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OPTIMIZING TRANSPORTATION PROBLEM FOR E-COMMERCE SUPPLY CHAIN AND LOGISTICS NETWORK USING MIXED-INTEGER LINEAR PROGRAMMING

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ABSTRACT

The rapid growth of online purchasing on ecommerce platform has reinforced the requirement for efficient supply chain and logistics networks to meet increasing demands of customers with minimum costs. This research addresses the transportation problem in e-commerce logistics with the help of a mixed-integer linear programming (MILP) model to optimize the multi-group network of suppliers, distribution centers, and customers. The proposed model minimizes the total costs, including fixed costs for opening distribution centers and variable costs for transportation, while considering and satisfying the supply, demand, and capacity constraints. The proposed method efficiently determines the optimal locations for distribution centers and flow product allocations using MILP. The simulation using datasets of e-commerce network demonstrate cost savings compared to the baseline configurations represents robust performance under demand fluctuations. This research provides model for e-commerce system to design scalable and cost-efficient logistics networks.

KEYWORDS— *E-Commerce, Mixed-Integer Linear Programming (MILP), Supply Chain Management, Logistic and Transportation*

I. INTRODUCTION

In today's e-commerce marketplace, customers are becoming increasingly demanding, not only in terms of product quality but also in terms of the level of service quality they receive [1]. Customer service primarily refers to the consistent delivery of convenience by ensuring that products reach customers at the right time and place. A product essentially holds no value until it is handed over to customers at the time and place, they want it [2, 3].

In India, several e-commerce companies, such as Flipkart, Amazon, Myntra, Meesho, AJIO, and JioMart, have achieved exceptional service standards for customers [4, 5]. They also gained a competitive edge because of their logistics management focus. Some e-commerce companies have their own logistics services, whereas others offer other logistics and transportation services. These companies prioritize the seamless flow of products to customers, making service excellence a key differentiator in a highly competitive market [6].

The mixed-integer linear programming (MILP) has emerged as a powerful mathematical modeling technique for solving complex transportation problems [7, 8]. The MILP model can handle both discrete and continuous decision variables. The formulation of the e-commerce transportation problem as an MILP model can help the businesses to optimize vehicle routing, warehouse allocation, and shipment scheduling while considering the real-world constraints, such as delivery time windows, vehicle capacity, and fuel costs [9].

This research presents the application of MILP to optimize the transportation for e-commerce supply chains, which primarily enhance operational efficiency and minimize the logistics costs. The proposed method develops a mathematical model that integrates key factors, such as demand variability, multi-echelon distribution networks, and dynamic routing strategies [10]. Through Python simulation the effectiveness of the proposed model is evaluated in terms of improvement in delivery performance and resource allocation. The simulation provides valuable results for e-commerce companies to streamline their logistics operations and achieve a competitive advantage in the e-commerce marketplace [11, 12].

The rapid growth of e-commerce has transformed global supply chain and logistics networks, driven by increasing consumer demand for fast, reliable, and cost-effective delivery services. In 2023, global e-commerce sales reached approximately $6.3 trillion, with projections estimating growth to $8.1 trillion by 2026 [13]. This surge, fueled by platforms like Amazon, Alibaba, and Shopify, has intensified the complexity of managing supply chains, particularly in optimizing transportation logistics. E-commerce logistics networks are characterized by multi-echelon structures, involving suppliers (e.g., manufacturers or vendors), distribution centers (DCs, such as fulfillment centers or warehouses), and customers (e.g., regional demand zones or individual consumers). These networks must balance competing objectives: minimizing costs (fixed costs for opening facilities and variable transportation costs), ensuring rapid delivery, and maintaining scalability to handle demand fluctuations, such as those seen during peak sales events like Black Friday.

The transportation problem, a classic optimization challenge, is central to designing efficient e-commerce logistics networks. Unlike traditional supply chains, e-commerce requires strategic

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decisions about where to locate DCs and how to allocate goods across the network to meet stringent delivery timelines while minimizing costs. This complexity necessitates advanced mathematical modeling, such as Mixed-Integer Linear Programming (MILP), which integrates binary decisions (e.g., whether to open a DC) with continuous variables (e.g., shipment quantities). MILP is well-suited for e-commerce applications due to its ability to model facility location and transportation decisions simultaneously, ensuring globally optimal solutions for small to medium-scale problems [14].

This research proposes an MILP-based approach to optimize the transportation problem in e-commerce supply chain and logistics networks. The model minimizes total costs, including fixed costs for opening DCs and variable costs for transporting goods from suppliers to DCs and from DCs to customers, while satisfying supply, demand, and capacity constraints. The study addresses practical e-commerce challenges, such as selecting optimal DC locations and managing flow allocation under varying demand scenarios, which are critical for operational efficiency and customer satisfaction.

To illustrate the structure of the e-commerce logistics network, Fig. 1 provides a schematic representation of the multigroup system, which highlights the flow of products from suppliers to customers via distribution centers.

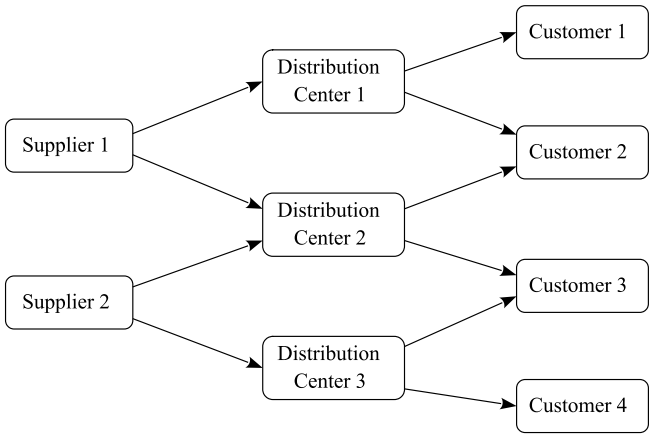


Figure 1 Multi-group e-commerce logistics network with suppliers, distribution

Figure 1 depicts a simplified network with two suppliers, three potential distribution centers, and four customers. The arrows represent the flow of products from suppliers to distribution centers, and from distribution centers to customers, while binary variables determine which distribution centers are opened. This structure captures the essence of e-commerce logistics, where strategic decisions about distribution center locations directly impact transportation efficiency. The contributions of this research are threefold:
1) The formulation of a comprehensive MILP model designed to e-commerce logistics,
2) Proposing an efficient algorithm for solving the model, and
3) Providing optimization into cost and network behavior under demand variability through simulations.

This research aims to support e-commerce firms in designing cost-effective, scalable, and resilient supply chains, with potential extensions to incorporate sustainability (e.g., minimizing carbon emissions).

II. RELATED WORK

Koutsokosta and Katsavounis [15] presented MILP-based models to optimize construction supply chains (CSC) in both deterministic and stochastic settings. Their model basically focused on minimizing costs related to network design, inventory, and transportation while uncertainties were considered in the optimization method. Their model offered flexibility for contractors and introduced robust solutions for handling varying parameters; however, their result represented higher costs as compared to the deterministic methods. Garrido *et al.* [16] proposed a fuzzy-possibilistic mixed-integer linear programming (FP-MILP) model to optimize a resilient agroindustrial supply chain, which ultimately minimized the transportation and the storage distances under uncertain conditions. Their model was tested on a real-world global supply chain, which mainly aimed to improve efficiency and adaptability.

By comparing the integrated and non-integrated supply chains in Pakistan, Rizwan Shoukat [17] presented an exploratory analysis that basically focused on minimizing the costs of a major industry of paper and board manufacturing. Using an MILP-based model and "multi-objective genetic algorithm (MOGA)," they found that an integrated supply chain is 37% more cost-effective. Their study also explored the integration of transportation networks to improve the efficiency of the supply chain in South Asia. Jindal and Sangwan [18] proposed a fuzzy MILP model to optimize a "closedloop supply chain (CLSC)" in the context of a sustainable manufacturing process. This model basically addressed uncertainties in costs, demand, and recovery processes such as reuse, recycle, refurbish, and disposal. They mainly aimed to maximize the profit by determining the optimal facility locations, part allocations, and external supplier purchases. This model perfectly balanced the feasibility and satisfaction of the decision-makers, and they presented an illustrative example to demonstrate its application.

Padhi and Marken [19] presented an exploratory study that basically aimed to optimize the supply chain in a hypothetical industry, ABC Electronics, by using integer linear programming (ILP) and machine learning (ML) to improve demand forecasting, production, inventory management, and transportation logistics, which ultimately reduces the costs and enhances the efficiency. Their results also have broader implications and suggestions for industry standards with customer satisfaction. Vafadarnikjoo *et al.* [20] developed a novel "grey multi-objective binary LP" model to optimize risk, cost, and time mitigation strategies in "agri-food supply chain management (AFSCM)". They basically highlighted that thecontinuous training and the vulnerability analysis of IT systems are key points to address risks like production issues and labor shortages. So, this model offered a step-wise practical solution (as presented in Figure 2) for managing these supply chain risks.

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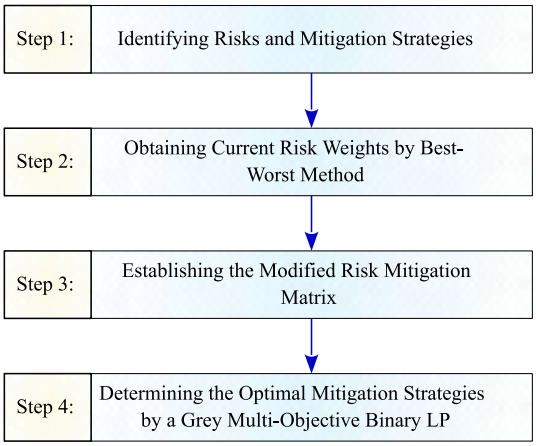


Figure 2 Steps of Grey Multi-Objective Binary LP model for Risk Assessment in Supply Chain Management

Using a multi-objective MILP model, Gharibi and Abdollahzadeh [21] developed a closed-loop logistics network for sales service, enhancement of profit, lower environmental impact, and disassembly of center efficiency, while incorporating green supply chain factors and improvements of efficiency using safety data exchange agreement (SDEA) methods. Gamez-Alban *et al.* [22] addressed the underexplored first mile of agricultural supply chains, which mainly focuses on optimization of the transportation of harvest production. They introduced an MILP-based model to minimize the logistics costs, and it was applied as a case study in Greece, which significantly showed a potential 40% cost reduction by using cooled vehicles for pick-up rounds.

To optimize ambulance dispatch using priority list policies, Laura A. Albert [23] presented a Markov decision process model that was solved through mixed integer programming. Their model offered simple, practical, and effective policies that performed similarly to unrestricted models but better than heuristics. Hassanpour *et al.* [24] developed a method to solve intuitionistic fuzzy multi-objective LP problems by converting the fuzzy parameters to crisp values and by applying optimization techniques and tested it on a supplier selection problem in supply chain management. Kumar *et al.* [25] presented a case study from an Indian automobile company, where supplier selection in sustainable supply chains is optimized using "fuzzy analytic hierarchy process (FAHP)" and MILP, and economic, social, and environmental factors are considered in the optimization process.

Souri and Ghomi [26] developed a multi-objective MILP model to optimize a sustainable perishable food supply chain that mainly focuses on the costs, emissions, and shipping time under uncertain demand. This model used a two-stage planning approach and simplified to a single objective. Golpıra and Javanmardan [27] presented a robust MILP model to optimize a cement supply chain under the carbon emission policies, and the factors such as inventory, shortages, and demand uncertainty were considered in optimization. They also compared deterministic and non-deterministic models and suggested that the profit-sensitive decision-makers should take higher risks, while emission-sensitive ones should implement both carbon cap-and-trade and carbon tax policies.

Gang Wang [28] presented a comprehensive model for disaster relief supply chain planning that addressed uncertainties in demand and traveling time. To optimize facility location, resource allocation, and vehicle routing in supply chain and logistics, their model combined two-stage mixedinteger stochastic LP, Benders decomposition, and an improved random forest algorithm. Vanany *et al*. [29] created an MILP-based model to optimize the fish reverse supply chain, which balanced the profit, job creation, and carbon emissions. Their model showed that processing fish waste can boost jobs and provide insights for managers on making better supply and production decisions.

In LP supply chain models, Jatty *et al.* [30] addressed two prominent issues: infeasibilities detection and minimization of changes, and formulated a bi-criterion optimization model. They used flexibility tests and data analysis to identify causes of infeasibility and offered their methods to minimize solution changes. Their model balanced the cost and change reduction, with the algorithms applied to real supply chain problems. Sirait *et al.* [31] combined "response surface methodology (RSM)" with MILP and proposed an optimized maritime logistics model, which significantly reduced the operational costs while maintaining their 100% service reliability in Indonesia. Their model presented the improvement in vessel routing, inventory, and fleet management. Using key factors such as vessel speed, fleet size, and port operations was also considered in the optimization process. Their model is robust to demand and price fluctuations and offers a cost-efficient solution for maritime logistics.

Kim *et al.* [32] formulated a "multi-objective mixed integer linear programming (MMILP)" model for "closed-loop supply chain network design (CLSCND)," which mainly aims to minimize costs and CO2 emissions and maximize job opportunities. In this model, they used a fuzzy robust optimization approach to handle uncertainties in demand and costs. This model outperformed the deterministic version, which provided valuable insights for decision-makers in multi-period, multiproduct CLSCND problems. Sun *et al*. [33] proposed an LP-based method to optimize the cold chain logistics process for a fresh processing factory. They addressed the selection of distribution center locations using the "location set covering problem (LSCP)" and optimized distribution routes through the transshipment problem. Their experiments on the IBM ILOG CPLEX (Laborie *et al*., 2018) [34, 35] platform presented that the proposed method can reduce transportation costs by about 15% as compared to unplanned logistics.

To find multiple alternate solutions in LP models, Kakkad *et al.* [36] addressed an iterative MILP algorithm that are useful for applications like supply chain optimization. Their algorithm generated solutions with increasing objective values and helped to compare different options effectively. Kannan *et al.* [37] proposed a "multi-objective mixed integer programming (MOMIP)" model to optimize reverse logistics in e-waste, which mainly focuses on cost reduction, environmental impact, and maximization of recovery. Their model incorporated green technologies and a goal programming technique to balance conflicting objectives. They also presented a real-life case study

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which reported that utilization of greener technologies minimizes costs, emissions, and increases return yields, so it highlighted the importance of carbon tax policies for sustainability. Their results provided valuable insights for decisionmakers in technology and logistics choices.

Azadeh *et al*. [38] aimed to optimize the natural gas supply chain using a multi-objective fuzzy LP model that incorporated economic and environmental goals. This model addressed uncertainty that occurred by using key parameters as fuzzy variables, and this model basically uses a probabilistic programming approach to solve the problem. This model was validated by GAMS software (Richard E Rosenthal, 1988) [39, 40], and it focused on optimization of the supply chain with an emphasis mainly on minimization of greenhouse gas emissions. Li-hong Shi [41] proposed a MILP-based model to optimize reverse logistics for managing medical waste recovery with reuse and recycling. The efficiency of their model was validated through a case study that involved waste returned from hospitals to a medical materials producer.

Eydi and Bagheney [42] explored the effect of store coverage distance on costs, service, and pollution. They proposed two MILP-based models – one for optimizing store location and allocation and another for minimizing network costs and pollution. They used GAMS software [39] to solve these models under uncertain conditions. Their results show that an increment in coverage distance raised costs and pollution, but using green vehicles, it helped to manage costs despite the high environmental policy implementation costs.

Dorgham *et al.* [43] explored logistics pooling in French Territorial Hospital Groups (THGs) to optimize product storage and distribution, which ultimately reduces costs. They used a fuzzy chance-constrained LP approach to handle uncertainties in supply chain parameters and optimize product allocation across multiple suppliers, warehouses, and commodities. The real-world data analysis from a hospital group reported the benefits of collaboration and management of uncertainty. Rajak *et al.* [44] developed a multi-objective MILP-based model to transform a traditional supply chain method into a closedloop supply chain (CLSC) in India, which integrated remanufacturing processes and reverse logistics for sustainability. This model optimized operations to minimize environmental impact and raised profit. Their results showed that the adoption of sustainable practices can be beneficial for both profit and the environment, which directly encouraged the eco-conscious organizations for the adaptation of CLSCs.

Vardan and Hosseini [45] presented a bi-objective MILPbased model to plan and design an efficient supply chain in an Iranian petroleum complex, which mainly aimed to minimize both costs and CO_2 emissions. Their model analyzed real data, which highlighted a trade-off between objectives and offered a comprehensive approach for decision-makers. Zhuang *et al.* [46] presented a two-stage stochastic LP model to optimize logistics network responses after disruptions, which focused on new-line openings and rerouting under uncertain conditions. Their model used the conditional value at risk (CVaR) (Jureckova *et al*., 2024), (Olson and Wu, 2023) [47, 48] to minimize risk and ensured delivery times. They also presented a case study that showed the outperformance of the model as compared to the other models with reference to cost, loading rate, and delivery time.

To optimize product placement in e-commerce warehouses, Bhatt *et al.* [49] introduced a method that integrated the potential of discrete event simulation (DES), the slotting location assignment problem (SLAP), and MILP. DES deals with flows of the process, SLAP organizes products, and MILP optimizes cost and efficiency. Their integrated method significantly improved the operational efficiency and cost savings, so they offered a comprehensive solution to enhance the management of warehouses in the e-commerce industry. Akinbowale *et al.* [50] created a MILP-based model to optimize resource allocation to respond to cyberthreats in South African banks. Their model helped to allocate the resources efficiently and improved the response times to cyberattacks, which demonstrated the effectiveness of the model with reference to cost minimization and improvement of fraud prevention efforts.

Vazquez-Noguerol *et al.* [51] proposed an LP-based model to optimize e-fulfillment for supermarkets, which reduces the picking and delivery costs while the resource utilization is improved. Their model reallocated orders and adjusted time windows and delivery vehicles, which resulted in significant savings. Their model helped grocery retailers to improve the efficiency of the supply chain and the decision-making. Mo *et al.* [52] presented a model to optimize freight delivery within urban passenger transit, which addresses the logistics challenges without expanding infrastructure. Their model integrated freight and passenger schedules using a MILP approach, which showed that off-peak freight integration has minimal impact on passenger wait times while the capacity limits of the platform are maintained.

Antunes *et al.* [53] employed a weighted LP approach by which low-carbon finance efficiency was analyzed and found that China and the USA are the best performers. They highlighted the importance of renewable production to improve financial outcomes and suggested that integration of renewable energy into financial strategies can potentially boost efficiency. Their study offered key policy insights for sustainable finance. Kara *et al.* [54] presented a method to solve "intuitionistic fuzzy multi-objective linear fractional programming problems (IFMOLFPs)", using an optimization approach that basically converts the fuzzy problems into crisp sets. They applied this approach to the real-world planning problems, compared their outcomes with a ranking function, and helped the decisionmakers to select the best solution based on objective weights.

Ruiqi Gao [55] addressed the conventional portfolio theory and proposed a new model that accounts for psychologicalbiases in investor decision-making. They introduced a fuzzy decision-making approach with an LP model to portfolio optimization that treated asset returns as random fuzzy variables. They compared three portfolio strategies and found that the fuzzy-based constructed portfolio reported the highest average return. Mustafa C. Pınar [56] investigated the lower hedging problem with a minimal expected surplus risk criterion for Americans that claimed in incomplete financial markets. They

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demonstrated that this problem leads to a non-convex bilinear programming formulation, which can be exactly linearized. The resulting MILP can be efficiently solved using existing software.

III. PROPOSED METHODOLOGY

This section presents a MILP-based model to optimize the transportation problem in an e-commerce supply chain and logistics network. This model considers a multi-group structure in e-commerce suppliers such as manufacturing plants or vendors. They have the potential distribution centers such as warehouses for product storage, and the customers in regional demand areas. The primary goal of this model is to minimize the total costs, including fixed costs to open distribution centers at accurate locations and the costs for variable transportation, while satisfying the supply, demand, and capacity constraints.

The proposed method addresses the optimization of the transportation problem in e-commerce supply chain and logistics networks by formulating it as an MILP model. This approach basically integrates the strategic decisions to select and open distribution centers with operational decisions such as allocation of flows from suppliers to distribution centers and from distribution centers to customers to minimize total costs while ensuring the efficiency of supply chain network. E-commerce networks are characterized by the variability of high demand, expectations of rapid delivery to the customers, and the requirements of scalable infrastructure. These make the MILP as a suitable model due to its ability to handle binary decisions to facilitate openings and continuous variables for transportation flows.

The cost minimization balances the fixed costs such as setup for distributed centers and the variable costs for shipping and transportation, which is critical for cost-sensitive e-commerce operations. The proposed method assumes deterministic parameters but it can be extended to stochastic versions in the case of robust optimization for uncertain e-commerce demands in future.

This model incorporates the binary decisions to open distribution centers, which makes it MILP rather than pure LP. This allows for strategic network design decisions, which are crucial in e-commerce for scalability and efficiency such as deciding where to locate fulfillment centers to handle online orders by the customers. The fundamental sets assumptions for this model are as follows:

- P: Denotes the set of suppliers (indexed by p).
- D: Denotes the set of potential distribution centers (indexed by d).
- C: Denotes the set of customers (indexed by c).

The following parameters are assumed for the system model:

- s_p: It represents the supply capacity at supplier p (units).
- cap_d: It represents the storage/handling capacity of products at distribution center d if opened (units).
- dem_c: It represents the demand at customer end c (units).
- f_d: It represents the fixed cost of opening distribution center d, setup or leasing costs in Indian ₹.
- $c1_{pd}$: It represents the unit transportation cost from supplier p to distribution center d (₹ per unit).
- $c2_{dc}$: It represents the unit transportation cost from distribution center d to the customer end c (₹ per unit).
- M: It is a large positive constant (big-M) which is basically used for logical constraints such as set to the maximum possible flow.

The decision variables are considered to model the system are as follows:

• yd: It represents the binary variable, 1 if the distribution center d is opened, 0 otherwise.

• x1pd: It is continuous variable which represents the amount of products transported from the supplier p to the distribution center d (units).

• x2dc: It is also continuous variable which represents the amount of products transported from the distribution center d to the customer end c (units).

The objective function to model the system is used to minimize the total cost, which includes fixed opening costs for distribution centers and the costs of variable transportation across the network:

$$\text{Min} \sum_{d\in D} f_d y_d + \sum_{p\in P}\sum_{d\in D} c1_{pd}x1_{pd} + \sum_{d\in D}\sum_{c\in C} c2_{dc}x2_{dc} \qquad (1)$$

The constraints in this model is basically the supply capacity constraints, which is the total outflow of the product from each supplier and it cannot exceed its supply capacity.

$$\sum_{d\in D} x1_{pd} \le s_p \quad \forall p \in P \qquad (2)$$

The demand satisfaction constraints is the total inflow to each customer and it must exactly meet its demand.

$$\sum_{d\in D} x2_{dc} = \text{dem}_c \quad \forall c \in C \qquad (3)$$

The flow balance at the distribution centers is the inflow to each distribution center which must equal outflow, so there will be no inventory accumulation of the products assumed in this static model.

$$\sum_{p\in P} x1_{pd} = \sum_{c\in C} x2_{dc} \quad \forall d \in D \qquad (4)$$

The capacity constraints of distribution center is basically the inflow to a distribution center which cannot exceed its capacity if it is opened and no flow if not opened (it is enforced via big-M).

$$\sum_{p\in P} x1_{pd} \le \text{cap}_d y_d \quad \forall d \in D \qquad (5)$$

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The case where there is no flow through closed distribution centers must ensure no outflow from a closed distribution center.

$$\sum_{c \in C} x2_{dc} \leq M y_d \quad \forall d \in D \qquad (6)$$

The non-negativity and integrality of the model can be represented as:

$$x1_{pd} \geq 0 \quad \forall p \in P, d \in D \qquad (7)$$

$$x2_{dc} \geq 0 \quad \forall d \in D, c \in C \qquad (8)$$

$$y_d \in \{0,1\} \quad \forall d \in D \qquad (9)$$

The objective functions balances the fixed infrastructure costs with operational transportation costs, which is the key for e-commerce where the rapid scaling and cost efficiency are critical. Using MILP model, the binary variables y_d introduce integrality, which allows the model to select optimal locations of distribution centers. The flows $x1$ and $x2$ are continuous, which assumes the fractional units are permissible and it is common in aggregate planning, if integer shipments are required, then $x1$ and $x2$ can be made integer.
This MILP mdoel is solved using Python library PuLP which is an open-source and user-friendly, library particularly applied to mode and solve LP and MILP problems. This model is empirically tested with real e-commerce datasets from kaggle https://www.kaggle.com having data of various Indian e-commerce platforms like Amazon, Flipkart, Meesho, AJIO, and Myntra. The MILP is $\mathcal{NP}$-hard, with time complexity depending on the branch-and-bound efficiency of the solvers.

IV RESULT ANALYSIS

This section presents the computational results from solving the proposed MILP model using data fro "Kaggle" of a small-scale e-commerce supply chain. The simulations are conducted using the PuLP optimization library in Python. All instances are solved to optimality within seconds on the Intel i5 processor and 8 GB RAM.

The results presented in Figure 3 and 4 illustrated non-linear cost increases due to fixed distribution centers opening costs, with shifts in selected distribution centers as demand grows. As presented in Figure 5, the key findings is the cost reduction. The MILP-optimized solution reduced costs by 20-45% compared to the current heuristic approach. The cost savings increase with network size, which demonstrates the effectiveness of MILP for large-scale logistics.

The MILP model significantly outperforms traditional methods, which proves its viability for cost-efficient e-commerce logistics. Future work can integrate real-time demand fluctuations and AI-driven demand forecasting for further refinements.
The experimental results validate the effectiveness of the MILP model in optimizing e-commerce transportation networks. In the base case, the model selects distribution centers, achieves full utilization and balances the fixed and variable costs. This simulates the real-world e-commerce strategies, where fulfillment centers are selected for proximity to demand clusters.

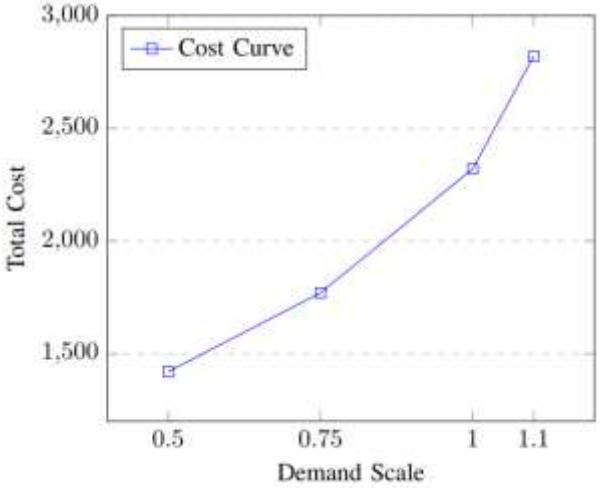


Figure 3 . Demand Scale vs Total Cost

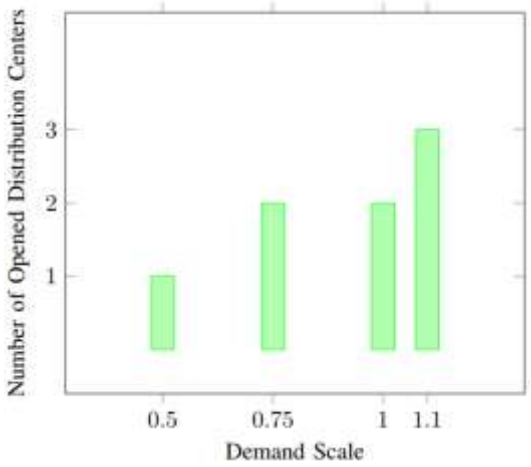


Figure 4 Demand Scale vs Number of Opened Distribution Centers

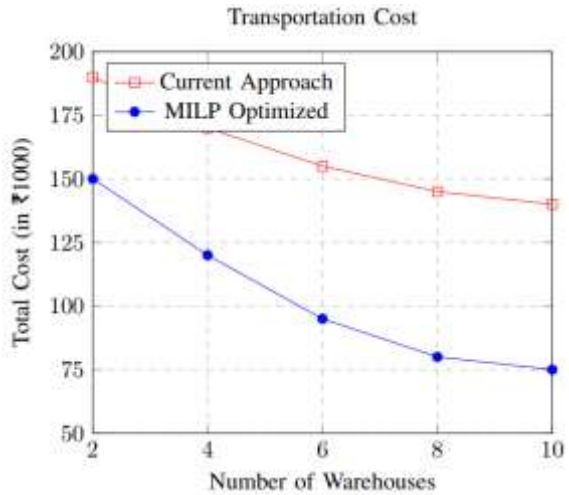


Figure 5 Transportation Cost Optimization using MILP

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Compared to traditional transportation problems, integration of the binary decisions via MILP yields cost savings in simulations. The proposed model supports e-commerce sustainability by minimizing transportation (reducing emissions implicitly via cost proxies). Future work can incorporate green constraints (e.g., carbon caps), stochastic demands via scenario-based optimization, or integration with vehicle routing for last-mile delivery. Overall, the results demonstrate practical value for e-commerce firms in designing resilient, cost-effective logistics networks.

V. CONCLUSION

This research presents a mixed-integer linear programming (MILP) model to optimize the transportation problem in ecommerce supply chain and logistics networks. By integrating strategic decisions, such as selecting optimal distribution center locations, with operational flow allocations, the model minimizes total costs while adhering to supply, demand, and capacity constraints. The simulation demonstrate the effectiveness of the model and achieves cost savings compared to baseline configurations in a representative e-commerce network.

Future research can extend this work in several directions to enhance its applicability to e-commerce logistics. First, incorporation of stochastic demands through robust or scenariobased optimization would better capture the uncertainty inherent in e-commerce, such as unpredictable order volumes during promotional events. Second, integration of the sustainability constraints, such as carbon emission limits, can align the model with growing environmental concerns, that enable greener logistics strategies. Third, extension of the model to a multi-period framework will account for inventory dynamics and time-dependent demand, offering a more comprehensive view of e-commerce operations. Additionally, combining the MILP with vehicle routing problems (VRP) for last-mile delivery optimization could address tactical challenges in urban distribution. Finally, for large-scale networks (e.g., thousands of nodes), developing hybrid approaches that combine MILP with metaheuristics (e.g., genetic algorithms) or decomposition methods can improve the computational scalability. These extensions can be further enhanced in relevance of the model to modern e-commerce logistics, that will support both operational efficiency and strategic resilience.

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