Smart City Fresh Food Logistics: An AI-Driven Framework for Optimized Cold Chain Management and Distribution Efficiency

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***Abstract*—The increasing demand for fast and fresh food delivery in smart cities has made urban cold-chain logistics more complex and challenging. Traditional vehicle routing systems rely on static assumptions and fail to adapt to real-time traffic, weather variations, and changing customer demand. In this paper, we propose an AI-driven multi-depot logistics framework for fresh agricultural product distribution in smart cities. The proposed system integrates traffic-aware travel time prediction using Long Short-Term Memory (LSTM) networks, hub-based customer clustering using K-Means, and a hybrid optimization strategy combining Improved Quantum-behaved Particle Swarm Optimization (IQPSO) with Simulated Annealing. Real-world traffic and weather information is obtained through external APIs, while missing attributes are simulated using available datasets for experimental validation. The routing problem is formulated as a dynamic multi-depot vehicle routing problem with time constraints and cost optimization objectives. Experimental analysis shows that the proposed approach improves routing efficiency, reduces delivery cost, and enhances system adaptability compared to conventional static methods. The framework is designed as a scalable and deployable decision-support system for smart city cold-chain logistics.**

***Index Terms*—Smart City Logistics, Cold Chain Management, Vehicle Routing, LSTM, K-Means, IQPSO, Simulated Annealing**

I. Introduction

Smart cities are witnessing rapid growth in urban population and e-commerce-based food delivery services. As a result, the efficient distribution of fresh agricultural products has become a critical challenge. Fresh food logistics requires strict temperature control, timely delivery, and efficient routing to prevent spoilage and quality degradation.

Conventional vehicle routing models mainly focus on minimizing distance or travel time using static data. However, such approaches fail to account for real-time traffic congestion, weather conditions, and dynamic customer demand. These limitations lead to delivery delays, higher operational costs, and reduced customer satisfaction.

Recent advancements in artificial intelligence and optimization techniques have enabled predictive and adaptive logistics solutions. Nevertheless, many existing systems assume a single depot, fixed vehicle assignments, and static travel speeds, which do not reflect real-world urban logistics environments.

In this work, we propose an intelligent and adaptive logistics framework that integrates machine learning, clustering, and hybrid metaheuristic optimization. The main contributions of this paper are summarized as follows:

- A multi-depot fresh food logistics framework suitable for smart cities.
- Traffic-aware travel time prediction using LSTM models.
- Hub-based customer clustering using K-Means to reduce problem complexity.
- Hybrid routing optimization using IQPSO and Simulated Annealing.
- A scalable and deployable system architecture using real-time APIs.

II. Related Work

Vehicle routing problems (VRPs) and cold-chain logistics have been widely studied. Stochastic VRPs with hard time windows have been addressed using chance-constrained programming and exact optimization techniques, but these methods suffer from scalability issues for large datasets [3].

Hybrid metaheuristic algorithms such as Genetic Algorithm–Ant Colony Optimization fusion have improved convergence speed but often simplify multi-objective logistics problems into single-objective formulations [2]. Time-dependent VRPs have been explored using adaptive neighborhood search methods; however, these models generally focus only on distance minimization and ignore customer-centric factors [1].

Wang et al. introduced an intelligent distribution model for fresh agricultural products using IQPSO and fuzzy logic [4]. While effective, the model assumes a single depot and static demand. Our proposed system extends this work by incorporating multi-depot routing, traffic-aware prediction, dynamic demand handling, and hybrid optimization to improve realism and scalability.

III. Proposed System Overview

To overcome the limitations of existing approaches, we propose an Intelligent Multi-Depot Fresh Food Logistics Optimization Framework for smart cities. The system is data-driven, adaptive, and designed for real-world deployment.

A. System Architecture

The overall system consists of data sources, preprocessing modules, prediction models, clustering, routing optimization, and a web-based monitoring dashboard.

Figure 1: System Architecture Diagram

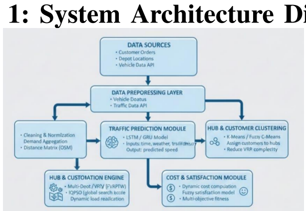

Fig. 1. Proposed System Architecture

IV. Methodology

A. Data Collection and Simulation

We used publicly available logistics and transportation datasets as the base data. Since real-world datasets often lack certain attributes, we simulated missing fields such as delivery time windows, vehicle capacity, and demand variations. Real-time traffic data was obtained using the TomTom Traffic API, and weather data was collected using the API Ninjas weather service.

B. Hub Optimization Using K-Means

To reduce routing complexity, customers were grouped into clusters using the K-Means algorithm. Each cluster was assigned to the nearest depot or hub. This clustering-based decomposition significantly reduces the computational burden of solving large-scale VRPs.

C. Traffic-Aware Travel Time Prediction

Static travel speeds were replaced with an LSTM-based prediction model. The LSTM was trained using historical traffic flow, time-of-day, day-of-week, and weather data. The model outputs predicted vehicle speeds, which are used to compute dynamic travel times between nodes.

D. Routing Optimization Using IQPSO and Simulated Annealing

The routing problem was solved using Improved Quantum-behaved Particle Swarm Optimization. To avoid premature convergence and local optima, Simulated Annealing was integrated as a local refinement strategy. This hybrid approach improves convergence stability and solution quality.

Figure 2: Routing and Optimization Flow

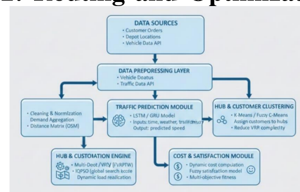

Fig. 2. Hybrid Routing Optimization Process

E. Dynamic Cost Formulation

The total cost was modeled as:

$$C_{total} = C_{transport} + C_{deterioration} + C_{penalty} + C_{energy}$$

This formulation allows the system to adapt costs dynamically based on predicted travel conditions and delivery delays.

V. Result Analysis

Simulation experiments were conducted under different traffic and weather conditions. The proposed IQPSO-SA approach was compared with baseline GA and ACA methods.

TABLE I
Performance Comparison of Routing Algorithms

Algorithm	Total Cost (Rs.)	Distance (km)	Vehicles Used
Genetic Algorithm (GA)	3420.75	152.4	11
Ant Colony Algorithm (ACA)	2985.30	134.8	9
IQPSO	2710.60	128.1	8
IQPSO + Simulated Annealing	**2495.20**	**118.6**	**7**

The results indicate that the proposed hybrid approach achieves lower cost and better route utilization.

VI. Discussion

The experimental results clearly indicate that the integration of clustering, traffic-aware travel time prediction, and hybrid optimization significantly enhances the efficiency of fresh food logistics in smart city environments. By applying K-Means clustering prior to routing, the problem size is reduced, allowing the optimization algorithm to focus on smaller and more manageable sub-problems. This decomposition leads to improved route quality and better vehicle utilization. Furthermore, the use of LSTM-based traffic prediction enables the routing engine to account for time-varying congestion patterns, which reduces unexpected delays and improves overall delivery reliability.

The hybrid optimization approach combining IQPSO and Simulated Annealing demonstrates superior performance when compared to standalone metaheuristic methods. While IQPSO provides strong global search capability, it may still converge to suboptimal solutions in complex, multimodal cost landscapes. The integration of Simulated Annealing introduces controlled randomness, allowing the algorithm to escape local optima and explore better routing solutions. Although this hybrid strategy increases computational overhead, the resulting improvements in cost reduction, route efficiency, and system robustness justify the additional complexity for smart city cold-chain logistics applications.

VII. Conclusion

In this paper, we proposed an AI-driven multi-depot logistics framework designed to address the challenges of fresh food distribution in smart cities. The proposed system integrates LSTM-based traffic-aware travel time prediction, K-Means-based hub optimization, and a hybrid IQPSO–Simulated Annealing routing strategy. By moving beyond static assumptions and single-depot constraints, the framework provides a more realistic and adaptive solution for urban cold-chain logistics.

The results demonstrate that the proposed approach achieves lower distribution costs, improved route efficiency, and better vehicle utilization compared to conventional routing algorithms. Additionally, the use of real-time traffic and weather APIs enhances system responsiveness, while data simulation enables controlled and repeatable experimentation. Overall, the framework offers a scalable and deployable solution that bridges the gap between theoretical optimization models and real-world smart city logistics systems.

VIII. Future Work

Although the proposed framework demonstrates promising results, several enhancements can be explored in future work. One important direction is the implementation of fully real-time route re-optimization, where routing decisions are continuously updated based on live traffic conditions and vehicle status. Advanced large-scale routing techniques such as Adaptive Large Neighborhood Search (ALNS) can be incorporated to handle significantly larger customer sets and dense urban networks more efficiently.

Further improvements can be achieved by leveraging high-performance computing and advanced learning models. GPU-accelerated optimization methods, parallel genetic algorithms, and distributed computing frameworks such as Spark, Ray, or Dask can be used to improve scalability and reduce execution time. Additionally, Graph Neural Networks can be explored for more accurate traffic prediction, and advanced clustering methods such as mini-batch K-Means or density-based clustering can be applied to further enhance system performance in large-scale smart city deployments.

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