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Government Influence on AI investment and energy leakage mitigation technology in SCM: Duality modeling and scenario analysis

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ABSTRACT

This study investigates the economic dynamics within a supply chain management (SCM) involving manufacturers, agents, and retailers. It focuses on strategies to mitigate energy leakage (EL) through the integration of artificial intelligence (AI) technology and the imposition of EL taxes. A simulation-based optimization model is used to find different optimal scenarios. Through a series of optimized scenarios, the research examines the impacts of these interventions on SCM efficiency, profitability, and sustainability. The findings reveal that while the introduction of EL taxes initially increases operational costs, it effectively causes an improvement in energy efficiency. At the same time, significant investments in AI technology reduce energy wastage, leading to enhanced profitability and sustainability across the SCM. The research concludes with recommendations for SCM entities to actively invest in AI technology and for governments to impose taxes as a penalty. Additionally, it suggests further exploration of collaborative investments and emerging technologies to enhance SCM sustainability.

1. Introduction and related research

Supply Chain Management (SCM) involves the management of materials, information, and finances as they move from supplier to manufacturer to wholesaler to retailer to consumer [17,24,44]. Effective SCM aims to enhance efficiency, reduce costs, and ensure timely delivery of goods and services. The integration of advanced technologies such as artificial intelligence (AI) and block-chain has significantly improved transparency, decision-making, and operational resilience in SCM. However, many SCM face challenges such as inefficiencies, increased operational costs, and environmental impact due to energy leakage (EL). Despite extensive research on SCM practices and technological integration, there is a significant gap in addressing EL specifically. Choudhury et al. [9] explore SCM resilience during epidemics, advocating for flexible SCM and digital integration. Our study, in contrast, investigates AI's role in mitigating EL, providing novel insights into technology adoption and governmental influences on sustainability practices within SCM. Sun et al. [38] discuss the societal impacts of technology-driven logistics and SCM, emphasizing how technological advancements can lead to significant improvements in societal outcomes. This research aligns by emphasizing technological advancements in SCM but specifically focuses on AI's role in EL mitigation, contributing to broader sustainability goals and operational efficiency improvements. Risso et al. [30] discuss blockchain technology's potential in SCM, emphasizing its role in enhancing SCM transparency, security, and traceability. In this way, this research aims to fill this gap by focusing on the development of AI-driven strategies to mitigate EL, thereby enhancing both the efficiency and sustainability of SCM. Lee et al. [4] provided an integrated framework showing that the joint deployment of AI, subsidies, and green finance improves CO_2 mitigation outcomes. This is echoed in earlier work that linked green bonds and subsidies to optimal green technology investment in emission-intensive industries [15]. In line with these findings, Lee and Hussain [14] analyzed the socioeconomic effects of energy consumption and found green financing to be a critical enabler in guiding sustainable consumption behaviors and investments.

Abbreviations: AI, Artificial intelligence; EL, Energy leakage; ELRT, EL resistance technology; SCM, Supply chain management.

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The integration of AI in SCM is revolutionizing the industry by optimizing processes, enhancing decision-making, and improving efficiency. Hussain et al. [1] explored how governmental support impacts AI investment and energy leakage mitigation in supply chain management (SCM), using a duality-based modeling approach. Hussain et al. [2] examined local government decision-making in China, developing a game-theoretic model to address haze management through AI-driven tools. AI-driven solutions can predict demand, manage inventory, and automate routine tasks, leading to significant cost savings and reduced waste [10,32]. The use of AI in SCM also supports sustainability goals by identifying and mitigating inefficiencies, such as EL, thereby promoting more eco-friendly practices. Our study extends this by applying AI specifically to mitigate EL, employing duality modeling and scenario analysis to optimize AI investments amidst regulatory complexities. Pournader et al. [28] provide a comprehensive review of AI applications across SCM, illustrating its potential to enhance operational efficiency, accuracy, and responsiveness. Samadhiya et al. [31] explore AI's impact on disruption management in dynamic supply chains, highlighting its role in improving SCMresilience and responsiveness. They did not address EL mitigation through AI-driven decision-making models which is the main goal of our study. Senapati et al. [35] utilize AI for group decision-making in healthcare supply chains, showcasing its application in optimizing logistics and operational efficiency. They failed to optimize EL mitigation strategies across diverse industrial sectors. Toorajipour et al. [40] provide a systematic review of AI's broad applications in SCM, highlighting its diverse benefits across various sectors. However, the specific application of AI to mitigate EL within SCM remains underexplored. This study addresses this critical need by leveraging AI to target energy inefficiencies, providing a novel approach to resource optimization and environmental sustainability. In broader models, research by Lee et al. [8,9], and [16] emphasized renewable energy integration, carbon-neutrality games, and risk-based purchasing strategies. These approaches prioritize synergy between environmental objectives and firm-level profitability.

The interplay between SCM and tax policies is crucial for optimizing global operations and achieving cost efficiency. Strategic tax planning within SCM can minimize tax liabilities and ensure compliance with diverse international tax regulations. Deng et al. [11] explore the impact of tax policies and organizational structures on global SCM designs, stressing the necessity of strategic planning in managing complex international tax environments. Our study complements this by examining how tax policies influence AI investment strategies for EL mitigation, providing practical guidance for navigating international tax environments while enhancing SCM sustainability. In the domain of transnational SCM, He et al. [15] examine financing strategies under varying tax systems, highlighting how tax differentials influence financing decisions and operational efficiencies. They failed to explore how financial decisions can support sustainable SCM practices through technological advancements. Mezatio et al. [26] develop a mathematical model integrating carbon tax considerations and horizon planning to optimize supply chains in the textile industry, illustrating the role of strategic planning and regulatory adherence in achieving sustainability goals. Our research complements this by integrating AI for EL mitigation, showcasing innovative approaches to enhance environmental sustainability in SCM operations. Zhou et al. [47] review SCM under carbon tax frameworks, stressing the significance of regulatory compliance and strategic planning in achieving sustainability goals. They did not consider the integration of AI technologies for EL mitigation. Babagolzadeh et al. [7] address challenges in cold SCM under demand uncertainty and carbon tax regulations. In contrast, our research narrows the focus to AI-driven strategies for EL mitigation in SCM, offering a targeted approach that complements broader sustainability efforts in temperature-sensitive logistics.

Managing EL within SCM is essential for improving efficiency and sustainability. Implementing AI-driven solutions can effectively identify and mitigate EL by optimizing energy use, monitoring real-time data, and automating corrective actions. By addressing EL, SCM practices can enhance operational efficiency, reduce costs, and contribute to broader sustainability goals, ensuring a more eco-friendly and resilient supply chain. Li et al. [22] study the environmental impacts of leakage in compressed air energy storage systems, emphasizing the importance of effective leakage management for sustainability and efficiency. Our study aligns by addressing EL, but we extend this by proposing AI-based strategies for mitigation within broader SCM contexts, emphasizing operational efficiency and sustainability. Qiao et al. [29] address EL in communication systems, proposing techniques to improve data transmission efficiency and accuracy. Our research expands this scope to SCM, proposing AI-driven strategies for leakage mitigation that enhance data transmission efficiency and accuracy within supply chains. While Ávila et al. [6] focus on sustainability in urban water management through green energy systems for leakage management, our study differs by specifically integrating AI technologies to mitigate EL across diverse SCM contexts. Shao et al. [36] optimize energy efficiency and leakage in water distribution systems, underscoring the importance of efficient water treatment and distribution strategies. However, there is a lack of focused research on AI-driven solutions for EL across diverse SCM contexts. This study is essential as it proposes innovative AI-based strategies for EL mitigation, enhancing operational efficiency, and contributing to broader sustainability goals within supply chains.

Our research introduces several novel contributions to the field of SCM with a focused emphasis on EL mitigation using AI and game theory. While existing literature broadly explores AI applications across SCM, our study stands out by specifically targeting the critical issue of EL within SCM. This focused approach addresses a significant gap in sustainability and operational efficiency, highlighting the potential of AI-driven solutions to optimize resource utilization and minimize environmental impact. Considering methodology, our research uses duality modeling and scenario analysis techniques which enable the development of robust strategies for AI investment in SCM, specifically aimed at mitigating EL. By employing game theory principles, we enhance our analytical framework to account for strategic interactions among stakeholders in SCM networks. This integrated approach not only improves decision-making precision but also allows us to simulate various competitive and cooperative scenarios, offering insights into optimal investment strategies under different regulatory and market conditions. We systematically examine how governmental influences shape AI investment decisions and regulatory compliance strategies for EL mitigation. By providing actionable insights for policymakers and SCM practitioners, our study contributes to navigating complex regulatory landscapes and promoting sustainable practices within global SCM. Our study advances the field by proposing innovative AI-driven solutions tailored to address EL challenges in SCM. These solutions not only enhance operational efficiency and resilience but also align with broader sustainability objectives, making significant strides towards achieving environmentally responsible SCM practices on a global scale.

Considering the contribution of the study, our study significantly impacts social aspects by enhancing the resilience and efficiency of SCM practices. By integrating AI-driven strategies for EL mitigation, our research promotes safer and more reliable supply chains. This contributes to societal well-being by ensuring timely delivery of goods and services, thereby supporting economic stability and consumer satisfaction. Economically, our research provides substantial benefits by optimizing operational costs within SCM through AI technologies. By mitigating EL, organizations can reduce unnecessary expenditures associated with inefficient energy use. This improves profitability and competitiveness in global markets, fostering economic growth and sustainability. From an environmental perspective, our study makes significant strides towards sustainability within SCM. By effectively managing EL through AI-driven solutions, we minimize the environmental impact associated with resource wastage and carbon emissions. This supports global efforts to mitigate climate change and promotes eco-friendly practices across supply chains. In terms of governance, our research offers insights into regulatory implications and policy frameworks for integrating AI in SCM. By examining how governmental influences shape AI investment strategies and regulatory compliance for EL mitigation, we contribute to creating a conducive regulatory environment. This helps in navigating complex global SCM landscapes and promoting responsible corporate governance practices. By addressing these dimensions comprehensively, our study not only advances the academic understanding of SCM but also provides actionable insights for policymakers, industry practitioners, and stakeholders. It paves the way for sustainable and inclusive growth in SCM practices, aligning economic prosperity with environmental stewardship and social responsibility on a global scale. This study has different objectives which are below;

- Firstly, this study investigates the practices and identifies gaps in optimal AI based EL tax on the stakeholders of SCM.
- Secondly, optimal AI based EL resistance technology (ELRT) investment within the stakeholders of SCM.
- Thirdly, it studied the optimal pricing strategies in SCM to maximize the profit of stakeholders of SCM.

The remainder of this paper is organized as follows: Section 2 presents the research analysis, detailing the methodology and data used for this study. Section 3 discusses the results and provides an in-depth interpretation of the findings. Finally, Section 4 offers the conclusions and recommendations based on the research outcomes.

2. Research analysis

In the optimization process, we used a simulation-based optimization technique considering the experiment design method. In terms of method, we improved the earlier studies [20,21] and considered it in the SCM portfolio.

2.1. Case study and modeling

2.1.1. Problem setting

Guangdong Province, as a focal point for this SCM case study, is of paramount importance due to its pivotal role in China's economic landscape. Anchored by global cities such as Guangzhou and Shenzhen—renowned hubs for technology, manufacturing, and logistics—Guangdong boasts an advanced economic infrastructure. It has a track record of early adoption of cutting-edge technologies, particularly in AI. This provides a unique and fertile environment to explore the transformative potential of AI in modern SCM operations.

AI-driven applications, including machine learning algorithms for inventory optimization, and autonomous systems for logistics management, have already demonstrated significant impacts in SCM. AI-powered robots capable of interacting with humans and performing complex tasks offers an additional dimension to the technological evolution of SCM in Guangdong. These humanoid robots can handle material handling, order fulfillment, and last-mile delivery, further automating processes and enhancing responsiveness in SCM networks. Guangdong's strategic location adjacent to Hong Kong further elevates its status as a critical global trade and logistics hub. This amplifies the influence of innovative AI-driven SCM strategies not only within the province but also in shaping global SCM practices. The research aims not only to optimize operational performance but also to promote sustainable, environmentally responsible practices, establishing a replicable model for other dynamic economic regions worldwide.

2.1.2. Mathematical modelling

In developing our mathematical model for SCM, Table 1 outlines essential parameters such as production costs, transportation costs, inventory levels, and demands followed by [20,21]. Additionally, we integrate parameters for EL resistance investment and tax considerations into the model. The mathematical model (Eq. (1)) incorporates these parameters alongside constraints (Eqs. (2)-(5)) to optimize decision variables while balancing efficiency gains with regulatory and economic constraints. This systematic approach aims to enhance SCM sustainability while ensuring cost-effective operations in dynamic business environments.

Table 1
Notations, parameters, and decision variables.

Parameters	Description
ρ_m	Product Price (Manufacturer)
q	Market Production Capacity
μ_c	Carbon Price
C_m	Unit Production Cost (Manufacturer)
ε	Emission Allowance (Production)
ρ_a	Product Price (Agent)
ϵ	Price Elasticity of Production
c_a	Supply Cost (Agent)
ρ_r	Product Price (Retailer)
d_r	Retail Demand
c_r	Purchase Cost (Retailer)
a	Demand sensitivity
t_m	Tax on EL of manufactures
t_a	Tax on EL of agents
t_r	Tax on EL on retailers
i_m	Investment on ELRT of manufactures
i_a	Investment on ELRT of agents
i_r	Investment on ELRT of retailers
φ_m	Profit of manufacturer
φ_a	Profit of agent
φ_r	Profit of retailer
Decision variables	
l_{tm}	Tax on EL of manufactures (1 for implement, 0 for not implement)
l_{ta}	Tax on EL of agents (1 for implement, 0 for not implement)
l_{tr}	Tax on EL on retailers (1 for implement, 0 for not implement)
l_{im}	Investment on ELRT of manufactures (1 for implement, 0 for not implement)
l_{ia}	Investment on ELRT of agents (1 for implement, 0 for not implement)
l_{ir}	Investment on ELRT of retailers (1 for implement, 0 for not implement)

(1) **Production and transportation costs are fixed**: These costs are assumed to be stable over the modeling period, reflecting standardized pricing agreements or long-term contracts.
(2) **No technological barriers among stakeholders**: All participants within the SCM possess the technological capabilities to fully integrate AI solutions, including humanoid robotics, ensuring seamless interoperability.
(3) **Homogeneous products**: All products in the model are considered identical in terms of quality and specifications, simplifying inventory and demand forecasting.
(4) **No uncertainty in the SCM**: The model assumes deterministic conditions without disruptions (e.g., geopolitical risks, natural disasters, or unexpected demand surges).
(5) **Stable economic environment**: Macroeconomic factors such as inflation, interest rates, and exchange rates remain constant during the analysis period.
(6) **AI Integration including humanoid robotics**: The model assumes the presence and operational readiness of AI technologies such as machine learning algorithms for forecasting, optimization engines for decision-making, and humanoid robots for physical tasks (e.g., material handling, order picking, assembly assistance, and logistics operations). This assumption enables the model to reflect a forward-looking SCM environment that leverages the full potential of AI for enhanced efficiency and sustainability.

Eqs. (1), (2), and (3) depicted the profit functions of manufacturers, agents, and retailers in the SCM system, respectively, incorporating variables related to tax implications and AI technology investments for EL mitigation. These equations quantify the financial outcomes based on market dynamics, operational efficiencies, and regulatory compliance concerning energy efficiency initiatives. As it is focused in the duopoly game, the model is description of duopoly consideration in the SCM. Constraints (4), (5), and (6) encapsulate operational boundaries within SCM, ensuring that investments in AI technology adhere to tax regulations and enhance EL resistance without compromising profitability.

Maximize

$$\varphi_m = \rho_m q - c_m q + \mu_c \varepsilon - t_m l_{tm} + i_m l_{im} \tag{1}$$

$$\varphi_a = \rho_a d\varepsilon - c_a q - t_a l_{ta} + i_a l_{ia} \tag{2}$$

$$\varphi_r = \rho_r d_r - c_r d_r - t_r l_{tr} + i_r l_{ir} \tag{3}$$

Subject to:

$$d_r = a(\rho_m - \rho_r) \tag{4}$$

$$\rho_m, \rho_a, \rho_r \geq 0 \tag{5}$$

$$l_{tm}, \ l_{im}, \ l_{ta}, \ l_{ia}, l_{tr}, \ l_{ir} \in \ \{0, 1\} \tag{6}$$

2.2. Simulation in SCM

The optimization process in our study utilizes simulation modeling with Arena software, depicted in Fig. 1. Initially, decision variables (l_{tm}, l_{im}) are initialized for each manufacturer, aiming to maximize. The optimization iterates until all manufacturers' decisions stabilize, as illustrated in Fig. 1. Subsequently, the process where each agent determines optimal (l_{ta}, l_{ia}) to maximize. This iterative approach continues, focusing on retailers to maximize (l_{tr}, l_{ir}), like earlier stages. Throughout this system, decision variables are iteratively adjusted until stability is achieved. The optimal decisions derived from these iterations are then used to conduct multiple experiments. If the desired outcomes are not met, the experiments are rerun (Fig. 2). A sensitivity-based duopoly model by Hussain et al. [3] revealed how AI can optimize emission reduction in SCM when paired with subsidy incentives. Stackelberg and evolutionary game models were used in other studies to simulate the behavior of firms and governments under cap-and-trade schemes and regional collaboration frameworks [5,6,18]. This structured approach allows for a comprehensive exploration of nine scenarios within our duopoly model (Table 2), ensuring robust analysis and strategic decision-making in SCM optimization.

3. Results and discussions

3.1. Optimized scenario one

The findings of a scenario where the SCM comprising a manufacturer, an agent, and a retailer operates under a different financial structure and EL mitigation strategy (Fig. 3). The prices of the products at each level are optimized, with the ρ_m at 3 RMB per unit, ρ_a at 4 RMB per unit, and ρ_r at 5.5 RMB per unit. This pricing structure supports significant profits, though fluctuation in the optimal structure of product price. The φ_m is 9 million RMB, the φ_a is 9.3 million RMB, and the $\varphi_r$is 9.5 million RMB, indicating a well-functioning SCM with efficient cost management. The decision variables, with the t_m and t_a both get to 1, indicating active measures taken by the manufacturer to address energy efficiency. These decisions initially fluctuate but reach an optimal balance at the 16th simulation experiment. This fluctuation reflects the dynamic nature of optimizing energy efficiency strategies within the operational and financial constraints of the SCM.The t_m for the manufacturer is 4 RMB per one hundred units, reflecting a regulatory effort to reduce energy wastage. To control this, the manufacturer has invested 3 million RMB as$i_m$specifically for EL mitigation. And the decisions about l_{tm} and l_{im} are one indicating the implementation of both strategies. This investment in ELRT demonstrates a strategic move towards enhancing operational efficiency and adopting advanced technologies to improve sustainable SCM.

From a practical point of view, these results highlight the importance of regulatory compliance and technological investment in maintaining profitability while promoting sustainability. The manufacturer's investment in ELRT indicates an active approach to reducing operational inefficiencies. This strategic investment not only helps minimize the tax burden due to EL but also enhances the overall efficiency of the manufacturing process. By investing in AI technology, the manufacturer is likely to experience reduced energy wastage, leading to lower operational costs and increased long-term profitability. Furthermore, this investment can lead to a competitive advantage by positioning the manufacturer as a leader in sustainable practices within the industry. For the SCM, the reduction in EL and the subsequent cost savings can result in lower prices for consumers, potentially increasing demand, and market share. By optimizing these decisions through simulations, the SCM can achieve an optimal balance between profitability and environmental responsibility, ensuring long-term sustainability and competitive advantage in the market.

The consideration of AI technology for EL mitigation in the SCM scenario aligns with [1] findings, demonstrating the practical application of AI in enhancing operational efficiency and reducing energy-related costs. Similarly, this study confirms the findings of Fu et al. [12], who emphasized the crucial role of regulatory compliance in promoting low-carbon practices. Moreover, this study aligns with the findings of [13], who introduced an AI framework for predicting operational energy consumption in office buildings, illustrating the potential of AI to optimize energy use and enhance efficiency. In line with these findings, Lee and Hussain [14] analyzed the socioeconomic effects of energy consumption and found green financing to be a critical enabler in guiding sustainable consumption behaviors and investments.

3.2. Optimized scenario two

Fig. 4 outlines the financial dynamics and energy-related decisions

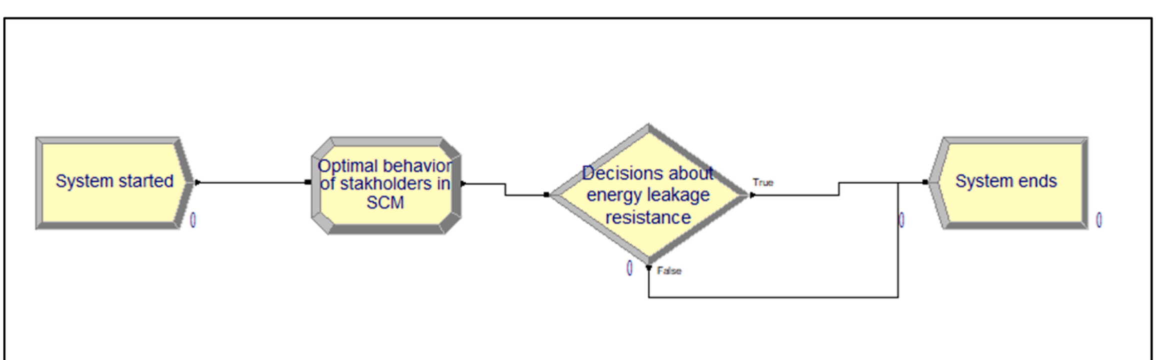

Fig. 1. Simulation model for SCM (Arena software).

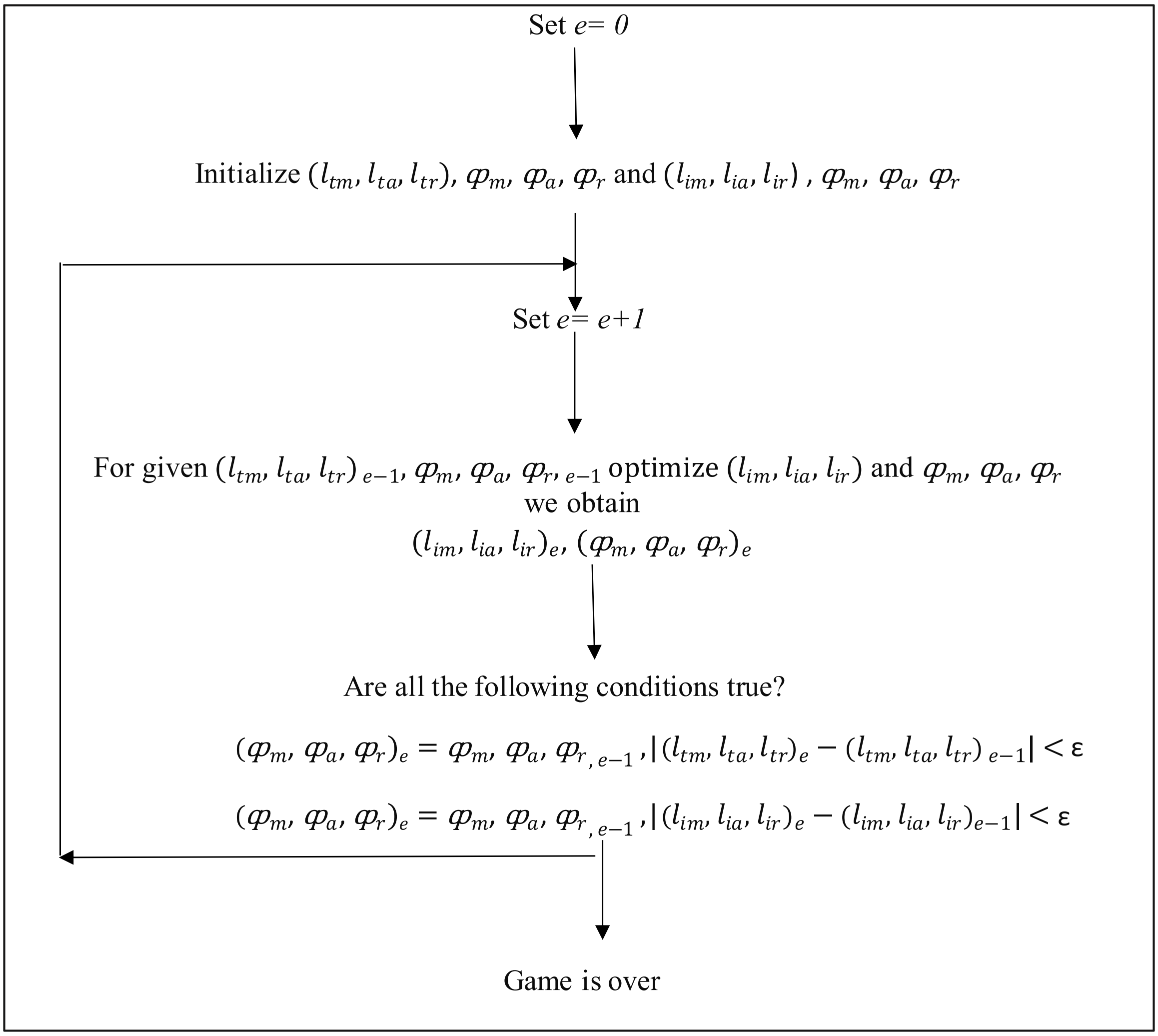

Fig. 2. Dual gaming of energy resistance.

Table 2
Duopoly payoff gaming matrix.

Government- Based strategy	Tax on EL of manufactures Tax on EL of manufactures	Tax on EL of agents Tax on EL of agents	Tax on EL on retailers Tax on EL on retailers
Stakeholders-Based strategy			
Investment on EL resistance of manufactures	1st quadrant $\|_{l_{tm}=1,\ l_{ta}=0,\ l_{tr}=0}$ $\|_{l_{im}=1,\ l_{ia}=0,\ l_{ir}=0}$	2nd quadrant $\|_{l_{tm}=1,\ l_{ta}=0,\ l_{tr}=0}$ $\|_{l_{im}=0,\ l_{ia}=1,\ l_{ir}=0}$	3rd quadrant $\|_{l_{tm}=1,\ l_{ta}=0,\ l_{tr}=0}$ $\|_{l_{im}=0, l_{ia}=0,\ l_{ir}=1}$
Investment on EL resistance of agents	4th quadrant $\|_{l_{tm}=0,\ l_{ta}=1,\ l_{tr}=0}$ $\|_{l_{im}=1,\ l_{ia}=0,\ l_{ir}=0}$	5th quadrant $\|_{l_{tm}=0,\ l_{ta}=1, l_{tr}=0}$ $\|_{l_{im}=0, l_{ia}=1, l_{ir}=0}$	6th quadrant $\|_{l_{tm}=0, l_{ta}=1, l_{tr}=0}$ $\|_{l_{im}=0,\ l_{ia}=0,\ l_{ir}=1}$
Investment on EL resistance of retailers	7th quadrant $\|_{l_{tm}=0,\ l_{ta}=0,\ l_{tr}=1}$ $\|_{l_{im}=1,\ l_{ia}=0,\ l_{ir}=0}$	8th quadrant $\|_{l_{tm}=0, l_{ta}=0,\ l_{tr}=1}$ $\|_{l_{im}=0,\ l_{ia}=1,\ l_{ir}=0}$	9th quadrant $\|_{l_{tm}=0,\ l_{ta}=0,\ l_{tr}=1}$ $\|_{l_{im}=0,\ l_{ia}=0,\ l_{ir}=1}$

within a SCM consisting of a manufacturer, an agent, and a retailer. Analyzing the prices, profits, and investment in ELRT reveals several important insights. The prices at various levels of the SCM indicate a typical markup strategy: the ρ_m at 4 RMB per unit, the ρ_a at 6 RMB per unit, and the ρ_r at 7 RMB per unit. This markup structure ensures that each intermediary in the SCM adds value and covers their operational costs while securing a profit. The profits are substantial at each level, with the manufacturer earning φ_m10 million RMB, the agent φ_a11 million RMB, and the retailer φ_r12 million RMB. This distribution suggests a well-functioning SCM with adequate demand to sustain such high profits.

EL is a critical concern, addressed differently by each SCM entity. The manufacturer faces a tax of t_m5 RMB per one hundred units for EL, indicating regulatory pressure to reduce energy wastage. To mitigate EL, the agent has invested t_a 3 million RMB in AI technology, showing a progressive approach to adopting advanced technologies to enhance efficiency. This investment aims to optimize energy usage and reduce the overall cost associated with energy waste, potentially leading to higher profitability in the long run.

The decision variables, with the l_{tm} and the l_{ta}, both get to one, indicating active measures taken by the manufacturer and agent, respectively. These decisions fluctuate but find an optimal balance in the 15th simulation experiment. This fluctuation and eventual optimization can be interpreted through the dynamic environment where numerous factors such as cost, efficiency, and technological adaptation play significant roles.

These results elaborate on the importance of strategic investments in technology and compliance with environmental regulations in sustaining profitability and operational efficiency. The manufacturer's compliance with EL taxes and the agent's investment in AI technology highlight a balanced approach toward regulatory adherence and innovation. This approach not only ensures immediate profitability but also positions the SCM for future sustainability by reducing energy wastage and improving operational efficiency. These findings support the

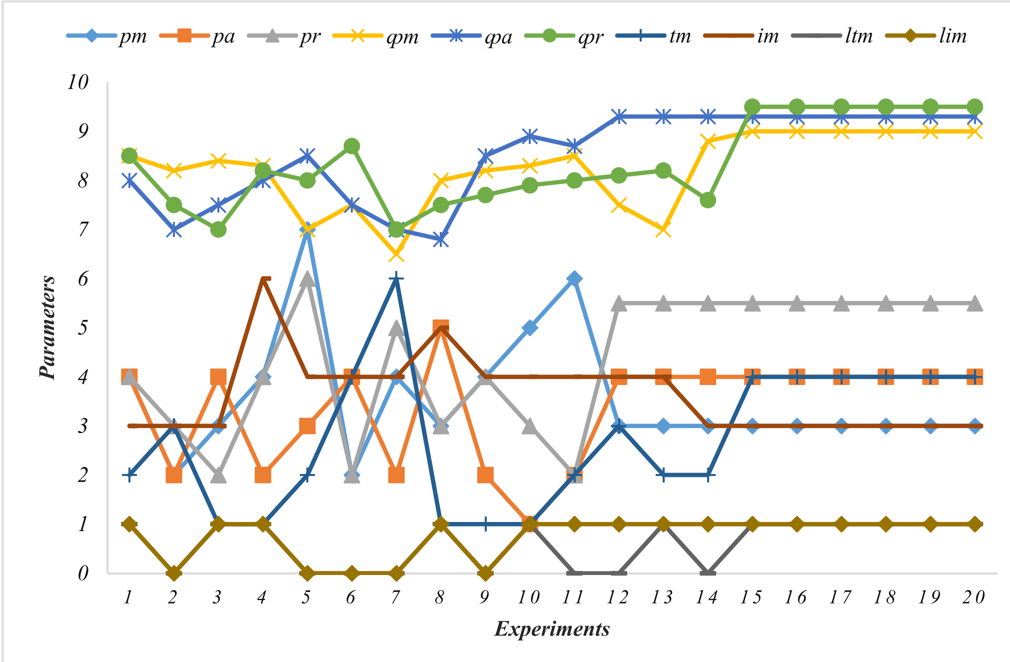

Fig. 3. Optimized scenario one.

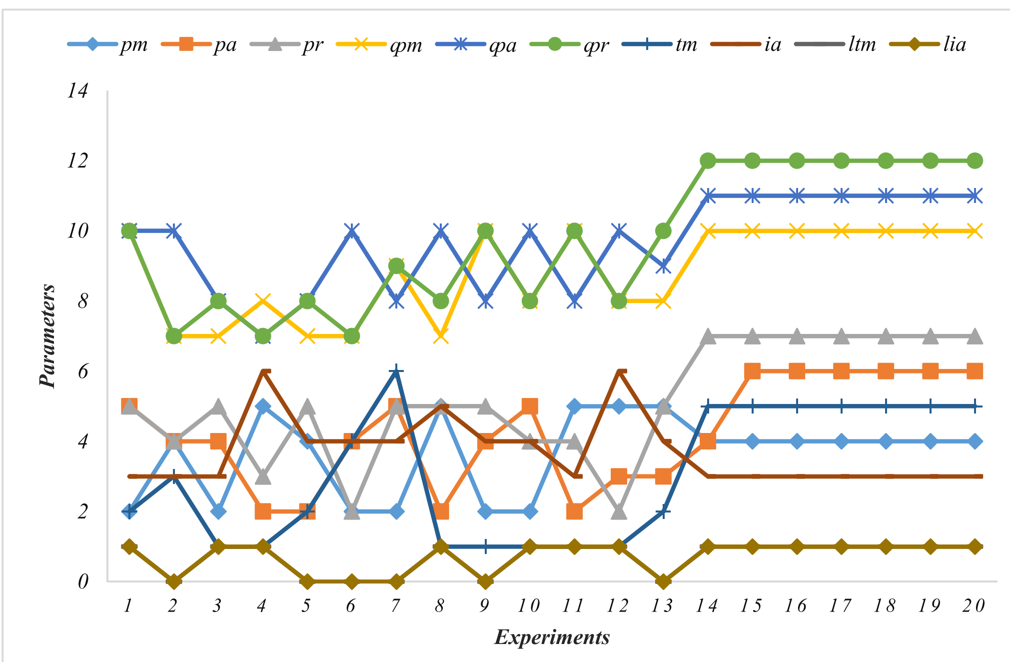

Fig. 4. Optimized scenario two.

findings of [14], who explored the decision-making problem for product outsourcing with flexible production under global SCM. The emphasis on strategic investments and regulatory compliance in this scenario aligns with their insights into flexible and adaptive decision-making to optimize SCM operations. Furthermore, the results align with the research by Huang and Zou [16], who discussed human behavior in computational settings, emphasizing the role of adaptive strategies and technological adoption in enhancing operational efficiency. Lastly, the scenario reflects the themes explored by [23] in their study on enterprise digital transformation and SCM, demonstrating how digital and AI-driven approaches can lead to significant improvements in efficiency and sustainability. By leveraging advanced technologies and adhering to regulatory requirements, the SCM not only ensures profitability but also positions itself for long-term success in a competitive and dynamic market environment.

3.3. *Optimized scenario three*

This scenario provides insights into the financial and operational dynamics of the SCM under specified pricing and profit structures, along with investments aimed at energy efficiency (Fig. 5). The prices across the SCM are set at 3 RMB per unit $\rho_m$for the manufacturer, 4 RMB per

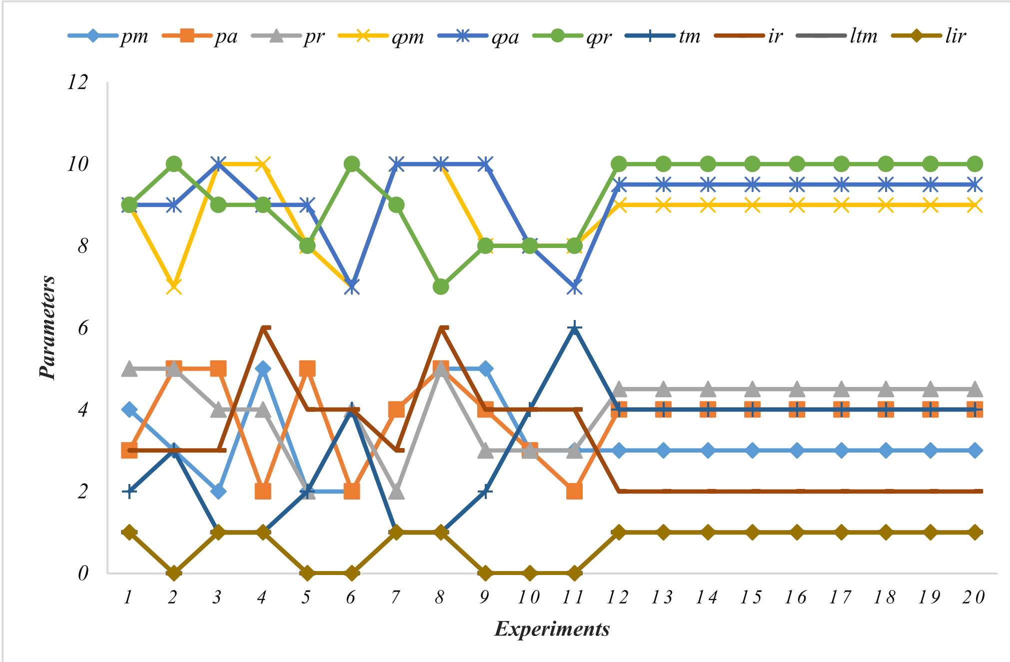

Fig. 5. Optimized scenario three.

unit $\rho_a$for the agent, and 4.5 RMB per unit $\rho_r$for the retailer. Despite low prices, the SCM maintains significant profitability, with the manufacturer earningφ_m 9 million RMB, the agent φ_a9.5 million RMB, and the retailer φ_r10 million RMB. This indicates a well-managed cost structure and efficient operations across the SCM. The manufacturer faces a t_m of 4 RMB per one hundred units due to EL, highlighting the regulatory emphasis on reducing environmental impact. In response, the retailer has invested i_r2 million RMB in AI technology for EL mitigation. This investment suggests a strategic effort by the retailer to enhance energy efficiency, which can lead to reduced operational costs and compliance with environmental standards.The decision variables, with the l_{tm} and the l_{ir} both are 1, indicate active measures by the manufacturer and retailer to address energy-related issues. These decisions initially fluctuate but find an optimal balance at the 15th simulation experiment. The fluctuation reflects the trial-and-error process of optimizing energy efficiency strategies within the operational and financial constraints of the SCM.

These findings are consistent to the findings of [25], who evaluated the impact of carbon tax policy on manufacturing and remanufacturing decisions in a closed-loop SCM. The results of this scenario align with the research by [27], who discussed the development of novel phase change materials with low leakage rates for new energy storage building applications, highlighting the importance of technological advancements in energy efficiency. Additionally, the scenario reflects the themes explored by [33] regarding the implementation of cognitive agent infrastructures for smart mobility and orchestrated systems for transport and mobility research. Practically, these results underscore the importance of collaborative efforts across the SCM to achieve sustainability and efficiency. The manufacturer's compliance with EL taxes and the retailer's investment in AI technology demonstrate a combined approach to addressing regulatory requirements and reducing operational inefficiencies. This strategy not only helps minimize the tax burden and energy wastage but also positions the SCM for enhanced long-term sustainability. By investing in AI technology, the retailer can reduce EL, leading to lower operational costs and increased profitability. This investment can also improve the retailer's market reputation by demonstrating a commitment to sustainability. For the SCM, the reduction in EL and associated costs can result in lower product prices, potentially increasing demand, and market share.

3.4. Optimized scenario four

Fig. 6 demonstrates how different factors and decisions impact the profits of manufacturers, agents, and retailers over a series of experiments. The X-axis represents these simulation experiments, and the Y-axis shows the optimal indicators. Initially, ρ_m, ρ_a, and ρ_r are 4 RMB, 5 RMB, and 6 RMB, respectively. The initial profits for each are φ_m10 million RMB for the manufacturer, 12 million RMB $\varphi_a$for the agent, and 13 million RMB $\varphi_r$for the retailer. The agent generates a t_a of 4 RMB per five hundred units due to EL, while the manufacturer invests i_m5 million RMB in AI technology to mitigate EL. These decisions l_{ta} and l_{im}(indicated as 1) are simulated over 12 experiments. The X-axis represents these simulation experiments, and the Y-axis shows the optimal indicators.

The results indicate that the decisions regarding the tax on the agent and the investment by the manufacturer cause fluctuations initially but lead to optimal outcomes by the 12th simulation. The initial fluctuations can be attributed to the adjustment period where the market and stakeholders respond to the new costs and investments. Over time, the manufacturer's investment in AI technology helps reduce EL, thereby increasing efficiency and reducing long-term costs. The tax on the agent causes penalty and better energy management practices. These decisions contribute to more stable and optimal profit levels across the SCM. This study aligns with the findings of [34], who explored the implementation of orchestrated systems for transport and mobility research. The adaptive strategies and technological investments highlighted in this scenario reflect the innovative approaches discussed in their research. Furthermore, the emphasis on energy management and efficiency in this scenario is consistent with the findings of [39], who incorporated gas pipeline leakage failure modes in risk evaluations of integrated energy systems. Both studies consider the importance of addressing energy inefficiencies and leveraging advanced technologies to enhance overall system performance. The dynamic adjustments and emotional responses of stakeholders to new costs and investments in this scenario also parallel the adaptive strategies and regulation of emotions discussed by [43]. This underscores the significance of continuous adaptation and

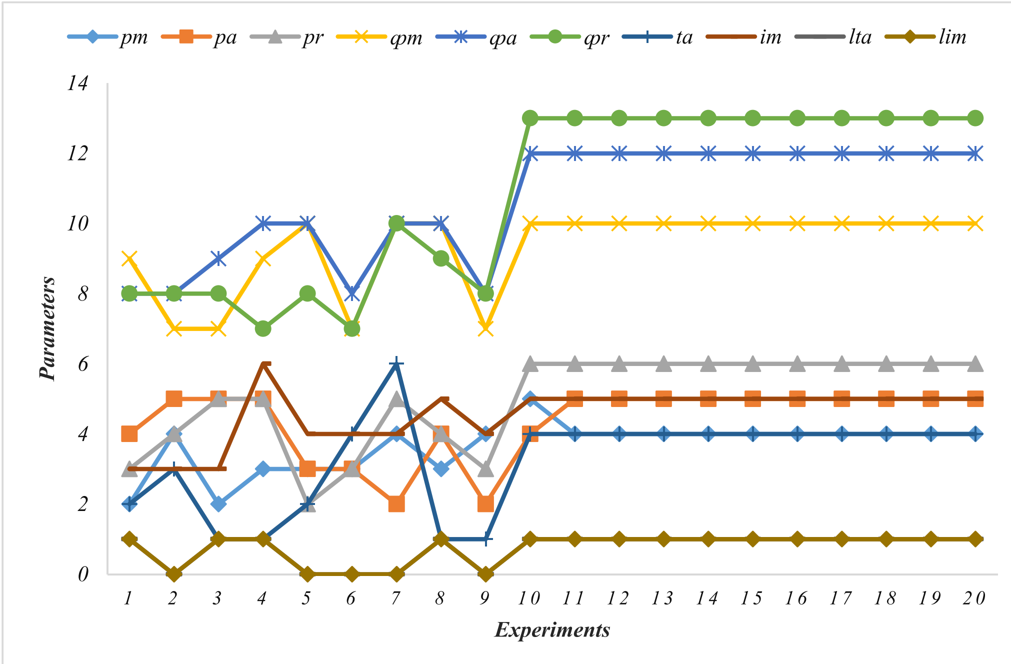

Fig. 6. Optimized scenario four.

strategic decision-making in achieving optimal outcomes. Finally, our findings highlight the importance of strategic investments and regulatory compliance in sustaining profitability and operational efficiency, aligning with broader trends in SCM and technological innovation.

3.5. Optimized scenario five

The simulation results of this scenario provide insights into the economic dynamics within the SCM involving manufacturers, agents, and retailers, focusing particularly on EL mitigation strategies. The product prices are set at ρ_m3 RMB per unit for the manufacturer, 4 RMB per unit $\rho_a$for the agent, and 5 RMB per unit ρ_r for the retailer. Initially, the profits are φ_m9 million RMB for the manufacturer, φ_a is 9.5 million RMB for the agent, and φ_r10 million RMB for the retailer. Two key decisions influence the simulation: t_a imposed on the agent at 4 RMB per five hundred units, and i_a a 5 million RMB investment by the agent in AI technology to mitigate EL. These decisions are implemented and assessed over nine simulation experiments, with the X-axis representing these experiments and the Y-axis indicating the optimal indicators (Fig. 7).

Initially, the imposition of the EL tax and the investment in AI technology caused fluctuations in the profits and optimal indicators.

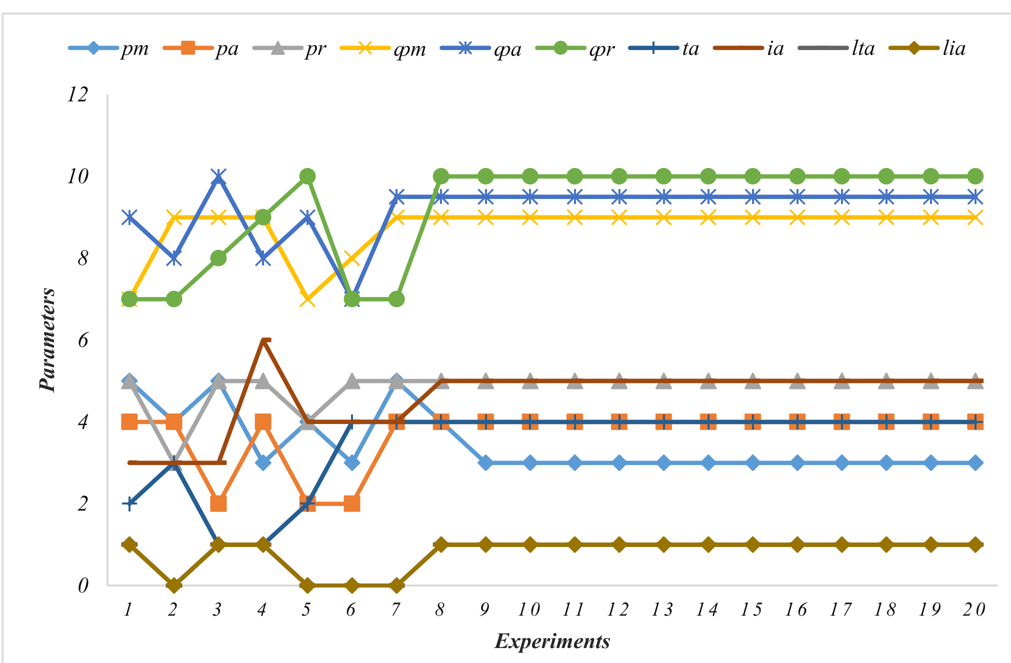

Fig. 7. Optimized scenario five.

These fluctuations are a result of SCM adjusting to the new costs and the benefits brought about by AI technology. The tax EL increases operational costs for the agent, pushing them to improve their energy efficiency to reduce the tax burden. At the same time, the investment in AI technology begins to yield benefits by decreasing energy wastage and improving overall efficiency. As the simulations progress, these adjustments stabilize, leading to optimal outcomes by the ninth experiment. The stabilization reflects the successful adaptation of the agent to the new conditions, demonstrating that the investment in AI technology pays off by significantly reducing EL and associated costs. This, in turn, enhances the agent's profitability and positively impacts the entire SCM. This study aligns with the findings of [45], who explored the impact of taxes and subsidies on promoting investment in green technologies within SCMs considering consumer preferences for green products. Furthermore, Zhang et al. [46] revealed the impact of an energy-water-carbon nexus-based joint tax management policy on the economic system. Our scenario's focus on ELtax and AI investments parallels their findings on the importance of integrated tax management policies in enhancing environmental and economic outcomes. In terms of AI, the research by [2] on using AI to reduce energy costs in a post-combustion carbon capture plant underscores the critical role of AI in improving energy efficiency. Our scenario's investment in AI technology to mitigate EL aligns with their findings, demonstrating how AI can significantly reduce operational costs and enhance sustainability.

3.6. Optimized scenario six

The simulation results illustrate the effects of EL mitigation strategies on the SCM involving manufacturers, agents, and retailers. In this scenario, the product prices are set at ρ_m4 RMB per unit for the manufacturer, ρ_a5 RMB per unit for the agent, and ρ_r5.5 RMB per unit for the retailer. Initially, the profits areφ_m 9 million RMB for the manufacturer, φ_a10 million RMB for the agent, and φ_r10.5 million RMB for the retailer. The t_a imposed on the agent at 3 RMB per five hundred units, and a 4 million RMB $i_r$has been done by the retailer mitigate EL. These decisions are implemented and assessed over 16 simulation experiments, with the X-axis representing these experiments and the Y-axis indicating the optimal indicators (Fig. 8). As the simulations progress, the fluctuation adjustments stabilize, leading to optimal outcomes by the 16th experiment. The stabilization reflects the successful adaptation of the SCM to the new conditions, demonstrating that the investment in AI technology pays off by significantly reducing EL and associated costs. This, in turn, enhances the retailer's profitability and positively impacts the entire SCM by improving overall efficiency and reducing operational costs. These simulation results indicate that while initial fluctuations are expected due to the introduction of new costs and investments, the strategic decision to invest in AI technology and address EL results in improved efficiency and profitability. By the 16th simulation, the SCM reaches an optimal state, highlighting the long-term benefits of proactive energy management and technology investments.

The results in this scenario support the findings of [4], who explored the impact of human AI skills on organizational innovation, emphasizing the role of digital organizational culture in enhancing technological adaptation. Similarly, Huang et al. [16] highlighted the significance of green SCM practices and their positive impact on the triple-bottom-line performance in emerging economies. The emphasis on EL mitigation through AI technology in our scenario resonates with their insights into the benefits of sustainable SCM practices. In terms of tax, the research by [19] on optimal energy taxes and subsidies underscores the importance of addressing carbon leakage through strategic fiscal measures. The implementation of an ELtax in our findings aligns with their recommendations for using taxes and subsidies to promote energy efficiency and reduce environmental impact. By leveraging advanced technologies and adhering to regulatory requirements, our findings not only ensure profitability but also position itself for long-term success in a competitive and dynamic market environment. The findings highlight the importance of strategic investments and regulatory compliance in sustaining profitability and operational efficiency, aligning with broader trends in SCM and technological innovation.

3.7. Optimized scenario seven

In this scenario, the product prices are ρ_m5 RMB per unit for the manufacturer, 6 RMB per unit is ρ_a, and 6.5 RMB per unit is ρ_a. Initially, the profits are φ_m 9 million RMB for the manufacturer, φ_a9.5 million RMB for the agent, and φ_r10 million RMB for the retailer. The decisions

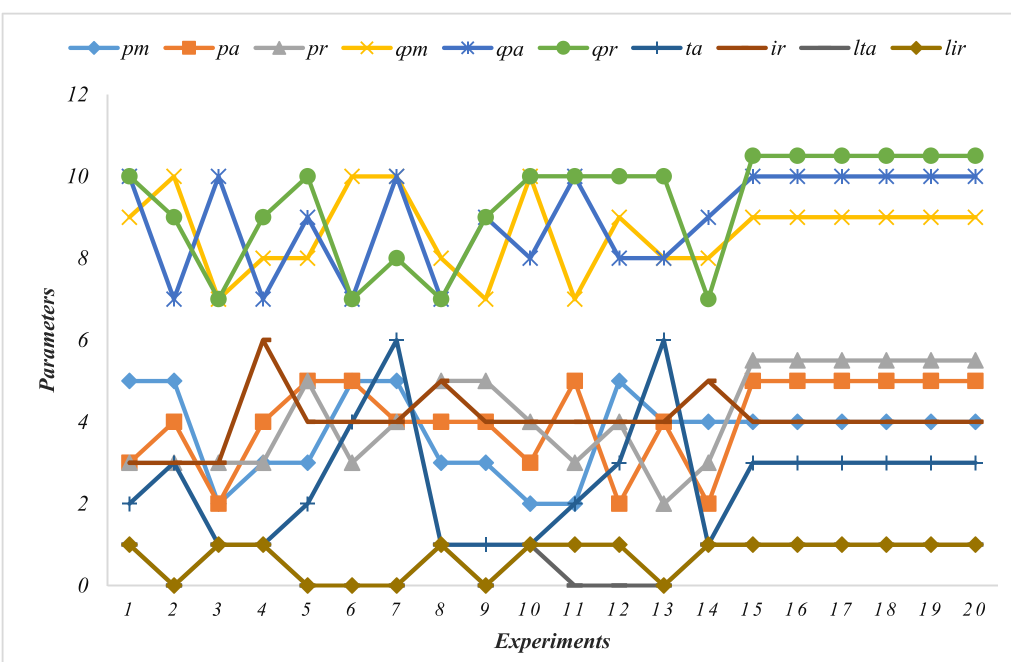

Fig. 8. Optimized scenario six.

about l_{tr} and l_{im} are one respectively in this scenario which indicates the imposition of both strategies. At_r imposed on the retailer at 6 RMB per one thousand units, and a i_m4 million RMB investment by the manufacturer to mitigate EL. These decisions are implemented and assessed over 12 simulation experiments, with the X-axis representing these experiments and the Y-axis indicating the optimal indicators (Fig. 9). Initially, the induced EL tax on the retailer and the manufacturer's investment in AI technology caused fluctuations in the optimal indicators. These fluctuations result from the SCM adjusting to the new costs and the benefits brought about by AI technology. The tax on EL increase's operational costs for the retailer, pushing them to improve their energy efficiency to reduce the tax burden. Simultaneously, the manufacturer's investment in AI technology begins to yield benefits by decreasing energy wastage and improving overall efficiency.

As the simulations progress, these adjustments stabilize, leading to optimal outcomes by the 12th experiment. The stabilization reflects the successful adaptation of the SCM to the new conditions, demonstrating that the investment in AI technology pays off by significantly reducing EL and associated costs. This, in turn, enhances the profitability of the entire SCM, including the retailer, who benefits from the reduced energy costs, and the manufacturer, who sees a return on their investment in AI technology. These insights align with studies by [18] on optimizing inventory decisions under carbon tax mechanisms, [37] on AI-driven modular nuclear reactor projects, [38] on technology-driven logistics in SCM, and [8] on optimal carbon tax rates in dynamic models. The simulation findings consider that while initial fluctuations are expected due to new costs and investments, strategic decisions such as investing in AI technology to mitigate EL lead to enhanced efficiency and profitability. By the 12th simulation, the SCM achieves an optimal state, emphasizing the long-term advantages of active energy management and technology investments.

3.8. Optimized scenario eight

The simulation results illustrate the effects of EL mitigation strategies within a SCM involving manufacturers, agents, and retailers. In this scenario, the product prices are ρ_m4 RMB per unit for the manufacturer, ρ_a5 RMB per unit for the agent, and ρ_r6 RMB per unit for the retailer. Initially, the profits are φ_m9 million RMB for the manufacturer, 10 million RMB $\varphi_a$for the agent, and 11 million RMB φ_r for the retailer. At the same time,t_r at 5 RMB per one thousand units, and a 4 million RMB i_r to mitigate EL. These decisions are implemented and assessed over a series of simulations, with the X-axis representing the simulation experiments and the Y-axis indicating the optimal indicators (Fig. 10). The tax on EL increase's operational costs for the retailer. The agent's investment in AI technology, though substantial at 4 million RMB, is aimed at mitigating EL. This investment is expected to improve the agent's operational efficiency by reducing energy wastage, which in turn lowers the costs associated with EL over time. Initially, the imposition of these measures causes fluctuations in the profits and optimal indicators due to the adjustment period where the market and stakeholders respond to the new costs and investments. The fluctuations are visible in the graph, with the X-axis representing the sequence of simulations and the Y-axis reflecting the optimal indicators. The simulation results indicate that while initial fluctuations are expected due to the introduction of new costs and investments, the strategic decision to invest in AI technology and address EL results in improved efficiency and profitability for the entire SCM. The retailer's energy management practices improve, reducing their tax burden, and the agent's investment in AI technology leads to significant cost savings and increased profitability. The SCM reaches an optimal state, demonstrating the long-term benefits of proactive energy management and technology investments.

The decisions about $l_{tr}$and $l_{ia}$are one respectively in this scenario which indicates the imposition of both strategies. By imposing a tax on EL for retailers, a financial penalty is created to minimize energy waste. This tax acts as a regulatory measure, compelling retailers to adopt more sustainable energy practices to avoid incurring additional costs. The tax encourages retailers to focus on improving their energy management systems, leading to reduced energy consumption and lower environmental impact. This measure not only supports environmental goals but also drives retailers to be more cost-effective and energy efficient. On the other hand, investing in AI technology for EL mitigation at the agent level introduces a layer of technological innovation into the SCM. Agents, who play a critical role in coordinating and managing logistics, can leverage AI to monitor, analyze, and optimize energy usage throughout the SCM. AI systems can detect inefficiencies and energy

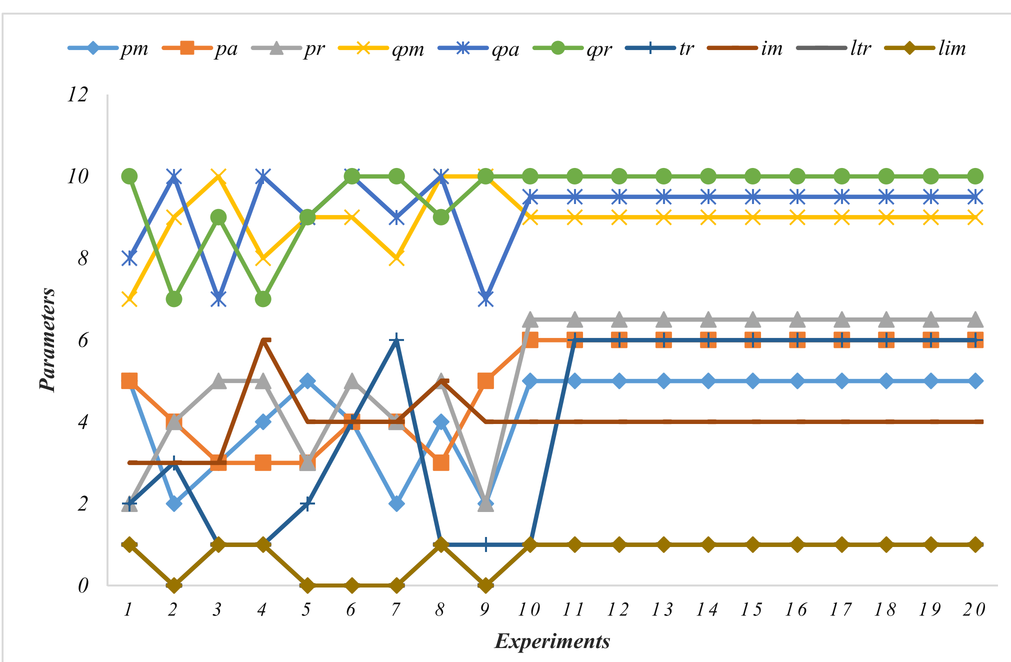

Fig. 9. Optimized scenario seven.

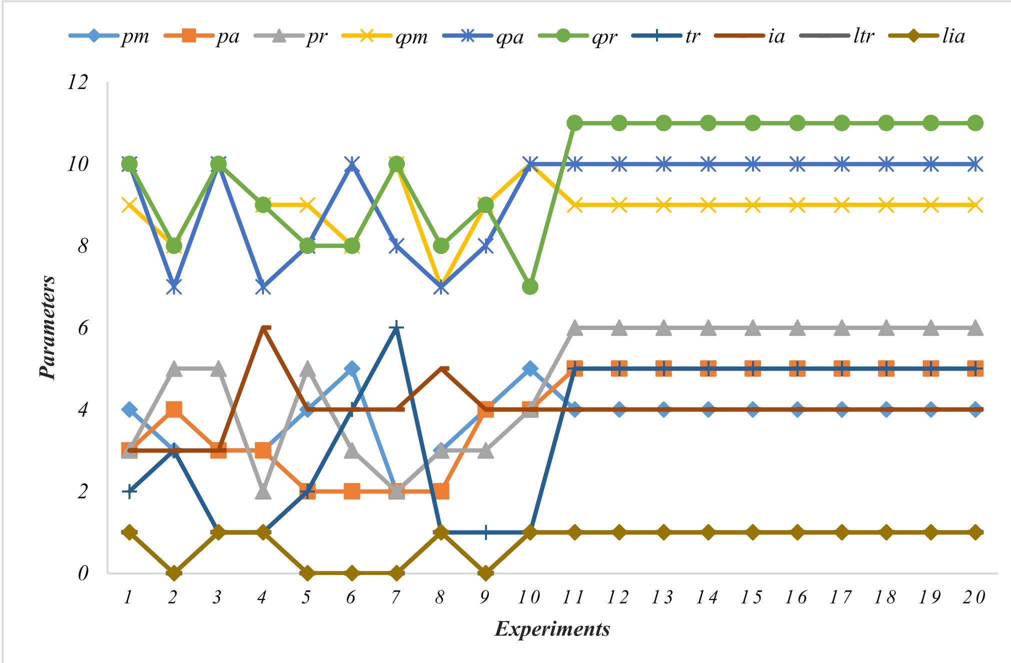

Fig. 10. Optimized scenario eight.

leaks in real time, providing actionable insights that enable agents to implement corrective measures swiftly. This proactive approach ensures that energy usage is continuously optimized, reducing waste and improving overall SCM efficiency.

The outcomes consider that strategic investments in AI technology to address EL contribute to enhanced efficiency and profitability throughout the SCM. The retailer's adoption of advanced energy management practices reduces their tax burden, while the agent's AI investment drives substantial cost savings and profitability gains. These findings align closely with research by [41] on AI applications in financial systems, [42] on regulatory-driven SCM. Together, these studies sustain the strategic importance of AI technologies in fostering sustainable SCM practices and operational excellence.

3.9. Optimized scenario nine

The simulation results offer valuable insights into the effects of EL mitigation strategies within a SCM comprising manufacturers, agents, and retailers (Fig. 11). Initially, the manufacturer sets the product price at ρ_m of 3 RMB per unit, the agent at$\rho_a$of 3.5 RMB per unit, and the retailer at ρ_r of 4 RMB per unit. The initial profits are φ_m5 million RMB for the manufacturer, φ_a 7 million RMB for the agent, and φ_r9 million

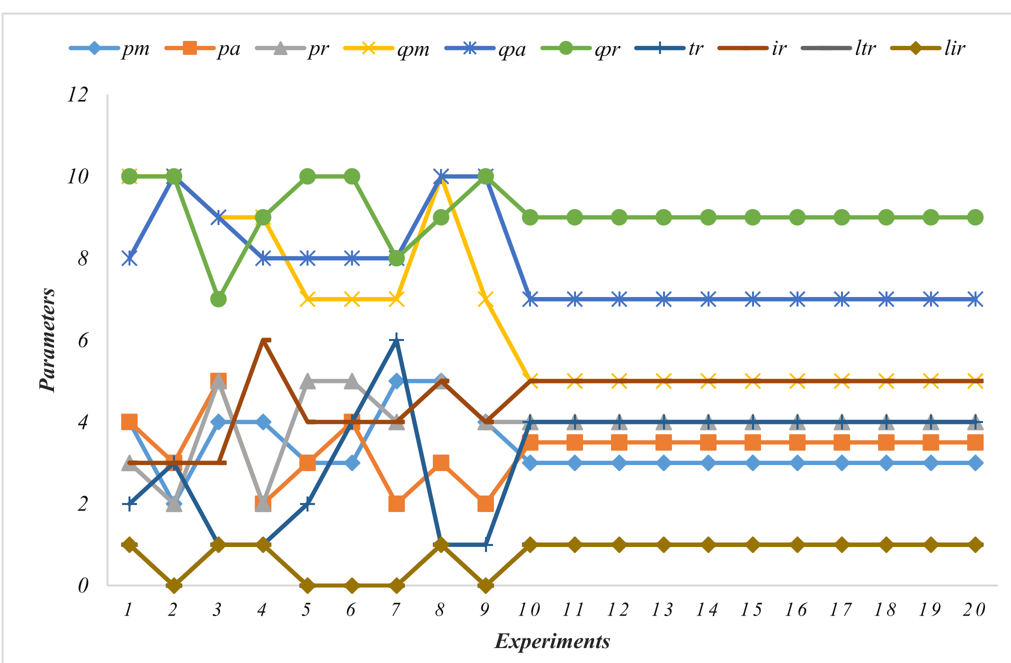

Fig. 11. Optimized scenario nine.

RMB for the retailer. The decisions implemented include t_r 4 RMB per one thousand units imposed on the retailer and a i_r of 5 million RMB investment by the retailer in mitigating EL. Over the line of the simulations, these initial adjustments begin to stabilize. The retailer starts to see the benefits of the AI technology investment, as it leads to a reduction in energy wastage and, consequently, lower operational costs. This improved energy efficiency helps mitigate the impact of the EL tax, gradually leading to an increase in the retailer's profitability. As the retailer becomes more efficient, the entire SCM benefits from the enhanced energy management practices, resulting in a more optimal and profitable state. By the end of the simulation series, the SCM reaches an optimal state where the initial costs and investments pay off. The retailer's energy efficiency improvements reduce the impact of the EL tax, while the manufacturer and agent also benefit from the overall improved efficiency in the SCM. This demonstrates the long-term benefits of proactive energy management and strategic investments in technology, leading to a more sustainable and profitable SCM.

The decisions about $l_{tr}$and $l_{ir}$are one respectively in this scenario which indicates the imposition of both strategies. Implementing a tax on EL for retailers and investing in AI technology for EL mitigation are both strategic decisions aimed at enhancing sustainability and operational efficiency.

By imposing a tax on EL, retailers are punished to reduce energy waste, as the financial penalty for inefficiency creates a direct economic motivation to improve energy management practices. This regulatory approach not only promotes environmental responsibility but also encourages retailers to adopt more sustainable practices, leading to a reduction in their carbon footprint. Simultaneously, investing in AI technology for EL mitigation represents a forward-thinking approach to addressing energy inefficiency. AI technologies can provide advanced monitoring and analytics capabilities, enabling retailers to identify and rectify energy leaks with greater precision and speed. These technologies can predict and prevent future energy wastage through machine learning algorithms, which adapt to patterns and anomalies in energy usage data. The integration of AI in energy management allows for real-time adjustments and long-term optimization, leading to significant cost savings and improved environmental performance. These insights are supported by related studies, such as [3] on AI applications in improving energy systems, Anugrah et al. [5] on green SCM strategies, and Golafshani et al. [13] on AI frameworks for predicting energy consumption in buildings. Together, these studies reinforce the critical role of AI and proactive management in achieving sustainable and efficient SCM.

3.10. Comparative analysis across scenarios

Specifically, the reasons behind the varying impacts of AI investments across scenarios are not sufficiently explored why, for instance, do retailer-focused AI investments lead to significant benefits in some cases, whereas manufacturer-led investments are more effective in others? Additionally, there is no in-depth discussion on how the combination of strategies (such as the simultaneous imposition of EL taxes and AI adoption interacts differently in each scenario, nor how these decisions shape the profitability and sustainability outcomes across the SCMtiers. The lack of detailed comparison makes it difficult for readers to understand why certain strategies work better in specific contexts and to draw generalizable insights for practice. Furthermore, key performance indicators such as profit margins, energy efficiency improvements, and EL tax reductions fluctuate across scenarios, but these differences are not systematically explained. As a result, readers are left without a clear understanding of the cause-and-effect relationships or the trade-offs between AI investments at different levels of the SCMand the imposition of EL taxes. Overall, a more thorough comparative analysis could have strengthened the study by clarifying the conditions under which certain strategies are most effective and helping stakeholders make more informed decisions in balancing sustainability goals with operational efficiency.

4. Conclusions, recommendations and future directions

This study focused on the economic dynamics within a SCM comprising manufacturers, agents, and retailers, with a particular focus on EL mitigation strategies and the integration of AI technology. Using a simulation-based optimization model, different optimal decisions have been manipulated. Firstly, the implementation of an EL tax, while initially increasing operational costs, effectively manage the entities to enhance their energy efficiency. Simultaneously, substantial investments in AI technology significantly reduce EL, leading to improved efficiency and profitability across the entire supply chain. The SCM experiences initial fluctuations as it adjusts to new costs and investments in AI technologies. However, these adjustments stabilize over time, showing successful adaptation to the new conditions. By the conclusion of the simulation periods, all scenarios achieved an optimal state, revealing the long-term benefits of active energy management and technological investments. The introduction of AI technology not only benefits the direct investor, be it an agent, retailer, or manufacturer, but also has positive effects throughout the entire SCM system. Enhanced energy management practices lead to reduced operational costs, increased profitability, and improved sustainability for all involved entities. The findings of this study align with existing literature on green SCM management, the role of AI in improving energy efficiency, and the benefits of integrated tax management policies. This study reinforces the importance of strategic investments in technology and regulatory measures to promote sustainable practices.

4.1. Recommendations

Based on these findings, several recommendations are proposed. SCM entities should actively invest in AI technology to mitigate EL. Despite the initial costs, the long-term benefits in terms of reduced energy wastage and improved efficiency are significant. Governments and regulatory bodies should consider imposing taxes on EL to adopt more sustainable practices. These taxes should be designed to encourage continuous improvement in energy management. Entities within the SCM should collaborate on investments in AI technology. Joint investments can spread the cost burden and ensure that the benefits of improved efficiency and reduced EL are shared across the SCM system. Continuous monitoring of energy usage and the effectiveness of AI technology is essential. The entities should remain adaptable and be prepared to make further investments or adjustments as necessary to maintain optimal efficiency.

Businesses should seek government subsidies and support for investments in green technologies. Such support can reduce the financial burden of initial investments and accelerate the adoption of sustainable practices. Further research should explore the long-term impacts of combined regulatory measures and technological investments on SCMsustainability. Studies should also investigate the potential for integrating other emerging technologies, such as blockchain, to enhance transparency and efficiency in energy management within SCM.

By implementing these recommendations, SCM entities can achieve significant improvements in energy efficiency, profitability, and sustainability, positioning themselves for long-term success in a competitive and dynamic market environment.

4.2. Future directions

Specifically, the absence of a detailed comparative analysis between the nine scenarios leaves gaps in understanding the factors that influence the effectiveness of different strategies, such as why AI investments at different levels (retailers, manufacturers, agents) yield varying results. Additionally, the study does not consider the potential impacts of real-world constraints, such as market volatility, regulatory shifts, or data uncertainty, on the simulation outcomes. Future research could address these gaps by conducting in-depth comparative studies across scenarios, incorporating real-world data validation, and exploring the sensitivity of results to changes in external conditions. By explicitly acknowledging these limitations and suggesting targeted areas for further investigation, future studies could build a more robust and practical understanding of effective strategies for energy management and sustainability in SCM systems.

Ethical approval

This article does not contain any studies with human participants or animals performed by each author.

CRediT authorship contribution statement

Jafar Hussain: Writing – original draft, Project administration. **Benjamin Lev:** Supervision. **Jifan Ren:** Software, Formal analysis.

Declaration of competing interest

None.

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Data availability

Data will be made available on request.

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