

Tracing Uncertainty in Reverse Logistics: A Decision Support System for Zero Defect Remanufacturing Quality and Quantity Control

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Abstract: The growing emphasis on circular economy principles has highlighted the importance of efficient remanufacturing processes in reducing waste and maximizing resource utilization. However, uncertainties in reverse logistics—specifically related to the quality, quantity, and timing of returned products—pose significant challenges for achieving defect-free remanufacturing. This paper proposes a Decision Support System (DSS) based on decision tree machine learning models to address uncertainties in remanufacturing. The DSS analyses key variables such as return timing and product condition to optimize remanufacturing outcomes by incentivizing early returns and improving product quality and return predictability. Additionally, the system integrates Zero Defect Manufacturing (ZDM) principles by leveraging real-time data and predictive analytics to minimize defects in remanufactured products. The paper discusses the implications of this approach for managing reverse logistics uncertainties and outlines future research directions for refining and implementing the DSS in practical settings. By bridging predictive analytics with sustainable manufacturing practices, the proposed framework contributes to more efficient and resilient remanufacturing systems within the circular economy.

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1. INTRODUCTION

The circular economy has emerged as a transformative approach to sustainable manufacturing, focusing on minimizing waste and maximizing resource utilization. Circularity enhances the reuse of parts, materials, and products. It increases in managing of returning quantity and state, including the uncertainty in recovery and customer's experience (Mancusi et al., 2023b). Remanufacturing plays a critical role within this paradigm, enabling the recovery, refurbishment, and reintegration of end-of-life (EOL) or end-of-use (EOU) products into the supply chain. This process preserves the embedded value of materials and manufacturing processes, offering both environmental and economic benefits (Singhal et al., 2020). However, implementing remanufacturing processes is riddled with challenges, particularly in the domain of reverse logistics. The uncertainties associated with reverse logistics complicate operational planning and decision-making (Mancusi et al., 2023b). These uncertainties not only hinder the efficient recovery of materials but also make it difficult to maintain defect-free production systems (Bressanelli et al., 2018). Among these challenges, the quality of returned products is critical. Variations in usage, environmental exposure, and handling conditions can significantly impact the feasibility of remanufacturing. Simultaneously, the quantity and timing of returns often fluctuate due to unpredictable consumer

behavior, market dynamics, and logistical constraints, further exacerbating planning complexities (Guide & Van Wassenhove, 2009). Thus, when the quality of end-of-X products varies significantly, ensuring high-quality production processes becomes a major challenge, especially in circular approaches like remanufacturing. In this scenario, Zero Defect Re-Manufacturing (ZDRM) is an effective strategy that applies Zero Defect Manufacturing (ZDM) principles to tackle the uncertainties in remanufacturing, particularly regarding the condition and quality of returned products and components (Mancusi et al., 2023a). The adoption of ZDM in reverse logistics may be beneficial during inspection and sorting, as early defect detection reduces costs and enhances efficiency. Moreover, reconditioning and remanufacturing prevent new defects, while testing and quality assurance ensure remanufactured products meet original standards. ZDM has emerged as an advanced quality management method, integrating predictive analytics, real-time monitoring, and automation to eliminate defects and achieve sustainable production. According to Psarommatis and Azamfirei (2024), ZDM principles have evolved significantly in recent years, transitioning from reactive defect detection to proactive defect prevention strategies enabled by Industry 4.0 technologies. This evolution aligns with the increasing emphasis on sustainability in manufacturing, particularly within the circular economy framework (Alexopoulos et al., 2023; Psarommatis et al., 2022). By leveraging tools such as digital twins, IoT-

enabled quality monitoring systems, and AI-driven predictive models, ZDM facilitates defect-free operations while enhancing resource efficiency and minimizing environmental impact (Psarommatis et al., 2020). ZDM strategies focus on both product and process quality—ensuring components meet required specifications while optimizing manufacturing systems to prevent new defects. This dual focus on product integrity and process efficiency makes ZDM an essential framework for advancing remanufacturing within closed-loop supply chains (Panagou et al., 2023). Addressing these uncertainties requires innovative solutions that combine predictive analytics with robust decision-making frameworks. Recent advancements in AI and machine learning (ML) offer promising tools to navigate these challenges. Decision tree models can provide interpretable and efficient methods for managing structured decision-making processes in remanufacturing. These models can analyse diverse parameters—such as return timing, product condition, and incentives—to guide decisions that optimize quality and quantity outcomes (Arena et al., 2022). The objective of this study is to develop a DSS based on decision tree machine learning models to manage uncertainties in reverse logistics effectively. By focusing on the timing of returns as a critical variable, the study explores strategies to enhance the quality and quantity of returned products. Specifically, this research seeks to answer the following questions:

R1: How can decision tree-based models predict and manage these uncertainties effectively?

R2: How can a decision support system based on decision trees be designed to optimize return timing and incentivize early returns, ensuring higher quality and sufficient quantity of products for remanufacturing?

By addressing these questions, this paper aims to contribute to the broader goal of enhancing the sustainability and efficiency of remanufacturing systems within the circular economy framework. The remainder of the paper is organized as follows. Section 2 illustrates the theoretical background of the uncertainties in reverse logistics and the predictive model used in remanufacturing. Section 3 presents the methodology for developing the DT-based DSS. Section 4 discusses the key findings. Finally, Section 5 depicts the conclusions and future research perspectives.

2. STATE OF THE ART

2.1 Uncertainty in Reverse Logistics

Reverse logistics, integral to the circular economy, involves the flow of products from consumers back to producers for reuse, remanufacturing, or recycling. Despite its potential, reverse logistics faces significant uncertainties in the quality, quantity, and timing of returned products (Guide & Van Wassenhove, 2009). These uncertainties complicate forecasting and operational decisions, reducing the efficiency and effectiveness of remanufacturing systems (Bressanelli et al., 2018). The literature analysis underlines a research gap in the simultaneous management of multiple uncertainties (de Lima et al., 2022) and the lack of comprehensive models that integrate consumer behavior, market trends, and economic factors (Agrawal et al., 2015).

Quality: Variability in the condition of returned products poses a significant challenge. Factors such as product usage, environmental exposure, and handling during transit can lead to inconsistencies in quality. These variations often necessitate extensive inspection and sorting processes, adding to operational costs (Singhal et al., 2020). Moreover, complexities such as component degradation, incomplete returns, and the presence of incompatible materials further exacerbate quality challenges (Mancusi et al., 2023a). Technological solutions like automated inspection systems and sensor-based evaluations have been proposed to mitigate these issues, but their integration into existing systems remains a challenge (Panagou et al., 2023).

Quantity: For instance, promotional campaigns or regulatory changes can lead to sudden spikes in returns, while periods of inactivity may result in supply shortages (Bressanelli et al., 2018). Studies have identified a lack of standardization in return processes as a critical factor contributing to quantity uncertainty (Mancusi et al., 2023a). Predictive modeling using historical return data and real-time monitoring can be used to explore to address these fluctuations and forecast future conditions (Okumus et al., 2016).

Time of return: The time of returns is rarely consistent, further complicating planning efforts. Delayed returns can lead to quality degradation, while early returns may disrupt inventory management. Mancusi et al. (2023a) highlight that time of return uncertainty often interacts with market dynamics and customer behavior, influencing the overall stability of reverse logistics systems. Incentivization schemes and advanced forecasting tools, such as machine learning models, have been proposed to address these issues (Arena et al., 2022).

2.2 AI in Predictive Models

Artificial intelligence (AI) has revolutionized predictive analytics, enabling advanced modeling and optimization in complex systems like reverse logistics. ML techniques, particularly decision trees, offer interpretability and scalability, making them ideal for remanufacturing applications (Guide & Van Wassenhove, 2009). AI-driven models can integrate diverse data sources, such as historical return trends, product lifecycle information, and real-time condition assessments, to predict return quality and timing more accurately. This capability not only enhances operational efficiency but also supports sustainable practices by minimizing waste and maximizing resource utilization (Bressanelli et al., 2018; Psarommatis et al., 2020). Emerging technologies such as digital twins and IoT-enabled devices further enhance the predictive capabilities of AI models by providing real-time data and enabling dynamic adjustments to decision-making processes (Alexopoulos et al., 2023). By leveraging AI and ML, businesses can develop decision-support systems that address the inherent uncertainties of reverse logistics. These systems provide actionable insights, helping organizations balance quality and quantity considerations while optimizing timing for returns. Recent advancements in hybrid AI models, combining decision trees with other machine learning techniques like random forests or gradient boosting, offer additional robustness and accuracy for

complex scenarios in remanufacturing (Arena et al., 2022). The development of ZDM methodologies has also gained momentum with the advent of advanced data-driven technologies. Psarommatis, May, and Azamfirei (2024) emphasize the role of hybrid models that combine traditional quality management techniques with machine learning algorithms to address complex challenges in manufacturing systems. These approaches, such as integrating gradient boosting methods with decision tree models, offer enhanced accuracy and scalability for managing variability in production processes. The literature further highlights the need for holistic frameworks that not only address process-level quality improvements but also ensure compatibility with sustainability goals, thereby bridging the gaps in existing ZDM applications within circular economy systems.

2.3 Decision Trees in Remanufacturing

Decision tree (DT) is a widely used supervised machine learning technique in decision analysis, based on a tree-like model of decisions and logical rules. It is considered a simple and visual tool capable of handling complex problems and adapting to inference tasks such as the prediction of target variable values by partitioning the input dataset into homogeneous subsets based on a given set of attributes (Grąbczewski, 2014). The DT's hierarchical model defines which class data belongs to through the data points splitting process, based on the attributes of the data points. The DT consists of three types of nodes: root node, internal node, and leaf node, with branches as conjunctions leading to another node. The root node represents the best predictor, the internal nodes are in-between, and the leaf nodes represent the target class (Bishop, 2006). DT models have emerged as effective tools for addressing uncertainties in remanufacturing. By providing a structured approach to decision-making, these models enable businesses to predict outcomes and optimize processes based on specific parameters (Soares et al., 2021). In remanufacturing, decision trees can analyze diverse variables, including product condition, return timing, and cost factors, to support strategic planning. For instance, Arena et al. (2022) demonstrated the utility of decision trees in predictive maintenance strategies, showcasing their adaptability in similar contexts. Additionally, the hierarchical structure of decision trees makes them suitable for integrating multiple sources of uncertainty, such as those related to market trends, consumer behavior, and logistical constraints (Psarommatis et al., 2020).

3. DATA-DRIVEN DECISION SUPPORT SYSTEM

The remanufacturing process within the circular economy faces several challenges, primarily due to the inherent uncertainties in reverse logistics, including, as said before, fluctuations in product quality, timing of returns, and the volume of returned products. These uncertainties affect operational planning, often resulting in inefficiencies, increased costs, and suboptimal resource utilization. To effectively address these challenges, it is crucial to develop a DSS that integrates predictive models, real-time data, and optimization algorithms to guide decision-making processes. A DSS would provide decision-makers with valuable insights to manage the dynamic and complex nature of reverse

logistics, ensuring timely and efficient remanufacturing operations. It may improve product quality, reduce risks associated with delayed returns, and help predict return volumes more accurately. Thus, the goal is to develop a decision tree-based DSS that can support companies in managing the complexities of reverse logistics, optimizing remanufacturing processes, and aligning with the broader sustainability objectives of the circular economy. Particularly, the work is focused on reverse logistics within remanufacturing by prioritizing product quality through ZDM principles to minimize defects and enhance decision-making for dynamic and uncertain return scenarios.

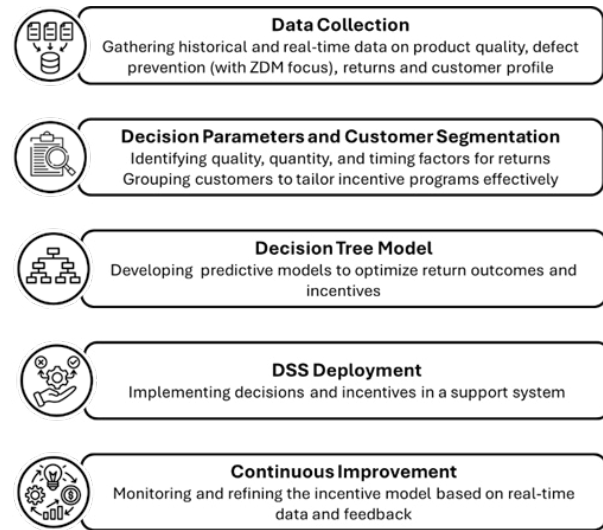


Figure 1. Overall workflow for generations of proposed DSS on continuous improvement approach for remanufacturing applications.

To address the uncertainties in remanufacturing effectively, the basic idea is not only identifying these uncertainties but also seeking to provide strategies and solutions to handle them. Particularly, when the uncertainties of quality, quantity, and timing interact, they can create complex scenarios. For example, if returns are late, their quality may also be degraded, and the quantity might be lower than expected. Thus, a potential solution integrated into the proposed DSS consists of return incentives and a management-based strategy. The implementation of incentives for customers to return products within a specific time frame, such as discounts or rewards, may help to improve the predictability of returns and reduce variability. This strategy can be especially beneficial for managing quality uncertainty. Indeed, the sooner a product is returned, the less likely it is to have undergone wear and tears that could affect its quality. Early returns often mean a reduced degradation risk, which leads to higher-quality products being available for remanufacturing. Additionally, it is worth mentioning that, when customers are incentivized to return products within a defined period, companies can better predict the volume of returns. This helps to ensure that resources (e.g., remanufacturing capacity, inventory management) are optimally allocated. Early return incentives also allow for more evenly distributed return volumes, minimizing the impact of promotions or seasonal fluctuations that often cause sudden spikes in returns. Thus, early return incentives give companies a more predictable timeline, reducing the

uncertainty related to reverse logistics. To incentivize early returns, companies can design dynamic reward systems where the incentive increases with the speed of the return.

In the following, the processing steps for the development of the proposed DSS (Fig. 1) will be examined by focusing on the specific implemented strategies and adopted technologies. The first step of the DSS is Data Collection which involves collecting and integrating both real-time data and historical data from various sources directly related to (i) product quality and defect prevention, including:

- Real-time Defect Data: integration of quality sensors, automated inspection systems, and defect detection technologies to identify defects early in the manufacturing (and remanufacturing) process.
- Predictive Maintenance Data: monitoring machine performance in real-time to ensure that production processes are not affected by potential failures or deviations, ensuring a defect-free process.

And (ii) remanufacturing processes, such as:

- Customer Returns: data from return logs, customer interactions, and product lifecycle history.
- Product Condition: condition assessments based on return inspection reports (leveraging sensor technologies or IoT-based systems, visual inspection, etc.).
- Market Dynamics: sales trends, return campaigns, promotional schedules, and other external market factors.
- Return Timing: historical patterns of return times and the impact of timing on product condition and remanufacturing costs.
- Return Quantity: volume predictions based on historical returns data, seasonal trends, and promotional campaigns.

The second step of the DSS consists of the identification of the different parameters affecting the uncertainties. These form the basis for the development of the decision tree model. It integrates predictive models and machine learning algorithms to forecast uncertainties and optimize decision-making:

- Predictive Quality Models: by using historical data and real-time inputs, these models can predict the condition of returned products based on variables like usage patterns, environmental factors, and handling during return logistics. They help determine whether products are likely to be high, moderate, or low quality upon return.
- Predictive Return Timing Models: these models can predict the likelihood of when returns will occur (early, on-time, or late) based on customer behavior, product category, and market dynamics. They can adopt regression analysis or time series forecasting techniques to estimate return timing.

- Quantity Forecasting Models: these models can estimate the return volume based on historical return patterns, promotional campaigns, and seasonality factors by implementing demand forecasting techniques to predict return quantities (e.g., ARIMA models, machine learning regression, ensemble methods...).

As said, the main strategy in the proposed DSS is the integration of early return incentives to improve the timing and quality of returned products. The incentive structure is dynamically adjusted by the DSS based on real-time data and predictive insights to ensure it aligns with business goals and customer engagement strategies. The DSS determines the optimal incentive level for early returns based on (i) Customer Behavior Modelling: the DSS tracks customer behavior, offering higher rewards for early returns based on predicted return timing and product value, and (ii) Incentive Scaling: the incentives can vary dynamically (e.g., a percentage discount or reward points) depending on the predicted quality and timing of the return:

- Early Return that may correspond to a high incentive.
- On-time Return that may correspond to moderate incentive.
- Late Return that may correspond to low or no incentive.

Finally, the DSS automatically adjusts the reward structure based on patterns of early or late returns observed over time.

The third step involves the development of a decision tree model, which helps guide remanufacturing decisions based on the uncertainties in return quality, timing, and volume. The DT includes the following key levels based on its structure (see also Fig. 2):

Root Node: the first point of decision-making, where the system determines the timing of the return (early, on-time, or late).

Intermediate Nodes: based on the return timing, the system evaluates the quality of the product. If the product is returned early, it's expected to be of high quality; if on-time, it's moderately good; if late, the quality may have degraded.

Leaf Nodes: the system's actions based on product quality and return timing: (i) high-quality returns (early) lead to direct remanufacturing with minimal effort; (ii) moderate-quality returns (on-time) require inspection and repairs before remanufacturing; (iii) low-quality returns (late) require full inspection, part replacement, or potentially recycling if remanufacturing isn't feasible.

The fourth step is the deployment of the DSS. Indeed, once the model is implemented and validated, it can be deployed to guide real-time decision-making regarding the management of returned products. The system can predict and manage uncertainties effectively by classifying returns based on quality, quantity, and timing, and suggesting appropriate actions. The DSS will provide valid support for decision-makers in the remanufacturing process. The adoption of the decision tree enables an intuitive visualization of the final

decision, including the return outcome and incentive recommendation for the customer. Additionally, decision-makers can test different return incentive structures and assess how changes in incentives or return timings might affect remanufacturing outcomes.

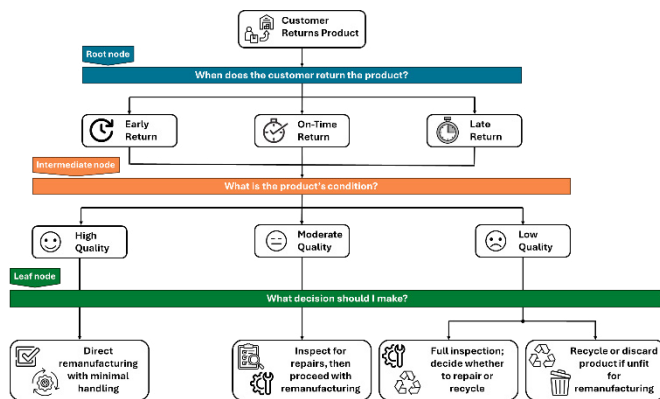


Figure 2. Schematic of the decision tree including the key steps for remanufacturing application.

Finally, the fifth step of the DSS incorporates real-time feedback loops to continually optimize the system based on performance. The system monitors key performance indicators (KPIs) such as return volumes, processing time, defect rates, and cost savings from early return incentives. Thus, based on the real-time data, the incentive levels and predictive models are adjusted regularly. Particularly, if the system detects an increase in late returns, it might adjust incentives to encourage earlier returns.

4. DISCUSSION

Managing uncertainties in reverse logistics is a critical step toward improving the efficiency and sustainability of remanufacturing systems. The proposed DSS leverages decision tree models to predict and manage the core uncertainties related to the quality, quantity, and timing of returned products. By focusing on return timing as a key variable, the DSS aims to provide actionable insights that mitigate the risks associated with unpredictable returns. The quality of returned products significantly impacts remanufacturing outcomes. Early returns are likely to be of higher quality, reducing the need for extensive rework or disposal. Similarly, managing the timing of returns helps ensure a steady supply of reusable components, addressing quantity uncertainty and improving inventory management. The DSS's ability to analyze various scenarios and provide clear decision pathways enhances its practical applicability in real-world remanufacturing contexts (Gonzalez et al., 2015). Incentivizing early returns is a strategy to address timing uncertainty. By offering dynamic rewards, companies can influence customer behavior to return products at optimal times, ensuring higher quality and predictable return volumes. For example, offering increased incentives for returns made within a specific timeframe before the product reaches the end of its lifecycle can improve both quality and quantity outcomes (Arena et al., 2022). The impact of such incentive mechanisms extends beyond operational improvements. It fosters stronger customer engagement and promotes sustainable behavior, aligning with circular economy principles. However, the

design of these incentives must account for various factors, including customer preferences, product types, and economic viability, to ensure long-term success (Alexopoulos et al., 2023). The use of decision tree models within the DSS provides a structured and interpretable approach to managing reverse logistics uncertainties. Unlike black-box machine learning models, decision trees offer transparency in decision-making, allowing businesses to understand the rationale behind each recommendation. Decision trees are effective in handling various types of data, making them suitable for analysing factors such as product condition, return timing, and cost considerations. By setting thresholds for key variables, the DSS can provide clear guidelines for managing returns. For instance, it can identify the optimal return period to maximize quality while minimizing costs associated with rework or disposal (Psarommatis et al., 2020). The proposed DSS for managing reverse logistics uncertainties aligns closely with the advancements in ZDM outlined by Psarommatis and Azamfirei (2024). By integrating real-time feedback mechanisms and predictive models, the DSS exemplifies the proactive defect prevention strategies emphasized in modern ZDM practices supporting data-driven decision-making and continuous process improvement (Psarommatis et al., 2022). Also, by ensuring that returned products meet quality standards before re-entering the supply chain, the DSS supports the broader goal of achieving defect-free production processes (Alexopoulos et al., 2023). Moreover, the inclusion of incentive-based mechanisms for improving return timing and product quality resonates with the holistic outlook advocated in recent ZDM research. However, as Psarommatis et al. (2024) argue, the successful implementation of such systems requires a balanced approach that considers technological, organizational, and economic factors to ensure their scalability and sustainability in real-world settings. Despite their advantages, decision trees have limitations. They require continuous data updates to remain accurate and may become less effective if underlying patterns change. Addressing these limitations through hybrid models, such as combining decision trees with random forests or gradient boosting, can enhance their robustness and adaptability (Arena et al., 2022). The proposed DSS provides a foundation for managing uncertainties in reverse logistics, but further steps are needed to realize its full potential. Future research should focus on testing the DSS in real-world scenarios, particularly in collaboration with case companies. Gathering empirical data will help refine the model and improve its accuracy and reliability. Practical implementation challenges, such as data availability, system integration, and customer engagement, must also be addressed. Ensuring that the DSS can seamlessly integrate with existing enterprise systems is critical for its adoption. Additionally, the design of incentive mechanisms must be tailored to different product types and customer segments to maximize their effectiveness (Mancusi et al., 2023a). Exploring the use of hybrid AI models, and incorporating decision trees with other machine learning techniques, can further enhance the DSS's predictive capabilities. Future iterations of the DSS could also incorporate adaptive learning features, allowing it to adjust to changing conditions and improve over time. By addressing these future directions, the DSS can evolve into a

comprehensive tool for managing reverse logistics uncertainties, contributing to more sustainable and efficient remanufacturing systems within the circular economy framework.

5. CONCLUSIONS

This study has presented a DSS based on decision tree models to address the uncertainties in reverse logistics for remanufacturing processes. The DSS focuses on managing the quality, quantity, and timing of returns by providing predictive insights and optimizing return strategies. By emphasizing early returns through incentivization, the system aims to improve both product quality and return volumes. DSS leverages decision trees for clear, interpretable decision-making, integrating key variables like product condition and return timing. This approach supports the principles of ZDM, enhancing both product and process quality. By incorporating real-time data through IoT and digital twins, the system ensures continuous monitoring and adjustment to maintain high remanufacturing standards. Future research should test and validate the DSS in industrial remanufacturing settings to further refine its predictive capabilities. Collaboration with industry partners and exploration of hybrid AI models can enhance the system's robustness and adaptability. Overall, the proposed DSS contributes to more sustainable and efficient remanufacturing systems within the circular economy framework.

REFERENCES

- Alexopoulos, K., Tsoukaladelis, T., Dimitrakopoulou, C., Nikolakis, N., & Eytan, A. (2023). An approach towards zero defect manufacturing by combining IIoT data with industrial social networking. *Procedia Computer Science*, 217, 403-412.
- Agrawal, A., Singh, R.K., Murtaza, Q. (2015). A literature review and perspectives in reverse logistics. *Resources, Conservation and Recycling*, 97, pp. 76-92.
- Arena, S., Florian, E., Zennaro, I., Orrù, P. F., & Sgarbossa, F. (2022). A novel decision support system for managing predictive maintenance strategies based on machine learning approaches. *Safety Science*, 146, 105529.
- Bishop, C. M., & Nasrabadi, N. M. (2006). *Pattern recognition and machine learning*, 4(4) p. 738. New York: Springer.
- Bressanelli, G., Perona, M., & Sacconi, N. (2018). Challenges in supply chain redesign for the circular economy: A literature review and a multiple case study. *International Journal of Production Research*, 56(1-2), 36-57.
- de Lima, F. A., Seuring, S., & Sauer, P. C. (2022). A systematic literature review exploring uncertainty management and sustainability outcomes in circular supply chains. *International Journal of Production Research*, 60(19), pp. 6013-6046.
- Gonzalez, E. D., Sarkis, J., Huisingh, D., Huatuco, L. H., Maculan, N., Montoya-Torres, J. R., & De Almeida, C. M. (2015). Making real progress toward more sustainable societies using decision support models and tools: introduction to the special volume. *Journal of Cleaner Production*, 105, 1-13.
- Grąbczewski, K. (2014). *Meta-Learning in Decision Tree Induction*. Springer International Publishing Switzerland. ISBN 9783319009599.
- Guide, V. D. R., & Van Wassenhove, L. N. (2009). The evolution of closed-loop supply chain research. *Operations Research*, 57(1), 10-18.
- Mancusi, F., Fruggiero, F., & Panagou, S. (2023a). Mapping uncertainty sources affecting circularity: A holonic approach. *Proceedings of the 9th International Conference on Control, Decision, and Information Technologies (CoDIT)*.
- Mancusi, F., Fruggiero, F., & Pham, D. T. (2023b). The Remanu-Leasing Model Towards a Convenient and Sustainable Product Circularity. In *International Workshop on Autonomous Remanufacturing* (pp. 377-387). Cham: Springer Nature Switzerland.
- Okumus, D., Gunbeyaz, S. A., Kurt, R. E., & Turan, O. (2023). Towards a circular maritime industry: Identifying strategy and technology solutions. *Journal of Cleaner Production*, 382, 134935.
- Panagou, S., La Cava, G., Fruggiero, F., & Mancusi, F. (2023, September). Selective complexity determination at cost based alternatives to re-manufacture. In *IFIP International Conference on Advances in Production Management Systems* (pp. 215-228). Cham: Springer Nature Switzerland.
- Psarommatis, F., May, G., Dreyfus, P.-A., & Kiritsis, D. (2020). Zero defect manufacturing: State-of-the-art review, shortcomings, and future directions in research. *International Journal of Production Research*, 58(1), 1-17.
- Psarommatis, F. and Azamfirei, V., 2024. Zero Defect Manufacturing: A complete guide for advanced and sustainable quality management. *Journal of Manufacturing Systems*, 77, pp.764-779.
- Psarommatis, F., May, G. and Azamfirei, V., 2024. Zero defect manufacturing in 2024: a holistic literature review for bridging the gaps and forward outlook. *International Journal of Production Research*, pp.1-37.
- Psarommatis, F. and Kiritsis, D., 2022. A hybrid Decision Support System for automating decision making in the event of defects in the era of Zero Defect Manufacturing. *Journal of Industrial Information Integration*, 26, p.100263.
- Singhal, D., Tripathy, S., & Jena, S. K. (2020). Remanufacturing for the circular economy: Study and evaluation of critical factors. *Resources, Conservation and Recycling*, 156, 104681.
- Soares, J. C., Tereso, A. P., & Sousa, S. D. (2021). A decision-making model for the rework of defective products. *International Journal of Quality & Reliability Management*, 38(1), 68-97.