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Green E-Commerce Fulfillment Scheduling Under Diverse Carbon Policies

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Abstract

Traditional e-commerce operations management typically focuses on factors such as order processing efficiency and direct logistics costs, whereas research addressing energy consumption, especially that related to carbon emissions and the opportunity costs of delayed service, remains relatively scarce. Against the backdrop of global carbon reduction mandates, this paper aims to tackle the scheduling challenges faced by platform-based e-commerce fulfillment centers. By integrating multi-mode order-processing strategies, energy-consumption costs of automated guided vehicles (AGVs) and sorting equipment, carbon trading costs, and the realities of resource reallocation across distributed fulfillment nodes, this study proposes a novel platform operations scheduling problem that comprehensively accounts for carbon emissions and resource transfer. Notably, the model incorporates a service-level penalty mechanism, wherein the cost of delayed fulfillment is defined not merely as direct compensation, but as a comprehensive opportunity cost comprising platform reputation damage and potential customer churn. Given that both carbon trading costs and resource transfer costs are formulated as piecewise functions, the model represents a non-linear 0–1 integer programming problem. The paper linearizes the model and employs an exact solution method to obtain optimal schedules. Furthermore, the study examines the impact of different carbon emission policies on various operational costs and analyzes how price structures and carbon quotas affect total platform operating costs under service-level constraints. These findings offer e-commerce platform operators new insights and practical guidance for optimizing resource allocation and reducing carbon emissions in fulfillment operations, while preserving service reliability, thereby facilitating broader adoption of sustainable e-commerce practices.

Keywords: resource transfer; electronic commerce; platform resource scheduling; carbon emission policy; green logistics

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1. Introduction

As global environmental issues become increasingly severe, sustainable development has become a common goal pursued by countries worldwide [1]. In this context, green e-commerce and sustainable logistics have received significant attention from industry and academia. E-commerce operations, particularly warehousing and last-mile delivery, account for a rapidly growing share of urban energy consumption and carbon emissions [2,3]. In order to standardize and guide the development of green e-commerce, many countries and international organizations have issued various guidelines, including carbon trading schemes and logistics emission standards [4]. The Chinese government has also issued policies promoting green logistics and low-carbon urban delivery networks [5,6].

During large-scale promotional events, order volumes surge within a short period, generating numerous interdependent fulfillment tasks across distributed warehouses, sorting centers, and delivery nodes. Critical shared resources—such as AGVs, robotic picking arms, and refrigerated vehicles—must be dynamically redeployed among these nodes. Without coordinated scheduling, resource idleness and shortages coexist, leading to delayed fulfillment, SLA penalties, reputational damage, and customer churn. Meanwhile, equipment operation and inter-node transfers generate energy consumption and carbon emissions, which are further converted into costs under carbon trading, carbon cap, and carbon tax policies. Therefore, coordinating multi-warehouse equipment scheduling under service and carbon constraints is a pressing operational need for green e-commerce fulfillment.

Current green e-commerce initiatives often focus on the application of green technologies such as packaging materials and vehicle electrification while neglecting the important role of scientific management [7]. Scientific management methods are an effective means of reducing energy consumption and carbon emissions [8–10]. To the best of our knowledge, research on platform-level resource scheduling considering energy consumption and carbon emissions across interconnected fulfillment nodes remains insufficient. This paper aims to integrate the concepts of green operations with e-commerce scheduling methods, extending existing scheduling theories to address the actual characteristics of platform fulfillment, such as shared resource pools, order-driven task generation, and resource reallocation across distributed warehouses. Based on in-depth research into this issue, a new method for scheduling green e-commerce fulfillment operations is proposed. The innovative aspects of this paper include the following:

(1) Model integration gives rise to new coupled scheduling decisions. This paper integrates multi-mode resource-constrained project scheduling, cross-node resource redeployment, differentiated carbon policies, and service-level penalty mechanisms within a unified analytical framework. It reveals the joint decision mechanism of "resource transfer–execution mode–carbon emission cost," as well as the interaction between the SLA opportunity cost and carbon cost, requiring scheduling decisions to tradeoff the additional carbon cost caused by expediting activities against the platform reputation loss caused by delays.

(2) Model integration generates new mathematical structural properties. The model contains two structurally different sources of nonlinearity: piecewise carbon costs and resource-flow consistency. The former is handled through the auxiliary variable $\eta = C' \cdot \theta$, while the latter requires $z_{ijk} > 0$ and $y_{ijk} = 1$. Since these two sources involve disjoint sets of auxiliary variables, they need to be linearized separately and exactly.

(3) Model integration yields new managerial insights. Different carbon policies not only change the ranking of total costs but also lead to an asymmetric cost–carbon price slope and shift the "expedite–accept delay" switching point between the SLA penalty and carbon cost. Platforms should accordingly set expediting thresholds and carefully select scheduling modes and carbon-policy response strategies in quota-tight scenarios.

2. Literature Review

2.1. E-Commerce Fulfillment and Project Scheduling

The Resource-Constrained Project Scheduling Problem (RCPSP) concentrates on the reasonable arrangement of project activities and corresponding resources to achieve predefined optimization targets and improve resource utilization efficiency [11]. Different from conventional critical path approaches, the RCPSP explicitly incorporates resource-related constraints, which makes it a better fit for practical business contexts and attracts widespread academic interest [12,13]. The basic single-mode RCPSP assumes one single execution alternative for each activity and only considers renewable resource constraints.

Under such settings, resource availability stays unchanged in every time unit, and the primary scheduling target is project duration minimization. Decades of research have extended the basic RCPSP into multiple derivative forms, such as discrete time–cost trade-off problems, resource-leveling problems, multi-project RCPSP and multi-mode RCPSP (MRCPSP). As a representative extension, MRCPSP permits activities to be implemented under diverse modes, where each mode corresponds to unique durations and resource consumption profiles [14–16]. Existing review articles have delivered thorough comparisons and analyses for such RCPSP extensions [17–19].

Scheduling acts as a core component for platform-run e-commerce regarding operational management, order fulfillment and logistics coordination. E-commerce platforms are confronted with the dynamic allocation of scarce resources such as warehouse capacities, picking labor, transport vehicles and delivery staff for massive concurrent orders, subject to strict service-level agreements. E-commerce order fulfillment consists of a set of mutually-dependent scheduling decisions covering order batching, picker routing, product packing and shipment arrangement [20]. The online-retail Order-Allocation-on-Retailers (OAOR) problem, which assigns incoming customer orders to different fulfillment nodes in a distribution network, has attracted growing research interest in recent years. Vasconcelos et al. performed a systematic review covering more than 60 OAOR-related publications [21]. Their work established the baseline problem framework, summarized core problem features, and categorized existing solution approaches from the perspective of optimization mechanisms and policy types.

Nevertheless, order-processing tasks within e-commerce fulfillment networks can be completed via several alternative modes, for instance manual picking, semi-automated picking and fully-autonomous robotic picking [22]. These modes differ in processing durations, resource demands and energy-consumption intensities. Scheduling techniques built upon the Discrete Time–Cost Tradeoff Problem (DTCTP) framework cannot well handle such multi-mode selection scenarios. For this reason, this study adopts the more capable MRCPSP framework to formulate the e-commerce fulfillment scheduling problem.

2.2. Resource Transfer in Distributed Fulfillment Networks

Overall optimization performance of fulfillment operations heavily relies on high-efficiency utilization of renewable resources. Provided that precedence constraints are satisfied, resources can be reused among different activities, while resource transfer procedures will generate relevant transfer expenditures. Project scheduling considering resource transfer has attracted rising research attention in recent years. An innovative scheduling method that incorporates resource transfer time was put forward [23]. Within their genetic-algorithm design, both task-scheduling schemes and transfer-time information are encoded into chromosomes, which alleviates negative influences brought by transfer time under complicated scheduling cases. Targeting aircraft mobile assembly-line settings, the RCPSP with resource transfer time was studied and a hybrid optimizer integrating branch-and-bound technique and genetic algorithms was developed [24]. Multi-agent-system solutions for DRCMPSP with resource transfers were explored [25]. Their findings demonstrated that agent-based autonomous decision-making and coordination mechanisms support high-quality scheduling under complicated environments with frequent resource transfers. A Resource-Constrained Project Scheduling Problem with random durations was proposed [26]. Based on resource flow technology, they modelled the problem as a resource flow network and proposed a new mathematical model. Resource flow coding was employed to represent feasible solutions, a resource flow optimization model incorporating resource transfer time was developed, the resource flow reconstruction neighborhood operator was enhanced based on problem characteristics, and an efficient Tabu search algorithm

was designed for problem-solving [27]. By optimizing resource transfer time and costs, they achieved efficient scheduling of multiple projects.

Distributed e-commerce fulfillment networks face prominent resource-reallocation and transfer challenges. Inventories, facilities and labor resources need dynamic reassignment among warehouses, fulfillment hubs and last-mile delivery nodes. For platform-centered supply chains, resource transfer decisions cover not only physical goods transportation but also information exchange, contracts and multi-party stakeholder negotiations. Cross-warehouse inventory transshipment, which redistributes stocks among distribution centers to cope with demand volatility, has been widely investigated within e-commerce logistics research. E-order-fulfillment scheduling models were investigated and the necessity to coordinate order-allocation and transshipment decisions was stressed so as to strike balances between service performance and operational expenses [28]. For omnichannel retail distribution systems, capacity-sharing strategies that treat physical stores as transfer hubs can realize considerable cost reduction [29].

In summary, although existing project scheduling methods consider resource transfer, they do not pay sufficient attention to energy consumption and carbon emissions during the transfer process.

2.3. Energy Consumption of E-Commerce

Fast-growing e-commerce businesses have reshaped urban logistics and warehouse operations at the cost of increased environmental burdens. Energy use and carbon emissions generated by e-commerce businesses (especially warehouse picking systems, automatic sorting equipment and last-mile delivery networks) have become critical sustainability concerns for platform operators as well as policy regulators [30]. Warehouse activities equipped with automated guided vehicles (AGVs) and robotic picking systems create considerable energy demands [31]. Current green e-commerce practices mostly concentrate on packaging innovations and vehicle electrification, whereas intelligent operational management as a carbon-mitigation tool receives relatively limited research attention. In response to this gap, researchers have begun to explore scheduling-based approaches that explicitly account for energy consumption and carbon footprint in e-commerce logistics systems.

In the domain of electronic commerce, researchers have increasingly recognized the importance of incorporating carbon emission constraints into logistics and fulfillment scheduling. An integrated production and transportation scheduling model for e-commerce supply chains under carbon emission constraints was developed, demonstrating that coordination between production and transportation decisions can effectively reduce both costs and carbon footprints [32]. In platform supply chains, carbon cap-and-trade mechanisms are increasingly influencing online selling channel selection and pricing strategies. Research has examined how different carbon allowance allocation rules—such as grandfathering and benchmarking—influence channel selection decisions in e-commerce platform supply chains [33]. Under mixed carbon policies combining carbon taxes and carbon trading, Stackelberg game models have been constructed to explore optimal emission-reduction decisions in platform supply chains, considering consumer low-carbon preferences and blockchain-enabled carbon footprint tracing. For last-mile delivery, energy-aware optimization models have been developed for truck-drone cooperative delivery systems, explicitly capturing slope-dependent energy consumption and balancing energy costs with time-window delay penalties [34]. Robust optimization models for e-commerce closed-loop supply chain networks under carbon policies have been developed to minimize both total costs and carbon emissions simultaneously [35].

This article compares the costs of the following three main carbon emission policy tools. Carbon trading sets an aggregate emission cap, allocates allowances to regulated entities, and allows participants to buy or sell allowances [6]. A carbon cap imposes an absolute limit on emissions. It can be enforced either as a hard constraint, where emissions exceeding the cap are prohibited, or as a soft constraint, where excess emissions incur a penalty [36]. A carbon tax is a price-based instrument in which the regulator sets a tax rate and emitters pay a charge per unit of emissions. It provides a predictable carbon price, but its abatement effectiveness depends on the tax level [37]. These instruments differ in emission certainty, price certainty, operational flexibility, and the way penalties or revenues are generated. Carbon trading and carbon caps provide greater emission certainty, whereas a carbon tax provides greater price certainty. Carbon trading offers more flexibility through allowance trading and can reward low-carbon scheduling by allowing the sale of surplus allowances when emissions are below the quota. A carbon cap directly restricts emissions or penalizes emissions beyond the cap. A carbon tax internalizes the carbon cost of all emissions and thus encourages energy reduction even below the cap. In the context of e-commerce fulfillment, these differences can lead to different scheduling decisions, resource transfer patterns, and total fulfillment costs. Accordingly, this study models carbon trading, carbon cap, and carbon tax policies in the fulfillment scheduling problem and compares their effects on operational costs under service-level constraints.

2.4. Summary

After decades of development, the RCPSPs have been extensively studied, with research gradually shifting toward incorporating resource transfers and carbon emissions. However, few studies have integrated carbon emissions and carbon trading into their models, and even fewer have comprehensively optimized for carbon emissions, resource transfer timing, and resource transfer costs. Furthermore, despite the growing importance of AI-driven decision-making and algorithmic coordination in electronic commerce platforms, the application of project scheduling methodologies to platform operations, multi-agent coordination, and strategic interaction among platform participants remains underexplored.

The comparison in Table 1 shows that no existing study jointly captures transfer–mode–carbon coupling: studies with carbon taxes and multi-mode scheduling [10,16] assume zero deployment/transfer cost, whereas studies with resource transfer [23,24] assume a single mode and no carbon cost. A specific comparison with other articles is shown in Table 1. This paper fills exactly this gap by formulating a carbon-policy-switchable MRCPSP in which integer equipment-transfer flows, execution mode selection, and the policy-state-dependent carbon cost are determined jointly, and by deriving an exact linearization that keeps the three carbon-policy variants solvable on a common instance. This enables a like-for-like comparison of how carbon trading, carbon cap, and carbon tax reshape transfer and mode decisions under service-level constraints—a comparison that single-policy or transfer-free models cannot provide.

Table 1. Main literature highly relevant to this research.

References	Energy Consumption	Carbon Emissions	TOU	Carbon Trading	Carbon Cap	Carbon Tax	Resource Transform	
							Time	Cost
Adhau et al. (2013) [25]							√	
Okubo et al. (2015) [12]	√							
Ren et al. (2020) [24]							√	
Alipouri (2021) [26]							√	
Du et al. (2021) [13]	√		√					
Ma et al. (2022) [23]							√	

Table 1. *Cont.*

References	Energy Consumption	Carbon Emissions	TOU	Carbon Trading	Carbon Cap	Carbon Tax	Resource Transform	
							Time	Cost
Javanmard et al. (2022) [14]	√		√					
Aramesh et al. (2023) [15]	√	√	√					
Pouramin et al. (2024) [16]	√	√	√			√		
Yao et al. (2025) [10]	√	√						
This work	√	√	√	√	√	√		√

Note: "√" denotes that the cited study incorporates this particular aspect.

3. Problem Description and Mathematical Modeling

3.1. Problem Description

In an e-commerce platform's fulfillment ecosystem, various types of operational activities—including order picking, packing, sorting, transportation, and last-mile delivery—must be coordinated under resource constraints and precedence relationships. The platform's fulfillment network can be depicted as a directed acyclic graph, analogous to project network diagrams in traditional scheduling literature. A fulfillment operation $\mathcal{P}$ contains $N + 1$ activities. An activity is denoted by i, $i \in \mathcal{P}$, $i = 0, 1, 2, \ldots, N$. Activities 0 and N are dummy activities that do not consume time or resources. Activity 0 signifies the start of the fulfillment process, and N signifies its completion. The fulfillment network is thus represented by a directed acyclic graph $\mathcal{G} = (\mathcal{P}, \mathcal{A})$, where $\mathcal{P}$ is the set of all nodes in $\mathcal{G}$, and each node corresponds to an operational activity. $\mathcal{A}$ is the set of all arcs in $\mathcal{G}$. Each arc represents an immediate precedence relationship between activities indicates that activity i is the immediate predecessor of activity j, and activity j can only start after activity i is completed. The fulfillment network is provided with K shared critical resources for all activities, with each resource k having a supply capacity of R_k. These critical resources may include automated guided vehicles (AGVs), autonomous mobile robots (AMRs), sorting equipment, and delivery vehicle fleets. Each activity i has a set of execution modes M_i. For each mode m, $m \in M_i$, the activity duration is d_{im}, and its demand for resource k is r_{imk}. Typically, shorter activity durations require more resources. Therefore, the scheduling optimization problem proposed in this paper is essentially a synthesis of the mode selection problem and the resource flow optimization problem.

In e-commerce fulfillment networks, costly and energy-intensive critical equipment—such as robotic picking systems, AGVs, and refrigerated delivery vehicles—is typically shared across multiple fulfillment centers, distribution warehouses, and delivery routes. And fulfillment operations are usually distributed across different geographic locations, which means that different activities are usually located at different warehouses, sorting centers, or delivery zones. Thus, when an activity ends, the equipment may need to be transferred to other activities. If no other activity requires the equipment, it must be returned to the equipment depot. In large-scale e-commerce fulfillment networks, shared equipment such as robotic fleets and refrigerated trucks is often expensive and energy-intensive. Transporting equipment from depots to fulfillment centers, transferring it between facilities, and returning it from facilities to depots incurs significant costs and energy consumption. If equipment resource transfer paths can be fully optimized in fulfillment scheduling, it could significantly reduce operational costs. For each resource k, assume that its energy consumption cost and energy consumption during the fulfillment process are all proportional to distance. f_k is introduced to represent the energy consumption per unit distance of resource k. Denote the transportation distance between fulfillment center i and fulfillment center j by Δ_{ij}. The total energy consumption generated by transportation is $\Delta_{ij} \cdot f_k$.

3.2. Mathematical Model

The parameters and decision variables involved in the problem description and model construction of this study are shown in Table 2.

Table 2. Description of main symbols.

	Indexes	Δ_{ij}	Transportation distance between fulfillment center i and fulfillment center j
i,j	Indexes of activities	e_k	Power of resource k, i.e., energy consumption per unit of time
m	Execution mode index	ℓ_k	Price per unit of energy consumed in resource k
k	Resource index	t_k	The operating-time coefficient of resource k
t	Time index	γ_k	The Carbon emission coefficient of resource k
	Parameters	$\overline{C}$	The carbon cap or the carbon quota for the fulfillment operation
$\mathcal{D}$	The fulfillment operation	$\overleftarrow{p}$	The unit purchase price of carbon credits
$\mathcal{A}$	The set of immediately precedence relationships between activities	$\vec{p}$	The unit selling price of carbon credits
P_i	The set of precedence activities of activity i	ω	The opportunity cost incurred for each day an order is delayed
M_i	The set of execution modes of activity i	EST_i	The earliest start time of activity i
D	The service-level agreement (SLA) deadline for the fulfillment operation	LST_i	The latest start time of activity i
K	The set of renewable resources		Decision variables
R_k	Total availability of renewable resources k, $k \in K$	x_{imt}	0–1 decision variable; $x_{imt} = 1$ indicates that activity i is executed under mode m and starts at time t; otherwise, $x_{imt} = 0$
r_{imk}	The demand for renewable resources k when activity i is performed with mode m	y_{ijk}	$y_{ijk} = 1$ indicates that resource k is transferred from activity i to activity j; otherwise, $y_{ijk} = 0$
f_k	Energy consumption per unit distance transported for equipment k	z_{ijk}	Integer variable, which represents the quantity of resource k transferred from activity i to activity j

This study formulates the fulfillment scheduling problem as an MRCPSP considering energy consumption and carbon emissions, with the objective of minimizing total costs. The scheduling problem of e-commerce fulfillment operations must also account for total energy consumption cost (TECC) and carbon trading cost (CTC). In fulfillment operations, total energy consumption is primarily determined by high-energy-consuming critical equipment, such as robotic systems, AGVs, and refrigerated vehicles, which represent typical renewable resources. Therefore, this paper calculates the total energy consumption costs of fulfillment operations based on the utilization of high-energy-consuming critical equipment. The total energy consumption costs mainly include Operational Energy Cost (OEC) and Resource Transfer Energy Cost (RTEC). Among these, OEC primarily refers to the energy consumption cost generated by equipment resources during order fulfillment execution. The OEC of fulfillment operations can be calculated based on the power of resources, working hours, and energy prices, as follows:

$$OEC = \sum_{i \in \mathcal{D}} \sum_{m \in M_i} \sum_{t=EST_i}^{t=LST_i} (x_{imt} \cdot \sum_{k \in K} r_{imk} \cdot e_k \cdot t_k \cdot d_{im} \cdot \ell_k) \quad (1)$$

Furthermore, considering that the transfer of critical equipment between fulfillment centers and distribution nodes is based on the transportation distance among facilities

within the fulfillment network and the energy consumption per unit distance, RTEC can be calculated as follows:

$$RTEC = \sum_{i\in\mathcal{D}}\sum_{j\in\mathcal{D}}\sum_{k\in K}\left(z_{ijk}\cdot\Delta_{ij}\cdot f_k\cdot\ell_k\right) \tag{2}$$

Therefore, the total energy consumption cost incurred by fulfillment operations is $TECC = OEC + RTEC$.

The carbon emissions generated by critical equipment during operations are calculated by multiplying the energy consumption by the carbon emission factor. The carbon emission factor is determined by the type of energy used by equipment. For example, diesel-powered delivery trucks and gasoline-powered forklifts have different carbon emission factors. Based on the carbon emission factors and the energy consumption of equipment during operations, the carbon emissions generated by fulfillment operations during order processing, referred to as Operational Carbon Emissions (OCE), can be calculated as follows:

$$OCE = \sum_{i\in\mathcal{D}}\sum_{m\in M_i}\sum_{t=EST_i}^{t=LST_i}\left(x_{imt}\cdot\sum_{k\in K} r_{imk}\cdot e_k\cdot t_k\cdot d_{im}\cdot\gamma_k\right) \tag{3}$$

During the transportation of critical equipment, energy consumption also occurs, thereby generating corresponding carbon emissions, namely Transportation Carbon Emissions (TCE). The TCE of fulfillment operations is calculated as follows:

$$TCE = \sum_{i\in\mathcal{D}}\sum_{j\in\mathcal{D}}\sum_{k\in K}\left(z_{ijk}\cdot\Delta_{ij}\cdot f_k\cdot\gamma_k\right) \tag{4}$$

Therefore, the carbon emission generated by fulfillment operations is: $PTCE = OCE + TCE$.

For the fulfillment operations, when the total carbon emissions fail to meet the limit $\overline{C}$, the remaining carbon emissions can be sold. When the total carbon emissions exceed the $\overline{C}$, carbon emissions must be purchased. Therefore, the carbon trading cost (CTC) of the fulfillment operations is a piecewise function, as follows:

$$CTC = \begin{cases}\left(PTCE-\overline{C}\right)\times\vec{p}, & if\ \overline{C}\geq PTCE\\ \left(PTCE-\overline{C}\right)\times\overleftarrow{p}, & if\ \overline{C}\leq PTCE\end{cases} \tag{5}$$

The final completion time of the fulfillment cycle, which is the completion time of the end dummy activity in the fulfillment network, can thus be expressed by the following equation:

$$T = \sum_{m\in M_N}\sum_{t=EST_N}^{LST_N} t\cdot x_{Nmt} \tag{6}$$

The service-level agreement (SLA) deadline for order fulfillment is D. If the actual fulfillment time T exceeds D, the platform incurs not only direct compensation costs but also long-term losses such as customer churn and reputation damage. To capture this comprehensively, we define ω as the platform's integrated opportunity cost per unit time of delay. Therefore, the total service-level penalty cost (TPC) can be expressed as

$$TPC = \omega\cdot\max(0,\ T-D) \tag{7}$$

The TPC is linearized by the following method:

$$TPC\ = \omega\cdot\varphi \tag{8}$$

$$\varphi \geq\ T-D \tag{9}$$

$$\varphi \geq 0 \tag{10}$$

Thus, the total Fulfillment Cost (FC) can be directly calculated as follows:

$$FC = OEC + RTEC + CTC + TPC \tag{11}$$

The precedence relationship constraints should first be satisfied between activities in the fulfillment operations, as follows:

$$\sum_{m=1}^{M_i} \sum_{t=EST_i}^{LST_i} (t + d_{im}) \cdot x_{imt} \leq \sum_{m=1}^{M_i} \sum_{t=EST_i}^{LST_i} t \cdot x_{jmt}, \quad \forall (i,j) \in \mathcal{A} \tag{12}$$

If the quantity of critical resource k flowing from activity i to activity j is greater than 0, i.e., $z_{ijk} > 0$, it means that there is a resource flow between project i and project j, i.e., $y_{ijk} = 1$. Otherwise, $y_{ijk} = 0$. Therefore, the following consistency constraints exist among the decision variables.

$$\begin{cases} y_{ijk} = 1, & if \ z_{ijk} > 0 \\ y_{ijk} = 0, & if \ z_{ijk} = 0 \end{cases}, \quad \forall k \in K, \forall i,j \in \mathcal{P} \tag{13}$$

For critical equipment $\forall$ k $\in K$, which is reused across activities, the conservation principle of node resource flow must be ensured. That is, the total amount of resource k flowing into activity i is equal to the total amount of resource k flowing out of the activity, and this amount is not less than r_{imk}, namely

$$\sum_{j \in \mathcal{P} \setminus \{0,N\}} z_{ijk} = \sum_{j \in \mathcal{P} \setminus \{0,N\}} z_{jik} \geq \sum_{m=1}^{M_i} \sum_{t=EST_i}^{LST_i} x_{imt} \cdot r_{imk}, \ \forall k \in K, \ \forall i \in \mathcal{P} \tag{14}$$

The locations of the start dummy activity and the end dummy activity can be identified as equipment centers. These two dummy activities should also comply with the principle of resource flow conservation, that is, the amount of resources flowing out from the start dummy activity is equal to the amount of resources flowing into the end dummy activity, both being R_k, $\forall k \in K$. Therefore, the following constraints need to be added:

$$\sum_{i \in \mathcal{P}} z_{0ik} = R_k, \ \forall k \in K \tag{15}$$

$$\sum_{i \in \mathcal{P}} z_{iNk} = R_k, \ \forall k \in K \tag{16}$$

During the implementation process, each activity can only select one execution mode, subject to the following constraints:

$$\sum_{m \in M_i} \sum_{t=EST_i}^{LST_i} x_{imt} = 1, \quad \forall i \in \mathcal{P} \tag{17}$$

The value ranges of the decision variables are defined as follows:

$$x_{imt} \in \{0, \ 1\}, \ \forall i \in \mathcal{P}, \ m \in M_i, \ EST_i \leq t \leq LST_i \tag{18}$$

$$y_{ijk} \in \{0,1\}, \ \forall \mathrm{i} \in \mathcal{P}, \ \forall \mathrm{j} \in \mathcal{P}, \forall k \in K \tag{19}$$

$$z_{ijk} \in \mathbb{Z}_{\geq 0}, \ \forall i \in \mathcal{P}, \ \forall j \in \mathcal{P}, \ \forall k \in K \tag{20}$$

In summary, the mathematical model for the e-commerce fulfillment scheduling problem considering resource transfer is formulated as follows, with the objective of minimizing the total cost:

$$Min \ FC = OEC + RTEC + CTC + TPC \tag{21}$$

s.t.

(12)–(20)

3.3. Linearization

(21) is a non-linear programming problem model, which is difficult to solve using solvers. To facilitate the processing by solvers in subsequent work and improve the solution efficiency for large-scale problems, we linearize Equations (5) and (13) in this section.

For Equation (5), we first introduce an auxiliary decision variable $\theta \in \{0,1\}$. Here, $\theta = 1$ indicates that the carbon emission limit is not exceeded, while $\theta = 0$ means the limit is exceeded. Let $C' = PTCE - \overline{C}$, then the piecewise function (5) can be expressed as

$$CTC = C' \cdot \vec{p} \cdot \theta + C' \cdot \overleftarrow{p} \cdot (1 - \theta) = C' \cdot \overleftarrow{p} + \vec{p} \cdot C^{'} \cdot \theta - \overleftarrow{p} \cdot C^{'} \cdot \theta \tag{22}$$

Since $C' = PTCE - \overline{C}$, where $PTCE$ is an expression of decision variables, $C' \cdot \theta$ involves the multiplication of decision variables and thus requires linearization. In this paper, another auxiliary decision variable η is introduced to represent $C' \cdot \theta$. Therefore, Equation (22) is linearized as

$$CTC = C' \cdot \overleftarrow{p} + \vec{p} \cdot \eta - \overleftarrow{p} \cdot \eta \tag{23}$$

η is subject to the following constraints:

$$\eta \leq M * \theta \tag{24}$$

$$\eta \geq -M * \theta \tag{25}$$

$$\eta \leq C' + M * (1 - \theta) \tag{26}$$

$$\eta \geq C' - M * (1 - \theta) \tag{27}$$

The relationship between θ and C′ is explicitly expressed as

$$C' \leq M \cdot (1 - \theta) \tag{28}$$

$$C' \geq -M \cdot \theta \tag{29}$$

M is a sufficiently large constant. Formulas (23)–(29) constitute the linearized form of the piecewise function (5).

For the linearization of Equation (13), the following constraints are introduced to ensure that $y_{ijk} = 1$ whenever $z_{ijk} > 0$:

$$z_{ijk} \leq M \cdot y_{ijk} \tag{30}$$

When $y_{ijk} = 0$, z_{ijk} can only be 0. When $y_{ijk} = 1$, z_{ijk} can be any integer not exceeding M.

To ensure that $y_{ijk} = 0$ when $z_{ijk} = 0$, a sufficiently small positive number ε is introduced, and the following constraints are added:

$$z_{ijk} \geq \epsilon \cdot y_{ijk} \tag{31}$$

Formulas (30) and (31) represent the linearized form of the non-linear constraints (13).

In summary, the linearized problem model corresponding to (22) is as follows:

$$\text{Min } FC \tag{32}$$

s.t.

(12), (14)–(20), (23)–(31)

4. The Impacts of Different Carbon Policies

In Section 3, a model was constructed for the fulfillment scheduling problem under the carbon trading policy. However, there are various types of carbon policies. In addition to the carbon trading policy, they mainly include carbon cap, carbon tax, and carbon offset. For e-commerce platforms, carbon-offset policies typically require platforms to invest in external emission-reduction projects such as forest conservation or renewable-energy development. In the context of short-term, high-intensity promotional events like "Singles' Day" or "Prime Day," carbon offset is often not economical compared to operational adjustments. This section will construct models for the fulfillment scheduling problem under carbon cap and carbon tax policies, so as to provide more comprehensive and targeted decision-making support for e-commerce platform operators through systematic comparison.

4.1. Carbon Cap

The carbon cap policy sets a limit on carbon emissions for platform compliance operations. Throughout the entire order processing and delivery process, the platform's carbon emissions must not exceed this limit, and exceeding it will trigger a penalty mechanism. Given that the total carbon emissions generated by the above-mentioned fulfillment plan is $PTCE$, define $\overline{C}$ as the set carbon cap, and introduce a penalty coefficient p_{cap}, which is typically represented by a value greater than 0. The larger the value, the greater the penalty intensity. Therefore, under the carbon cap policy, the corresponding carbon emission cost CTC_{cap} is constructed as follows:

$$CTC_{cap} = \begin{cases} p_{cap} \cdot \left(PTCE - \overline{C}\right), & if\ PTCE > \overline{C} \\ 0, & if\ PTCE \le \overline{C} \end{cases} \tag{33}$$

The linearization of CTC_{cap} can be performed in the manner described in Section 3.3. An auxiliary decision variable $\delta \in \{0, 1\}$ is introduced, where $\delta = 1$ indicates that the total carbon emissions of the fulfillment operation exceed the carbon emission cap under the carbon cap policy, and $\delta = 0$ indicates that the total carbon emissions do not exceed the carbon emission cap. Let $C'' = PTCE - C_{cap}$, then the piecewise function (33) can be expressed as

$$CTC_{cap} = p_{cap} \cdot C'' \cdot \delta \tag{34}$$

In this section, the auxiliary decision variable is used again to represent $C'' \cdot \delta$. Therefore, Equation (34) is changed to

$$CTC_{cap} = p_{cap} \cdot \eta \tag{35}$$

η is subject to the following constraints:

$$\eta \le M * \delta \tag{36}$$

$$\eta \ge -M * \delta \tag{37}$$

$$\eta \le C'' + M * (1 - \delta) \tag{38}$$

$$\eta \ge C'' - M * (1 - \delta) \tag{39}$$

The relationship between δ and C'' is explicitly expressed as

$$C'' \le M \cdot \delta \tag{40}$$

$$C'' \ge -M \cdot (1 - \delta) \tag{41}$$

The total cost of the fulfillment operation can be calculated as $FC_{\text{cap}} = OEC + RTEC + CTC_{\text{cap}} + TPC$. Therefore, the mathematical model for the green e-commerce fulfillment scheduling problem under the carbon cap policy is

$$\text{Min } FC_{\text{cap}} \tag{42}$$

s.t.

(12), (14)–(20), (30), (31), (35)–(41)

4.2. Carbon Tax

Under the carbon tax policy, the modeling of carbon emission costs is primarily based on the product relationship between carbon emissions *PTCE* and the carbon tax rate. The more total carbon emissions generated by the program, the higher the carbon tax cost. For the determination of the carbon tax rate, different countries and regions have formulated different carbon tax rates according to their own conditions. This paper defines p_{tax} as the carbon tax rate, so the carbon emission cost can be expressed as

$$CTC_{tax} = PTCE \cdot p_{tax} \tag{43}$$

The total cost of the fulfillment scheduling can be expressed as $FC_{\text{tax}} = OEC + RTEC + CTC_{\text{tax}} + TPC$. Therefore, the linear programming model for the green e-commerce fulfillment scheduling problem under carbon tax is

$$\text{Min } FC_{tax} \tag{44}$$

s.t.

(12), (14)–(20), (30), (31), (43)

5. Case Study

Through field research and interviews, and with reference to the project scheduling network and industry practices, we conduct a study on the models proposed in this paper using an e-commerce platform's promotional event fulfillment operation as a case study. The fulfillment network of this platform is distributed across three fulfillment centers located in cities A, B, and C. Note that the following data are estimated reference values for scenario comparison and theoretical analysis. The fulfillment activity network structure is shown in Figure 1, where each circle represents an operational activity. The fulfillment operation consists of 22 non-dummy activities, with the start and end activities being dummy activities that do not occupy resources or consume time. Each activity has three execution modes, and each mode has specific resource requirements and duration. We selected three types of critical high-energy-consuming equipment resources as renewable resources, denoted as k_1, k_2, and k_3, which represent automated guided vehicles (AGVs), robotic picking arms, and refrigerated delivery trucks, with availabilities of 4 units, 3 units, and 5 units, respectively.

Table 3 presents detailed information of the fulfillment operation under three modes, including the resource requirements and duration under each mode. For example, the requirements of activity A_2 (order batching) for the three renewable resources under its three execution modes are [(4, 0, 3), (3, 0, 2), (3, 0, 1)], respectively. The tuple (3, 0, 2) indicates that under mode 2, activity A_2 requires 3 AGVs, 0 robotic picking arms, and 2 refrigerated delivery trucks. The durations of A_2 are [10, 12, 15], meaning that the completion times of A_2 under the three modes are 10 h, 12 h, and 15 h, respectively. The distance from City A to City B is 20 km, from City B to City C is 25 km, and from City A to City C is 40 km. The service-level agreement (SLA) deadline for the fulfillment operation is 73 h. The unit penalty cost is 1500 yuan per hour.

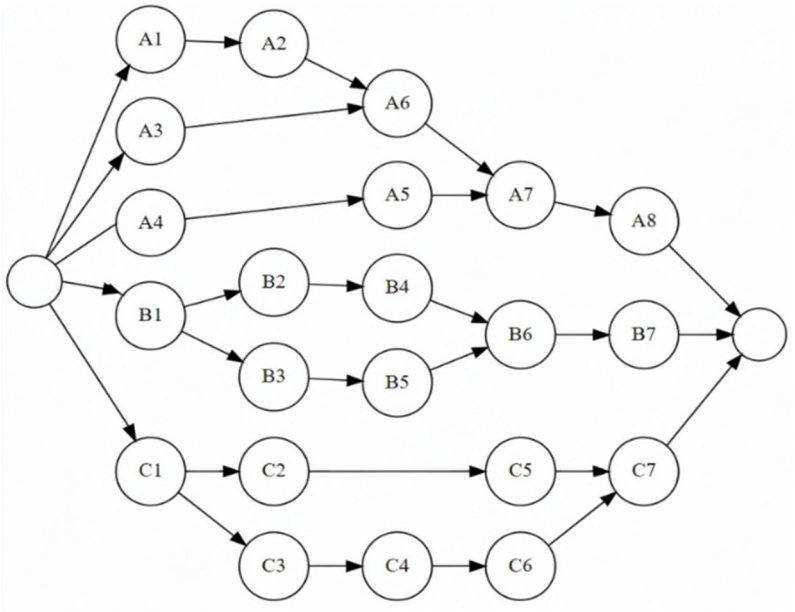


Figure 1. Fulfillment activity network.

Table 3. Details of activities in the fulfillment operation.

Activity ID	City	Activity Name	Precedence Activities	Resource Demands	Durations
0		Start	-	[(0, 0, 0), (0, 0, 0), (0, 0, 0)]	[0, 0, 0]
A_1	A	Order receiving and validation	0	[(3, 0, 0), (2, 0, 0), (1, 0, 0)]	[4, 5, 6]
A_2	A	Order batching and sorting	A_1	[(4, 0, 3), (3, 0, 2), (3, 0, 1)]	[10, 12, 15]
A_3	A	Inventory allocation and reservation	0	[(0, 0, 1), (0, 0, 0), (0, 0, 0)]	[4, 6, 6]
A_4	A	Packing material preparation	0	[(0, 0, 0), (0, 0, 0), (0, 0, 0)]	[6, 6, 6]
A_5	A	Order picking (batch retrieval)	A_4	[(0, 1, 0), (0, 0, 0), (0, 0, 0)]	[6, 8, 8]
A_6	A	Packaging and labeling	A_2, A_3	[(0, 3, 0), (0, 2, 0), (0, 1, 0)]	[5, 6, 7]
A_7	A	Sortation by delivery zone	A_5, A_6	[(0, 3, 0), (0, 2, 0), (0, 1, 0)]	[7, 9, 10]
A_8	A	Loading and dispatch preparation	A_7	[(0, 4, 0), (0, 3, 0), (0, 1, 0)]	[10, 12, 14]
B_1	B	Order receiving and validation	0	[(4, 0, 2), (3, 0, 2), (3, 0, 1)]	[6, 8, 9]
B_2	B	Warehouse slotting and storage	B_1	[(0, 0, 1), (0, 0, 0), (0, 0, 0)]	[5, 6, 6]
B_3	B	Replenishment planning	B_1	[(0, 0, 0), (0, 0, 0), (0, 0, 0)]	[6, 6, 6]
B_4	B	Order picking (batch retrieval)	B_2	[(3, 0, 0), (2, 0, 0), (1, 0, 0)]	[7, 9, 10]
B_5	B	Packaging and labeling	B_3	[(0, 3, 0), (0, 2, 0), (0, 1, 0)]	[8, 10, 12]
B_6	B	Sortation by delivery zone	B_5	[(0, 0, 0), (0, 0, 0), (0, 0, 0)]	[5, 5, 5]
B_7	B	Loading and dispatch preparation	B_6	[(0, 3, 0), (0, 2, 0), (0, 1, 0)]	[4, 5, 6]
C_1	C	Order receiving and validation	0	[(5, 0, 4), (4, 0, 3), (3, 0, 3)]	[8, 10, 12]
C_2	C	Inventory allocation and reservation	C_1	[(0, 1, 0), (0, 0, 0), (0, 0, 0)]	[3, 5, 5]
C_3	C	Order picking (batch retrieval)	C_1	[(0, 3, 0), (0, 2, 0), (0, 1, 0)]	[6, 7, 8]
C_4	C	Packaging material preparation	C_3	[(0, 0, 0), (0, 0, 0), (0, 0, 0)]	[5, 5, 5]
C_5	C	Packaging and labeling	C_2	[(0, 3, 0), (0, 2, 0), (0, 1, 0)]	[6, 8, 9]
C_6	C	Sortation by delivery zone	C_4	[(0, 3, 0), (0, 2, 0), (0, 1, 0)]	[6, 7, 8]
C_7	C	Loading and dispatch preparation	C_5, C_6	[(0, 0, 0), (0, 0, 0), (0, 0, 0)]	[7, 7, 7]
N		End	A_8, B_7, C_7	[(0, 0, 0), (0, 0, 0), (0, 0, 0)]	[0, 0, 0]

Of the three renewable resources, AGVs (k_1) and refrigerated delivery trucks (k_3) run on diesel, whereas robotic picking arms (k_2) run on electricity. The relevant operating and transfer parameters of the three resources are shown in Table 4. For the convenience and consistency of calculation, the parameters of the multi-arm robot are set according to the amount of diesel consumed by a diesel generator to produce the same amount of electricity, based on the generator's conversion efficiency. Additionally, bio-diesel blended fuel is used for power generation, so the carbon emission factor is slightly lower.

Table 4. Parameters related to renewable resources.

Parameters	Descriptions	k_1	k_2	k_3
R_k	Availabilities of resources	4	3	5
γ_k	Carbon emission factors (unit: $kgCO_2/L$)	2.63	2.31	2.63
e_k	Energy consumption per unit time (unit: L/h)	18	15	25
l_k	Price per unit of energy consumption (unit: ¥/L)	7	8	7
f_k	Energy consumption per unit distance transported (unit: L/km)	3.6	1.0	3.13

This paper will analyze the impact of different carbon prices and carbon quotas under three carbon policies on the scheduling objectives of the fulfillment operation.

5.1. Scheduling Result

For the carbon trading policy, the carbon quota is set at 100 tons, and the carbon price is set at (88, 78). That is, $\overline{C} = 100$ tons, $\overleftarrow{p} = 88$ ¥/ton, and $\vec{p} = 78$ ¥/ton. For the carbon cap policy, the carbon cap is also set at 100 tons, and the unit penalty under the carbon cap policy is set at 83 ¥/ton, i.e., $p_{\text{cap}} = 83$ ¥/ton. The carbon tax rate under the carbon tax policy is also set at 83 ¥/ton, i.e., $p_{\text{tax}} = 83$ ¥/ton. All algorithms are implemented using Python 3.8. The hardware computer is an HP Optiplex 3070 equipped with a 3.00 GHz Intel Core i5-9500 CPU and 16 GB of memory. The computation time limit is set to 3 h, and the optimality gap is 2.26%, and the scheduling results obtained via Gurobi are shown in Table 5.

Table 5. Solution results under different policies.

Policy	Total Cost	Energy Costs	Carbon Emission Cost	Service-Level Penalty Cost	Resource Transfer Cost	Carbon Emission	Fulfillment Duration
Carbon trading	228,969.9	205,801.6	5121.6	15,000.0	3046.7	158.2	83
Carbon cap	199,036.2	180,014.3	4399.0	10,500.0	4122.9	153.0	80
Carbon tax	171,824.0	151,058.3	11,910.5	6000.0	2855.2	143.5	77

As can be seen from Table 5, different carbon policies have a significant impact on the scheduling results. Under the current parameter settings, the carbon tax policy has the lowest total cost and the shortest completion time. The carbon trading policy has the highest total cost and the longest completion time. The reason is that the carbon tax policy charges all carbon emissions, prompting scheduling plans to choose low-emission and short-duration modes. Under the carbon trading policy, when allowances are insufficient, carbon allowances must be purchased at the purchase price, which is higher than the selling price, resulting in higher excess emission costs. The carbon cap policy only charges for excess emissions at a fixed penalty rate, so its cost is between the two. Under the parameters used in this paper's example, carbon policies change the optimal scheduling. Under the carbon trading policy, the optimal solution has the longest delays and the highest TPC, with the platform relatively more inclined to "accept delays" rather than speed up. Therefore, carbon policies shift the acceleration-delay tradeoff, and the platform needs to dynamically set urgency thresholds instead of fixedly "always rushing orders" or "accepting delays under carbon trading".

Figure 2 shows the Gantt chart of fulfillment scheduling under the carbon trading policy, where the dashed line segments indicate the additional precedence relationships generated by resource flows. The fill color of each activity bar identifies the fulfillment node (and thus the city) to which the activity belongs: blue bars denote activities A1–A8 at node A, green bars denote activities B1–B7 at node B, and orange bars denote activities C1–C7 at node C, with the activity ID labeled inside each bar.

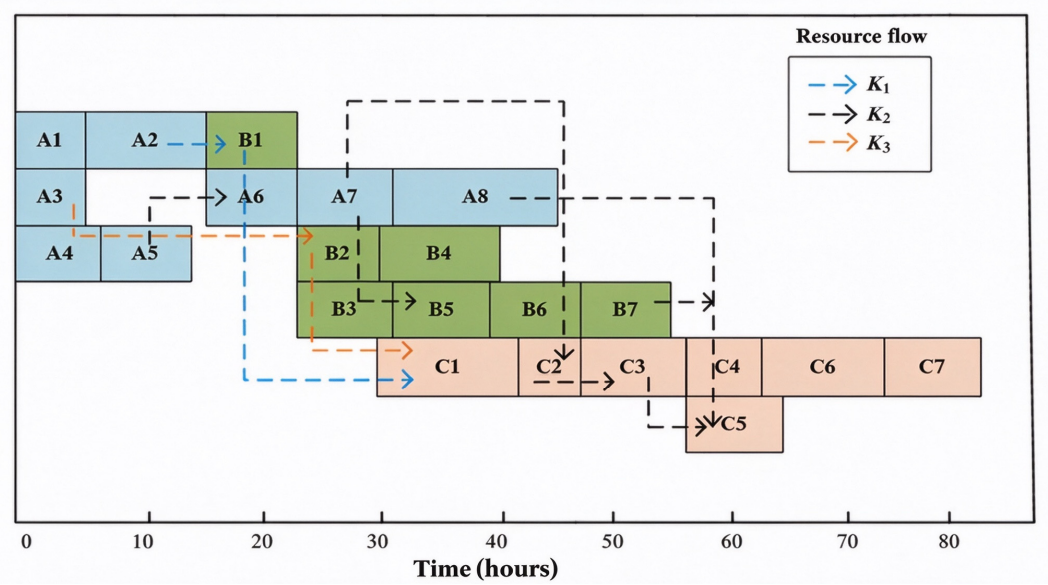


Figure 2. Fulfillment scheduling result under carbon trading policy.

5.2. Carbon Price-Based Analysis

We set the carbon quotas under each policy to 100 tons and 200 tons, respectively, aiming to analyze the impact of carbon price fluctuations on related costs in scenarios where the carbon quota (carbon cap) is lower than the total carbon emissions and where it is higher than the total carbon emissions. The specific carbon prices for the three different carbon policies are as follows:

(1) Carbon trading policy: The carbon prices are defined in the form of $(\overleftarrow{p}, \vec{p})$, specifically $[(88, 78), (90, 80), (92, 82), (94, 84), (96, 86), (98, 88), (100, 90), (102, 92), (104, 94)]$, with the unit being ¥/ton.

(2) Carbon cap policy: If carbon emissions exceed the carbon cap, there will be an excess penalty. The carbon emission cost is calculated by multiplying the excess carbon emissions by the penalty coefficient p_{cap}. In this paper, the penalty coefficient is further uniformly defined as the carbon price under this policy, and the relevant values are the median values of the carbon prices defined in the carbon trading policy, i.e., $[83, 85, 87, 89, 91, 93, 95, 97, 99]$, with the unit being ¥/ton.

Figure 3 shows the total cost of the carbon trading policy for different carbon quotas. When the carbon quota is set at 100 tons, the total cost increases as the carbon price rises. This is because the fulfillment operation needs to purchase excess quotas, so the higher the carbon price, the higher the purchase cost. However, when the carbon quota is 200 tons, the total cost shows a downward trend with an increase in the carbon price, generating profits. This is because the fulfillment operation can sell surplus quotas and generate sales revenue, which increases with the carbon price.

Figure 4 illustrates the total cost of the carbon cap policy for various carbon caps. When the carbon quota is set at 100 tons, the total cost increases as the carbon price rises. Since this policy only imposes penalties on the amount exceeding the carbon quota according to a fixed coefficient, the cost growth rate is lower than that of the carbon trading policy under the same quota. When the carbon quota is 200 tons, there is no need to pay penalty costs since the carbon emissions do not exceed the quota. Therefore, the total cost remains basically stable, as the carbon emission cost under the carbon cap policy remains zero.

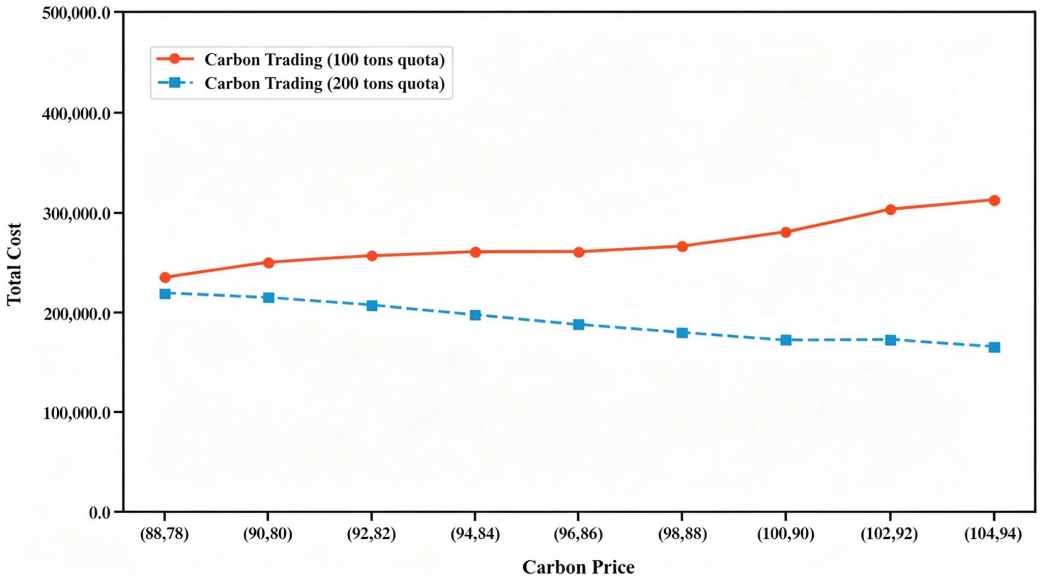


Figure 3. Total cost of the fulfillment operation under carbon trading policy.

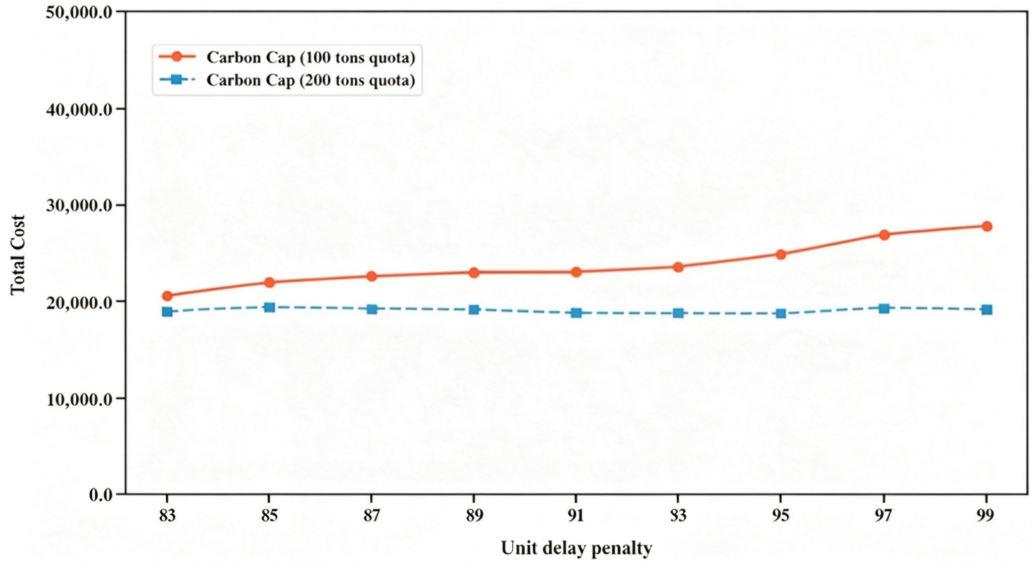


Figure 4. Total cost of the fulfillment operation under carbon cap policy.

5.3. The Effect of Carbon Quota or Carbon Cap

The carbon price under the carbon trading policy is fixed at (88, 78), while the carbon prices under both the carbon cap policy and the carbon tax policy are set at 83. Meanwhile, the carbon quota or carbon cap is adjusted within the range of (80, 240) with an increment of 20 tons each time, aiming to analyze the impact of changing the carbon quota (carbon cap) on the relevant costs of each carbon policy when the carbon price is fixed. Additionally, if the carbon quota exceeds the total carbon emissions of the fulfillment operation, the cost incurred under the carbon trading policy will exceed a critical threshold and turn into a profit for the platform.

The changing trends of total costs and carbon emission costs under various carbon emission policies are shown in Figures 5 and 6. As the carbon quota (carbon cap) rises, the costs under the two policies (excluding the carbon tax policy) both decrease with the increase of carbon quotas (carbon caps). Since the cost under the carbon tax policy is not affected by the carbon quota, its cost curve appears as a horizontal straight line. When the

carbon quota (carbon cap) is lower than carbon emissions, the costs under the carbon cap policy and the carbon trading policy are very close. Since the carbon price for purchase under the carbon trading policy is slightly higher, the total cost and carbon emission cost under the carbon trading policy are slightly higher than the corresponding costs under the carbon cap policy. When the carbon quota increases to a specific threshold, where its value exceeds the total carbon emissions of the fulfillment operation under the framework of the carbon trading policy, the relevant costs incurred under the carbon trading policy will be negative. This is because the excess carbon credits can be sold through transactions, which in turn are converted into the revenue of the platform. In contrast, when the carbon cap exceeds the total carbon emissions of the fulfillment operation, the excess credits cannot be sold under the carbon cap policy and thus no additional profit can be generated. Therefore, the carbon emission cost under the carbon cap policy becomes zero, having no impact on the fulfillment cost. Hence, when the carbon price is fixed, from the perspective of cost, the carbon trading policy is the most beneficial for the cost control of the e-commerce fulfillment operation.

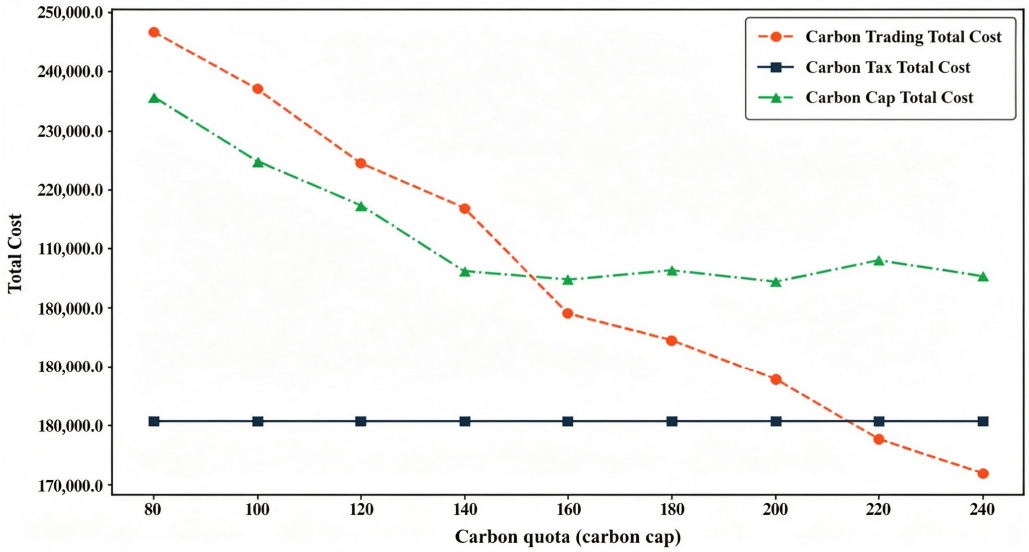


Figure 5. Total cost for different carbon quotas.

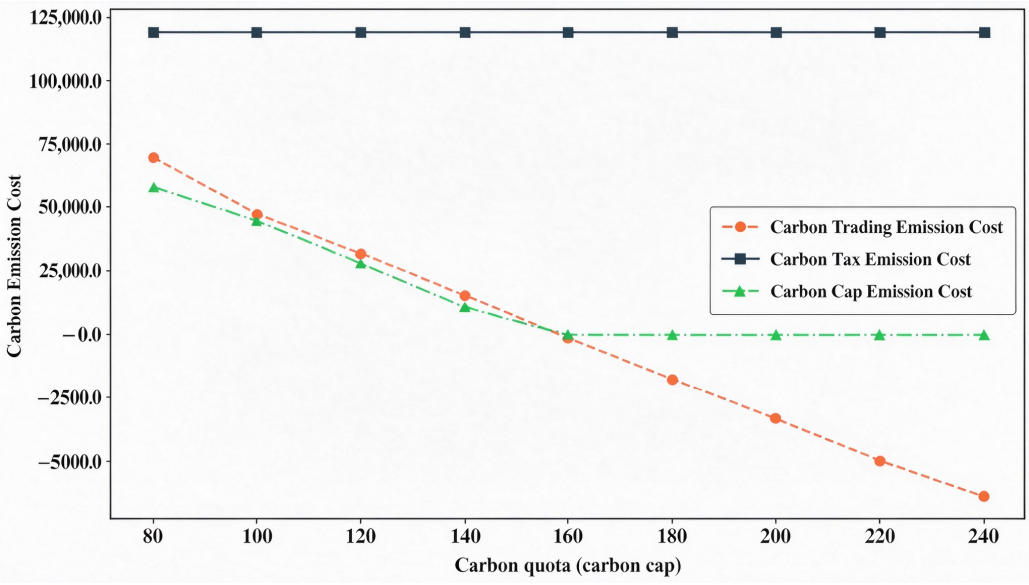


Figure 6. Carbon emission cost for different carbon quotas.

5.4. Discussion

Through this case study, we find that different carbon policies have a significant impact on the cost of e-commerce fulfillment operations. For a high-energy-consuming fulfillment network, it is essential to select different scheduling schemes according to the currently implemented carbon policy. At present, the carbon policy being implemented in China is carbon trading, supplemented by carbon caps. The carbon tax policy is still in the stage of research and demonstration and has not been fully implemented. From the perspective of this case, under the carbon trading policy, e-commerce platforms can generate profits by selling surplus carbon emission quotas. Therefore, the carbon trading policy is a more market-oriented carbon emission policy, which will endow high-energy-consuming fulfillment operations with stronger motivation for energy conservation and emission reduction.

The energy consumption and carbon emission costs of the fulfillment operation are substantial, among which the carbon emission costs are highly sensitive to carbon prices and carbon emission quotas. To reduce the costs of fulfillment operations, platform decision-makers must fully consider the impact of energy consumption and carbon emissions on the fulfillment cost, in addition to traditional constraints such as resource limitations and SLA delay penalties. Especially under the carbon trading policy, if the carbon quotas can be fully utilized and the price difference between carbon purchases and sales can be leveraged, the fulfillment cost will be significantly reduced. The method proposed in this paper can fully balance the impacts caused by energy consumption, carbon emissions, delay penalties, and resource transfers, and provide an optimal scheduling scheme for the e-commerce fulfillment network.

6. Conclusions

The e-commerce industry plays an important role in China's economic and social development, with logistics and fulfillment operations being critical components of platform competitiveness. This paper conducts in-depth research on the fulfillment scheduling problem based on the green operation concept, and proposes a scheduling approach that comprehensively considers factors such as energy consumption and carbon emissions. The MRCPSP modeling method is employed to construct mathematical models corresponding to different carbon policies. A real-world e-commerce promotional event was used to verify the proposed model and subject it to a comprehensive case analysis. The case analysis explores the impact of different carbon emission policies on the various costs of the fulfillment operation. Further analysis is conducted on how different carbon prices and quotas (caps) under various policies affect the cost of the fulfillment operation. This article estimates the impact on costs under three different carbon policies, providing a reference for platform operators' decision-making. But for real-world e-commerce operations, platform operators should evaluate green fulfillment scheduling schemes according to locally enforced carbon-policy parameters as well as platform-specific network and business constraints.

This study provides innovative modeling ideas and methods for fulfillment scheduling in green e-commerce operations. It also offers e-commerce platform operators strong theoretical support and practical guidance on achieving optimal resource allocation and reducing carbon emissions. The research results can help platforms to improve operational efficiency, reduce their environmental impact and enhance their competitiveness in sustainable e-commerce. Therefore, this work provides new insights into sustainable development and efficient management in the e-commerce industry, and will promote the popularization and application of green operation concepts.

This paper conducts in-depth research into the fulfillment scheduling problem under different carbon policies. It constructs a non-linear problem model and then linearizes it.

Nevertheless, the resulting mathematical model remains NP-hard. Our preliminary computational tests show that off-the-shelf solvers can handle the small-scale fulfillment instances used in this paper but struggle with large-scale platform-wide fulfillment-scheduling problems. Therefore, proposing an efficient solution algorithm for the e-commerce fulfillment scheduling problem constitutes a direction for future research.

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Abbreviations

The following abbreviations are used in this manuscript:

AGV	Automated Guided Vehicle
AMR	Autonomous Mobile Robot
CTC	Carbon Trading Cost
DTCTP	Discrete Time–Cost Tradeoff Problem
FC	Fulfillment Cost
MRCPSP	Multi-Mode Resource-Constrained Project Scheduling Problem
OAOR	Order-Allocation-on-Retailers
OCE	Operational Carbon Emissions
OEC	Operational Energy Cost
PTCE	Platform Total Carbon Emissions
RCPSP	Resource-Constrained Project Scheduling Problem
RTEC	Resource Transfer Energy Cost
SLA	Service-Level Agreement
TCE	Transportation Carbon Emissions
TECC	Total Energy Consumption Cost
TPC	Total Service-Level Penalty Cost

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