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Research Article

Integrated Location–Allocation and Dynamic Routing for E-commerce Networks Under Demand Uncertainty

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Abstract:

E-commerce logistics networks are under increasing pressure to strike a balance between operational efficiency and service quality under unstable patterns of demand. The classical planning models treat facility location and vehicle routing as a set of independent optimization problems, which do not reflect important interdependencies between strategic network design and operational dispatch decisions. These decision layers are combined in a two-stage stochastic programming framework with distribution facilities in place before demand is realized, and operational flexibility is retained by taking recourse actions of dynamic routing decisions. The former is the determination of facility activation and the initial demand zone assignments in the face of uncertainty, and the latter is the adaptive construction of vehicle routes as the customer orders become known. Rolling horizon heuristics allow path replanning within operating windows, which can handle real-time arrivals of orders without the need to add too much computational load. Geospatial road network data provides realistic estimates of distances that accommodate real driving routes and city topography. The validation of simulation has shown that the efficiency in transportation, cost reduction, and responsiveness of service are significantly improved as compared to traditional centralized or static planning strategies. The combined framework is specifically useful where third-party logistics providers, online grocery delivery businesses, and business-to-consumer retailers are dealing with uncertain demand and managing distributed customer bases with strong demand expectations in terms of delivery time.

1. Introduction and Problem Context

The digitalization of retail business has radically changed the logistics processes and established complicated problems concerning the optimization of the delivery network. The fourth quarter analysis shows that there are continued growth trends in electronic commerce in various retail products, with the total e-commerce sales showing continued quarterly growth that is reflective of basic changes in consumer purchasing behavior patterns [1]. This growth includes the incorporation of the old retail segments into the online environment as well as digitally native expressions of business that, together, result in the large quantities of small-parcel deliveries that demand highly advanced logistics strategies.

The last part of delivery operations, which involves distributing facilities to the individual consumer locations, is a critical challenge with specific operational constraints and cost structures. In contrast to consolidated linehaul transportation, where the economies of scale play in favor of the carriers, the destinations in this delivery phase are dispersed, service needs are individualized, and the navigation of the urban environment is complicated [2]. The uncertainty in demand patterns, where there is a significant variation in order volumes and geographic distributions in temporal cycles, also adds to the operational challenges. All these variations are based on various influencing factors such as promotional activities, seasonal trends, weather patterns, and changing consumer preferences that cannot be determined using deterministic methods [3].

The modern logistics networks have to satisfy conflicting goals at the same time: to reduce the spending on operations and to retain the service quality that is popular among customers,s so asto promptly satisfy their demand. Conventional computational methods of optimization usually break down the network design problem, with facility location choices and vehicle routing activities being treated as separate planning activities. This sequential decision model is less efficient in reflecting the interdependencies among strategic network structure and operational routing efficiency, especially where there are uncertain conditions of demand [3].

Mathematical modeling of logistics networks has developed to include stochastic aspects, giving the realization that the future state of demand cannot be established precisely upon making strategic investments. Two-stage stochastic programming models offer a structured solution to this uncertainty-based decision-making, a category of decisions that is made before resolving the uncertainty stage is accomplished, and decisions that are made after the information is revealed in the second stage [4]. Facility location and allocation of capacity in the logistics scenario are strategic choices made at the first stage, and vehicle routing and dispatching schedule are operational choices made at the second stage in response to the demand trends that have been realized [4].

2. Theoretical Framework and Model Architecture

Integrated location-routing as a problem with uncertainly known future is mathematically based on stochastic programming theory, which offers conceptual rigorous frameworks for making decisions when the future is probabilistically known but not deterministically predictable. A two-stage stochastic program with recourse is the best paradigm according to which decision-makers commit themselves by making initial decisions prior to the uncertainty being cleared, and subsequent reactions are made upon the availability of information [5]. This framework is especially good in logistics planning, whereby strategic infrastructure decisions are made before operation dispatch decisions, which react to the daily realizations of demand.

The two stages are differentiated by the formal structure that identifies the variables of decision, the parameters, and the constraints. Decisions at the first stage are usually discrete decisions like facility activation decisions, capacity installation decisions, or resource allocation decisions, which require prior commitment. The first-stage variables used in the logistics application are binary variables (the presence of an opening distribution facility at candidate locations) and continuous variables (capacity levels at the activated locations). The related costs are fixed facility establishment costs, lease or purchase costs of real estate, as well as the baseline operational costs without regard to the throughput volume [5].

Decisions at the second stage are the acts of recourse performed after the decision to uncertainty has been made, and they are adjusted to the particular situation that arises. In the case of vehicle routing, binary assignment indicators (indicating which facility to serve a customer in a particular scenario), binary arc traversal variables (making vehicle paths), and continuous variables (following the service time or vehicle loading) are second-stage variables. The goal is that the expected total cost is minimized, which is a combination of first-stage costs, incurred with certainty, and second-stage costs, scenario-probability weighted costs, which depend on the realized demand [5].

The constraint structure makes decisions feasible and logical at both stages of decision-making. Constraints interrelate variables in the first and second stages such that the second-stage variables must only use the first-stage-established resource or facility. In any case, conventional vehicle routing assumptions are in place, such as flow conservation at the nodes, vehicle capacity limitation, route time limitations, and subtour elimination [5].

The combination of facility location and vehicle routing in one optimization provides significant trade-offs between the structure of the network and operating efficiency. This trade-off analysis has been extended by the stochastic formulation, which acknowledges that optimal facility configurations are dependent on demand variability patterns [6].

3. Solution Methodology and Algorithmic Approach

The intricacy of integrated location-routing problems has led to the development of specialized solution methods that are optimism optimistic in determining the solution at the cost of realistic levels of tractability. Even the simplest deterministic versions of the vehicle routing problem fall in the NP-hard category of complexity, that is, there are no known polynomially time algorithms to provide optimal solutions to large-scale problems [6]. This, combined with the integration with the facility location problems and stochastic demand models, makes the perfect optimization impossible with realistic problem sizes in real-world commercial contexts. Therefore, decomposition schemes and heuristic techniques are critical in deriving some useful solution schemes.

Decomposition methods take advantage of the problem structure to break the integrated model into smaller, manageable subproblems that can be addressed individually with coordination mechanisms that guarantee the overall quality of the solution. In one classical model, the decisions of the facility location master problem are isolated, and then the routing subproblem decisions take place, elevating the facility configuration in response to a routing cost feedback [7]. The master problem chooses which facilities to open based upon fixed cost and estimated routing cost, whereas subproblems calculate actual routing costs at each candidate facility configuration. The methods of cutting planes produce constraints that gradually reduce the lower bound of optimal costs of the master problem, directing the search to better solutions by systematic reduction of bad facility configurations.

The practical nature of vehicle routing as a dynamic problem when customer orders arrive in a sequence, not known in advance, presents further challenges to the solution of the problem of optimal routing, as opposed to the traditional problem of optimal routing, which is dynamic in character. The dynamic vehicle routing issues involve the need to have decision policies that determine how to allocate emerging orders to vehicles and when to commit vehicles to particular routes as information becomes available over time [8]. Rolling horizon methods give practical solutions to dynamic routing, an approach that addresses a sequence of pre-planning routing problems whose finite planning horizons are updated as time advances. At every decision epoch, the algorithm is used to maximize routes of known orders in the current time window, considering the forward-looking period, to execute the first part of the solution, before the algorithm re-optimizes based on the new information or the increase in the planning horizon.

The heuristic construction and improvement processes allow the quick creation of high-quality routing solutions subject to the time constraints of operational decision-making demands. Local search improvement techniques improve starting solutions by exploring local neighborhoods in an iterative process, looking at small changes to existing solutions, and accepting those that are discovered [6].

4. Experimental Design and Validation Framework

To empirically validate integrated location-routing models, it is necessary to have carefully constructed computational experiments that are sufficient to represent the key attributes of the problem and to allow the model to be analyzed analytically. The evaluation of model performance when it comes to analyzing it in various conditions of demand and operational conditions can be explored through the use of simulation-based evaluation [9]. Experimental design involves the specification of problem instances, such as geographical area, candidate sets of facilities, demand trends, and operational specifications, and specification of the baseline comparison strategies and performance measures to be used in quantitative assessment.

Geographical representation usually generalizes the service area into discrete areas of demand based on natural geographical or administrative lines. Postal code areas offer convenient aggregations of space, which trade off spatial resolution to compute manageability since each delivery address can be aggregated into a representative zone centroid without necessarily modeling all the possible destinations [9]. The candidate facility set is a list of possible distribution center locations that are identified based on strategic factors that include distance to transportation facilities, availability of real estate, and coverage of a major concentration of demand.

The characterization of demand is an important point of customer order design since the stochasticity of the customer orders is the main uncertainty in the optimization problem. The empirical basis of demand modeling is historical transaction data, which is collected based on the actual records of business operations over a long duration, and the volume of orders and geographic distribution are extracted [9]. The patterns of demand across zones can be identified statistically through historical analysis of how different zones display demand, and this is not just an average volume, but also variance, and correlation structures affecting the best network designs. Scenario generation methods convert these empirical distributions into discrete sets of scenarios, which can be optimized computationally through sampling algorithms that ensure that critical statistical properties are preserved, but the size of the set is kept small to ensure tractability.

Baseline comparison strategies will likely give the points at which the integrated model will be compared to the performance improvement of lower or more traditional methods. The centralized static routing base indicates classic logistic operations in which all the deliveries are made in the same central warehouse, with routes being scheduled per day, with full prior information of the orders [10]. Performance assessment uses various indicators that represent various aspects of logistics network efficiency, such as transportation efficiency, economic performance, and service quality [10].

5. Performance Analysis and Comparative Results

The computational analysis of integrated location-routing optimization indicates that there are significant performance benefits along several evaluation dimensions as compared to traditional planning methods. The facility structure that has been determined under two-stage stochastic programming usually has an average number of facilities whose locations are strategic to balance transportation efficiency with the cost of infrastructure [11]. The scale of problems to which optimal solutions are applicable, based on the parameters of demand density, cost structure, and the scale of a problem, is that metropolitan-scale problems are often solved by multiple facilities located in different regions instead of on one extreme, centralized, or on the other extreme, over-proliferated small facilities.

The distribution of geography of the chosen facilities expresses the demand concentration patterns as well as the uncertainty feature of the best solutions. Facilities are located strategically close to high-demand operating areas to reduce transportation distances to most of the delivery locations, which is in line with traditional facility location concepts [11]. Stochastic optimization, however, makes subtle positioning changes based on the strong solution as opposed to the deterministic solution, and occasionally a location with greater flexibility is preferred to serve multiple demand areas as opposed to locations that are as close as possible to individual large areas. This behavior of hedging is a consequence of the fact that the model takes variability in demand as a scenario into account and will value factory configurations that ensure acceptable performance under a wide range of possible demand realizations instead of only taking the most probable or average realizations.

One of the main performance benefits of combined optimization schemes is transportation efficiency. The integration of facility location and routing allows finding network structures that reduce the overall distance of the vehicles traveled, yet maintain operation constraints [11]. Computational experiments invariably show large distance savings over baseline strategies, with composite strategies incurring quantifiably reduced total vehicle-miles traveled compared to single-facility operations that are carefully planned or multi-facility structures that are not planned to explicitly address routing.

Measurements of service quality offer alternative performance lenses to the cost-minimization goals. Improvements in service time measures that are normally seen with integrated location-routing strategies are a combination of the beneficial effect of shorter transportation distances and an increase in operational flexibility. The use of integrated optimization methods is more likely to produce more uniform service time distributions of a smaller variability than the baseline strategies [12].

6. Applications and Strategic Implications

The unified location-routing optimization model demonstrates a wide range of applications in a variety of logistic situations that are typified by unpredictability in demand and time sensitivity of the service. One of the logical areas of application where the flexibility of the methodology is of specific value is the use by third-party logistics providers of multi-client delivery networks [3]. Such organizations run delivery operations with a diverse group of clients that are retailers that have different product lines, patterns of order, and service needs. Due to the irregularity of the volume of shipments and destinations per day with each client, aggregate demand at the network level is uncertain even when the client-specific patterns can be partially predictable. This uncertainty can be factored in through strategic positioning of facilities undertaken in a way that takes into consideration the scenarios via optimization to achieve operational efficiency when the conditions of the client mix change.

The economic value proposition of third-party logistics applications continues to be the direct cost minimization, but also competitive positioning and consideration of a client relationship. Efficiency in transportation translates to reduced per-shipment operating costs, which result in affordable pricing proposals when offering bids to client contracts [3]. Improvement of performance in service times is to be used in the differentiated service offerings at premium pricing possibilities time-sensitive delivery segments. The dynamic nature of optimized network designs will give the buffer capacity to ensure that the demand wave of clients does not result in the degradation of service provision, and the ability to retain clients over the long term due to reliability.

The application opportunities of online grocery delivery operations are especially interesting because of the unique nature of the operational processes of the sector, with restrictions of perishability and unpredictability of the time of the order, and high expectations of delivery within a very short period. Consumer grocery orders are delivered continually, which has a shorter lead time during working days, since buying decisions are usually made shortly before the required consumption periods [4]. This time dynamics compares to the old type of retail e-commerce, in which orders are collected at night and completed in batches the next day, and requires the true dynamic routing strategies that can use the orders at real-time or near-real-time intervals.

B2C e-retailers that have an established distribution network can use integrated optimization techniques on the tactical decision level to increase the use of the current network [3]. Logistics optimization has both environmental sustainability implications that go beyond the personal gains of an organization to the wider effects on society. The emissions of the transportation industry make up major parts of the overall greenhouse gas inventories in developed economies, and urban freight processes are major causes of air quality problems in metropolitan areas [2].

Main body of manuscript should be written using times new roman and 11 punto. The reference should be given in bracket for journal [1], for book [2], for e-book [3], for conference presentation [4] and for web site [5]. For all references, list the first six authors; add "et al." if there are additional authors. Please cite reference as following if you need mention name : "Akkurt (2009) has performed an experiment fort his purposes [2]". The formula should be given as in equation 1.

Table 1: *Decision Variables and Cost Components in Two-Stage Stochastic Framework [5]*

Stage	Decision Type	Variable Category	Cost Structure
First Stage	Facility Activation	Binary indicators	Fixed establishment costs
	Capacity Installation	Continuous variables	Real estate lease/purchase
	Resource Allocation	Discrete choices	Baseline operational costs
Second Stage	Customer Assignment	Binary assignment indicators	Scenario-dependent routing
	Vehicle Routing	Binary arc traversal variables	Distance-based transportation
	Service Scheduling	Continuous time/load variables	Probability-weighted recourse

Table 2: *Computational Complexity and Solution Methodologies [6-8]*

Problem Component	Complexity Class	Solution Approach	Key Technique	Computational Benefit
Vehicle Routing Problem	NP-hard	Decomposition methods	Master-subproblem separation	Tractable subproblems
Facility Location		Cutting plane methods	Progressive constraint tightening	Lower bound refinement
Integrated Location-Routing		Rolling horizon heuristics	Sequential static optimization	Real-time adaptability
Dynamic Order Assignment		Greedy insertion algorithms	Minimum incremental cost	Fast initial solutions
Route Optimization		Local search procedures	Neighborhood exploration	Near-optimal quality

Table 3: *Experimental Design Components and Validation Parameters [9, 10]*

Design Element	Representation Method	Data Source	Analysis Technique	Purpose
Geographic Scope	Postal code zones	Administrative boundaries	Spatial aggregation	Computational manageability
Facility Candidates	Distribution center locations	Transportation infrastructure	Strategic positioning	Coverage optimization
Demand Patterns	Order volume distributions	Historical transaction data	Statistical analysis	Uncertainty modeling
Scenario Generation	Discrete scenario sets	Empirical distributions	Monte Carlo sampling	Stochastic representation
Baseline Strategy 1	Centralized static routing	Single warehouse origin	Deterministic planning	Traditional comparison
Baseline Strategy	Decentralized static	Multiple facility	Fixed allocation	Multi-depot

2	routing	locations		benchmark

Table 4: Performance Metrics Across Optimization Strategies [11, 12]

Strategy Type	Facility Configuration	Transportation Efficiency	Service Time Performance	Spatial Flexibility	Demand Adaptability
Centralized Static	Single warehouse	Lowest efficiency	Longest average time	Limited coverage	No adaptation
Decentralized Static	Multiple fixed facilities	Moderate efficiency	Moderate time	Regional coverage	Limited adaptation
Integrated Stochastic	Strategically distributed	Highest efficiency	Shortest average time	Optimal coverage	Full adaptation
Deterministic Multi-facility	Average-demand placement	Reduced efficiency	Above-average time	Fixed coverage	Minimal adaptation

7. Conclusions

The combination of facility location and dynamic vehicle routing in single stochastic optimization models works toward the basic constraints of the conventional logistics planning paradigms. The integrated framework is able to make more robust network designs that sustain performance with a wide range of demand realizations by explicitly modelling demand uncertainty with scenario-based representation and recourse decisions that provide operational routing flexibility. The two-stage vessel fits well with strategic infrastructure commitments and the tactical operational responses, as it acknowledges their difference in terms of time scales and contains the necessary interdependencies. The application of rolling horizons offers viable tools for adapting to new information continuously in the course of operational implementation, striking a balance between the responsiveness requirements and the computational tractability requirements. Computational validation establishes significant gains in various aspects of performance, such as transportation, minimization of cost, and service time improvement, as compared to traditional baseline strategies. The framework demonstrates a generalized applicability to the third-party logistics processes, online grocery delivery service, and the conventional retail distribution network that is experiencing the demand volatility issue. Direct economic benefits are accompanied by environmental co-benefits in the form of fewer vehicle-miles traveled in support of sustainability goals, in addition to operational efficiency goals. The practical value and quality of the solution can be expanded by adding inventory positioning decision-making, a multi-modal transportation facility, and machine learning demand forecasting in the future.

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- **Ethical approval:** The conducted research is not related to either human or animal use.
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