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ORIGINAL RESEARCH

AI-enhanced simulation for sustainable production in pulp and paper industry

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Abstract

This study investigates how environmental policies influence production planning in environmentally sensitive manufacturing systems, particularly in the paper and pulp industry. Despite growing regulatory pressure and consumer awareness, existing research often overlooks the integration of environmental policies with operational uncertainty. To address this gap, we propose the Environmental Hedging Point Policy (EHPP) as a strategic framework that draws on optimal control theory to dynamically balance sustainability and operational performance under uncertainty. Our approach combines simulation-based optimization with multi-objective particle swarm optimization and K-means clustering to evaluate trade-offs between cost, customer satisfaction, and environmental impact. We model a dynamic demand environment shaped by eco-conscious customer preferences and test policy scenarios using data from a paper manufacturing system involving both recyclable and virgin paper inputs. The results provide actionable insights for policymakers and manufacturers, supporting sustainable production planning under uncertainty.

Keywords AI-enhanced simulation · Simulation optimization · Land-use management · Paper and pulp · Environmental control policy · Unreliable manufacturing systems

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1 Introduction

Despite growing regulatory pressure and consumer awareness, existing research often overlooks the integration of environmental policies with operational uncertainty. Optimal control theory provides a mathematical framework for dynamically managing production systems by adjusting control variables in response to system states and external disturbances (Assid, Gharbi, & Pellerin, 2025). In this study, we extend the classical Hedging Point Policy (HPP), a widely applied production and inventory control method in unreliable manufacturing environments (Afshar-Bakeshloo et al., 2018), to incorporate environmental objectives, forming the Environmental Hedging Point Policy (EHPP). EHPP leverages control theory principles to optimize production decisions, balancing operational costs, customer satisfaction, and environmental sustainability under uncertainty.

The Industrial Revolution has driven substantial technological progress and economic growth; however, it has also inflicted environmental harm. Rapid industrialization has led to pollution, deforestation, climate change, and other environmental problems (Lamb et al., 2021). A report by the United States Environmental Protection Agency estimates that industrial activities contribute to 23% of global greenhouse gas emissions, which is a major driver of climate change (Hockstad & Hanel, 2018).

The paper and pulp industry has significantly harmed the environment through its resource-intensive processes, including water, energy, and chemical usage, leading to air and water pollution. Also, deforestation driven by this industry has a profound impact on the ecosystem, causing soil erosion, loss of biodiversity, and increased greenhouse gas emissions. Substantial waste generation can take years to decompose and cause further harm to the environment (Jiang et al., 2021). According to a study by the Environmental Paper Network, the paper industry is accountable for 10% of global carbon emissions and the loss of 4 billion trees each year (Lührmann et al., 2019). Thus, mitigating the adverse environmental impacts of the paper and pulp industry is imperative.

The paper and pulp industry faces significant operational challenges, including machine failures, fluctuating demand influenced by environmental awareness, and uncertainties in raw material availability due to regulatory and resource constraints (Jiang et al., 2021). These characteristics make HPP especially suitable for managing production, as it adjusts production rates based on inventory and system reliability. However, traditional HPP does not consider environmental factors explicitly. Our proposed EHPP incorporates environmental parameters, such as switching between virgin and recyclable paper inputs, to address sustainability goals within production planning.

Growing environmental awareness among consumers has put policymakers and manufacturers in a dilemma. In recent years, public pressure pushed policymakers to introduce new environmental regulations. These regulations can be divided into three main categories: a) persuasive, b) punitive, and c) mixed (Kounetas & Tsekouras, 2008; Rahmati et al., 2023; Sonsale et al., 2023). Persuasive policies encourage manufacturers to cut emissions voluntarily by providing financial incentives, which may include subsidies, tax credits, low-interest or green loans, and grants to support investments in cleaner technologies or sustainable production processes. Punitive policies impose strict regulatory measures, while mixed policies combine both approaches simultaneously (Rietbergen et al., 2002).

Each policy has several advantages and disadvantages in different contexts. In this situation, the policymaker's dilemma is choosing the most effective policy. This study aims to evaluate the adaptation and effectiveness of these policies within the paper and pulp industry.

The changing nature of the market is a stimulus for researchers to consider demand dynamically because the assumption of constant demand makes manufacturers' production planning imprecise. In the literature, a direct correlation between demand and customer satisfaction is shown (Amacher et al., 2004; Ibanez & Grolleau, 2008). Customer satisfaction is closely linked to marketing and production planning (Amacher et al., 2004; Liu et al., 2012). While previous studies linked customer dissatisfaction to the backlog (Afshar-Bakeshloo et al., 2018; Behnamfar et al., 2022; Fahimnia et al., 2015; Gharbi et al., 2024), production and marketing efforts are also affected by increasing consumers' environmental awareness (Liu et al., 2012). In the present work, customers' favor of eco-friendly products causes fluctuation in demand rate. The more the manufacturers switch to eco-technology, the wider their market becomes.

Therefore, manufacturers seek pathways to adopt new measures, including environmental technologies, to appeal to the public. By implementing these measures, the paper and pulp industry can minimize its environmental impact and become more sustainable in the long run (Del Rio et al., 2022). While these measures alleviate adverse environmental impacts, they also come with several disadvantages, such as high maintenance and operational costs and lower production rates (Chen et al., 2024; Tushman & Anderson, 1986). In the stochastic and dynamic contexts of production systems, being susceptible to random failure and repair time, manufacturers need a strategy to achieve economic and environmental goals. In this context, optimal control theory plays a key role in the design and success of such strategies.

Environmental policies in manufacturing often involve parameters, like emission targets and resource usage limits, that must be optimized dynamically et al., 2024). EHPP addresses this critical gap by integrating such parameters into the hedging policy framework, enabling manufacturers to proactively respond to both operational uncertainties and sustainability imperatives. This integration supports the triple bottom line by simultaneously minimizing costs, reducing customer dissatisfaction, and lowering environmental impact.

In this study, the EHPP is employed to manage paper and pulp production, considering dynamic environmentally conscious customer demand within the framework of conservation regulations. The research objective is to minimize total cost, inventory cost, and customer dissatisfaction associated with environmentally friendly product usage.

Thus, our main research question is: What policies prove to be the most cost-effective in an environmentally sensitive customer context? In this study, cost-effectiveness is evaluated based on two primary cost metrics: inventory cost and production cost. Additionally, customer satisfaction is considered a critical performance objective to reflect the responsiveness of the system to environmentally conscious demand.

In the present study, after reviewing the theoretical background, a research model is formulated, emphasizing objective functions and regulations. Subsequently, the research approach is discussed in detail, and a simulation-based optimization model is employed to determine the final solutions. The paper delves into the primary findings, contributions, constraints, and notable implications. Ultimately, it provides practical insights for professionals.

2 Literature review

Organizations are increasingly urged to incorporate ecological considerations into their strategic planning, aiming to mitigate threats to long-term environmental sustainability (Fahimnia et al., 2015; Sarkis, 2012). This is particularly critical in resource-intensive sectors such as paper and pulp manufacturing, which are associated with deforestation, high energy consumption, water usage, chemical pollution, and substantial waste generation (Jiang et al., 2021; et al., 2019). At the same time, environmentally conscious consumer preferences are reshaping demand patterns, while policymakers continue to introduce diverse environmental instruments, ranging from voluntary guidelines and ecolabeling schemes to binding regulations such as emissions caps and land-use restrictions. These concurrent pressures add new layers of complexity and uncertainty to operational planning and production control.

To better understand these intersecting challenges, a growing body of research has examined production control policies and environmental strategies in flexible production manufacturing systems (FPMS). However, as summarized in Table 1, most existing studies consider these aspects in isolation (focusing on either operational efficiency or environmental goals) without addressing their interaction under demand uncertainty and regulatory complexity. Table 1 highlights key studies based on whether they account for dynamic demand, customer satisfaction, environmental factors, and system-level features such as transportation (TR), preventive maintenance (PM), and shared facilities (SF). Few studies propose integrated control policies that respond to multiple objectives simultaneously.

Our study contributes to this gap by developing a holistic environmental hedging policy that aligns service level, environmental performance, and cost objectives in the context of the paper and pulp industry. Methodologically, the contribution lies in embedding a simulation-based optimization framework in which control thresholds are learned and refined through data-driven search within the simulation environment, rather than being imposed a priori. This allows the proposed policy to respond simultaneously to stochastic demand, machine disruptions, and evolving environmental constraints, addressing a key limitation identified in the recent modelling and simulation literature.

The following sections provide a structured review of the relevant literature: Sect. 2.1 focuses on production control policies under uncertainty, and Sect. 2.2 explores how environmental policies have been incorporated into operational models. Each section concludes by identifying limitations that motivate our proposed simulation–optimization framework.

2.1 Control policies

The HPP is designed to regulate production rates by aligning them with inventory levels, forming a designated safety stock level (threshold level). This ensures fulfilment of customer demand during fluctuations or periods of system failure (Davoodi & Amelian, 2018; Diop et al., 2019). As discussed by Entezaminia et al. (2020), A considerable portion of the research undertaken in this field has focused on crucial elements of production system control.

From a modelling standpoint, threshold-based policies are particularly attractive because they can be embedded naturally within discrete-event and hybrid simulation models, enabling performance evaluation under stochastic machine failures, variable demand, and transportation delays (Brailsford et al., 2019). The optimal control strategy for the manufacturing and transportation system is initially built upon the classical HPP framework introduced by Akela and Kumar in 1986. Following the control policy research, Kenne and Gharbi (2004) introduced an optimal control approach for a single-machine manufacturing system incorporating failure and random repairs. In their model, the machine's operational capacity (reflecting its availability status over time) is represented as a stochastic process modelled using a Markov chain. This approach captures transitions between working and failing states. The goal is to determine the production rate that mitigates the inventory cost. Elaborating on the control policy research, others consider the non-deterministic context of the problem.

Table 1 Summary of Key Literature on Production Control and Environmental Policies in FPMS

Authors	Customer Satisfaction	Dynamic Demand	Environmental Consideration	Propose New Policy	FPMS	Manufacturing Features
Dadashpour et al. (2020)			✓	✓	✓	TR
Magnanini and Tolio (2020)				✓	✓	MD
Berthaut et al. (2010)				✓	✓	PM
Afshar-Bakeshloo et al. (2018)	✓		✓	✓	✓	
Behnamfar et al. (2022)	✓	✓	✓		✓	
M. Assid et al. (2020)				✓	✓	SF
Entezaminia et al. (2020)			✓	✓	✓	
Ben-Salem et al., (2015a, 2015b)			✓	✓	✓	
Gharbi et al. (2022)				✓	✓	SL
Polotski et al. (2019)				✓	✓	MD
Kenné et al. (2012)		✓		✓	✓	CL
Dhahri et al. (2022)				✓	✓	RT
Bensoussan and El Ouardighi (2023)		✓	✓	✓		
R R Corsini, Costa, and Framinan (2023)		✓		✓	✓	PC
Morad Assid et al. (2023a)				✓	✓	MR
Yang and Zhang (2022)	✓					PR
This Research	✓	✓	✓	✓	✓	

(TR: Transportation PM: Preventive Maintenance MD: Machine Degradation PC: Product Changeover MR: Manufacturing-Remanufacturing PC: Pricing CL: Closed-Loop supply chain SL: Shelf Life SF: Shared Facilities RT: Retailer)

Recent extensions of this modelling paradigm increasingly rely on simulation-based optimization, where analytical solutions are replaced or complemented by numerical learning procedures embedded in simulation experiments (do Amaral et al., 2022). Berthaut et al. (2010) examined inventory control policies to determine the optimal production rate and preventive maintenance. The findings indicate that implementing a control policy close to the optimum results in a substantial cost reduction compared to a combination of the hedging point policy and a classic maintenance policy. Hatami-Marbini et al. (2020) explored a network of manufacturing machines using HPP with perishable goods and constant demand. The researchers discovered that the optimal scenario resulted in a quarter reduction in terms of expected costs.

Building on these foundations, several studies have demonstrated that integrating simulation with surrogate modelling or metaheuristic search allows near-optimal control parameters to be identified efficiently, even in high-dimensional or non-convex policy spaces (Krawczyk & Arabas, 2025). In a novel approach, Sajadi et al. (2011) introduced a method that combines optimal control theory and discrete-event simulation, integrating experimental design and response surface methodology to determine the optimal production rate solution.

Some studies propose a stochastic dynamic programming method, which results in the numerical resolution of Hamilton–Jacobi-Bellman (HJB) equations (Megoze Pongha et al., 2023; Polotski et Al., 2018). They studied the management of production and control of a single product that includes both manufacturing and remanufacturing operations with machines prone to failure and repair. This research aims to suggest a (re)manufacturing policy aimed at minimising the combined costs of holding and backlog. Assid et al., (2023a, 2023b) utilise a simulation-based approach to address production control in hybrid manufacturing-remanufacturing systems (HMRS), which meet demand by either remanufacturing returned items or manufacturing new ones.

More recently, simulation-based optimization frameworks have been increasingly applied to production control problems, where control policies are iteratively refined within the simulation environment rather than fixed analytically. In these approaches, surrogate models (metamodels) are used to approximate the simulator, guiding optimization and learning in high-dimensional or non-convex policy spaces while reducing computational cost (do Amaral et al., 2022; Pineda et al., 2025). Such frameworks allow near-optimal control parameters, including production rates, maintenance thresholds, and inventory policies, to be efficiently identified under interacting uncertainties such as machine degradation, stochastic demand, and evolving environmental constraints, making them particularly suitable for environmentally-extended HPP-type policies.

Recent studies in the simulation literature have demonstrated the power of combining simulation with optimisation and data-driven experimentation to evaluate complex operational policies. For example, hybrid simulation–optimisation approaches have been used to develop production control strategies for perishable supply chains (Gailan Qasem et al., 2023) and for hybrid manufacturing–remanufacturing systems (Thammatadatrakul & Chiadamrong, 2019), where closed-form solutions are infeasible. Similarly, simulation toolkits have enabled autonomous control in serial production networks (Müller-Boyaci & Wenzel, 2016), highlighting the practical utility of iterative policy refinement within stochastic environments. Beyond manufacturing, simulation-based analyses have also been applied in healthcare settings to assess multi-objective outcomes, including cost, service, and environmental performance (Kar et al., 2025; Petering et al., 2015). Collectively, these contributions illustrate that simulation-based frameworks, particularly when coupled with data-driven optimisation, provide a robust platform for exploring adaptive policies under uncertainty, offering insights directly relevant to extending operational policies to include environmental objectives in flexible production manufacturing systems.

Some research adds to the complexity of the problem by considering machine degradation, preventive maintenance, shelf life, shared facilities, and transportation. Magnanini and Tolio (2020) proposed a threshold-based control policy for Preventive Maintenance. They provided insights for the managers, assisting them in making effective operational decisions. Berthaut et al. (2010) propose a near-optimal control policy for cost reduction. They apply an experimental approach based on simulation to determine control parameters and propose that a combination of the HPP and an adapted preventive maintenance strategy proves to be effective. Gharbi et al. (2022) formulate a control policy in a stochastic and dynamic environment involving perishable goods with limited and random shelf time. Utilizing a simulation-based optimization method, numerical illustrations indicate that when addressing a random shelf life, the devised control policy exhibits a decreased total cost compared to alternative policies in the existing literature. Assid et al. (2020) tackle a production control problem in HMRS operating in a dynamic and stochastic setting. The suggested control policy combines HPP and a stock-based setup strategy. Numerical outcomes indicate that utilizing mixed dedicated and shared facilities (MDSF) under the proposed control policy yields optimal cost performance. In their 2020 research, Dadashpour et al. identified the optimal hedging point, considering both inventory and transportation. They introduced a policy utilizing stochastic optimal control and impulse control theory, covering the entire supply chain from production to the end consumer. The primary objective was to minimize the total cost, encompassing holding/backlog and transportation costs. Corsini et al., 2023a, 2023b investigate the effectiveness of a new adaptive production control policy for a two-product, two-echelon supply chain subject to non-stationary customer demand in terms of fill rate. They propose a new production control strategy named the Adaptive Hedging Corridor Policy. While a great share of studies focus on Failure Prone Manufacturing System (FPMS), few studies have considered demand volatility and uncertainty (Behnamfar et al., 2022).

Addressing the challenge of incorporating environmental dimensions into production system control within a dynamic framework is an ongoing issue (Ben-Salem et al., 2015b). In their initial endeavours, Ben-Salem et al. (2014) present an HPP that seamlessly integrates environmental factors into a control strategy. Through an innovative experimental approach, they assess the model's efficacy, uncovering significant cost advantages over the classical HPP. In an EHPP proposed by Ben-Salem et al. (2015a), the threshold level is adjusted after surpassing emission limits to minimize overall expected costs and reduce reliance on low-emitting machines. Ben-Salem et al. (2015a) formulated a control policy encompassing preventive maintenance and production to address heightened emission rates due to degradation in a system. They also introduced an EHPP, for instance, where pollutant emissions surpassed permissible limits, resulting in the outsourcing of production to contractors. In a related context, Afshar-Bakeshloo et al. (2018) investigated scenarios where the main and low-emitting systems couldn't operate simultaneously, determining the optimal hedging point while considering cost, emissions, and customer satisfaction objectives. Extending this line of inquiry, Entezaminia et al. (2020) delved into the simultaneous operation of both main and low-emitting systems. Adding to the complexity of the problem, Dadashpour et al. (2020) proposed an environmental hedging point policy utilizing a simulation–optimization methodology. They integrated manufacturing and transportation systems and found the optimal level of production and transportation. Behnamfar et al. (2022) assess the impact of carbon emission regulations by employing EHPP in an FPMS. They utilize a simulation-based optimization approach, implementing a multi-objective particle swarm algorithm. Additionally, machine learning algorithms are leveraged to obtain predictions of decision variables. This comprehensive methodology provides decision-makers with an effective solution for dynamically planning operations in uncertain environments. Entezaminia et al. (2020) devised a new control policy for Not-Operating-Simultaneously (NOS) systems that is both cost-effective and eco-friendly. This policy is intended for businesses that are progressively investing in low-emitting systems and aims to assist managers in coordinating both low and high-emitting systems. Simulation-based modeling and response surface methodology are applied. The results demonstrate cost reductions and a decline in GHG emissions when employing new control policies for OS systems, in contrast to NOS systems. Despite the extensive literature on production control policies, existing studies rarely provide an integrated approach that simultaneously considers dynamic demand, machine failures, shared facility constraints, and environmental objectives. While some recent works have begun to incorporate environmental factors, few have addressed how such policies perform under multi-dimensional uncertainty. This gap highlights the need for comprehensive and flexible control frameworks that can align operational efficiency with evolving environmental policies and customer expectations.

2.2 Environmental policies

Policy instruments are recognized as the tools employed by governmental bodies to execute objectives outlined in public policies. These are commonly denoted as "governing instruments," "government tools," or "governance techniques." A prevalent classification of policy instruments encompasses regulatory, economic, and information-based modalities. Regulatory instruments involve direct interventions by governments, economic instruments use economic incentives, and information-based instruments provide information to influence behavior (Mengist et al., 2020). Policy instruments for environmental purposes are crucial for sustainable development. These instruments are designed to encourage individuals, businesses, and organizations to incorporate environmentally friendly practices into their daily operations. Implementing these policy instruments requires careful planning, monitoring, and enforcement to ensure they effectively reduce environmental harm and promote sustainability. The scope of these policies varies widely, and their core aim is usually to tackle a specific environmental issue. For instance, the U.S. Clean Air Act, passed in 1970, was the first environmental law to give the Federal government a serious regulatory role, and established the architecture of the U.S. air pollution control system. Aiming at diminishing water pollution, the Federal Water Pollution Control Act was passed in 1972. Additional mechanisms such as carbon pricing schemes (including taxes and cap-and-trade systems), as well as subsidies for green innovation, have since been adopted in various jurisdictions. There are a large number of studies documenting the correlations between carbon emissions markets and other important energy and financial markets (Jin et al., 2020; Yin et al., 2023).

Historically, land use has been governed by direct interventions such as zoning laws, the establishment of protected areas, and regulations for resource use in non-protected areas. However, in recent times, public and private actor coalitions have developed policy tools driven by market forces and demand to guide land use (Fischer et al., 2023). Land use is now managed through a combination of direct command-and-control measures, such as land use restrictions, and indirect public interventions through policies related to agriculture, forestry, trade, or macroeconomics.

The number of studies examining the impact of conservation interventions is on the rise (Burivalova et al., 2019; 2023). Reviews and meta-analyses drawn from the works of Busch and Ferretti-Gallon (2017) and Seymour and Harris (2019) indicate a correlation between the establishment of protected areas, the presence of indigenous communities, and payments for ecosystem services, leading to a reduction in forest loss. However, the impact of certification on mitigating forest loss appears to be minimal. Business-related initiatives, especially those involving supply chains, are still in the early stages, with uncertain effectiveness in curbing deforestation (Schleifer, 2023; Taylor & Streck, 2018).

From an operational modelling perspective, recent simulation studies emphasize that environmental policies cannot be evaluated independently of production dynamics, such as regulatory thresholds, consumer behavior, and technology choices interact in non-linear ways over time (Vieira et al., 2022; Zhu et al., 2025). Simulation-based experiments provide a natural platform for assessing such interactions when historical data are incomplete or policy regimes are evolving.

Recent research has increasingly leveraged simulation-based methods to evaluate and guide environmental policy under uncertainty. For instance, Monte Carlo simulations have been used to quantify future carbon emissions and inform climate policy in the Belt and Road region (Seidu et al., 2024), while urban air pollution has been modelled to support environmental policy decisions (Antoniou et al., 2024). Similarly, system simulation approaches have explored supply–demand interactions in science and technology innovation (Zhou et al., 2023), assessed carbon reduction effects in prefabricated building supply chains (Du et al., 2024), and evaluated the consequences of government policy reforms on environmental sustainability (Layani et al., 2023). Additionally, dynamic simulation and multi-player evolutionary game models have been applied to improve public participation in environmental governance (Chu et al., 2022). Collectively, these studies demonstrate the practical utility of simulation as a decision-support tool, enabling policymakers and industry leaders to anticipate the environmental consequences of different strategies and explore counterfactual scenarios, complementing the operational-focused simulation literature discussed in Sect. 2.1.

Despite the growing number of case studies and reviews, scholars assert that the evidence on the effectiveness of policy instruments remains insufficient (Börner et al., 2020; Game et al., 2018).

This limitation has prompted calls for computational experimentation frameworks that combine policy modelling with data-driven learning to explore counterfactual scenarios and policy mixes under uncertainty (Singh et al., 2021).

On the other side, policymakers should acknowledge the use of policy mixes, which involve a suitable combination of tools and strategies (Howlett et al., 2006; Howoldt, 2024). A deeper comprehension of the optimal combination, sequence, and targeting of different policy mixes is crucial. This necessitates empirical studies investigating policy instrument mixes tailored to specific country contexts (Lambin et al., 2014; Longato et al., 2024).

While land use and conservation policy studies have advanced, the effectiveness of policy mixes is still poorly understood due to methodological limitations and data access challenges. Most studies rely on either expert-based evaluations or remote sensing, both of which face validity and reliability concerns (Fischer, 2023; Sandström et al., 2020; Simmons et al., 2018). In conclusion, there is a noticeable gap in our understanding of the evaluation of mixed land use policies due to the lack of reliable data. In production planning research, this gap is compounded by the limited integration of environmental policy variables within dynamic simulation models that explicitly learn and adapt control parameters over time.

Specifically, we lack information on the effectiveness of various environmental policies and their combined impact in terms of environmental consequences, based on a typology of regulatory, economic, and information-based instruments. Furthermore, In the realm of production planning, there is an additional knowledge deficit in control policy research, concerning the dynamic nature of manufacturing systems. Moreover, scant consideration has been given to the environmental dimension of the manufacturing system. Addressing these gaps could provide valuable insights for policymakers and industry leaders alike.

In the present paper, we tackle the challenge of production planning of an FPMS in an unpredictable and changeable nature of manufacturing system. By embedding environmental policy variables and consumer environmental awareness within a simulation-based optimization framework, the proposed approach enables joint evaluation of operational, environmental, and policy outcomes. Our first step is to broaden the environmental scope of the problem by incorporating the environmental consciousness of consumers. Next, we formulate and assess land use policies. The approach we have implemented could serve as a valuable tool for manufacturers and policymakers, providing a holistic perspective on production planning and its environmental implications.

The main contributions of our research are i) the development of an environmental hedging point policy in a dynamic environment; ii) Environmental policy formulation and evaluation; and iii) tracking the environmental footprint of manufacturing strategies.

3 Problem statement

This study delves into a paper manufacturing system utilizing both recyclable and virgin paper as raw materials. Virgin paper refers to paper that is made from fresh wood pulp or other raw materials that have not been previously used for paper production. It is the opposite of recycled paper, which is made from wastepaper. Within this system, two distinct production facilities operate in parallel: The Main Manufacturing Unit (MMU) and the Environmentally-Friendly Unit (EFU). The MMU relies on virgin raw materials and is associated with relatively lower maintenance costs, faster processing times, and reduced production costs compared to the EFU. Conversely, the EFU specializes in processing recyclable materials, incurring higher maintenance costs and longer downtimes, while also requiring greater production expenditure despite its lower energy consumption. Manufacturers in this dual-unit system must contend with the challenges of balancing production between the MMU and EFU, managing inventory, backlog, and environmental costs, all while navigating the complexities of environmental policies imposed by policymakers.

4 Notation

The notations used throughout this paper are defined in Table 2. There are three approaches to environmental policies concerning land use: persuasive, punitive, and mixed (Bluff, 2018; Tou et al., 2024). In the persuasive category, manufacturers are given flexibility in meeting environmental footprint limits and are rewarded when they successfully reduce their footprint below the prescribed thresholds.

By doing so, manufacturers not only meet the regulatory requirements but also receive recognition and benefits for their efforts in going above and beyond the minimum standards. This approach encourages a cooperative relationship, emphasizing continuous improvement and sustainable practices. Conversely, the punitive approach enforces strict limits, imposing charges and penalties for exceeding them, compelling manufacturers to invest in eco-friendly technologies.

This approach aims to enforce compliance with stringent environmental regulations and hold manufacturers accountable for their impact on the environment. By imposing charges

Table 2 Notations

Parameter	Notation	Parameter	Notation
d_0	Initial demand rate	U_{EFU}	EFU's utilization ratio
P_1	Production rate of MMU	Θ_1	Land exploitation index of the MMU
P_2	Production rate of EFU	Θ_2	Land exploitation index of the EFU
x(t)	Inventory/backlog level at time t	L	Permissible standard limit of land exploitation
I(t)	Emission level at time t	C_{INV}	inventory cost per unit product per hour ($/product/time unit)
$P_1{}^{max}$	Maximum production rate of the MMU	C_b	Backlog Cost per unit product per hour
$P_2{}^{max}$	Maximum production rate of the EFU	C_{EFU}	EFU's utilization cost per hour
L	Cumulative amount of land exploitation in each reference period	T	EFU's utilization cost per hour
MTTF	Mean Time To Failure	α	EFU's state: up (1) and down (0)
$MTTR_1$	Mean Time To Repair of the MMU	β	MMU's state: up (1) and down (0)
$MTTR_2$	Mean Time To Repair of the EFU	η	Modulus of permissible standard limit of exploitation
C_E	land cost per unit of violation	Z_i	Hedging level i = 1,2
q	land recovery threshold	K(t)	land recovery rate

Under this policy, manufacturers are allowed to exceed the set limit, but they are rewarded when they actively strive to exploit less than the prescribed limit. In other words, while there is a defined limit in place, the emphasis is placed on encouraging manufacturers to voluntarily reduce their emissions below that limit

for exceeding the limit, policymakers create a strong deterrent against non-compliance and motivate manufacturers to invest in technologies and practices that help them stay within the defined boundaries. The punitive policy acts as a regulatory tool to ensure manufacturers prioritize environmental responsibility and take active measures to reduce their emissions to avoid financial penalties. Finally, the mixed category combines elements of both approaches by implementing punitive measures alongside persuasive incentives, aiming to achieve a balance between enforcement and voluntary emission reduction efforts. This comprehensive examination sheds light on the diverse policy approaches available to policymakers, each with unique implications for environmental responsibility within manufacturing processes.

As illustrated in the conceptual framework (Fig. 1), the system under study has two production units. The first unit, conventional production(p_1), has the production rate of p_1(t,) with recovery rate k(t-r) and the inventory level, namely x(t). p_1 contributes to Land exploitation (l) at the rate $p_1 \times \theta_1$. Once the inventory level crosses z_1 or z_2 and the cumulative amount of land exploitation exceeds environmental limitation ($L \times \eta$), a feedback signal is sent.

A variety of factors, such as Land exploitation, costs, customer satisfaction, and EFU utilization are influenced by the adopted policy. The primary objective of each policy is to diminish the production environmental footprint and costs by pushing manufacturers from conventional production toward EFU. This eventually leads to a lower level of land exploitation. However, EFU poses higher production costs, longer repair times ($MTTR_1 < MTTR_2$),

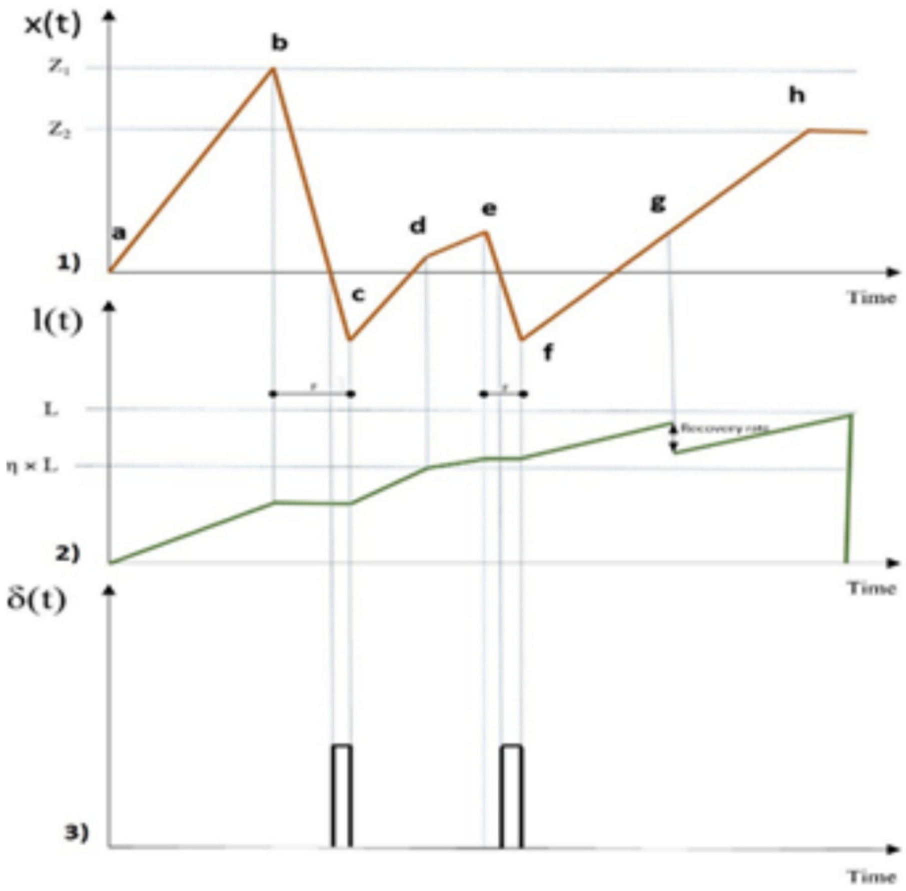

Fig. 1 Graphical evolution: inventory (1), emissions (2), and customer dissatisfaction (3) over time

and lower production rates P_1 max > P_2 max as it utilizes relatively modern technologies and has limited sources of raw materials. Customer satisfaction is a driving factor for manufacturers, which in this study is influenced by backlog. A lower production rate and more occurrences of failure of EFU lead to more backlog, where a decrease in customer satisfaction is predictable. While customer satisfaction can be influenced by multiple factors, including price, quality, and accessibility, this study specifically associates it with the level of backlog. In this study, dynamic demand reflects changing customer preferences in response to the manufacturing environmental performance. Specifically, environmentally conscious customer awareness is defined as the tendency of customers to favor and increasingly purchase products from firms that adopt environmentally friendly practices. This is modeled by linking increased EFU production to higher customer demand in subsequent periods. Such demand responsiveness captures a key behavioral trend where customers reward green production efforts, thereby influencing both demand levels and customer satisfaction.

Although the ultimate goal of each policy is to mitigate the environmental impact of the production line, policymakers grapple with the challenge of determining the most effective approach. On the one hand, the implementation of punitive laws could incline manufacturers to reduce land exploitation to avoid exceeding environmental limitations and penalties. In this situation, EFU could be a key solution for manufacturers to reduce their environmental footprint. Also, the persuasive policy offers financial rewards, and it is by nature less strict. This policy could be accepted by manufacturers more easily compared to the former policy. The final policy is a combination of persuasive and punitive measures in a way that provides the decision-makers with more flexibility in terms of facing financial penalties or receiving rewards. While these policies incentivise EFU, the associated challenges, such as a lower production rate, extended repair times, and elevated production costs, introduce complexity into the production planning process. Given the considerations discussed earlier, the decision-maker faces the intricate task of identifying the optimal solution to minimise costs, enhance customer satisfaction, and promote environmentally friendly production. The subsequent summary encapsulates the overall context and primary assumptions addressed within this paper:

- The continuous-time Markov chain regulates the evolution of machine status (Up and Down) over time.
- The hedge level Z_1 needs to surpass Z_2. Given that our suggested control policy is a modification of the EHPP, it is imperative to uphold its policy framework
- Supply availability is unlimited.
- Maintenance incurs no cost, and the repaired machine is restored to a like-new condition.
- Exploitation index follows a uniform distribution probability [a,b]
- Shortage of the product resulted in a backlog.
  • Mean Times to Failure for both manufacturing units are the same ($MTTF_1$ =$MTTF_2$).
- MMU's actual cost is based on the time of its exploitation.
- The eco-friendly unit products maintain the same level of quality as those produced by the main manufacturing unit.
- The customer demand is dynamic.

The system under investigation is formulated as a continuous or discrete model, wherein the state variables (x(t), l(t), d(i), α(t), β(t)) characterise the system's dynamic behavior. Random failure of FPMS defines the availability and unavailability of the system. While land exploitation, inventory level, and demand vary regularly, the model is continuous, and their dynamic behavior is presented by Eqs. (1), (2), and (3). Where $\dot{x}$(t) represents the inventory level, calculated as the difference between production and demand in each period. The land exploitation rate, $\dot{l}$ (t), is determined based on the production rate and the land exploitation index. Finally, $\dot{d}$ (i) denotes the amount of demand, which is calculated based on the environmentally friendly unit utilization ratio from the previous period.

$$\dot{x}(\mathrm{t}) = \mathrm{p1}(\mathrm{t}, \alpha) + \mathrm{p2}(\mathrm{t}, \beta) - \mathrm{d}, \ \mathrm{x}(0) = \mathrm{x0} \tag{1}$$

$$\dot{l}(\mathrm{t}) = \mathrm{p1}(\mathrm{t}, \alpha) \times \theta 1 + \mathrm{p2}(\mathrm{t}, \alpha) \times \theta 2, \ \mathrm{t}\ [\mathrm{ti}, \mathrm{ti}+1], \ \mathrm{l}(\mathrm{ti}) = 0, \ \mathrm{ti} = \mathrm{i} \times \mathrm{Pr}, \ \mathrm{i} = 0,1, \ldots, \mathrm{N} \tag{2}$$

$$\dot{d}(\mathrm{i}) = \mathrm{d0} \times \frac{\mathrm{T2(i)}}{T0} \ \mathrm{i} = 0,1, \ldots, \mathrm{N} \tag{3}$$

The land exploitation index follows a uniform probability distribution denoted as θ [a,b]. Since those responsible for land exploitation often cannot accurately assess the quantity and quality of land use during production. Moreover, factors such as spatial variations, geographical influences, and climate change contribute to uncertainty in measuring pollution levels.

The objective of an optimal control policy is to minimize the average cost in the long term. The decision space needs to be restricted as follows.

$$0 \leq p_1(t) \leq P_1^{max} \tag{4}$$

$$0 \leq p_2(t) \leq P_2^{max} \tag{5}$$

4.1 Cost function

The Inventory and backlog cost function (g1) is defined by the following equation:

$$g_1(x(t)) = C_{inv} \times \max(x(t), 0) + C_b \times \max(-x(t), 0) \tag{6}$$

Equation 6 captures the total holding and shortage costs over time. When the inventory level x(t) is positive, the function applies to the inventory holding cost C_{inv}. Conversely, when x(t) is negative, indicating a backlog or unmet demand, the backlog cost C_b is applied. This formulation allows the model to dynamically account for both surplus and shortage situations in the production system. The land exploitation cost functions are described below:

$$g_2^{Pu}(ti) = C_E \times \max(l(ti) - L, 0),\ i = 1, \ldots, N,\ t_i = i \times pr \tag{7}$$

$$g_2^{Pe}(ti) = C_E \times \min(l(ti) - L, 0),\ i = 1, \ldots, N,\ t_i = i \times pr \tag{8}$$

$$g_2^{Mix}(ti) = C_E \times (l(ti) - L),\ i = 1, \ldots, N,\ t_i = i \times pr \tag{9}$$

Equations 7, 8, and 9 are dedicated to punitive, persuasive, and mixed policies, whereas in Eq. 7, only penalties are applied. In contrast, in persuasive policy (Eq. 8), only rewards are specified for manufacturers when they exploit less land than the limit ($I(t_i) < L$). Equation 9 represents the combination of policies where penalty and reward are considered.

The cost of EFU depends on the time of the production system switch to p2 in each reference period. Calculation of the EFU cost is presented below:

$$g_3(ti) = C_{EFU} \times (t_i - t_{si}),\ t_i = I \times pr,\ i = 1, \ldots, N \tag{10}$$

also, the rate of EFU utilization is calculated as follows:

$$UEFU = \frac{\sum_{i=1}^{N}(ti - tsi)}{N \times Pr} \tag{11}$$

Customer satisfaction is affected by various factors such as the quality and price of the product, and manufacturer response time and it is also influenced by product availability (Golroudbary & Zahraee, 2015). In this research, product availability is responsible for customer satisfaction. As an objective function, DMs aim to diminish the time of product unavailability for customers.

The customer dissatisfaction state variable, defined by δ(t) is shown below:

$$\text{If } l(t) \geq \eta \times L \tag{12}$$

$$\delta(t) = \begin{cases} 1 \alpha(t) = 0 and x(t) \leq 0 \\ 0 \end{cases}$$

$$\text{If } l(t) < \eta \times L \tag{13}$$

$$\delta(\mathrm{t}) = \begin{cases} 1 \beta(t) = 0 and x(t) \leq 0 \\ 0 \end{cases}$$

The progressive behavior of the customer dissatisfaction is shown in Fig. 1 It means whenever the inventory level face backlog (x(t) ≤ 0), t is set to 1 and in other circumstances 0. So, DMs seek to lessen the area below the chart. The expected Long-run average dissatisfaction is calculated:

$$\mathrm{g4(ti)} = \log_{\mathrm{N}\rightarrow\infty} \frac{1}{\mathrm{N} \times \mathrm{Pr}}\ \mathrm{E} \int_{0}^{\mathrm{N}\times\mathrm{Pr}} \delta(\mathrm{t}) \tag{14}$$

4.2 Expected long-run average cost

As suggested by Sajadi (2011), two common types of objective functions are widely used in the literature: expected overall discounted cost and expected long-run average cost. In this study, we adopt the long-run average cost criterion, as our primary objective is to determine optimal production rates that minimize the total cost (e.g., inventory and backlog costs) over the long run. This approach aligns with long-term operational efficiency and is well-suited for continuous production systems. Long-term average cost refers to the average cost per unit of output over a long period. It is calculated by dividing the total cost over the long term by the total output over the same period. We aim to reduce the expected long-run average cost over an extended period for g_1,g_2,g_3 and g4. The cost function is defined as:

$$\mathrm{J}\,(\mathrm{x},\,\mathrm{l},\,\alpha,\,\beta) = \lim_{\mathrm{N}\rightarrow\infty} \frac{1}{N \times \mathrm{P}r} E\left\{ \int_{0}^{N\times Pr} \mathrm{g1(x(T))dt} + \sum_{i=1}^{N} \left[\mathrm{g2(ti)} + \mathrm{g3(ti)} + \mathrm{g4(ti)}\right] \right\} \tag{15}$$

4.3 Control policy

The goal of our control problem is to determine the best production rates in order to minimize the long-term average total cost (see Eq. 15). Since solving the related system of HJB equations is too complex to do analytically (as noted by Rishel, 1975; Kenne & Gharbi, 2004; Sajadi et al., 2011), heuristic methods are typically used. According to Gharbi and Kenne (2005), two common approaches are: the hedging point policy and the singular perturbation method. In our study, we developed a feedback control model based on the Extended Hybrid Production Problem (EHPP). Ben Salem (2015a) proposed an EHPP that adapts inventory and backlog based on considerations of both costs and emissions. In this model, the land exploitation index value l(t) is added to detect the moment production switches to p2 (l(t) > η × L). During p_1 working time, the production system time is monitored by recovery time (q). It means whenever the total working time of p_1 and p_2 passes the q(t > q), the recovery rate, namely k(l(t)), affects land exploitation by reducing from land exploitation capacity. The behaviour of the production system is described below:

$$1\,(\mathrm{t}) < \eta \times \mathrm{L}\,\&\,\mathrm{t} < \mathrm{q} \tag{16}$$

$$p1(t,\alpha) = \begin{cases} P1\max & x(t) < z1 \ and\ \alpha(t) = 1 \\ d & x(t) = z1\ and\ \alpha(t) = 1 \\ 0 & x(t) > z1\ or\ \alpha(t) = 0 \end{cases}$$

$$1\,(\mathrm{t}) < \eta \times \mathrm{L}\&\,\mathrm{t} > \mathrm{q(ti)} = \mathrm{l(ti)} - \mathrm{K(l(t))} < \eta \times \mathrm{L} \tag{17}$$

$$p1(t,\alpha)=\begin{cases} P1\max & \mathrm{x(t)} < \mathrm{z1 \ and}\ \alpha(\mathrm{t})=1 \\ d & x(t)=z1\ and\ \alpha(t)=1 \\ 0 & x(\mathrm{t}) > z1\ or\ \alpha(t)=0 \end{cases}$$

$$\text{If } \mathrm{l(t)} \geq \eta \times \mathrm{L} \tag{18}$$

$$P2(t,\beta)=\begin{cases} P2\max & \mathrm{x(t)} < \mathrm{z2 \ and}\ \beta(\mathrm{t})=1 \\ d & x(t)=z2\ and\ \beta(t)=1 \\ 0 & x(\mathrm{t}) > z2\ or\ \beta(t)=0 \end{cases}$$

To elucidate the dynamics of the proposed model, a graphical evolutionary diagram is presented in Fig. 1. This figure depicts the temporal evolution of three critical dimensions: inventory (sub-Fig. 1), land exploitation (sub-Fig. 2), and customer dissatisfaction (sub-Fig. 3). At the start point (a) production system starts with $P_1^{\max}$ till the stock level reaches the Z_1 level (b). Meanwhile, the manufacturer exploits land at the rate of $P_1^{\max} \times \theta_1$. At point b, failure occurs, and inventory level reduction starts. Whenever the production system faces a backlog, the customer dissatisfaction value is set to 1, and the land exploitation index remains fixed. Right after failure, the system recovers to its initial stage and exploits land at

Fig. 2 Research Model

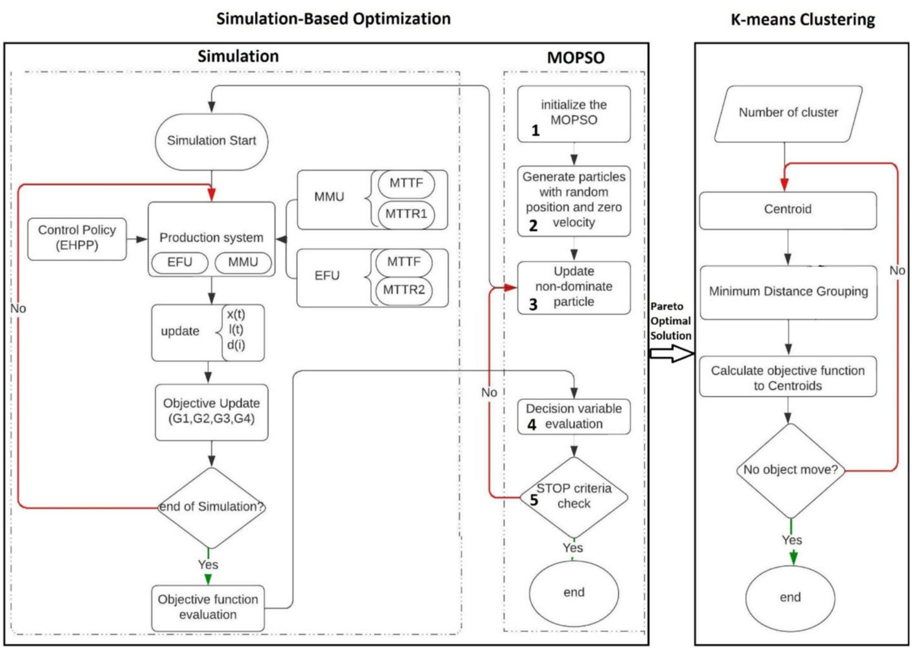

Fig. 3 The Research Methodology

the rate of $P_1{}^{max} \times \theta_1$ and the inventory level increases (c-d). When the land exploitation index hits the $\eta \times L$, the production system switches to $p_{2,}$ and while the inventory level is below z_2, the manufacturer exploits land at the rate of $P_2{}^{max} \times \theta_2$. During e–f, failures happen, and customer dissatisfaction during backlog is set to 1. At point g, the total working period time reaches the recovery limit. In this situation, the manufacturer's land exploitation faces with reduction equal to the recovery rate. It means the system has more capacity to use the land. At the end of the period, the land exploitation index resets to zero, and whether the sum of land is higher or lower than the limit is considered as a penalty or reward, respectively.

5 Research approach

This research aims to design and develop an environmental hedging point policy integrating economic, social, and environmental objectives. When the objective function is hard and expensive to evaluate, the Simulation-based optimization method could play a key role (Gosavi 2003; 2015). It is a method that merges the optimization method with the simulation process, and by discarding low-quality results, it can provide outputs quickly. Figure 2 shows the research model. The process begins with the problem statement, followed by simulation-based optimization. The generated solutions are then grouped using k-means clustering, after which the model undergoes validation. Finally, the results are analyzed and discussed.

The Particle Swarm Optimization (PSO) algorithm has been applied in the field of supply chain management to optimize various aspects such as inventory control, distribution network design, and.

demand forecasting (Mousavi et al., 2014). In the supply chain management literature, Particle swarm has been applied in various contexts (Babaveisi, 2018; Javanshir et al., 2012; Shankar et al. 2012; Si et al., 2024; Lalwani, 2013; Venkatesan and Kumanan, 2012). The research methodology is shown below (Fig. 3):

Figure 3 outlines a two-phase approach combining Multi-Objective Particle Swarm Optimization (MOPSO) and K-means clustering to solve a production planning problem with environmental considerations. In the first phase, MOPSO is initialized with a swarm of particles representing candidate solutions, each defined by random positions and zero initial velocities. During each iteration, the algorithm updates the set of non-dominated solutions based on multiple objectives (e.g., cost, environmental impact, customer satisfaction). For each particle, a simulation is run where a control policy is applied and the performance of two productions and MMU (Main Manufacturing evaluated using reliability parameters such as Mean Time To Failure (MTTF) and Mean Time To Repair (MTTR). System states and objectives are continuously updated until the simulation ends. After all particles are evaluated, the decision variables are updated, and the process continues until a stopping criterion (e.g., maximum iterations or convergence) is met.

In the second phase, the resulting Pareto-optimal solutions are passed to a K-means clustering algorithm. This phase groups similar solutions into clusters by iteratively updating centroids and assigning solutions to the nearest cluster based on objective function values. This clustering step facilitates the selection of representative trade-off solutions from the Pareto front, helping decision-makers better understand and explore the solution space. For a better understanding of the process, pseudocode is provided below.

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PSO is a population-based optimization method. The group of potential solutions is termed a swarm, with each member identified as a particle. These particles explore and seek their

Table 3 Initial parameters

Parameter	d	p_1	p_2	MTTF	$MTTR_1$	$MTTR_2$	Θ_1	Θ_2
Value	400 to 500	600	570	Exp (12)	Exp (0.6)	Exp (0.6)	0.26	0.13
Parameter	η	C_{inv}	C_B	C_E	T	L	K	Wood needed per tonne
Value	0–1.4	0/005	60	8	5760	400,000	55\% over 20 years	46–53\%

optimal solutions by leveraging their own experiences and those of other particles within the same swarm. Since our research copes with multi-objective optimization problems, we need to apply multi-objective PSO. The formulation is brought below:

$$\text{Min } \vec{f}\left(\vec{x}\right) = \{\vec{f}\,1\left(\vec{x}\right), \ldots, \vec{f}\,k\left(\vec{x}\right)\}\ \text{gi}(\vec{x}) \le 0,\ \ \text{i} = 1,\ \ldots,\ \text{N},\ \ \text{hi}\left(\vec{x}\right) = 0,\ \ \text{i} = 1,\ \ldots,\ \text{M} \tag{19}$$

$\left(\vec{x}\right) = [x_1, x_2, \ldots, x_n]^T$, $\vec{x} \in S$,

$\vec{x}$ are decision variables and $\vec{f}_I(\vec{x})$ are objective functions. $\vec{g}_I(\vec{x})$ and $\vec{h}_I(\vec{x})$ are equality and inequality constraints. Decision variable x_1 dominates x_2 only if × 1's objective function value is better than x_2. In the end, a set of non-dominant results will be achieved that do not perform better than others. The simulation model relies on a set of parameters adapted from Afshar-Bakeshloo et al. (2018) and BenSalem et al. (2015a), which are consistent with prior work in the context of EHPP. Table 3 presents the key input values used in the base case scenario. Environmental data, including land recovery rate and exploitation index, were sourced from Picchio et al. (2020), Del Rio et al. (2022), and UNECE/FAO (2023), ensuring the realism of our environmental impact modelling. MOPSO repetition is 100 with 10 particles starting point. Overall running time is 400,000 h with a 5760-h reference period.

6 Results

The initial non-dominated result has been shown below in Table 4. Z_1, Z_2 and η are decision variables, and g_1,g_2,g_3, and g_4 are objective functions.

6.1 Pareto optimal contour plot

Pareto optimal contour plot (Figs. 4, 5 and 6) generated by MOPSO for environmental policies demonstrates convergence toward the optimum point. Figures 4, 5, and 6 illustrate the values of the objective functions (customer dissatisfaction, EFU cost, inventory cost, and land cost) under the mixed, punitive, and persuasive policy scenarios, respectively. For example, in the mixed policy (Fig. 4), as the land exploitation index decreases, the associated land cost becomes comparable to that of the persuasive policy (Fig. 6). However, no strict correlation is observed between the land exploitation index and inventory level (Z) in this case. In

Table 4 Sample output

Result number	Z1	Z2	η	g1 Inventory Cost	g2 Land Cost	g3 EFU Cost	g4 Customer Dissatisfaction	Exploitation (ha)	UEFU (%)
1	295.8	259.89	0.29	7450.4	− 785.09	638.11	2.36	− 3,925,427.4	0.8
2	350.0	350.0	0.3	5079.68	− 758.16	633.92	2.24	− 3,790,818.9	0.8
3	256.95	258.34	0.01	8935.82	− 1746.31	787.71	2.18	− 8,731,553.4	0.99
4	219.57	163.32	0.12	12,829.9	− 1387.86	731.92	2.35	− 6,939,324.0	0.92
5	233.99	160.77	0.88	6241.99	− 336.21	217.42	2.35	1,681,064.4	0.27
6	122.47	170.0	0.8	6873.06	59.55	269.86	2.76	297,734.4	0.34
7	350.0	346.0	0.44	4280.77	− 59.95	292.51	1.76	− 299,765.1	0.37
8	120.0	120.43	0.78	2214.43	− 30.08	286.81	1.95	− 150,387.3	0.36
9	262.83	183.78	0.82	5573.61	− 131.7	256.18	2.15	658,484.4	0.32
10	211.32	145.83	0.41	12,847.76	− 391.15	576.82	2.63	− 1,955,751.9	0.72
11	336.94	335.49	0.71	423.48	180.13	217.94	1.95	900,631.5	0.31
12	220.82	127.81	0.14	14,636.22	− 1321.08	721.55	2.43	− 6,605,406.0	0.91
13	161.82	139.36	0.74	8078.9	− 154.96	311.09	2.4	− 774,796.8	0.39
14	261.85	261.85	0.4	7628.43	− 426.65	582.31	2.34	− 2,133,272.1	0.73
15	350.0	350.0	0.46	4820.83	− 96.41	299.46	1.71	− 482,047.2	0.37
16	238.67	137.03	0.72	7025.72	− 225.92	325.22	2.22	− 1,129,579.8	0.41
17	311.6	276.01	1.09	4436.6	1059.55	80.2	2.02	5,297,725.5	0.1
18	181.3	134.94	1.44	11,491.36	1479.4	342.34	2.24	7,397,022.5	0.0
19	248.43	145.81	0.37	12,673.19	− 527.83	598.09	2.71	− 2,639,133.3	0.75
20	350.0	350.0	0.27	5074.26	− 843.21	647.15	2.23	− 4,216,064.2	0.81
21	350.0	350.0	0.21	4358.18	1448.08	6.48	1.79	7,240,105.2	0.01

Table 4 (continued)

Result number	Z1	Z2	η	g1 Inventory Cost	g2 Land Cost	g3 EFU Cost	g4 Customer Dissatisfaction	Exploitation (ha)	UEFU (%)
22	227.93	227.93	1.29	9335.06	1478.38	0.52	2.03	7,391,912.2	0.92
23	237.59	237.59	0.09	9335.06	− 1485.84	747.15	2.26	7,429,195.2	0.94
24	120.0	120.0	0.3	2211.4	773.12	636.22	2.01	− 3,865,624.8	0.8
25	120.0	120.0	0.01	2415.2	1266.0	682.22	1.95	6,335,056.3	0.07
26	120.0	120.0	0.36	2111.92	− 560.0	603.06	1.9	− 2,799,988.8	0.76
27	350.0	187.05	0.83	5152.92	162.9	250.31	2.01	814,511.7	0.31
28	228.81	202.05	0.77	5582.19	− 17.01	290.06	2.2	− 235,064.1	0.36

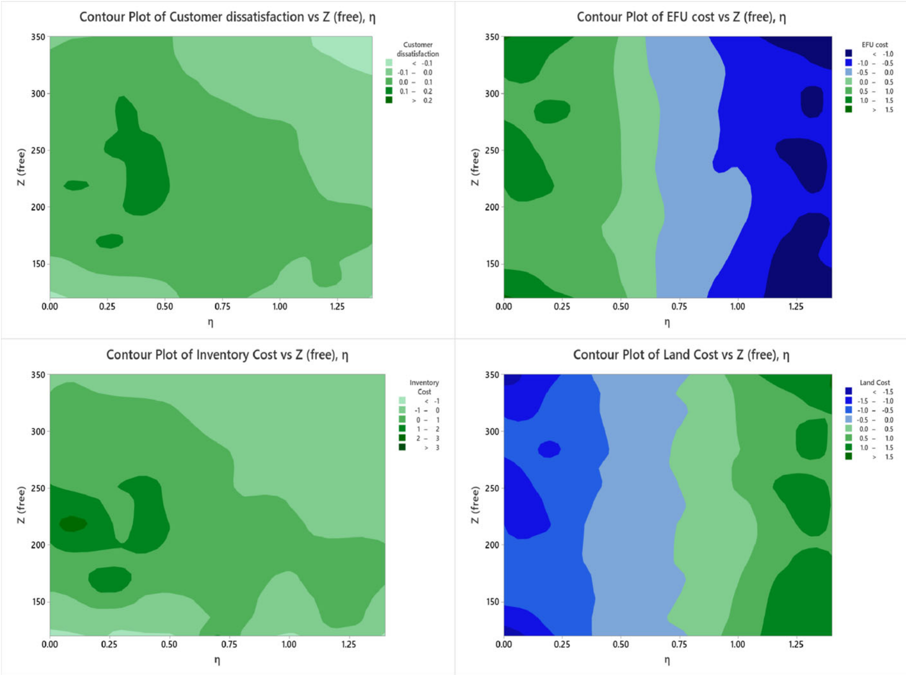

Fig. 4 Pareto Optimal Contour Plot—Mix Policy

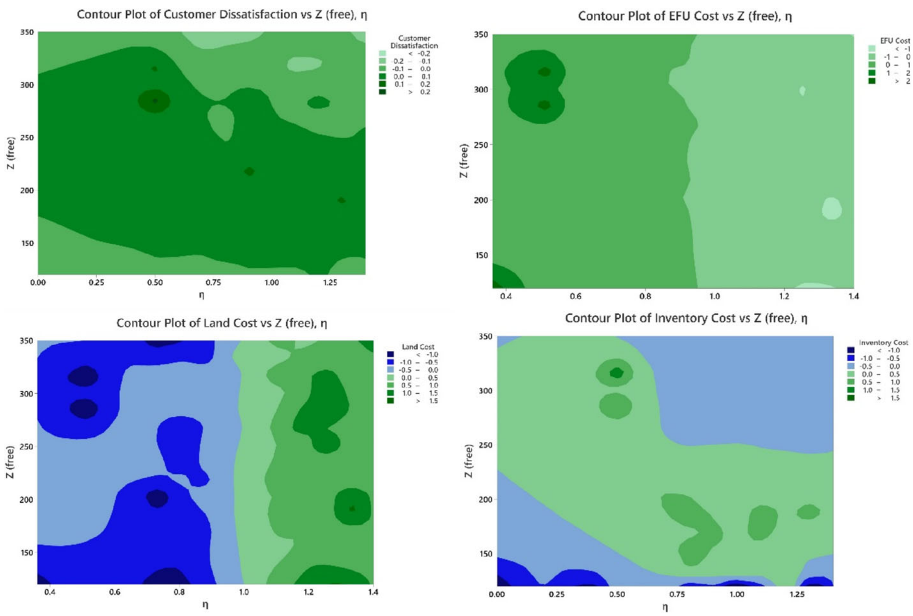

Fig. 5 Pareto Optimal Contour Plot—Punitive Policy

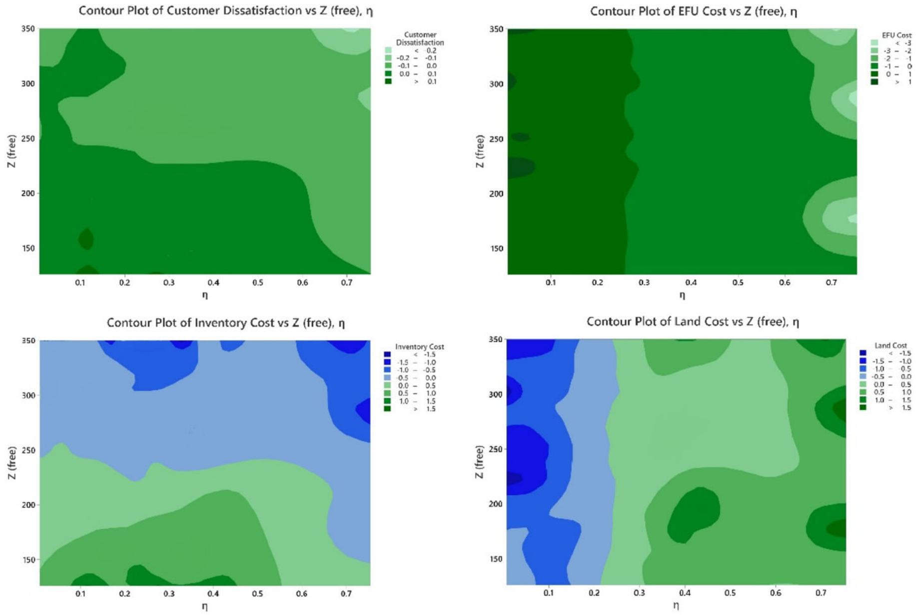

Fig. 6 Pareto Optimal Contour Plot—Persuasive Policy

contrast, EFU cost consistently increases across all policies when the land exploitation index decreases. Regarding inventory cost, the persuasive policy shows a negative correlation with inventory level, which is the opposite trend observed in the punitive policy. This highlights how different policy approaches influence the balance between sustainability objectives and operational performance. Since Z_1 and Z_2 correlation is 0.9, Z1 is assumed to be representative of Z in the Pareto optimal contour plot. The Z-score standardization is applied to the objective variables. This method transforms features to have a mean of 0 and a standard deviation of 1. It's particularly useful when features have different units or distributions. The formula for z-score standardization is:

$$\mathrm{x}_{\mathrm{standardized}} = \frac{x - \mu}{\sigma} \tag{20}$$

where x is the original feature value, μ is the meaning of the feature, and σ is the standard deviation.

6.2 K-means clustering

MOPSO's performance may deteriorate when applied to problems with a large number of objectives or decision variables. The computational complexity of maintaining the Pareto front and updating particles increases with the dimensionality of the problem (Parajapati 2021). While this limitation primarily affects the efficiency of the optimization process, it also introduces a secondary challenge: the difficulty in interpreting and analyzing the large set of non-dominated solutions produced. To support meaningful interpretation and aid decision-making, K-means clustering is employed as a post-optimization step to group similar solutions based on decision variables (Z_1, Z_2, η). K-means is a widely used technique for data categorization due to its effectiveness in identifying inherent patterns and clustering similar data points. By iteratively assigning data points to clusters based on their proximity to cluster centroids, K-means effectively segments the data set into distinct clusters. This clustering approach is particularly advantageous when the number of clusters is predefined, and the data underlying structure is not explicitly known (Han 2006).

The K-means algorithm utilizes the Euclidean distance function to assign objects to their nearest cluster centre. Its objective is to divide a group of objects into clusters, with each cluster represented by the average value of its objects. This procedure is repeated until the assignment of points to clusters remains consistent across consecutive iterations. Different techniques can be utilized for the initial phase and convergence criteria of K-means. For this particular study, Lloyd's algorithm was chosen due to its superior convergence capabilities when compared to alternative algorithms (Sadeghi et al., 2022). The execution of Lloyd's algorithm involves four distinct stages.

$$\textbf{Step 1}: \text{Randomly determining the centres of the clusters} \\ \times \left(\mu_{\mathrm{i}}^{(0)} = \mu_1^{(0)},\ \mu_2^{(0)},\ \mu_3^{(0)},\ \ldots\mu_{\mathrm{i}}^{(0)} = \mu_1^{(0)},\ \mu_2^{(0)},\ \mu_3^{(0)},\ \ldots\right) \tag{21}$$

The following two phases are subsequently reiterated until the averages converge or there is no noteworthy alteration in the comprehensive variance of the clusters.

$$\textbf{Step 2}: \mathrm{S}_{\mathrm{i}}^{(\mathrm{t})} = \{\mathrm{x_P} : \left\|\mathrm{x_P} - \mu_{\mathrm{i}}^{(\mathrm{t})}\right\|^2 \le \left\|\mathrm{x_P} - \mu_{\mathrm{i}}^{(\mathrm{t})}\right\|^2 \mathrm{and} \forall \mathrm{j},\ 1 \le \mathrm{j} \le \mathrm{k}\} \tag{22}$$

where $\mathrm{S_i}^{(\mathrm{t})}$ is cluster i at time t, $\mathrm{x_P}$ includes all points at the initial cluster, and k is the number of clusters.

Step 3: All clusters are updated based on the equation below:

$$\mu \mathrm{i}(\mathrm{t}+1) = \frac{1}{\mathrm{Si\ (t)}} \sum \mathrm{xj} \ \in \ \mathrm{Si}^{(\mathrm{t})} \mathrm{Xj} \mu \mathrm{i}^{(\mathrm{t}+1)} = \frac{1}{\mathrm{Si\ (t)}} \sum \mathrm{xjj} \ \in \ \mathrm{Si}^{(\mathrm{t})}\ \mathrm{Xj} \tag{23}$$

Step 4: Finally, $\mu_{\mathrm{i}}{}^{(\mathrm{T})} = \mu_1{}^{(\mathrm{T})}, \mu_2{}^{(\mathrm{T})}, \mu_3{}^{(\mathrm{T})}, \ldots$ are obtained as the final representatives of clusters.

MATLAB 2020 was used to run the K-means algorithm to compute clusters. Being an unsupervised clustering technique, the user is responsible for defining the initial number of clusters, denoted as "k". Various methods exist to determine the optimal number of clusters. In this context, an "optimum number" refers to the cluster count where members within each cluster exhibit maximum similarity while displaying significant dissimilarity with members from other clusters. One widely used and straightforward approach for determining this optimal value in K-means clustering is known as the elbow method (Everitt 2011). The Elbow method determines the number of clusters in K-means clustering by identifying the optimal cluster number based on the distortion of the data. It involves plotting the average degree of distortion against the number of clusters and identifying the "elbow" point on the curve, which represents the point of diminishing returns in terms of reducing distortion. As illustrated in Fig. 7, the elbow point on plots of all policies is three.

Due to its sensitivity to the initial centroid location, the K-means method may miss the global solution and easily trap the model in a local optimum. To prevent this, we developed a strict multi-run validation framework and went beyond a single-run method. To guarantee that the resulting clusters were stable and repeatable, the method was run in 50 separate trials, each of which was started with a different random seed. We used the Silhouette coefficient (Arbelaitz et al., 2013) and the Within-Cluster Sum of Squares (WCSS) (Jain, 2010) to confirm the structural integrity of these groups. In order to verify that the identified policy

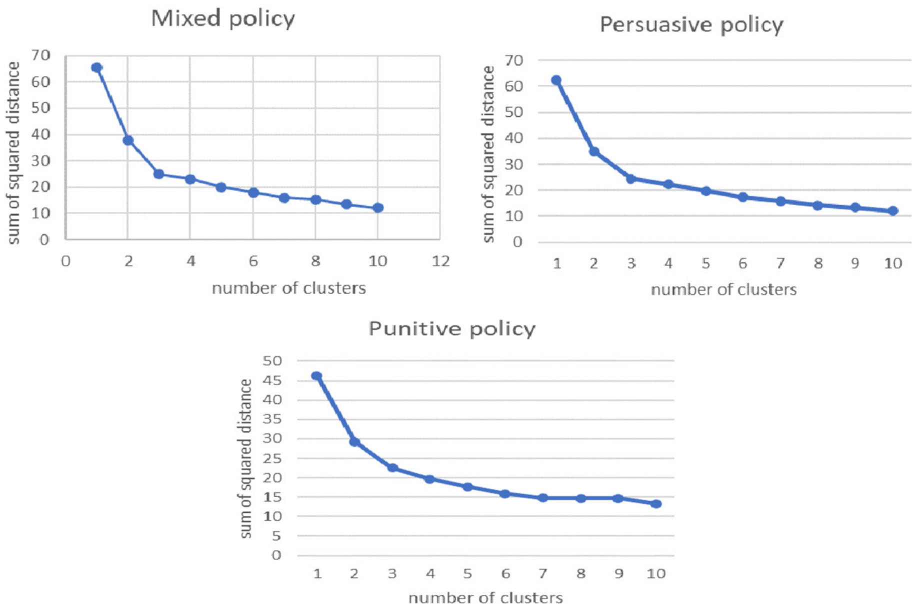

Fig. 7 The Elbow Point

regimes are both internally cohesive and distinct from one another, this stage supplied the mathematical baseline required.

6.3 Clustering analysis and validation

A thorough quantitative audit of the partition quality, solution stability, and k selection rationale was required to validate the clustering process. The elbow technique, where the WCSS demonstrated a significant cumulative drop from the k = 1 baseline before reaching the distinct plateau identified across all three policy scenarios, supported the determination of k = 3, as seen in Table 5.

Table 5: k selection rationaleWith Silhouette scores continuously above the structural validity threshold, the data in the table demonstrates that all three environmental policies attained high clustering quality. The Punitive policy also maintained a strong score of 0.62, demonstrating that k = 3 is still a suitable choice across various regulatory data structures, even if the Mixed policy showed the most distinct divisions with a Silhouette score of 0.78.

Table 5 k selection rationale

Policy Scenario	WCSS Reduction (to k = 3)	Average Silhouette Score	Max Centroid Variance
Mixed	74.2%	0.78	0.018%
Persuasive	68.5%	0.69	0.035%
Punitive	61.1%	0.62	0.058%

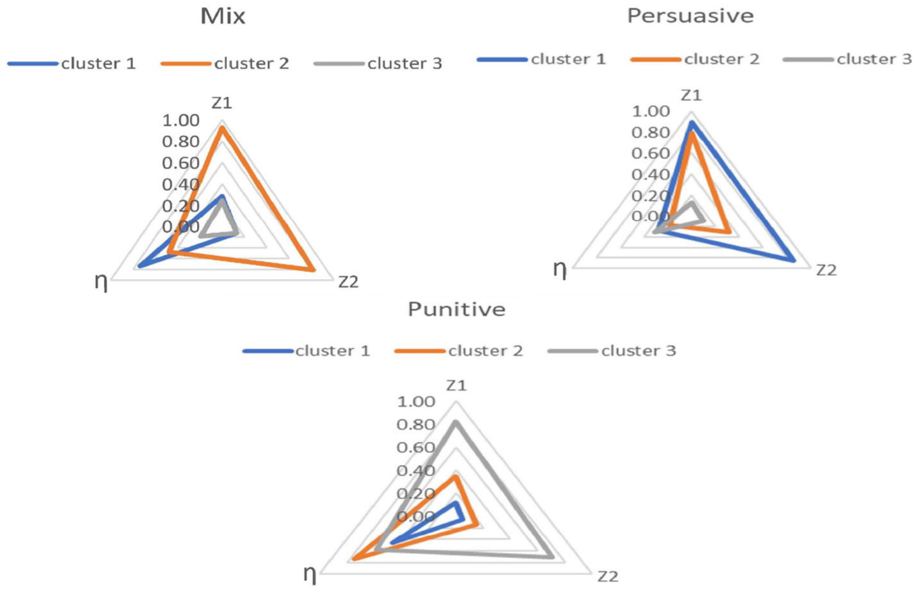

Fig. 8 Clustering Validity

The algorithm reliably and repeatedly converged to a stable global optimum in every situation, as seen by the insignificant maximum centroid variance—all of which remained far below 0.06%. Because of the clusters' high level of mathematical stability, it is possible to reliably examine how various regulatory frameworks affect industrial behavior by precisely capturing diverse and comprehensible policy regimes.

As illustrated in Fig. 8, the distribution of the standardized choice variables, namely the hedging levels Z1 and Z2 coupled with the land exploitation modulus η, offers crucial information about the operating strategies within each cluster. Clusters 1 and 3 preserve comparable configurations for the inventory criteria Z1 and Z2 in the Mixed policy scenario, but their environmental approaches are very different. Cluster 3 takes a cautious approach with the lowest η levels, whereas Cluster 1 has a high-exploitation tolerance with raised η values. Quantitatively larger inventory levels set Cluster 2 apart, suggesting a strategy that puts buffer stock ahead of environmental footprint restrictions. The clusters show a large fluctuation in Z2 under the Persuasive policy, suggesting that firms actively modify their secondary inventory criteria to optimize the financial incentives provided for remaining below the land exploitation restriction. In contrast, Z1 and Z2 are grouped considerably more tightly under the Punitive policy, indicating that the manufacturer's options for effective inventory tactics are limited by the possibility of severe financial penalties.

Figure 9 further clarifies the trade-offs between the four objective functions (g1 to g4) for the Mixed strategy, where each cluster denotes a distinct compromise between sustainability and operational goals. Although this efficiency is countered by a much higher assessment in land-related expenses (g2), Cluster 2 indicates a strategy for lowering customer discontent (g4), Environmentally Friendly Unit (EFU) costs (g3), and inventory costs (g1). In contrast, Cluster 1 demonstrates a primary focus on lowering EFU operational costs (g3) while maintaining performance levels that are on par with Cluster 2 in terms of customer satisfaction

Fig. 9 Clustering Validity (Mix Policy)

and inventory management. As a well-balanced middle-ground approach, Cluster 3 maintains modest levels of land exploitation and inventory holdings while controlling the higher production costs associated with EFU use. This quantitative mapping of the solution space illustrates effectively the clustering organizes the data to reveal significant patterns that aid in decision-making for manufacturers and legislators.

7 Discussion

In this study, we delve into the nuanced interplay between land conservation policies and production planning, specifically exploring their impact on customer satisfaction, inventory management, and production costs. Our analysis incorporates the dynamic considerations of failure-prone machinery units, environmental uncertainties, and consumer preferences for eco-friendly products. Introducing a novel environmental hedging policy within a stochastic framework, we employ a simulation-based optimization technique integrated with a multi-objective particle swarm algorithm. This approach not only offers a forward-looking perspective for policymakers to assess the efficacy of mitigating policies but also equips manufacturers with tools to dynamically optimize operations, enhancing both technical efficiency and environmental responsibility. The central research question driving our inquiry focuses on identifying the most cost-saving policies tailored for environmentally sensitive customers. Furthermore, the aim of overarching this paper is to critically evaluate the adaptation and implementation of these policies within the context of the paper and pulp industry. By delving into these dynamics, we aim to contribute valuable insights that bridge the gap between environmental conservation and operational efficiency in the realm of production planning.

As explained in previous sections, increasing environmental public awareness has pushed policymakers to adopt urgent, effective, and practical policies to curb the detrimental environmental impact of industries in all aspects. Environmental policies play a crucial role in

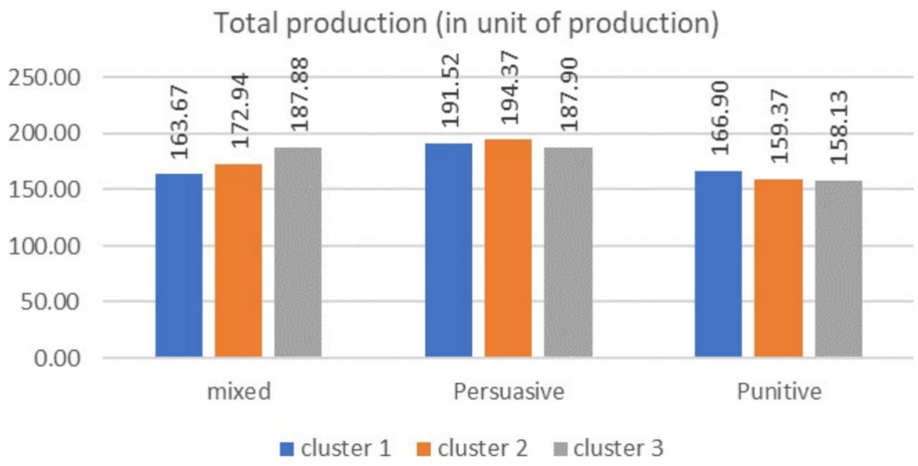

Fig. 10 Total Production

promoting sustainability and making industries more environmentally friendly. When comparing different types of environmental policies, it is important to consider their stringency and potential impacts on businesses' competitiveness. Stringent environmental regulations are often seen as a disadvantage to certain industries, as they may impose additional costs and constraints.

In this study, three general policies, including mixed, persuasive, and punitive, were proposed and imposed on a paper and pulp production unit as a case study. The underlying goal of each policy is to curb the extraction of raw timber and the consequent environmental detrimental effects, such as deforestation, by pushing manufacturers to employ environmentally friendly production technologies. In this study, 90 percent of recycled paper production is deemed an alternative to conventional production. Shifting toward this alternative not only leads to lower levels of raw timber extraction but also has other environmental benefits, such as lower levels of GHG emissions and energy consumption. Figures 10, 11, 12 and 13 illustrate the effects of imposing the above-mentioned policies on each cluster of results.

In this study, customer demand is influenced by the environmentally friendly awareness of customers. The premise posits that an increase in the production of environmentally friendly products by manufacturers directly corresponds to an expansion in their customer base, subsequently leading to elevated total production outputs. The graphical representation, depicted in Figure A, delineates the total production outcomes stemming from three distinct policies, each aligned with three representative clusters. This visualization elucidates the impact of environmental policies on total production, specifically through the implementation of punitive measures or incentives on land exploitation practices. Notably, the analysis reveals that the mixed and persuasive policy frameworks yield a more favourable average total production compared to the punitive approach. This indicates that these policies lead to a higher allocation of EFU (Environmentally Friendly Unit) utilization relative to MMU (Main Manufacturing Unit). Under the punitive policy, manufacturers appear less inclined to adopt EFUs. As a result, demand—and consequently, production—tends to decrease. In contrast, under the mixed and persuasive policies, manufacturers are encouraged to increase production rates to meet the higher demand stimulated by these supportive policy environments.

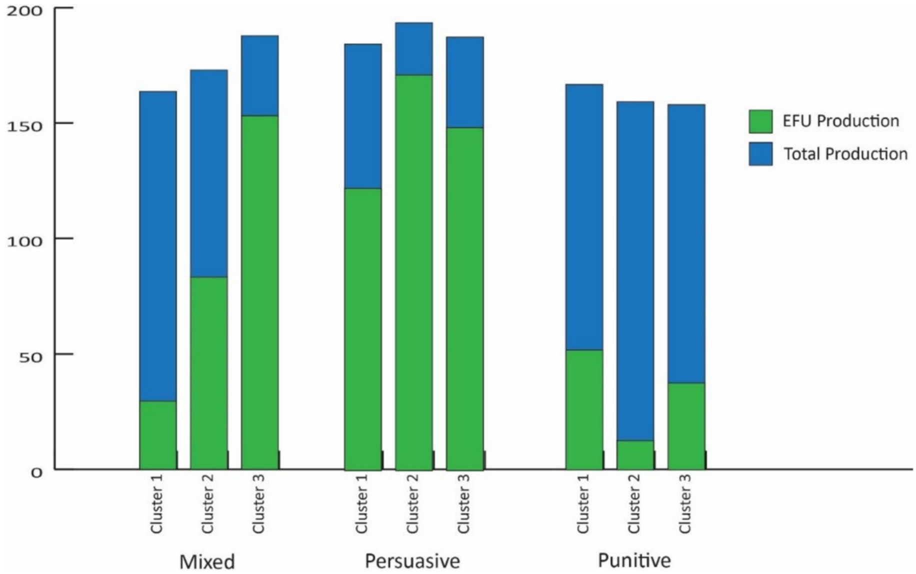

Fig. 11 EFU share of total production

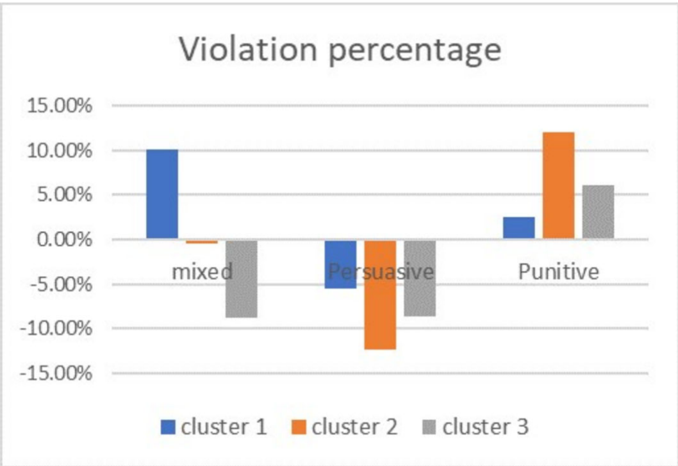

Fig. 12 Violation

Figure 11 shows the share of EFU of total production. It signifies the effect of new environmental policies on manufacturers' inclination to sustainable technology for paper and pulp products. EFU utilization varies widely among adopted policies. The most varied results among clusters belonged to the mixed policy. This is especially beneficial from the manufacturers' point of view, as they can choose the best option from a wide range of optimum results. Moreover, the share of EFU was at its highest under the persuasive policy, while the lowest amounts occurred under the punitive laws. According to Fig. 11, a high share of EFU in the Persuasive policy led to fewer land violations. As EFU benefit from a lower

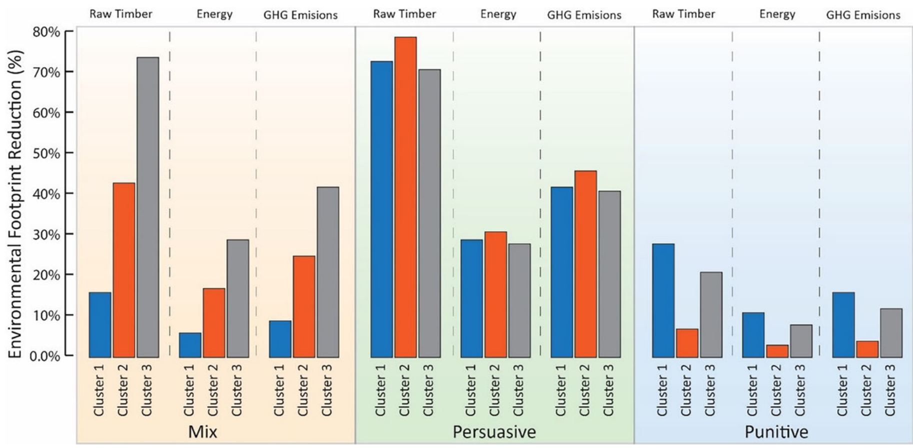

Fig. 13 Environmental Footprint Reduction

land exploitation rate, more utilization of EFU results in more saved land. On the contrary, Punitive policies ended with the lowest share of EFU compared to others. It may imply that a punitive approach toward EFU adoption does not work properly.

The environmental repercussions of various policy approaches are visually presented in Fig. 13. It becomes apparent that persuasive policies exert the most substantial influence on conserving wood resources, curbing energy consumption, and mitigating carbon emissions. In this context, the mixed policies demonstrate a remarkable degree of adaptability across their clusters, showing versatility in their environmental performance. However, under punitive policies, due to the lower utilization of environmentally friendly units, manufacturers not only experience reduced total production but also achieve the lowest percentage of environmental footprint reduction in terms of raw timber usage, energy consumption, and greenhouse gas emissions. It is noteworthy that punitive policies leave the most significant ecological footprint among the three approaches.

Viewed through the lens of the three pillars of environmental sustainability, persuasive policies appear to be particularly effective in capturing manufacturers' attention and driving their adoption of environmentally friendly technologies. Simultaneously, this policy garners increased consumer interest within the pulp and paper market by incentivizing the production of greener manufacturing products. This dual-sided approach aligns well with the overarching goal of enhancing environmental sustainability within the industry. Some limitations apply to our research because of complexities and challenges within manufacturing systems, highlighting the necessity of considering safety standards, uncertainties in data, and comprehensive environmental impact assessments for a more robust academic approach.

First, regulatory constraints can significantly impact research in manufacturing systems. Lack of consideration for safety standards and industry-specific regulations might lead to oversights into the proposed models or methodologies. Disregarding safety standards can affect the reliability and applicability of manufacturing systems (Signoret & Leroy, 2021). Second, uncertainties in data related to failure rates, production rates, and other variables can significantly impact the accuracy and reliability of manufacturing system models. Chen et al. (2004) addressed the challenges in data availability and highlighted the importance of considering uncertainties in manufacturing system modelling. Finally, estimating the environmental impact of manufacturing without incorporating the entire lifecycle, including logistics, distribution, and disposal, can lead to an incomplete assessment. Comprehensive models are imperative in assessing manufacturing systems' environmental impacts across their entire lifecycle, encompassing raw material extraction, production, distribution, and disposal phases (Cabeza et al., 2014; Valdez-Vazquez et al., 2024).

Future research may apply the developed environmental hedging policy and simulation-based optimization technique to other energy-intensive industries. By broadening the application of the control policy, we can assess its adaptability and effectiveness in diverse manufacturing settings, gaining insights into its potential impact on environmental conservation and operational efficiency beyond the paper and pulp industry. Additionally, integrating maintenance and quality control aspects into the manufacturing system represents a promising avenue for future exploration. This extension would involve considering the dynamic interactions between maintenance protocols, product quality control, and environmental performance within the production processes. Understanding how these elements intersect and influence one another can provide a more holistic approach to optimizing manufacturing operations while maintaining environmental responsibility. Furthermore, exploring the concept of shared facilities introduces another dimension to our research agenda. Investigating how shared facilities impact the implementation of environmental policies and the optimization of production planning adds complexity to our understanding. This direction could involve analyzing collaborative manufacturing spaces, where multiple entities share resources, and assessing the implications for environmental conservation and operational efficiency.

8 Conclusion

Our research has undertaken a comprehensive examination of the influence of land conservation policies on production planning, specifically within the paper and pulp industry. By grounding the Environmental Hedging Point Policy (EHPP) in optimal control theory, we offer a robust framework that addresses the complex interplay of operational uncertainties and sustainability objectives in manufacturing systems. The formulation of an innovative environmental control policy, integrated with a simulation-based optimization technique utilizing a multi-objective particle swarm algorithm, has provided valuable insights into the effectiveness of mixed, persuasive, and punitive policies in promoting sustainable production practices.

Findings from the simulation and clustering analyses revealed that persuasive and mixed policies significantly outperformed punitive approaches in encouraging the use of environmentally friendly units, reducing land violations, and minimizing environmental footprints. Moreover, persuasive policies were most effective in increasing customer satisfaction and total production due to their alignment with eco-conscious consumer behaviour. Mixed policies offered manufacturers a broader solution space, enhancing operational flexibility, while punitive policies resulted in the least favourable outcomes across environmental and production-related metrics.

From a managerial perspective, our findings offer several actionable insights:

Policy Design: Managers should prioritize persuasive and mixed policy instruments to align operational practices with sustainability goals and customer expectations.
Operational Planning: Integrating EHPP with simulation-based optimization provides a decision-support framework for dynamically adjusting production rates, maintenance schedules, and inventory policies under uncertainty (do Amaral et al., 2022; Pineda et al., 2025).

Strategic Investment: Firms may leverage mixed policy approaches to maintain flexibility while achieving environmental objectives, allowing better allocation of resources across production lines and facilities.
Stakeholder Engagement: Aligning policies with consumer and regulatory expectations enhances adoption and compliance, thereby reducing environmental violations and promoting sustainable brand reputation.

As we look to the future, expanding the application of our control policy to other energy-intensive industries presents an opportunity to assess its adaptability and impact in diverse manufacturing contexts. Additionally, the integration of maintenance and quality control considerations promises a more holistic understanding of the dynamic interactions within manufacturing systems. Exploring shared facilities introduces a new dimension, shedding light on collaborative manufacturing spaces' implications for environmental conservation and operational efficiency.

These future directions collectively contribute to a more nuanced understanding of sustainable production planning, offering policymakers and manufacturers a versatile, data-driven framework applicable across various industrial landscapes. As we navigate the complex intersection of environmental responsibility and operational optimization, these findings pave the way for informed decision-making and strategic planning in pursuit of a greener and more efficient manufacturing future (Singh et al., 2021; Vieira et al., 2022; Zhu et al., 2021).

Declarations

Conflict of interest The authors confirm that they do not have any connections or participation in any organization or entity with financial interests (including membership, employment, consulting, stock ownership, or other equity interests) or non-financial interests (such as personal or professional relationships, affiliations, knowledge, or beliefs) related to the subject matter or materials discussed in this manuscript.

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