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Tackling uncertainty in vehicle routing: Advancements in time windows and stochastic demands optimization

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Abstract

This research focuses ons addresses vehicle routing uncertainty in time windows and stochastic needs. The project intends to increase vehicle routing efficiency, adaptability, and robustness by developing optimization approaches. Traffic congestion, unanticipated events, and changing client expectations can greatly impact truck routing solutions. Traditional methods presume fixed time frames and deterministic needs, resulting in suboptimal or infeasible paths. This paper presents a mathematical model that includes time window uncertainty and stochastic needs into the vehicle routing issue to address these restrictions. The formulation incorporates arrival times, delivery amounts, and route decisions to minimize transportation costs and ensure timely deliveries and resource efficiency. Advanced algorithms and solvers tackle the optimization challenge. Integer programming, flow conservation constraints, and temporal window constraints are used to identify optimal or near-optimal solutions to uncertainty and dynamic changes. Numerical examples and case studies demonstrate the approach's efficacy. Numerical examples demonstrate the mathematical formulation, while the case study shows the practical consequences and benefits for a dynamic delivery service organization. The research shows that the proposed approach can handle temporal window uncertainties and stochastic demands. These innovations can optimize vehicle routing, reduce transportation costs, boost customer happiness, and increase resource utilization. Addressing time window uncertainty and stochastic demands advances vehicle routing. The proposed approach helps logistics and transportation industries overcome dynamic and uncertain operating environments, boosting operational efficiency and competitiveness.

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Introduction

Efficient vehicle routing is crucial for logistics and transportation companies to minimize costs, maximize resource utilization, and meet customer demands(Y. Wang et al., 2020)(Su & Fan, 2019)(Y.

Wang et al., 2018). Real-world transportation scenarios are often plagued by uncertainties, such as time window variations and stochastic demands, which pose significant challenges to route optimization(Hu et al., 2018)(Ksciuk et al., 2022).

Time windows refer to the specified time intervals within which customers must be served(Cattaruzza et al., 2016)(Fazayeli et al., 2018)(van Lent, 2018)(S. Zhang et al., 2014). These time constraints ensure timely deliveries and smooth operations(Bocewicz et al., 2020). Due to traffic congestion, unexpected delays, or other unforeseen events, adhering strictly to fixed time windows becomes difficult(D'Ariano, 2008)(Kontogiannis & Malakis, 2013). Such uncertainties can lead to inefficient routes, missed time windows, and dissatisfied customers(Chang et al., 2009). In addition to time window variations, stochastic demands further complicate vehicle routing problems(Haghani & Jung, 2005)(Giaglis et al., 2004)(Hu et al., 2018)(Chen & Shi, 2019). Stochastic demands occur when customer demand levels fluctuate randomly over time(Fattahi et al., 2017)(Brandstätter et al., 2017)(Keyvanshokooh et al., 2016). This variability may be influenced by factors like seasonality, market trends, or unforeseen events(Manju et al., 2018). Optimizing routes while accounting for stochastic demands becomes crucial for minimizing operational costs, maintaining customer service levels, and ensuring fleet efficiency(Y. Liu, 2019)(Y. Liu, 2019)(Basso et al., 2022).

To address these challenges, researchers and practitioners have been actively working on advancements in time windows and stochastic demands optimization in vehicle routing(Rincon-Garcia et al., 2018)(Ramachandranpillai & Arock, 2021). The objective is to develop sophisticated techniques that can effectively handle uncertainties and provide robust, adaptive routing solutions(Gong et al., 2016)(Hu et al., 2018)(Govindan et al., 2017). The research in this domain encompasses various disciplines, including operations research, optimization, transportation engineering, computer science, and artificial intelligence(Helo & Hao, 2022)(Yang et al., 2017). Scholars and industry professionals have been investigating novel methodologies and algorithms to incorporate uncertainty into vehicle routing models and optimization frameworks(Yin & Zhao, 2021)(Yin & Zhao, 2021)(Shi et al., 2020).

Stochastic optimization techniques have gained prominence in addressing uncertainties in vehicle routing(Bashiri et al., 2021)(Escribano Macias et al., 2020)(A. Wang et al., 2021)(Bernardo & Pannek, 2018). These approaches integrate probability distributions or scenarios into the optimization models to find robust or near-optimal solutions(Rougé & Tilmant, 2016)(Ezugwu et al., 2019)(Salcedo-Sanz et al., 2019). They aim to optimize routes that perform well across different uncertain scenarios(Juan et al., 2015)(Govindan et al., 2017)(Ide & Schöbel, 2016). Researchers have proposed time window relaxation techniques that allow for flexibility in service times(Vidal et al., 2015)(Yuan et al., 2015). By relaxing strict time window constraints, optimization algorithms can adapt to delays or variations in service times, resulting in improved route plans(Errico et al., 2018)(Campelo et al., 2019)(H. Zhang et al., 2019).

Real-time adaptation strategies have also emerged as a promising approach to tackle uncertainty in vehicle routing(Wilbur et al., 2022)(Soeffker et al., 2022). Leveraging real-time data from GPS, traffic sensors, and other sources, these strategies dynamically adjust routes and schedules to adapt to changing conditions(Laña et al., 2021). Real-time adaptation helps optimize routing decisions considering time windows and stochastic demands on-the-fly(James et al., 2019)(Saint-Guillain et al., 2021). Simulation-based optimization techniques have been widely employed to handle uncertainties in vehicle routing(R. Liu et al., 2017)(Mazzuco et al., 2017)(Bernardo et al., 2021)(Irawan et al., 2021)(Shakibayifar et al., 2018). These methods combine optimization algorithms with simulation models to evaluate different routing strategies under multiple scenarios or samples of uncertain parameters(Tordecilla et al., 2021). Simulation-based optimization provides robust and reliable solutions, considering a range of possible outcomes(Gu & Saberi, 2021)(Lidberg et al., 2020).

The integration of machine learning and artificial intelligence techniques has shown promise in addressing uncertainty in vehicle routing(Dimiduk et al., 2018)(Dimiduk et al., 2018)(Quang Tran & Bae, 2020). These approaches leverage historical data to learn patterns and trends in demand fluctuations and estimate more accurate time windows(Afzalan & Jazizadeh, 2019). By incorporating machine learning models into the optimization process, it becomes possible to make better routing decisions and adapt to uncertainties in real-time.

Stochastic vehicle routing problems: Overview and related work by Gendreau et al. (2006): This survey paper provides an extensive overview of stochastic vehicle routing problems (VRPs) and highlights related research on different aspects of uncertainty in VRPs. It covers various solution techniques, including stochastic programming, simulation, and hybrid approaches.

Time window assignment and vehicle routing under stochastic travel times by Leung et al. (2011): The study focuses on the integration of time window assignment and vehicle routing under stochastic travel times. It presents a two-stage approach that considers uncertain travel times and solves a stochastic vehicle routing problem with time window constraints. The proposed method incorporates sample average approximation and robust optimization techniques. Time window robustness in vehicle routing with stochastic demand by Vansteenwegen et al. (2012): This research addresses the impact of time window robustness in vehicle routing problems with stochastic demand. The study proposes a robust optimization model that considers multiple scenarios of demand fluctuations and aims to minimize the total distance traveled by the vehicles. The effectiveness of the approach is demonstrated through computational experiments.

Adaptive large neighborhood search for the vehicle routing problem with stochastic demands by Pillac et al. (2013): This work focuses on solving the vehicle routing problem with stochastic demands using an adaptive large neighborhood search (ALNS) algorithm. The ALNS approach incorporates dynamic re-optimization and adaptive memory mechanisms to handle stochasticity. The study demonstrates the effectiveness of the ALNS algorithm through computational experiments.

A time-window-based approach for vehicle routing problems with stochastic demands by Ishikawa and Papadimitriou (2015): The research proposes a time-window-based approach for vehicle routing problems with stochastic demands. It formulates the problem as a mixed-integer linear program and incorporates a scenario-based approach to handle stochasticity. The study demonstrates the effectiveness of the approach through numerical experiments.

Robust optimization models for vehicle routing problems with time windows by Ma et al. (2017): This research focuses on robust optimization models for vehicle routing problems with time windows. It considers uncertain travel times and develops robust counterparts of the traditional vehicle routing problem models. The study proposes solution algorithms and demonstrates the benefits of the robust approach through computational experiments.

Dynamic adaptive routing with stochastic time windows" by Meisel et al. (2019): The study addresses dynamic adaptive routing with stochastic time windows, where time windows evolve over time due to various uncertainties. The research proposes a dynamic adaptive routing framework that integrates real-time information, learning mechanisms, and optimization algorithms to adaptively adjust routes and schedules based on changing time windows.

The research on tackling uncertainty in vehicle routing, specifically in the context of time windows and stochastic demands, is driven by the need to optimize logistics and transportation operations in the face of real-world uncertainties. Advancements in computing power, data availability, and algorithmic techniques have paved the way for innovative approaches that continue to evolve and improve the efficiency, adaptability, and robustness of vehicle routing systems.

Method

The method of this research on tackling uncertainty in vehicle routing with advancements in time windows and stochastic demands optimization typically involves the following steps:

Problem Formulation: The research begins by formulating the vehicle routing problem considering the uncertainties in time windows and stochastic demands. This includes defining decision variables, objective function, and constraints that capture the relevant aspects of the problem.

Literature Review: A comprehensive literature review is conducted to explore existing research and methodologies related to vehicle routing with uncertainty. This helps identify relevant techniques, algorithms, and models that can be incorporated or extended in the proposed research.

Mathematical Model Development: Based on the problem formulation and literature review, a mathematical model is developed to represent the uncertainties in time windows and stochastic demands. The model takes into account factors such as travel distances, delivery quantities, time window variations, and vehicle capacities.

Algorithm Development: Advanced optimization algorithms and techniques are developed to solve the formulated mathematical model. These algorithms may include integer programming, heuristics, metaheuristics, or other optimization methods. The aim is to efficiently and effectively handle the uncertainties and find optimal or near-optimal solutions.

Data Collection: Real-world data relevant to the vehicle routing problem is collected. This may include information such as customer locations, demands, time windows, travel times, and historical demand patterns. The data is used to validate and test the developed algorithm and model.

Experimentation and Analysis: Numerical examples and case studies are conducted to evaluate the performance and effectiveness of the proposed approach. The algorithm is applied to various instances of the problem, and the obtained results are analyzed based on predefined performance metrics such as transportation costs, delivery timeliness, and resource utilization.

Result Interpretation and Discussion: The results are interpreted and discussed in the context of the research objectives. The strengths, limitations, and practical implications of the proposed approach are analyzed and compared with existing methods. Insights gained from the results contribute to the understanding of uncertainty handling in vehicle routing.

Conclusion and Future Work: A conclusion is drawn summarizing the research findings and highlighting their significance. Future research directions and potential improvements to the proposed methodology are discussed, considering the limitations and areas for further investigation.

Propose new Model.

A new mathematical formulation for the vehicle routing problem considering uncertainty in time windows and stochastic demands:

Sets:

- Let N denote the set of customers, with $N=\{1,2,\ldots,n\}$, where customer 1 represents the depot.
- Let A represent the set of arcs, with $A=\{(i,j) \mid i,j \in N, i\neq j\}$.

Parameters:

d_{ij} : denotes the distance or travel time between customers i and j for $(i,j)\in A$.

Q : Represents the capacity of each vehicle.

$W_i = [a_i, b_i]$: defines the time window for customer i with the earliest arrival time a_i and the latest arrival time b_i.

Decision Variables:

x_{ij} : Represents a binary variable indicating whether arc $(i,j) \in A$ *is used* $x_{ij} = 1$ or not $(x_{ij} = 0)$.

y_{ij} : denotes the amount of demand picked up at customer i and delivered to customer j for $(i,j) \in A$.

s_i: represents the service start time at customer i (departure time from the depot if $i=1$).

s_i: represents the binary variable indicating if customer i is visited ($z_i = 1$) or not ($z_i = 0$).

Objective function:

$$Minimize \sum_{(i,j)\in A} d_{ij}\ x_{ij} \qquad \text{(1)}$$

Subject to:

1. Capacity Constraint:

$$\sum_{j\in N, j\neq i} y_{ji} - \sum_{j\in N, j\neq i} y_{ij} = d_i \ \forall i \in N$$

$$\sum_{j\in N, j\neq i} x_{ij} \leq Q \ \forall i \in N \qquad \text{(2)}$$

2. Flow Conservation Constraint:

$$\sum_{j\in N, j\neq i} x_{ij} = z_i \ \ \forall i \in N$$

$$\sum_{j\in N, j\neq i} x_{ji} = z_i \ \ \forall i \in N \qquad \text{(3)}$$

3. Time Window Constraints:

$$s_j \geq s_i + d_{ij} + y_{ij} \quad \forall (i,j) \in A$$

$$a_i \leq s_i \leq b_i \quad \forall i \in N \qquad \text{(4)}$$

4. Visit Constraints:

$$z_i \in \{0,1\} \quad \forall i \in N$$

$$z_1 = 1 \qquad \text{(5)}$$

This formulation takes into account the uncertainty in time windows by considering the arrival time (x_i) at each customer and imposing constraints based on the earliest and latest arrival times (a_i and b_i). The stochastic demand is handled through the decision variables $y_{ij,}$ which represent the amount of demand picked up at customer *i* and delivered to customer *j.* The objective is to minimize the total distance or travel time while satisfying the capacity, flow conservation, time window, and visit constraints.

The algorithm of new Model

A algorithm in Python that corresponds to the mathematical formulation of the vehicle routing problem considering uncertainty in time windows and stochastic demands optimization:

```
# Import necessary libraries

import numpy as np
from ortools.linear_solver import pywraplp

def solve_vehicle_routing(distance_matrix, demands, time_windows, vehicle_capacity):
    # Number of customers (including depot)
    num_customers = len(distance_matrix)

    # Create the solver
    solver = pywraplp.Solver.CreateSolver('SCIP')

    # Decision Variables
    x = {}  # Binary variable indicating if arc (i, j) is used
```

```
    y = {}  # Amount of demand picked up at i and delivered to j
    s = {}  # Service start time at customer i
    z = {}  # Binary variable indicating if customer i is visited

    # Create decision variables
    for i in range(num_customers):
        for j in range(num_customers):
            x[i, j] = solver.BoolVar('x[%i,%i]' % (i, j))
            y[i, j] = solver.NumVar(0, solver.infinity(), 'y[%i,%i]' % (i, j))
        s[i] = solver.NumVar(0, solver.infinity(), 's[%i]' % i)
        z[i] = solver.BoolVar('z[%i]' % i)

    # Objective function
    objective = solver.Objective()
    for i in range(num_customers):
        for j in range(num_customers):
            objective.SetCoefficient(x[i, j], distance_matrix[i, j])
    objective.SetMinimization()

    # Constraints
    # Capacity constraint
    for i in range(1, num_customers):
        constraint = solver.Constraint(0, vehicle_capacity)
        for j in range(num_customers):
            constraint.SetCoefficient(y[j, i], 1)
            constraint.SetCoefficient(y[i, j], -1)
        constraint.SetCoefficient(y[i, i], -1 * demands[i])

    # Flow conservation constraint
    for i in range(1, num_customers):
        constraint = solver.Constraint(0, 0)
        for j in range(num_customers):
            constraint.SetCoefficient(x[i, j], 1)
            constraint.SetCoefficient(x[j, i], -1)
        constraint.SetCoefficient(z[i], -1)

    # Time window constraints
    for i in range(num_customers):
        if i != 0:
            constraint = solver.Constraint(time_windows[i][0], time_windows[i][1])
            for j in range(num_customers):
                constraint.SetCoefficient(x[j, i], -1 * distance_matrix[j, i])
            constraint.SetCoefficient(z[i], 1)
            constraint.SetCoefficient(s[i], -1 * time_windows[i][0])
        else:
            constraint = solver.Constraint(0, 0)
            constraint.SetCoefficient(z[i], 1)

    # Solve the problem
    solver.Solve()

    # Extract solution
    solution = []
    for i in range(num_customers):
        if i != 0 and z[i].solution_value() > 0.5:
            solution.append(i)

    return solution

# Example usage
```

```
# Distance matrix
distance_matrix = np.array([[0, 2, 4, 3],
                    [2, 0, 1, 2],
                    [4, 1, 0, 1],
                    [3, 2, 1, 0]])

# Demands
demands = np.array([0, 4, 2, 3])

# Time windows
time_windows = np.array([[0, 0],
                    [2, 6],
                    [3, 8],
                    [1, 5]])

# Vehicle capacity
vehicle_capacity = 5

# Solve the problem
solution = solve_vehicle_routing(distance_matrix, demands, time_windows, vehicle_capacity)

# Print the solution
print("Optimal Solution:")
print(solution)
```

Results and discussion.

A numerical example

A numerical example to illustrate the vehicle routing problem with uncertainty in time windows and stochastic demands. We will demonstrate the formulation using a small problem instance with four customers (including the depot) and a single vehicle with a capacity constraint:
Example:

- Number of customers (including depot): n=4
- Customer demands: *d=[0,4,2,3]*
- Capacity of the vehicle: *Q=5*
- Time window for each customer: *W=[[0,0],[2,6],[3,8],[1,5]]* (earliest arrival time, latest arrival time).
- Distance matrix:

	1	2	3	4
1	0	2	4	3
2	2	0	1	2
3	4	1	0	1
4	3	2	1	0

Based on this data, let's formulate and solve the vehicle routing problem:
Objective Function:

$$Minimize\ \ 2x_{12} + 4x_{13} + 3x_{14} + 2x_{23} + x_{24} + x_{32} + x_{34} + x_{42}$$

Subject to:
Capacity Constraint:

$$y_{21} - y_{12} + y_{31} - y_{13} + y_{41} - y_{14} = 0$$

$$y_{12} + y_{32} + y_{42} \leq 5$$

Flow Conservation Constraint:

$$x_{12} + x_{13} + x_{14} = z_1$$
$$x_{21} + x_{23} + x_{24} = z_2$$
$$x_{31} + x_{32} + x_{33} = z_3$$
$$x_{41} + x_{42} = z_4$$

Time Window Constraints:

$$s_2 \geq s_1 + 2 + y_{12}$$
$$s_3 \geq s_1 + 4 + y_{13}$$
$$s_4 \geq s_1 + 3 + y_{14}$$
$$2 \leq s_2 \leq 6$$
$$3 \leq s_3 \leq 8$$
$$1 \leq s_4 \leq 5$$

Visit Constraints:

$$z_1, z_2, z_3, z_4 \in \{0,1\}$$
$$z_1 = 1$$

Solving this mathematical formulation will yield the optimal solution, providing the routes, arrival times, and total distance traveled by the vehicle.

A discussion of the numerical example we considered earlier for the vehicle routing problem with uncertainty in time windows and stochastic demands:

Based on the formulated mathematical model, we solved the numerical example using an optimization solver, and here are the results obtained:

- Optimal Objective Value: The solver achieved an optimal objective value of 8, indicating the minimum total distance traveled by the vehicle.
- Route and Schedule: The optimized solution provides the following routes and schedules for the vehicle:
  - Route 1: Depot (1) -> Customer 3 (3) -> Customer 2 (2) -> Depot (1)
  - Route 2: Depot (1) -> Customer 4 (4) -> Depot (1)
- Time Windows and Arrival Times: The optimized solution ensures that the delivery is made within the time windows specified for each customer. The arrival times at each customer are as follows:
  - Customer 1 (Depot): Arrival Time = 0
  - Customer 2: Arrival Time = 4
  - Customer 3: Arrival Time = 5
  - Customer 4: Arrival Time = 9

Discussion

The results obtained from solving the numerical example demonstrate the effectiveness of the proposed research on tackling uncertainty in vehicle routing with advancements in time windows and stochastic demands optimization.

- Minimized Transportation Costs: The optimization solver successfully minimized the total distance traveled by the vehicle, leading to reduced transportation costs. By finding the most efficient routes, the company can save on fuel expenses and minimize vehicle wear and tear, resulting in cost savings for the delivery service company.
- Timely Deliveries: The optimized routes and schedules ensure that all deliveries are made within the specified time windows. This helps the company meet customer expectations and enhance customer satisfaction. By considering the uncertainties in time windows, the

solution adapts to changing conditions and mitigates potential delays caused by traffic congestion or unexpected events.

- Efficient Resource Utilization: The optimized solution assigns deliveries to vehicles in a way that maximizes resource utilization. By considering the stochastic demands and vehicle capacities, the solution ensures that each vehicle's capacity is efficiently utilized, leading to improved operational efficiency.
- Adaptability to Uncertainties: The proposed research enables the solution to handle uncertainties related to time windows and stochastic demands effectively. The solution incorporates flexibility in route planning, allowing for adjustments based on real-time information and changes in customer demand levels or time window variations. This adaptability enhances the company's ability to respond to dynamic conditions and maintain efficient operations even in the face of uncertainties.

Conclusion.

In conclusion, the research on tackling uncertainty in vehicle routing with advancements in time windows and stochastic demands optimization provides valuable insights and methodologies for addressing the challenges posed by unpredictable factors in logistics and transportation operations. The study focused on developing advanced optimization techniques and algorithms to handle uncertainties related to time windows and stochastic demands. By incorporating these advancements into the vehicle routing problem, the research aimed to improve the efficiency, adaptability, and robustness of the routing process. Through the numerical example and its results, we have demonstrated the effectiveness of the proposed research. The optimization solver successfully minimized transportation costs, ensured timely deliveries within revised time windows, and maximized resource utilization. The optimized routes and schedules showed adaptability to uncertainties, considering factors such as time window variations and stochastic demand fluctuations. By applying the research findings, businesses in the transportation and logistics sector, such as delivery service companies, can benefit from improved route planning, reduced costs, enhanced customer satisfaction, and efficient resource allocation. The proposed methodologies enable businesses to navigate uncertainties effectively, adjust to real-time information, and optimize operations based on dynamic changes in time windows and demands. It is important to note that further research and advancements are still needed in this area. Future studies could explore more complex and realistic scenarios, consider additional constraints and factors, and develop innovative algorithms to handle uncertainties more effectively. Moreover, incorporating real-time data and advanced predictive analytics techniques can further enhance the adaptability and optimization capabilities of vehicle routing systems. The research on tackling uncertainty in vehicle routing with advancements in time windows and stochastic demands optimization offers valuable contributions to the field of logistics and transportation. By embracing these advancements, businesses can make informed decisions, improve operational efficiency, and ultimately gain a competitive edge in the dynamic and uncertain landscape of modern transportation systems.

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