the inspection phase of returned products follows the exponential behaviour with the rate r and the total number of return products increases with the time with scale parameter α, and the remanufacturing of the inspected products follows the exponential distribution by the remanufacturing rate of r.

$$\frac{d}{dt}D_1(t)=r\left[a(1+\alpha t)-D_1(t)\right];\ \frac{d}{dt}D_2(t)=r\left[D_1(t)-D_2(t)\right] \tag{8}$$

Table 7. Input and output parameters of scenario VI.

S1 Inputs	S2 Inputs		S2 Output
	S1 Output	Intermediate Inputs	
a	$D_1(t)$	-	$D_2(t)$
r		-	
α		-	

- **Scenario VII:** When the inspection phase of returned products follows the exponential behaviour with the rate r and the total number of return products increases with the time with scale parameter α, and the remanufacturing of the inspected products follows the logistics distribution by the remanufacturing rate of r and the learning parameter η.

$$\frac{d}{dt}D_1(t) = r\left[ae^{\alpha t} - D_1(t)\right]; \ \frac{d}{dt}D_2(t) = \frac{r}{1+\eta e^{-rt}}\left[D_1(t) - D_2(t)\right] \tag{9}$$

Table 8. Input and output parameters of scenario VII.

S1 Inputs	S2 Inputs		S2 Output
	S1 Output	Intermediate Inputs	
a	$D_1(t)$	η	$D_2(t)$
r			
α			

- **Scenario VIII:** When the inspection of returned products follows the exponential behaviour with the rate r and the total number of return products increases with the time with scale parameter α, and the remanufacturing of the inspected products follows the logistics distribution by the remanufacturing rate of r and the learning parameter η.

$$\frac{d}{dt}D_1(t) = r\left[a(1+\alpha t) - D_1(t)\right]; \ \frac{d}{dt}D_2(t) = \frac{r}{1+\eta e^{-rt}}\left[D_1(t) - D_2(t)\right] \tag{10}$$

Table 9. Input and output parameters of scenario VIII.

S1 Inputs	S2 Inputs		S2 Output
	S1 Output	Intermediate Inputs	
a	$D_1(t)$	η	$D_2(t)$
r			
α			

Table 10. Closed-form solutions of the proposed modelling framework.

Models	$\boldsymbol{D_1(t)}$	$\boldsymbol{D_2(t)}$
Scenario I	$a(1-e^{-rt})$	$a[1-(1+rt)e^{-rt}]$
Scenario II	$a(1-e^{-r_1 t})$	$a\left[1-\left(\frac{r_1 e^{-r_2 t} - r_2 e^{-r_1 t}}{r_1 - r_2}\right)\right]$
Scenario III	$a(1-e^{-rt})$	$a\left[\frac{1-(1+rt)e^{-rt}}{1+\eta e^{-rt}}\right]$
Scenario IV	$a(1-e^{-r_1 t})$	$a\left[\frac{(1-e^{-r_2 t})r_1 - (1-e^{-r_1 t})r_2}{(r_1-r_2)(1+\eta e^{-r_2 t})}\right]$
Scenario V	$\frac{ar}{\alpha+r}(e^{\alpha t} - e^{-rt})$	$\frac{ar^2 e^{\alpha t}}{(a+r)^2} - \frac{ar^2 t e^{-rt}}{(a+r)} - \frac{ar^2 e^{-rt}}{(a+r)^2}$
Scenario VI	$a\left[1+\alpha t - \frac{\alpha}{r} - \left(1-\frac{\alpha}{r}\right)e^{-rt}\right]$	$a\left[1+\alpha t - \frac{2\alpha}{r} - rte^{-rt} + \alpha te^{-rt} - e^{-rt} + \frac{2\alpha e^{-rt}}{r}\right]$
Scenario VII	$\frac{ar}{\alpha+r}(e^{\alpha t} - e^{-rt})$	$\left[\frac{ar^2}{(\alpha+r)(\eta+e^{rt})}\right]\left[\frac{e^{(\alpha+r)t}}{(\alpha+r)} - t - \frac{1}{(\alpha+r)}\right]$
Scenario VIII	$a\left[1+\alpha t - \frac{\alpha}{r} - \left(1-\frac{\alpha}{r}\right)e^{-rt}\right]$	$\frac{a}{1+\eta e^{-rt}}\left[1-(1+rt)e^{-rt} - \frac{2\alpha}{r}(1-e^{-rt}) + \alpha t(1+e^{-rt})\right]$

Following table contains the solution of the above-mentioned model with the initial conditions $t = 0$, $D_1(t)$ and $D_2(t)$. This indicates that at the beginning, there were no products returned, and no products were re-manufactured.

To find the most effective scenario among all proposed models given in **Table 10**, different setups of parameters for $D_1(t)$ and $D_2(t)$ are examined.

5. Numerical Illustration

The proposed set of mathematical modelling frameworks has been validated using two distinct datasets to check the accuracy of the models. The first dataset comprises data of Nissan Car Sales (Nissan, 2024). The second dataset is of moto new motorcycle (Statistics Netherlands, 2023). This dataset resembles the demand generated by the consumer. According to the availability of the data, Nissan car sales data for 20 years (2005 Q1 - 2024 Q1) and Moto Motorcycle second-hand motorcycle data for 2 years (2021-2023). These products were selected based on the key criteria essential for remanufacturing processes. Additionally, these products have an established reverse flow to their designated return facilities.

To determine the input and output parameters of the scenarios mentioned in **Table 10**, i.e., total products returned ($a(t)$), cumulative number of retuned products collected, sorted, and tested by time t ($D_1(t)$), cumulative number of remanufactured products by time t ($D_2(t)$), rate of collection, sorting, and testing ($r_1(t)$), rate of remanufacturing in developing phase ($r_2(t)$), proportion of returned products (α), learning parameter for remanufacturing (η) through the non-linear least square (NLLS) method (Srinivasan and Mason, 1986) for the two datasets. The authors have utilised the SAS software package for the model parameter evaluation (SAS Institute, 2004). The next subsection consists of model parameters, validation, DEA, and the graphical analysis of the dataset.

5.1 Model Parameters

This study employed nonlinear least squares regression to estimate the model's unknown parameters and evaluate its efficiency. The parameter estimates for each dataset are shown in **Tables 11** and **12**, respectively.

Table 11. Scenario parameter values (estimated) of DS-I.

Parameters	a	r	r_1	α	r_2	η
Scenario I	288.824	0.031	-	-	-	-
Scenario II	531.460	-	0.0073	-	0.095	-
Scenario III	288.752	0.031	-	-	-	0.001
Scenario IV	280.616	-	0.9994	-	0.036	4.659
Scenario V	130.632	0.053	-	0.0116	-	-
Scenario VI	249.570	0.034	-	0.0025	-	-
Scenario VII	130.549	0.053	-	0.0116	-	0.001
Scenario VIII	149.736	0.046	-	0.0130	-	7.456

Table 12. Scenario parameter values (estimated) for DS-II.

Parameters	a	r	r_1	α	r_2	η
Scenario I	57.457	0.082	-	-	-	-
Scenario II	147.702	-	0.764	-	0.011	-
Scenario III	54.460	0.092	-	-	-	0.374
Scenario IV	119.556	-	0.014	-	0.708	0.021
Scenario V	14.976	0.279	-	0.043	-	-
Scenario VI	24.013	0.146	-	0.045	-	-
Scenario VII	14.024	0.329	-	0.044	-	0.794
Scenario VIII	12.733	0.262	-	0.097	-	0.289

5.2 Model Validation

A variety of comparative measures were used to assess the model's performance. **Tables 13** and **14** display the goodness-of-fit evaluation's findings.

The goodness-of-fit measures provide valuable quantitative insights into how closely the suggested models align with the observed data. Measures such as R^2 (C1), Bias (C2), Variance (C3), Mean Square Error (MAE) (C4), Root Mean Square Error (RMSE) (C5), and Root Mean Square Percentage Error (RMSPE) (C6) are calculated to check the accuracy of the models (Anand et al., 2022).

Valuable quantitative insights into how well the suggested models match the observed data are offered by the goodness-of-fit criteria.

Table 13. Performance evaluation metrics of DS-I.

Scenarios	C1	C2	C3	C4	C5	C6
Scenario I	0.992	1.926	4252.138	4.320	5.718	29.149
Scenario II	0.993	1.454	4129.199	4.256	5.109	26.399
Scenario III	0.993	1.927	4252.300	4.320	5.720	29.154
Scenario IV	0.997	0.662	4026.463	2.857	3.238	16.101
Scenario V	0.993	1.302	4134.864	4.567	5.297	26.219
Scenario VI	0.992	1.871	4248.935	4.314	5.634	28.907
Scenario VII	0.993	1.310	4134.378	4.569	5.299	26.221
Scenario VIII	0.993	1.519	4176.806	4.339	5.309	27.327

Table 14. Performance evaluation metrics of DS-II.

Scenarios	C1	C2	C3	C4	C5	C6
Scenario I	0.974	0.569	219.104	1.771	2.229	25.189
Scenario II	0.990	0.074	195.501	1.124	1.399	9.016
Scenario III	0.970	0.642	221.717	1.894	2.388	27.066
Scenario IV	0.988	0.111	191.370	1.201	1.513	9.228
Scenario V	0.996	0.014	197.431	0.736	0.911	7.175
Scenario VI	0.984	0.414	213.750	1.407	1.768	20.575
Scenario VII	0.995	0.028	197.948	0.768	0.953	8.387
Scenario VIII	0.989	0.107	200.456	1.222	1.464	14.283

It is crucial to remember that none of the eight suggested scenarios performed noticeably better than the others. The authors have applied two-stage DEA to compare their efficiencies using several input and output indicators.

5.3 Data Envelopment Analysis

DEA, based on linear programming, is utilized for evaluating the relative efficiency or performance of multiple DMUs. DEA measures the efficiency of a specific DMU i by comparing it to the performance of other DMUs in the group. Each DMU uses multiple inputs to generate multiple outputs, which are often measured in different units. Because of its many benefits, DEA is a good analytical tool for evaluating SC effectiveness (Yang et al., 2011).

DEA, initially introduced by Charnes et al. (1978) and subsequently extended by Banker et al. (1984), constitutes a robust technique within the broader framework of MCDM methodologies. The original CCR model by Charnes, Cooper, and Rhodes assumes constant returns to scale. The BCC model, introduced later by Banker, Charnes, and Cooper, accommodates variable returns to scale.

DEA often uses a "black box" approach, which avoids making assumptions about the internal workings of a DMU. It focuses on how inputs are converted into outputs, which is often sufficient for analysis. However, for systems like SCs, DEA can use multi-stage models. These models include intermediate measures, which are outputs from one stage and inputs for the next, as noted by (Sexton and Lewis, 2003; Agrawal et al., 2023). In these models, each stage can be seen as a separate decision centre, with overall control by a central manager. This manager aims to improve SC efficiency both within and between stages. Within each stage, decision centres try to allocate resources efficiently based on their needs, while externally, the focus is on increasing market share.

Studies by Liang et al. (2006) and Li et al. (2012) have explored SC dynamics as a buyer-seller game, examining both non-cooperative and cooperative frameworks. One widely used form of non-cooperative interaction is the Stackelberg model. It represents a simplified SC with the manufacturer acting as a leader and the retailer as the follower. In this context, the efficiency of the leader is prioritized; it is assessed using standard DEA methodologies, and subsequently, the follower's efficiency is evaluated conditional on the leader's performance. This approach reflects an implicit assumption that the leader's efficiency holds greater significance for overall SC performance. Conversely, under a cooperative paradigm, both stages are deemed equally crucial. Parties engage in collaborative efforts to maximize both collective and individual efficiencies. The intermediate measures play a pivotal role in facilitating this cooperation. In this case, the efficiency of each stage is evaluated concurrently, and its arithmetic mean represents the total efficiency of the SC.

The remanufacturing process is presented in **Figure 4**, where stage 1 is the collection, sorting, and testing phase and stage 2 is the development phase. The model includes $j = 1,2,...,8$ DMUs. The collection, sorting and testing phase consumes $x_i (i = 1,2,3,4)$ inputs and generates $z_d (d = 1)$ intermediate input. The development phase uses $z_d (d = 1)$ intermediate input from the collection, sorting, and testing phase and $x_p (p = 1,2)$ exogenous inputs and produces $y_r (r = 1)$ final output. **Table 15** presents the notations used in formulating the programming problems under non-cooperative and cooperative framework.

Table 15. Notations used in two stage DEA development.

Symbols	Definitions
DMU_j	j^{th} DMU, j = 1, 2, …,8
DMU_0	Reference DMU
x_{ij}	i^{th} input consumed by j^{th} DMU in stage 1
w_i	Weight of the i^{th} input of stage 1
x_{i0}	i^{th} input consumed by reference DMU
Z_{dj}	d^{th} output generated by j^{th} DMU in stage 1
μ_d	Weight of the d^{th} output in stage 1
Z_{d0}	d^{th} output generated by reference DMU
x_{pj}	p^{th} intermediate input consumed by j^{th} DMU in stage 2
w_p	Weight of the p^{th} intermediate input in stage 2
x_{p0}	r^{th} output generated by reference DMU
y_{rj}	r^{th} output generated by j^{th} DMU in stage 2
γ_r	Weight of the r^{th} output in stage 2
y_{r0}	r^{th} output generated by reference DMU
E_1^*	Efficiency of stage 1
E_2^*	Efficiency of stage 2
E	Total efficiency

5.3.1 Non Cooperative Method

In game theory, the term "non-cooperative game" can refer to either leader-follower models or normal form simultaneous-move games. One type of non-cooperative game involves a leader-follower structure. The leader-follower structure is commonly known as the Stackelberg model in the literature. In this study, the authors have assumed that the first stage functions as the leader, and its performance is considered to be of primary importance. Next, the efficiency of the second stage (the follower) is evaluated, given the condition that the efficiency of the leader stays fixed.

Consider a seller-buyer game where the collection, sorting, and testing phase represents the seller, and the remanufacturing phase represents the buyer. We posit that the collection, sorting, and testing phase functions as the leader, with the development phase as the follower. Following the methodology outlined by Liang et al. (2006), the authors have proceeded to evaluate the leader's efficiency using a standard Constant Returns to Scale (CRS) DEA model, formulated as:

$$
\begin{aligned}
& Max\ E_1 = \sum_d \mu_d z_{d0} \\
& Subject\ to \\
& \sum_i w_i x_{ij} - \sum_d \mu_d z_{dj} \geq 0, \quad j = 1,2,\dots,8 \\
& \sum_i w_i x_{i0} = 1 \\
& \mu_d, w_i \geq 0, \quad d = 1,\ i = 1,2,\dots,4.
\end{aligned}
$$

Above model assess the leader's maximised efficiency E_1^* and the optimal weights μ_d^* and ω_i^*. (Liang et al., 2006) evaluate the follower's efficiency subject to these optimal values, resulting in the following non-linear model:

$$
\begin{aligned}
& Max\ E_2 = \sum_r \gamma_r y_{r0} \\
& Subject\ to \\
& q\sum_d \mu_d z_{dj} + \sum_p w_p x_{pj} - \sum_r \gamma_r y_{rj} \geq 0, \quad j = 1,2,\dots,8 \\
& q\sum_d \mu_d z_{d0} + \sum_p w_p x_{p0} = 1 \\
& \sum_d \mu_d z_{d0} = E_1^* \\
& \sum_i w_i x_{ij} - \sum_d \mu_d z_{dj} \geq 0, \quad j = 1,2,\dots,8 \\
& \sum_i w_i x_{i0} = 1 \\
& \mu_d, w_i, \gamma_r, w_p, q \geq 0, \quad d = 1,\ i = 1,2,3,4, \quad r = 1, \quad p = 1,2.
\end{aligned}
$$

Note that $q\sum_d \mu_d z_{d0} + \sum_p w_p x_{p0} = 1$ and $\sum_d \mu_d z_{d0} = E_1^*$. Thus, one can conclude that $0 \leq q < \frac{1}{\sum_d \mu_d z_{d0}} = \frac{1}{E_1^*}$.

Therefore, d can be considered a parameter allowing the model to be treated as a linear program. After solving the above model, we get E_2^* and the optimal weights $\mu_d^*, \omega_i^*, \gamma_r^*, \omega_p^*$, and q^*. Once the individual efficiencies are evaluated, the total efficiency of the process can be determined using $E = \frac{1}{2}(E_1^* + E_2^*)$.

Likewise, one can design a procedure for the case where the buyer leads and the seller follows, i.e., the development phase is a leader and collection, sorting, and testing is a follower. Initially, the standard CCR ratio model is used to measure the efficiency of the development phase.

$$Max\ E_2 = \sum_r \gamma_r y_{r0}$$
$$Subject\ to$$
$$\sum_d \mu_d z_{dj} + \sum_p w_p x_{pj} - \sum_r \gamma_r y_{rj} \geq 0, \quad j = 1,2,...,8$$
$$\sum_d \mu_d z_{d0} + \sum_p w_p x_{p0} = 1$$
$$\mu_d, w_p, \gamma_r \geq 0, \quad d = 1,\ p = 1,2, \quad r = 1.$$

After solving the above LPP, we get the optimal weights $\mu_d^*, \omega_p^*, \gamma_r^*$ and the optimal efficiency of the buyer as E_2^*. To obtain the efficiency of the seller, provided the buyer's efficiency is equal to E_2^*, the following model is solved.

$$Max\ E_1 = u \sum_d u_d z_{d0}$$
$$Subject\ to$$
$$\sum_i w_i x_{ij} - u \sum_d \mu_d z_{dj} \geq 0, \quad j = 1,2,...,8$$
$$\sum_i w_i x_{i0} = 1$$
$$\sum_r \gamma_r y_{r0} = E_2^*$$
$$\sum_d \mu_d z_{dj} + \sum_p w_p x_{pj} - \sum_r \gamma_r y_{rj} \geq 0 \quad j = 1,2,...,8$$
$$\sum_d \mu_d z_{d0} + \sum_p w_p x_{p0} = 1$$
$$\mu_d, w_i, \gamma_r, w_p, u \geq 0, \quad d = 1,\ i = 1,2,3,4, \quad r = 1, \quad p = 1,2.$$

After solving the above model, we'll get the optimal weights μ_d^*, ω_i^* and the efficiency of the buyer E_1^*. Once the individual efficiencies are evaluated, the total efficiency of the process can be determined using $E = \frac{1}{2}(E_1^* + E_2^*)$.

In yet another frame of the game theory approach, one can see the presence of players who are equally dominating. For such a scenario, the authors have presented the cooperative method.

5.3.2 Cooperative Method

An alternative way to measure the efficiency of the two-stage process is to take a centralized perspective and find optimal weights for the intermediate factors that maximize the aggregate or global efficiency score.

Under a cooperative framework, the seller and buyer possess equivalent bargaining power and collaborate to achieve joint efficiency maximization. The aim of the cooperative DEA model is to optimize the efficiency of both stage 1 and stage 2, subject to the constraint that the weights assigned to intermediate measures are uniform.

$$Max\ E = \frac{1}{2}\left[\frac{\sum_d w_d z_{d0}}{\sum_i v_i x_{i0}} + \frac{\sum_r u_r y_{r0}}{\sum_d w_d z_{d0} + \sum_p v_p x_{p0}}\right]$$

Subject to

$$\frac{\sum_d w_d z_{dj}}{\sum_i v_i x_{ij}} \le 1, \quad j = 1, 2, ..., 8$$

$$\frac{\sum_r u_r y_{rj}}{\sum_d w_d z_{dj} + \sum_p v_p x_{pj}} \le 1, \quad j = 1, 2, ..., 8$$

$$w_d, v_i, u_r, v_p \ge 0, \quad d = 1, \quad i = 1, 2, 3, 4, \quad r = 1, \quad p = 1, 2.$$

The model mentioned above is referred to as the cooperative efficiency evaluation model. It focuses on maximizing the joint efficiency of stage 1 and stage 2. it also enforces a shared set of weights for the intermediate measures. The Charnes-Cooper transformation allows the model to be converted from Non-Linear Programming to Linear Programming.

A DMU is said to be efficient if both the stages (i.e. stage 1 and stage 2) are efficient, that is, $E_1^* = 1$ and $E_2^* = 1$. Hence $E^* = 1$.

5.4 Graphical Analysis

The accuracy of the proposed models concerning the original data is demonstrated in **Figures 6** and **7**.

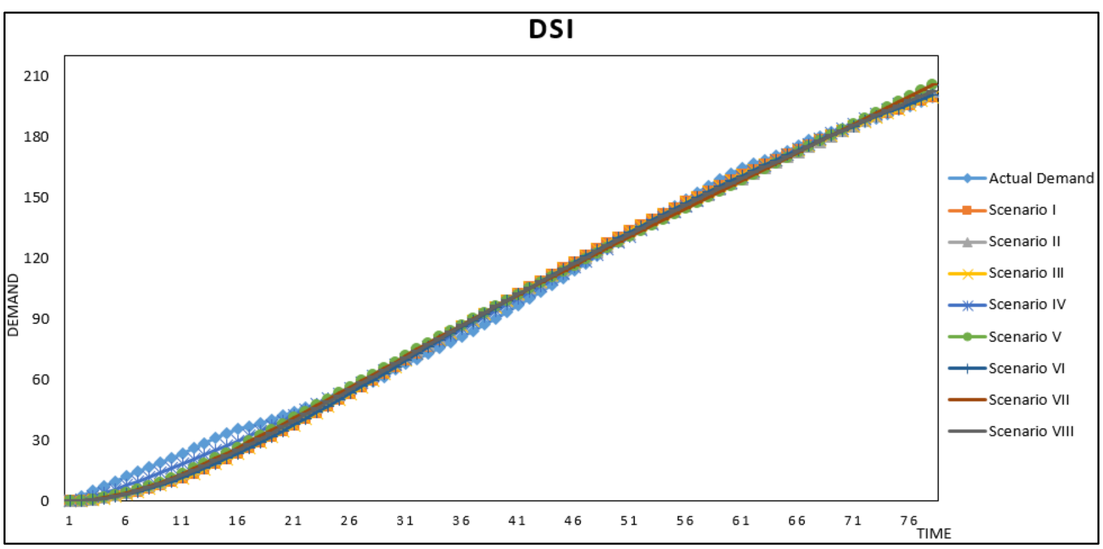

Figure 6. Graphical representation of DS-I.

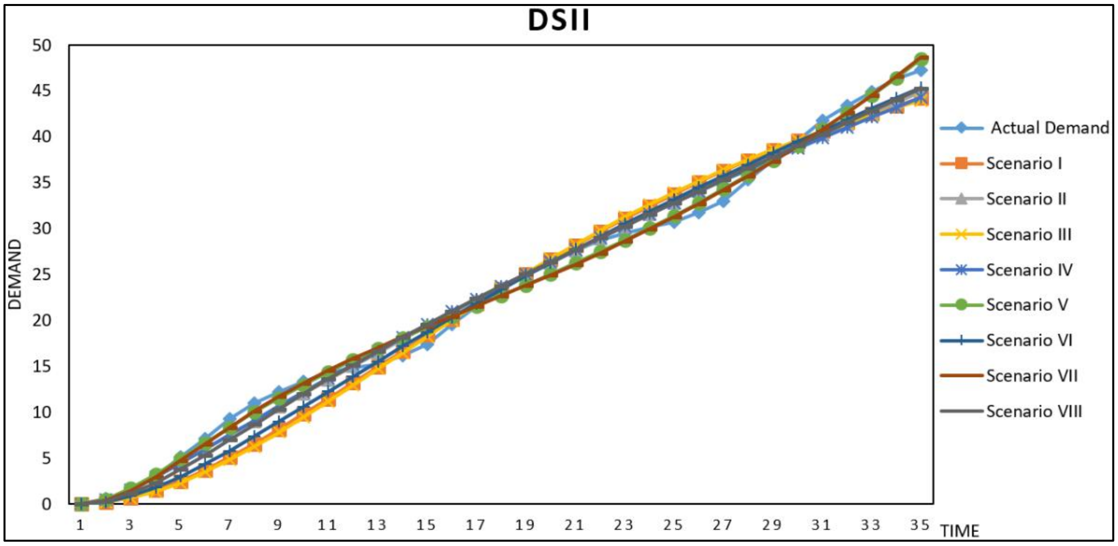

Figure 7. Graphical representation of DS-II.

The graphical representation illustrates a satisfactory fit with the original data, reflecting a favourable correspondence between the proposed model and the observed values.

6. Result Discussion

Two-stage DEA models as described, are used for analysing the efficiency of the overall process of remanufacturing products to satisfy the demand for the product. The inspection efficiency (Stage-1 efficiency) of a remanufacturing centre is an indicator of how well the centre is utilizing its market size and rate of inspection in generating the inspected product. While development efficiency (Stage-II efficiency) points out how efficiently the inspected products, learning parameter and rate of remanufacturing have been able to generate remanufactured products. **Tables 16** and **17** represent the decision matrix for DSI and DSII respectively.

Table 16. Normalised values of DS-I.

Decision Matrix I	a	r	r_1	α	r_2	η
Scenario I	1.127	1.0043	-	-	-	-
Scenario II	2.074	-	0.0576	-	5.813	-
Scenario III	1.127	1.0047	-	-	-	0.0007
Scenario IV	1.095	-	7.942	-	2.187	3.077
Scenario V	0.510	1.706	-	2.3997	-	-
Scenario VI	0.974	1.093	-	0.5088	-	-
Scenario VII	0.509	1.707	-	2.401	-	0.007
Scenario VIII	0.584	1.485	-	2.6906	-	4.921

The Lingo software was utilised for solving the linear programming problem. **Tables 18-19** shows the scores related to the three cases mentioned above. The results indicate multiple models for each dataset.

Table 17. Normalised values of DS-II.

Decision Matrix II	a	r	r_1	α	r_2	η
Scenario I	1.033	0.554	-	-	-	-
Scenario II	2.656	-	7.854	-	0.123	-
Scenario III	0.979	0.620	-	-	-	2.024
Scenario IV	2.150	-	0.146	-	7.877	0.115
Scenario V	0.269	1.874	-	1.501	-	-
Scenario VI	0.432	0.982	-	1.578	-	-
Scenario VII	0.252	2.209	-	1.535	-	4.297
Scenario VIII	0.229	1.760	-	3.386	-	1.564

Table 18. Efficiency scores of DS-I.

DMUs	Non-cooperative method						Cooperative method		
	S1 leader and S2 follower			S1 follower and S2 leader					
	E_1	E_2	E	E_1	E_2	E	E_1	E_2	E
Scenario I	0.999272	0.9617595	0.980516	0.999272	0.9617595	0.98051575	0.999272	0.96176	0.980516
Scenario II	1	1	1	1	1	1	1	1	1
Scenario III	1	0.960524	0.980262	1	0.960524	0.980262	1	0.960524	0.980262
Scenario IV	1	0.8694249	0.934712	1	0.8694249	0.93471245	1	0.869425	0.934713
Scenario V	1	1	1	1	1	1	1	1	1
Scenario VI	1	1	1	1	0.9681143	0.98405715	1	0.968114	0.984057
Scenario VII	1	1	1	1	1	1	1	1	1
Scenario VIII	1	1	1	1	1	1	1	1	1

Table 19. Efficiency score of DS-II.

DMUs	Non-cooperative method						Cooperative method		
	S1 leader and S2 follower			S1 follower and S2 leader					
	E_1	E_2	E	E_1	E_2	E	E_1	E_2	E
Scenario I	1	0.94573	0.972865	1	0.94573	0.972865	1	0.94573	0.972865
Scenario II	1	0.352053	0.675526	1	0.351053	0.675526	1	0.675526	0.675526
Scenario III	1	0.932098	0.966049	1	0.932098	0.966049	1	0.966044	0.966044
Scenario IV	1	1	1	1	1	1	1	1	1
Scenario V	1	1	1	1	1	1	1	1	1
Scenario VI	1	0.982311	0.991156	1	0.982311	0.991156	1	0.991156	0.991156
Scenario VII	1	1	1	1	1	1	1	1	1
Scenario VIII	1	1	1	1	1	1	1	1	1

The analysis of Nissan Car Sales Data, case 1 where the inspection phase is a leader and the remanufacturing phase is a follower, reveals performance variations across eight distinct scenarios. **Table 18**, columns 2 and 3, detail the efficiency levels for the respective inspection and development phases. In the initial inspection stage, seven of the eight scenarios demonstrated 100% efficiency, with scenario 1 representing the sole exception. This suggests overutilization of returned products and rate of inspection within scenario 1. Conversely, the development stage exhibited lower efficiency levels, with scenarios 1, 3 and 4 failing to achieve 100% efficiency. This indicates inefficiencies in the utilization of inspected products, rate of remanufacturing, and learning parameters within these scenarios. Column 4 of **Table 18** presents the overall efficiency of the remanufacturing operations. Notably, scenarios 1, 3 and 4 were identified as inefficient. Scenarios 3 and 4, despite achieving 100% efficiency in the inspection stage, demonstrated inefficiencies in the development stage, implying a failure to effectively utilize intermediate inputs. Scenario 1, however, exhibited inefficiency across both stages, indicating overutilization of inputs in both stages. Hence, we can conclude that in case 1 where inspection phase is a leader and development phase is a follower, out of 8 scenarios, for stage 1, seven of the eight scenarios were efficient, while in second stage, five of the eight scenarios were efficient. And overall, 5 of the eight scenarios were efficient.

Similarly, the case 2 where the inspection phase is a follower and the development phase is a leader, shows the similar pattern in the inspection stage depicted by the column 5. It shows that the out of eight distinct scenarios, every scenario is 100% efficient except scenario 1. This shows that it over utilise its initial input of returned products and rate of remanufacturing. On the other hand, four out of eight scenarios were efficient while the rest 4 were inefficient, scenarios 1, 3, 4 and 6 in their peer group represented in column 6. This shows that they overutilize their intermediate output of inspected product and exogenous inputs of rate of remanufacturing and learning parameter. Column 7 shows the overall efficiency of the development phase, and it depicts that out of 8 scenarios, only 4 were efficient, which are scenario 2, 5, 7 and 8.

For the case 3 of cooperative method, column 8 represents the inspection efficiency level and column 9 represents the development efficiency level. Every scenario has the efficiency score of 100% in inspection phase except scenario 1 which again indicates its overutilization of the input parameter. On the other hand, in column 9, four out of eight were efficient while scenario 1, 3, 4 and 6 were inefficient in development phase. This indicates that scenarios 2, 5, 7 and 8 had the overall efficiency score of 100%.

The analysis of Moto Motorcycle new car sales data, case 1 where the inspection phase is a leader and the development phase is a follower, reveals performance variations across the eight distinct scenarios. Table 19, columns 2 and 3 indicates the inspection and development efficiency scores respectively. All eight scenarios were efficient in the inspection phase. On the contrary, out of eight scenarios, four scenarios, scenario 4, 5, 7 and 8, had the efficiency level of 1 in development phase. Which indicate that scenarios 4, 5, 7 and 8 had the overall efficiency score of 1, shown in column 4, in the entire remanufacturing operations. These results indicate that even though all the eight scenarios efficiently utilised their returned products, and rate of collecting, sorting, and testing to have inspected product, but they did not efficiently convert these inspected products, rate of remanufacturing, and learning parameters to produce remanufactured goods.

Similarly, case 2 where the inspection phase is a follower, and the remanufacturing phase is a leader. **Table 19**, columns 5 and 6 shows the inspection efficiency and the development efficiency. In this case, every scenario has the efficiency score of 1 in inspection phase whereas only 4 scenario, scenarios 4, 5, 7 and 8, has the efficiency score of 1 in the remanufacturing phase. This concludes that scenarios 4, 5, 7 and 8 had the overall efficiency score of 1 shown in column 7 in the entire remanufacturing process.

In the case 3 of cooperative method, columns 8 and 9 represents the inspection and remanufacturing efficiency respectively. Every scenario had the efficiency score of 1 in the inspection stage whereas only 4 scenarios, scenarios 4, 5, 7 and 8 were efficient in the remanufacturing phase. This concludes that scenarios 4, 5, 7 and 8 had the overall efficiency score of 1 in the remanufacturing phase shown in column 10.

Table 20. Correlation matrix of DS-I.

Correlation	Non-cooperative method						Cooperative method		
	S1 leader and S2 follower			S1 follower and S2 leader					
	E_1	E_2	E	E_1	E_2	E	E_1	E_2	E
E_1	1	0.1078	0.113351	1	0.074583	0.080328	1	0.074579	0.080325
E_2	0.1078	1	0.999984	0.074583	1	0.999983	0.074579	1	0.999983
E	0.113351	0.999984	1	0.080328	0.999983	1	0.080325	0.999983	1

To better understand which stage has a dominant influence on overall revenue, a correlation analysis is conducted between stage-wise efficiencies and overall system efficiency. **Tables 20** and **21** report the correlation matrix for DSI and DSII, respectively, under non-cooperative and cooperative decision-making structures. This analysis provides insights into whether improvements in inspection efficiency or development efficiency are more critical for enhancing overall remanufacturing performance.

Table 21. Correlation matrix of DS-II.

Correlation	Non-cooperative method						Cooperative method		
	S1 leader and S2 follower			S1 follower and S2 leader					
	E_1	E_2	E	E_1	E_2	E	E_1	E_2	E
E_1	1	-0.07986	-0.10388	1	-0.07986	-0.10388	1	-0.07986	-0.10388
E_2	-0.07986	1	0.99971	-0.07986	1	0.99971	-0.07986	1	0.99971
E	-0.10388	0.99971	1	-0.10388	0.99971	1	-0.10388	0.99971	1

The correlation results clearly demonstrate that development-stage efficiency is strongly positively correlated with overall efficiency across both datasets and all decision-making structures. In contrast, inspection-stage efficiency shows a weak or negligible correlation with overall efficiency. This indicates that improvements in inspection efficiency alone have a limited impact on total system performance once a basic level of inspection capacity is achieved. Instead, the ability of the remanufacturing (development) stage to effectively convert inspected products into remanufacturing outputs is the primary driver of overall efficiency in the CLSC.

7. Managerial Implications

The findings of this study offer several actionable insights for managers responsible for designing and operating remanufacturing-based CLSC. The two-stage DEA results consistently show that the inspection phase (collection, sorting and testing) operates near optimal efficiency across most scenarios. The development phase remains the primary source of inefficiency. This suggests that managerial attention in many organisations is disproportionately concentrated on upstream return acquisition, while downstream remanufacturing capabilities remain under-optimised. Consequently, managers should strategically reallocate resources to the remanufacturing phase to address inefficiencies and enhance overall operational performance.

The correlation analysis provides strong empirical evidence that development-stage efficiency is the dominant determinant of overall remanufacturing performance. The near-perfect correlation between development efficiency and total system efficiency implies that marginal improvements yield significantly higher system-wide benefits compared to similar improvements in inspection activities. Managers should therefore prioritise investments in remanufacturing capacity planning, process standardisation and technology adoption rather than further intensifying inspection efforts that already operate efficiently.

From an operational perspective, managers can improve development stage efficiency by optimising remanufacturing rates, enhancing workforce learning through structured training programmes and adopting automation or advanced manufacturing technologies that reduce processing time and variability. Additionally, aligning inspection output volumes with the remanufacturing capacity can prevent congestion and underutilisation of intermediate inputs.

The comparative analysis of cooperative and non-cooperative decision-making structures further indicates that cooperative coordination between inspection and remanufacturing units consistently yields superior efficiency outcomes. This highlights the importance of cross-functional integration in remanufacturing operations. Managers are encouraged to implement collaborative planning mechanisms, shared performance metrics and incentive schemes promoting joint decision-making across stages. Such coordination facilitates smoother intermediate product flows, better synchronisation of capacities and reduced operational redundancies. Overall, the present study suggests organisations aiming to enhance remanufacturing efficiency should shift from a return-focused mindset to a remanufacturing-capability-driven strategy supported by cooperative governance structures. This strategic reorientation can substantially improve operational efficiency, reduce waste and strengthen the long-term sustainability of CLSCs.

8. Conclusion

In conclusion, the presented study offers valuable insights into the efficiency of remanufacturing operations.

- **RQ1:** The study establishes that a two-stage DEA framework, integrated with a structured remanufacturing model, is an effective quantitative approach for evaluating efficiency in CLSC. By explicitly modelling the inspection and development phases as sequential and interconnected stages, the approach enables simultaneous measurement of stage-wise and overall system efficiency.
- **RQ2:** The findings indicate that decision-making structure significantly influences remanufacturing efficiency. Cooperative decision-making consistently yields higher stage-wise and overall efficiency than a non-cooperative structure.

The analysis highlights that while the inspection phase consistently demonstrates high efficiency, the development phase consistently serves as a persistent bottleneck across multiple scenarios. Some inefficiencies in the development phase stem from inadequate utilization of inspected products, the rate of remanufacturing and the learning parameters, all of which collectively hinder overall operational performance. The correlation-based findings further reinforce that development-stage performance is the critical leverage point for managerial intervention. This underscores the need for coordinated and capacity-aligned remanufacturing strategies.

The non-cooperative approach reveals distinct challenges. When the inspection phase is a leader, the remanufacturing phase often fails to efficiently process intermediate inputs, resulting in inefficiencies across multiple scenarios. Conversely, when the remanufacturing phase is a leader, persistent inefficiencies suggest difficulties in achieving effective resource management and coordination between the two stages. In contrast, the cooperative approach consistently enhances overall efficiency of the process, particularly within the remanufacturing phase, by fostering improved integration and synchronization between inspection and remanufacturing phases. To advance the efficiency and sustainability of remanufacturing operations, organizations should prioritize the adoption of cooperative strategies that facilitate seamless collaboration between inspection and remanufacturing teams. By addressing these inefficiencies and embracing a cooperative operational model, organizations can optimize their remanufacturing processes, thereby ensuring long-term operational resilience and sustainability.

8.1 Scope for Future Research

While the proposed framework provides a comprehensive evaluation of two-stage remanufacturing efficiency still several avenues remain open for future research. The current model can be extended by incorporating stochastic demand and return uncertainty, allowing for more realistic representation of volatile market and consumer behaviour. Future studies may also consider multi-echelon and multi-product CLSC structures. The scalability can be enhanced by including multiple collection centres and remanufacturing facilities. Moreover, environmental and social performance indicators incorporation such as carbon emission and employment effects would strengthen these sustainability dimension of the analysis.

Conflicts of Interest

All authors declare that they have no conflicts of interest.

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AI Disclosure

The author(s) declare that no assistance is taken from generative AI to write this article.

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