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A Review on Vehicle Routing Optimization Problems

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Abstract

This review paper aims to provide a comprehensive overview of existing research on highway emergency vehicle routing optimization models and algorithms. The paper discusses the significance of effective emergency management in highway systems, outlines the primary objectives of vehicle routing optimization, and presents a taxonomy of optimization models and algorithms. Furthermore, the paper highlights recent advancements, challenges, and opportunities in the field.

Keywords

Vehicle routing model, optimization method, challenges, opportunities.

1. Introduction

An essential component of highway emergency response planning is the operational decisions associated with vehicle routing for emergency service delivery[1]. Vehicle routing decisions involve determining the most efficient routes for emergency vehicles, such as ambulances, fire trucks, and hazardous material response vehicles, to reach the incident locations and provide the required services. The optimization of these decisions is crucial for ensuring the prompt and effective response to emergencies and the efficient utilization of available resources.

Over the past several decades, numerous mathematical models and optimization algorithms have been developed to address the complex and challenging problems of emergency vehicle routing. These models and algorithms have been applied in various emergency response contexts and have contributed to significant improvements in the efficiency and effectiveness of emergency response systems. However, as the scale and complexity of transportation networks continue to grow, and the frequency and severity of emergencies continue to increase due to factors such as urbanization, climate change, and technological advancements, new challenges and opportunities are emerging in the field of highway emergency vehicle routing optimization[2].

The motivation for this review paper lies in the need to synthesize the current state of knowledge in the field of highway emergency vehicle routing optimization, identify gaps in the existing literature, and provide a roadmap for future research and applications. By doing so, we aim to support researchers, practitioners, and policymakers in their efforts to develop and implement more efficient, effective, and resilient emergency response systems and ultimately contribute to the well-being of society and the protection of human life.

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2. Taxonomy of Optimization Models

In this section, we provide a further extended discussion of the four primary categories of vehicle routing models for emergency situations: deterministic, stochastic, dynamic, and multi-objective models. These models play a critical role in determining the optimal routes for emergency vehicles, ensuring timely response and efficient resource allocation during crisis situations.

Table 1 Taxonomy of optimization models

Vehicle routing models		References
Deterministic routing models	CVRP	Máximo and Nascimento (2021)
	TWVRP	Wang and Zhao (2023)
Stochastic routing models	SCVRP	Marcella et al. (2023)
	STWVRP	Jie et al. (2022)
Dynamic routing models	DCVRP	Cai et al. (2022)
	DTWVRP	Ramachandranpillai and Arock (2021)
Multi-objective routing models	MOCVRP	Nguyen and Phung (2021)
	MOTWVRP	Khoo and Bonab (2021)

2.1. Deterministic Routing Models

Deterministic routing models assume that all parameters, such as demand, travel time, and vehicle capacities, are known with certainty. These models are relatively simple and computationally efficient, making them a popular choice in the literature. Some additional deterministic routing models include:

Capacitated Vehicle Routing Problem (CVRP)[3-15]: This model seeks to minimize the total travel time or distance of a fleet of vehicles with known capacities while meeting the demand at each location. It assumes that each vehicle has a fixed capacity, and the total demand served by each vehicle should not exceed its capacity.

Time Window Vehicle Routing Problem (TWVRP)[16-23]: This model extends the CVRP by incorporating time windows for each demand point, requiring vehicles to arrive within a specified time frame. The objective is to minimize the total travel time or distance while respecting the time window constraints.

2.2. Stochastic Routing Models

Stochastic routing models incorporate uncertainty in demand, travel time, and/or vehicle capacities by considering probability distributions or stochastic parameters. These models can provide more realistic solutions, as they account for the inherent uncertainty in real-world situations. Additional stochastic routing models include:

Stochastic Capacitated Vehicle Routing Problem (SCVRP)[24-28]: This model extends the CVRP by considering the stochastic nature of demand or travel time. The objective is to minimize the expected total travel time or distance while satisfying the vehicle capacity constraints.

Stochastic Time Window Vehicle Routing Problem (STWVRP)[29-34]: This model generalizes the TWVRP by introducing uncertainty in demand or travel time. The goal is to minimize the expected total travel time or distance while respecting the time window constraints with a pre-specified probability.

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2.3. Dynamic Routing Models

Dynamic routing models consider the temporal dimension, accounting for changes in demand, travel time, or vehicle capacities over time. These models can provide more accurate and adaptive solutions for emergency vehicle routing, as they can better represent the dynamic nature of real-world situations. Additional dynamic routing models include:

Dynamic Capacitated Vehicle Routing Problem (DCVRP)[35-37]: This model extends the CVRP by considering temporal variations in demand, travel time, or vehicle capacities, aiming to minimize the total travel time or distance over time while meeting the demand at each location.

Dynamic Time Window Vehicle Routing Problem (DTWVRP)[38-44]: This model accounts for time-varying demand, travel time, or vehicle capacities in the TWVRP, with the goal of minimizing the total travel time or distance while respecting the time window constraints over time.

2.4. Multi-objective Routing Models

Multi-objective routing models aim to optimize multiple conflicting objectives simultaneously, providing a set of Pareto-optimal solutions that represent trade-offs among the objectives. These models are particularly relevant in emergency situations, where decision-makers often need to balance various goals, such as minimizing travel time, maximizing coverage, and reducing costs. Additional multi-objective routing models include:

Multi-objective Capacitated Vehicle Routing Problem (MOCVRP)[45-47]: This model generalizes the CVRP by considering multiple objectives, such as minimizing total travel time, minimizing the number of vehicles used, and maximizing customer satisfaction. The goal is to find a set of Pareto-optimal solutions that represent trade-offs among these objectives.

Multi-objective Time Window Vehicle Routing Problem (MOTWVRP)[48-50]: This model extends the TWVRP by incorporating multiple objectives, such as minimizing total travel time, minimizing the number of vehicles used, and maximizing customer satisfaction while respecting the time window constraints. The objective is to identify a set of Pareto-optimal solutions that represent trade-offs among these objectives.

In summary, selecting the appropriate vehicle routing model is essential for ensuring an effective emergency response system. By understanding the differences among deterministic, stochastic, dynamic, and multi-objective models, researchers and practitioners can choose the most suitable approach for their specific problem and ensure that emergency vehicle routes are optimized to minimize response times, maximize coverage, and improve overall system performance.

Deterministic models offer a foundation for understanding the basic principles of emergency vehicle routing, and they can be useful for situations where uncertainty is minimal. However, in real-world emergency situations, there are often significant uncertainties in demand, travel times, and vehicle capacities. As a result, stochastic and dynamic models have gained popularity, as they can better handle uncertainty and provide more reliable and adaptive solutions.

Stochastic models are valuable for addressing stochastic variations in the problem parameters, which can lead to more realistic and adaptable solutions. Dynamic models, on the other hand, take into account the time-varying nature of demand, travel times, and vehicle capacities, providing more accurate solutions that adapt to changing conditions and needs.

Multi-objective models are particularly relevant in emergency vehicle routing problems, as decision-makers often need to balance various goals, such as minimizing travel time, maximizing coverage, and reducing costs. By incorporating multiple objectives, these models can provide a set of Pareto-optimal solutions that represent trade-offs among the objectives, helping decision-makers identify the most suitable solution for their specific context.

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By combining these models with the optimization algorithms discussed, researchers and practitioners can develop advanced methodologies for addressing the complex and dynamic nature of emergency vehicle routing problems.

3. State-of-the-Art Methods

In this section, we provide a further extended discussion of state-of-the-art methods for emergency vehicle routing problems. These methods are based on various routing models, each with specific characteristics that make them suitable for different emergency situations.

Table 2 State-of-the-art methods

Emergency vehicle routing problems	Primary categories	Optimization algorithms	References
CVRP	Exact algorithms	Branch and cut Branch and price Branch and bound	Li et al. (2021)
	Heuristic algorithms	Clarke-wright savings Nearest neighbor algorithm	
	Metaheuristic algorithms	Tabu search Simulated annealing Ant colony optimization	
VRPTW	Exact algorithms	Branch and price Branch and cut	Frey et al. (2023)
	Heuristic algorithms	Time-oriented nearest neighbor Route construction heuristics	
	Metaheuristic algorithms	Tabu search Particle swarm optimization Variable neighborhood search Hybrid genetic	
SDVRP	Exact algorithms	Branch and price	Ferreira et al. (2021)
	Heuristic algorithms	Route-first Cluster-second Insertion heuristics	
	Metaheuristic algorithms	Genetic algorithms Simulated annealing Large neighborhood search	
MDVRP	Exact algorithms	Branch and price Branch and cut	Montoya-Torres et al. (2015)
	Heuristic algorithms	Hierarchical clustering Sweep algorithms	
	Metaheuristic algorithms	Ant colony optimization Tabu search Genetic algorithms	

GVRP		Mixed-integer linear programming Heuristic algorithms Metaheuristic algorithms	Amiri et al. (2023)
VRPSPD	Exact algorithms	Branch and price Branch and cut	Guo and Wang (2023)
	Heuristic algorithms	Two-phase heuristics	
	Metaheuristic algorithms	Tabu search Ant colony optimization Genetic algorithms	
VRPB	Exact algorithms	Branch and price Branch and cut	Queiroga et al. (2020)
	Heuristic algorithms	Sweep-based heuristics Route construction heuristics	
	Metaheuristic algorithms	Genetic algorithms Tabu search Simulated annealing	

3.1. Capacitated Vehicle Routing Problem (CVRP)

CVRP methods aim to minimize the total travel distance or time while ensuring that each vehicle's capacity is not exceeded. These methods are suitable for situations where emergency vehicles have limited capacities, and resources must be efficiently allocated[51]. State-of-the-art methods for solving CVRP include:

Exact algorithms: Branch and cut, branch and price, and branch and bound algorithms are used to find optimal solutions to the CVRP.

Heuristic algorithms: Construction heuristics, such as Clarke-Wright savings algorithm and nearest neighbor algorithm, provide initial feasible solutions.

Metaheuristic algorithms: Genetic algorithms, tabu search, simulated annealing, and ant colony optimization are popular techniques for finding near-optimal solutions.

3.2. Vehicle Routing Problem with Time Windows (VRPTW)

VRPTW methods extend the CVRP by incorporating time window constraints for each demand point. The objective is to minimize the total travel distance or time while ensuring that vehicles arrive within the specified time windows [52,53]. State-of-the-art methods for solving VRPTW include:

Exact algorithms: Branch and price and branch and cut algorithms are employed to find optimal solutions to the VRPTW.

Heuristic algorithms: Time-oriented nearest neighbor and route construction heuristics generate initial feasible solutions.

Metaheuristic algorithms: Tabu search, particle swarm optimization, variable neighborhood search, and hybrid genetic algorithms are common approaches for obtaining near-optimal solutions.

3.3. Split Delivery Vehicle Routing Problem (SDVRP)

SDVRP methods allow for the splitting of demand among multiple vehicles, making them suitable for situations where emergency resources must be distributed among several locations.

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The goal is to minimize the total travel distance or time while satisfying demand[54-56]. State-of-the-art methods for solving SDVRP include:

Exact algorithms: Branch and price algorithms are used to find optimal solutions to the SDVRP.

Heuristic algorithms: Route-first, cluster-second and insertion heuristics generate initial feasible solutions.

Metaheuristic algorithms: Genetic algorithms, simulated annealing, and large neighborhood search are popular techniques for finding near-optimal solutions.

3.4. Multiple Depot Vehicle Routing Problem (MDVRP)

MDVRP methods consider multiple depots for vehicle dispatch, which can better represent real-world situations where emergency vehicles are distributed across various locations. The objective is to minimize the total travel distance or time while meeting demand[57]. State-of-the-art methods for solving MDVRP include:

Exact algorithms: Branch and price and branch and cut algorithms are employed to find optimal solutions to the MDVRP.

Heuristic algorithms: Hierarchical clustering and sweep algorithms provide initial feasible solutions.

Metaheuristic algorithms: Ant colony optimization, tabu search, and genetic algorithms are common approaches for obtaining near-optimal solutions.

3.5. Other Vehicle Routing Models

Apart from the models mentioned above, other vehicle routing models have been proposed in the literature to address specific challenges or requirements in emergency vehicle routing problems. These models include, but are not limited to:

Green Vehicle Routing Problem (GVRP)[58,59]: This model focuses on minimizing the total environmental impact, such as CO_2 emissions, by incorporating eco-friendly vehicle technologies and alternative fuels. State-of-the-art methods for solving GVRP include mixed-integer linear programming, heuristic algorithms, and metaheuristic algorithms, such as genetic algorithms and particle swarm optimization.

Vehicle Routing Problem with Simultaneous Pickup and Delivery (VRPSPD)[60-62]: This model considers the simultaneous pickup and delivery of goods or resources, making it suitable for emergency situations that require both resource distribution and collection. The objective is to minimize the total travel distance or time while satisfying demand and capacity constraints. State-of-the-art methods for solving VRPSPD include:

Exact algorithms: Branch and price and branch and cut algorithms are employed to find optimal solutions to the VRPSPD.

Heuristic algorithms: Two-phase heuristics, such as route-first and cluster-second, and insertion heuristics generate initial feasible solutions.

Metaheuristic algorithms: Tabu search, ant colony optimization, and genetic algorithms are common approaches for obtaining near-optimal solutions.

Vehicle Routing Problem with Backhauls (VRPB)[63-65]: This model addresses situations where vehicles must deliver goods or resources to demand points and collect goods or resources on the return trip. The goal is to minimize the total travel distance or time while meeting the demand and capacity constraints. State-of-the-art methods for solving VRPB include:

Exact algorithms: Branch and price and branch and cut algorithms are used to find optimal solutions to the VRPB.

Heuristic algorithms: Sweep-based heuristics and route construction heuristics provide initial feasible solutions.

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Metaheuristic algorithms: Genetic algorithms, tabu search, and simulated annealing are popular techniques for finding near-optimal solutions.

In summary, state-of-the-art methods for solving emergency vehicle routing problems have been developed based on various routing models, each with specific characteristics that make them suitable for different emergency situations. By understanding the strengths and limitations of each model and the corresponding solution methods, researchers and practitioners can choose the most suitable approach for their specific problem and ensure that emergency vehicle routes are optimized to minimize response times, maximize coverage, and improve overall system performance.

4. Current Challenges and Opportunities

In this section, we provide an extended discussion of current challenges and opportunities in the field of highway emergency vehicle routing optimization.

Table 3 Current Challenges and Opportunities

Aspect	Challenges	Opportunities
Scalability and real-time decision making	Computational complexity of the optimization models and algorithms	Parallel computing, distributed optimization, and online algorithms
Multi-objective optimization	Multiple conflicting objectives	Designing interactive decision support
Uncertainty and robustness	Inherently uncertain	Developing stochastic and robust optimization models
		Designing adaptive algorithms that can update solutions in real-time based on new information
Emerging technologies and data availability	Increasing availability of data from various sources	Developing data-driven optimization models
		Designing algorithms that can handle the complexity and dynamics of these new systems
		Evaluating the impact of these innovations on emergency response performance and resilience

4.1. Scalability and Real-time Decision Making

As the size of the problem instances increases, the computational complexity of the optimization models and algorithms grows exponentially. This makes it difficult to find optimal or near-optimal solutions within reasonable time frames. The challenge is further exacerbated when real-time decision-making is required in emergency situations. Developing scalable and efficient algorithms that can handle large-scale problems and provide solutions in real-time is a critical research direction. Opportunities include exploring parallel computing, distributed optimization, and online algorithms for faster decision-making.

4.2. Multi-objective Optimization

Emergency response planning often involves multiple conflicting objectives, such as minimizing response times, maximizing coverage, and minimizing costs. Traditional singleobjective optimization methods may not adequately capture these trade-offs. Multi-objective optimization techniques can help decision-makers identify the most suitable solutions based on their specific preferences and requirements. Current opportunities in this area include developing efficient algorithms for generating Pareto-optimal solutions, designing interactive decision support systems for emergency managers, and incorporating fairness and equity considerations into the optimization models.

4.3. Uncertainty and Robustness

Emergency situations are inherently uncertain, with unpredictable demands, travel times, and resource availability. Developing robust optimization models and algorithms that can handle uncertainty and provide reliable solutions is essential for effective emergency response planning. Current opportunities include developing stochastic and robust optimization models that can account for various sources of uncertainty, designing adaptive algorithms that can update solutions in real-time based on new information, and assessing the performance of these methods under different levels of uncertainty and risk.

4.4. Emerging Technologies and Data Availability

The increasing availability of data from various sources, such as traffic sensors, social media, and crowdsourcing platforms, presents new opportunities for improving emergency response planning. Additionally, emerging technologies, such as drones, autonomous vehicles, and the Internet of Things (IoT), can potentially transform the way emergency services are delivered. Current opportunities in this area include developing data-driven optimization models that can leverage these new data sources and technologies, designing algorithms that can handle the complexity and dynamics of these new systems, and evaluating the impact of these innovations on emergency response performance and resilience.

In conclusion, the field of highway emergency facility locating and vehicle routing optimization is evolving rapidly, with new challenges and opportunities arising from the increasing complexity and uncertainty of emergency situations, multi-objective optimization, and emerging technologies and data sources. By addressing these challenges and leveraging these opportunities, researchers and practitioners can develop innovative models, algorithms, and decision support systems that can significantly improve the efficiency, effectiveness, and resilience of emergency response systems.

5. Conclusion

In this review paper, we have provided an extensive overview of the state-of-the-art models, algorithms, and methods in the field of highway emergency vehicle routing optimization. We have discussed the various types of emergency vehicle routing models, as well as the optimization algorithms used to solve them. Furthermore, we have highlighted the challenges and opportunities in the field, including scalability, real-time decision-making, multi-objective optimization, uncertainty and robustness, and the impact of emerging technologies and data availability.

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