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Cost-Optimal Pathfinding Model for Multi-Echelon Logistics Network Design and Optimization: A Fourth-Party Logistics (4PL) Perspective

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Abstract. The adoption and integration of e-commerce strategies into existing business models have allowed many companies to broaden their customer base and boost profits. However, the lack of a cost-efficient logistics planning model often results in the unsatisfactory performance of complex multi-echelon supply chain networks. As transportation planning and scheduling are typically managed via independent entities within the supply network, one key challenge is achieving maximum asset utilization rates considering production flow, logistics cost, and delivery time constraints. This study leverages digital twin capabilities to propose a 4PL-oriented heuristics search model for omnichannel logistics planning and scheduling. The approach aims to enhance transportation flow and resource utilization while shortening waiting times within multi-echelon networks. An industrial case study is featured to validate its cost-effectiveness.

Keywords. Omnichannel, Digital twin, Network design and optimization, Fourth-party logistics provider, Cost-optimal pathfinding

Introduction

As turbulent post-COVID-19 events continue to disrupt global supply chains (SCs), more businesses rely on warehousing and fulfilment outsourcing to overcome resource deficiency and achieve cost savings [1]. Relying on multi-echelon networks to alleviate inventory deficits, the adoption of e-commerce business strategies to meet consumer expectations for faster delivery times and increased product varieties have resulted in reduced network resiliency and susceptibility to supply and demand-based disruptions. While third-party logistics providers (3PLs) can support last-mile delivery operations for noncomplex supply networks cost-effectively, larger enterprises utilizing multi-echelon networks require advanced digital solutions and streamlined SC processes to handle logistical roles. Fourth-party logistics providers (4PLs), a term coined by Accenture in the 1990s, allow companies to focus on developing value-adding products by providing holistic logistical operations ranging from order and supplier management to legal

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compliance [2]. In addition, 4PL partners can also incorporate 3PL services to strategically improve resource flow via efficient logistics planning and scheduling approaches to minimize cost and ensure on-time deliveries [3].

As an emerging technology in many digitalization roadmaps, SC digital twins (DT) can provide end-to-end (E2E) visibility across the network, simulation-based analysis and solution verification, and decision support mechanisms [4]. In addition to managing supply and production-based functional tasks such as production planning and scheduling, DTs can facilitate the implementation of business models [5] to boost profits based on the current market context. Hence, this study aims to establish a DT-enabled 4PL system to optimize multi-mile logistical planning and scheduling operations using a heuristics search model. With considerations for the global parameters of the entire supply chain, the proposed approach can provide effective solutions designed to maximize resource utilization while keeping costs low and maintaining On-Time In-Full delivery performance. In addition, the cost-optimal pathfinding model can aid disruption mitigation, and its effectiveness is demonstrated in an industrial use case of a 4PL small and medium enterprise. Through the optimization mechanism, 4PL partners can boost SC resilience and improve the robustness and flexibility of existing logistical operations for complex networks.

The structure of this paper is as follows. Section 2 reviews recent works involving 4PL-based optimization and DT applications in logistics. Section 3 proposes a DT-enabled 4PL optimization system and outlines the heuristics search model, while section 4 demonstrates its effectiveness through an industrial case study. Lastly, section 5 summarizes the work done and highlights future research prospects.

1. Literature Review

1.1. Fourth-party Logistics Optimization

Existing studies on prevailing multi-mile logistical challenges are widely explored for various domains ranging from public transportation to consumer packaged goods. This section highlights recent advances in the techniques and applications used for 4PL-related network planning optimizations. Building on the success of e-commerce business strategies in the urban context, Janjevic et al. presented a multi-echelon location-routing approach to support last-mile omni-channel deliveries [6], while Guo et al. designed a framework to support logistics transition based on the multi-level socio-technical transition theory [7]. Optimization-oriented studies have yielded positive findings, with Yin et al. proposing a two-stage nonlinear stochastic programming model to facilitate efficient 4PL delivery [8], and Melkonyan et al. utilizing an integrated multi-criteria decision aid and system dynamics simulation to support logistical network operations for food product distribution [9]. Meanwhile, Li et al. conducted a comparison between the krill herd algorithm and artificial fish swarm algorithm to improve the reliability and performance of 4PL networks in random disruption scenarios [10], and Wang et al. proposed a network design approach that maximizes the service satisfaction of both suppliers and customers under budget constraints [11].

Aiming to utilize alternative transportation modes, Moshref-Javadi and Winkenbach reviewed UAV-based logistics systems and their associated operational planning problems [12], whereas Liu et al. presented a hybrid multi-objective, meta-heuristic algorithm to support two-echelon e-grocery distribution networks via van, robot, and parcel locker resources [13]. Luigi et al. proposed a mixed-integer linear programming (MILP)-based network optimization approach featuring both drones and trucks to minimize routing costs [14]. Zhang et al. used a game-theoretical approach to highlight the value of 4PL financing modes [15]. Qian et al. proposed a two-stage stochastic winner determination model by integrating hybrid mitigation strategies to cope with disruptions [16]. Zhang et al. presented a multi-objective distributionally robust model for disaster relief with considerations for fairness, timeliness, and operational costs [17].

1.2. Digital twin-enabled logistics planning

Leveraging on real-time connectivity, network simulations, and solution generation capabilities, SC DT-enabled systems are increasingly adopted to support stakeholders in generating value-adding solutions within logistics domains [18]. To enhance supply network visibility, Moshood et al. reviewed DT technologies facilitating development of logistical benchmarks, predictive diagnostics, and cyber-physical linkages [19], whereas Marmolejo-saucedo proposed an information-sharing tool to improve risk visibility for products and processes within pharmaceutical logistical networks [20].

With emphasis on simulation aspects, Burgoas and Ivanov utilized discrete-event simulations to examine and improve food retail network resilience during COVID-19 [21], while Coelho et al. proposed a simulation-based in-house logistics system for design and planning operations using a modular approach [22]. In a construction logistics context, Lee and Lee leveraged real-time data from building information modeling (BIM) and geographic information system (GIS) to identify potential logistical risks and optimize routes [23]. For computational aspects, Bai et al. proposed a genetic algorithm for the control system of a holistic factory production line environment inclusive of logistical processes and routes to increase efficiency based on lean production theory [24]. Pan et al. presented a production logistics system utilizing multidisciplinary design optimization methods such as collaborative optimization and heuristics optimization algorithms to improve cost and production efficiency [25]. Shen et al. designed a fuzzy analytic hierarchy process to identify performance indicators for SC evaluation within tobacco logistics [26]. Marmolejo-saucedo developed a heuristics method based on vehicle routing and bin-packing problems to lower operational costs and optimize resources [27]. By combining a systematic layout design approach with an artificial bee colony algorithm within a textile manufacturer context, Zhang et al. enhanced manufacturing flexibility, shortened production cycles, and reduced logistical costs [28].

Nevertheless, from the literature mentioned above, existing studies on 4PL-based optimization techniques seldom consider the dynamic changes within inter-hubs, while DT-enabled logistics systems are often focused on individual production facilities and operated in silos. To fill this gap, a DT-enabled approach is proposed focusing on the dynamic properties of transportation resources to support 4PL network design and optimization.

2. Methodology

2.1. DT-enabled 4PL system for logistics planning and scheduling

In our previous work [29], [4], a multi-echelon SC network was designed with DT as an effective system to realize E2E visibility, workflow management, and disruption mitigation. Hence, bi-directional connectivity, simulation-based analysis, and data-driven solution generation capabilities are considered essential components towards establishing a functional DT for 4PL delivery network design and optimization. Figure 1 showcases a modular DT technology stack consisting of cyber-physical, representation, and computation layers to support transportation resource planning. The DT system adheres to the data-information-knowledge-wisdom (DIKW) hierarchy [30], serving as a circular data model to extract insights and value add towards process enhancement.

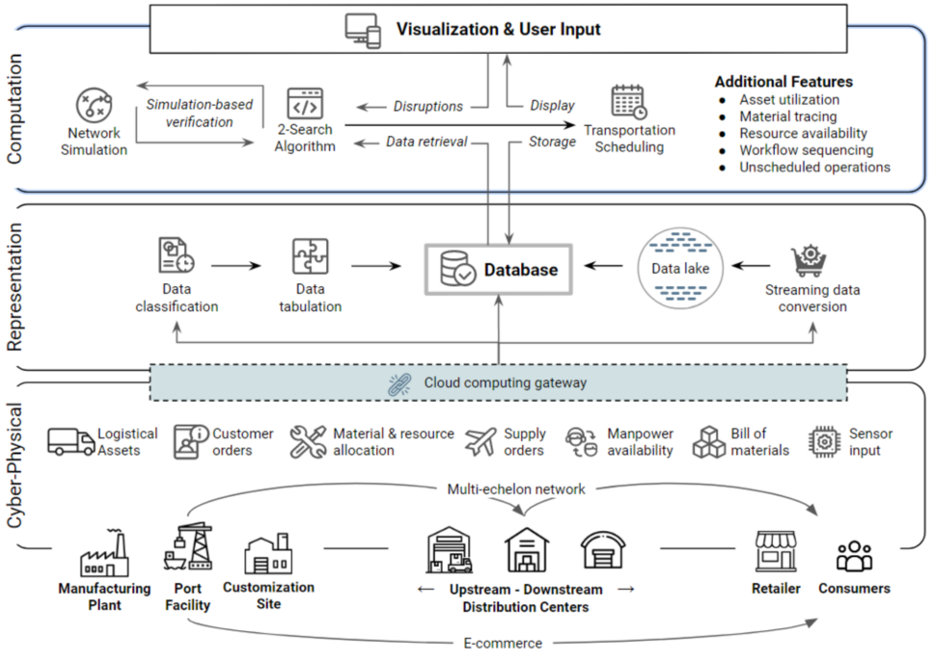

Figure 1. An overview of a 4PL-DT architecture for logistical planning and scheduling.

Within the multi-echelon SC network, supply entities (e.g., manufacturing and port facilities, customization sites) provide a continuous flow of finished goods (FG) for distribution, while upstream and downstream DCs manage the flow of goods and resources from regional to local areas before arriving at the retailers and consumers. Implementation of e-commerce strategies will result in FG transportation skipping the DC entities to arrive directly at end users.

Starting with the cyber-physical layer, raw data is acquired from sources such as logistical assets, customer orders, material and resource allocation, supply orders, manpower availability, bill of materials (BOM), and sensor inputs. This heterogeneous data passes through the cloud computing gateway for storage and retrieval in the common database. Here, fixed data types, such as order information, are processed via the data classification and tabulation modules before storage. Meanwhile, continuous data inputs from sensors are processed via the streaming data conversion module before temporary storage in the data lake. Subsequently, relevant information will be filtered out for database storage. Next, the representation layer processes raw data into information for storage and retrieval. Periodical datasets such as customer orders and resource allocation are classified and tabulated before entering the database, while continuous datasets such as sensor inputs pass through the streaming data conversion before being temporarily stored in the data lake. Relevant information, such as historical location, will be filtered for database storage. Lastly, the computational layer aims to derive valuable knowledge through optimization algorithms, while the simulation and transportation scheduling module provide stakeholders with wisdom essential for making informed decisions. Utilizing retrieved data from the common database, the search algorithm will provide an optimal transportation resource plan which is verified via the network simulation module. Once a feasible solution is identified, the transportation scheduling module will facilitate workflow planning for each transportation resource with considerations of utilization rate, material tracing, resource availability, sequencing, and unscheduled operations. Results are displayed through a front-end module with stakeholder requirements and disruption scenarios serving as data input for optimization and risk management.

By ensuring real-time connectivity, inputs and dynamic changes can be processed immediately, while the simulation module can support scenario-based analysis, solution verification, and evaluation of alternative business models such as make-to-stock and make-to-order strategies.

2.2. Heuristics search method for transportation scheduling

Emphasizing the DT-driven computational aspects, a heuristics search optimization model is designed to derive a feasible delivery schedule. Using information pertaining to the network hubs (e.g., DC locations, availability), network (e.g., connections between hubs, delivery attributes), and packages (e.g., storage and vehicle availability), an overview of the algorithm is highlighted in Figure 2.

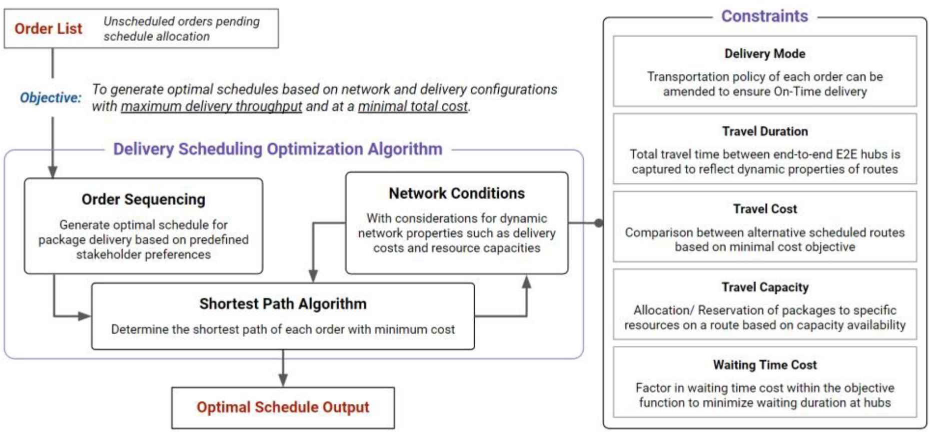

Figure 2. Process flow of the heuristics search optimization model for 4PL transportation scheduling.

To generate an optimal schedule, the main scheduling algorithm consists of (1) order sequencing, (2) shortest path algorithm, and (3) network condition constraints. The shortest path algorithm is time-dependent and expands on the Two-Step-Search methodology proposed by Yang et al. [31] to generate optimal schedules. Based on network and delivery configurations for maximizing delivery throughput and minimizing the total cost, this algorithm also factors in five constraints: (1) Delivery mode, (2) Travel duration, (3) Travel cost, (4) Resource capacity, and (5) Waiting time cost.

Based on the initial unscheduled order list, the order sequencing module considers delivery requirements and preferences, such as the required use of specific transportation resources for certain products/orders. As such, the module prevents inappropriate schedule sequencing as limited delivery resources might result in nonoptimal resource capacity consumption in some routes. To ease this time-computional expensive process, a preferred sorting sequence can be applied based on priority, earliest start time, latest arrival time, and package size. Besides a deterministic sorting rule, another approach would be to utilize the heuristic algorithm to find the optimal order sequencing based on local searches until a better solution is found. However, this approach will be computationally expensive for medium or large order sets (>50 orders).

Next, the shortest path algorithm consists of two steps, with the first step involving the creation of an arrival-time-minimal-cost (atmc) discrete function based on a minimal cost to travel from the origin hub till the end hub. The second step features a procedure to extract the hub sequence with the earliest arrival time and at minimal cost. The output should include a sequence of visited hubs, arrival and waiting times, and the total travel cost for each order/ at each hub. The network conditions portray the dynamic network properties and are linked to the earlier five constraints. Here, the travel duration, travel cost, travel capacity, and waiting time cost are factored in when establishing the atmc function at each cost, while the delivery mode constraint is used to identify potential solutions based on the earliest arrival time at the end hub and latest arrival time (due date) of the delivery order. The optimal schedule output generated will be forwarded to each transportation resource for implementation through an iterative process between the shortest path algorithm and the network conditions.

3. Case Study

To demonstrate the effectiveness of the DT-enabled 4PL optimization approach on real-life industrial scenarios, a multi-mile logistics network for a medium-sized 4PL enterprise is used as a testbed whereby the model is integrated within the logistics scheduler. With consideration to relevant factors, including resource capacity, departure time, travel duration and cost, the objective is to maximize production delivery flow at minimal total cost and duration. Additionally, this solution also complements the existing manufacturing execution system (MES) to provide real-time and uninterrupted E2E SC visibility (including transport modes) to improve logistical scenario planning and costing.

3.1. Establishing the logistical network model

Taking reference from the SC DT model in [4], a modular approach is adopted to facilitate software upgrades and algorithm switches for scalability. Network information and optimization results are stored via a PostgreSQL common database, while APIs are used to access the various functional modules within a web application. Three core datasets representing hub, network, and package information are required for the delivery scheduling algorithm to function. Hub information includes the ID, address, country, and logistical status. Network information includes the ID, availability, capacity, hub edges, travel cost and time, and distance. Package information includes ID, size, earliest start date, latest arrival time, and priority. Functional managers have individual access to perform assigned roles through a React.js front-end interface. Through the platform, constraints and configurations can be implemented for simulation and optimization functionalities, as highlighted in the architecture from Section 2.

3.2. Cost-optimal pathfinding optimization

Results from the heuristics search model are shown in Figure 3 (left), whereby every order is evaluated based on feasibility. The sequence of delivery packages can be configured prior to executing the algorithm based on stakeholder preferences (e.g., priority, size, earliest start date, and latest arrival time) to determine the most suitable approach. Visualization of data and the status of unfeasible solutions are also included with reasoning to aid clarity and improve end-user trust. Figure 3 (right) maps out the selected route via a geographic information system layout, summarizing relevant logistical information before stakeholder approval.

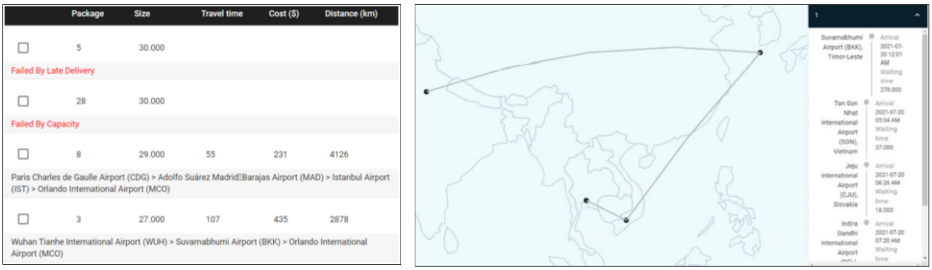

Figure 3. Optimal delivery schedule (left), visualization of optimal route details (right).

Experiments featuring small and medium-sized logistics networks (approximately 50 – 200 locations, 500 – 10,000 delivery routes) highlighted the effectiveness of the pathfinding algorithm. However, more extensive networks will require extended periods of time to generate an outcome, posing as a limitation. In practice, packages are usually sequenced based on standard delivery policies such as First-In First-Out, priority, and due date. This cost-optimal pathfinding model can also be applied across industries utilizing complex networks, such as hauling, fast-moving consumer goods, food and beverages, catering to e-commerce, retail, and direct distributorship business models.

4. Conclusion

Logistics scheduling is an essential process within supply chain management, but in industry practice, transportation scheduling is typically handled independently within local network hubs, resulting in suboptimal resource utilization. To enhance the performance of delivery scheduling in dynamic network environments, a DT-enhanced heuristics search model is proposed for multi-mile omnichannel logistical planning and scheduling. By streamlining the many processes previously operated in silos systematically, this system supports bias elimination and bridges experience gaps. The scientific contribution of the study include (1) a three-layered 4PL-oriented DT establishment, including cyber-physical, representation, and computation layers which interact to value-add towards logistical processes, (2) a cost-optimal pathfinding model for transportation resource scheduling and optimization, (3) consolidation of industry-approved logistical network constraints and conditions.

Through a 4PL enterprise case study, the cost-effectiveness of this 4PL-DT system was validated. Furthermore, the system value adds to existing 3PL enterprises by expanding their scope of operations to encompass resource management with multi-echelon networks. The transdisciplinary aspect involves supply chain logistics for network optimization, knowledge management for resource tracking, and decision support analysis for solution generation. Potential research directions include a global optimization scheduling mechanism to maximize delivery flow while minimizing total cost as an NP-hard problem. Further exploration of supervision algorithms, such as metaheuristics and reinforcement learning-based approaches, can overcome 5PL-related challenges, where a complete SC network from production to delivery has to be mapped and optimized.

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