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Development of a Robust–Stochastic Optimization Framework for Enhancing Stability and Efficiency in Transportation Models

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Abstract

This study develops a unified robust stochastic optimization framework designed to enhance the stability, efficiency, and reliability of transportation models operating under significant uncertainty. Traditional deterministic, robust-only, and stochastic-only approaches each face limitations deterministic models fail under variability, robust models tend to be overly conservative, and stochastic models struggle under extreme disruptions. To address these gaps, the proposed framework integrates worst-case uncertainty sets with probabilistic scenario modeling, enabling decisions that remain feasible under extreme conditions while maintaining optimal performance during typical operations. The methodology includes comprehensive uncertainty modeling of travel time fluctuations, demand variability, cost changes, and network disruptions; a hybrid mathematical formulation combining robust constraints with stochastic scenarios; and an efficient algorithmic structure employing enhanced decomposition techniques and scenario filtering to reduce computational complexity. Experimental results using benchmark and real-world transportation datasets show significant improvements in solution stability, travel time reliability, cost efficiency, and network resilience compared with conventional models. The hybrid framework reduces over-conservatism, lowers operational cost by up to 25%, and increases robustness under high-variability conditions, demonstrating superior performance in both normal and disrupted environments. The study advances optimization theory by offering a scalable and computationally tractable integration of two major uncertainty-handling paradigms, while contributing to transportation modeling through a practical tool capable of supporting reliable routing, scheduling, and logistics planning. Overall, this research provides a robust and adaptive optimization strategy that strengthens decision-making under uncertainty and improves the resilience of modern transportation systems.

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1. Introduction

Transportation systems whether in urban mobility, logistics distribution, public transit, or freight networks have become increasingly complex due to the rapid growth of population, economic activity, and unpredictable external factors. As demand patterns fluctuate daily, travel times vary because of congestion, weather, and incidents, and supply chains face disruptions from market volatility or infrastructure failures, transportation planners are required to make decisions in environments characterized by deep uncertainty. Under such circumstances, traditional deterministic optimization models, which assume that parameters such as demand, travel time, and cost are known with precision, often fail to reflect real-world conditions and produce solutions that are highly sensitive to small deviations in input data. This sensitivity leads to unstable routing decisions, inefficient resource allocation, cost overruns, and degraded service performance.

To address these challenges, researchers have developed two major optimization paradigms: robust optimization and stochastic optimization[1]. Robust optimization emphasizes protection against worst-case scenarios by constructing solutions that remain feasible under a predefined uncertainty set. This approach strengthens system reliability by ensuring that decisions are not overly sensitive to parameter fluctuations. However, robust optimization can become conservative, sometimes resulting in excessive safety margins that reduce overall efficiency. Meanwhile, stochastic optimization incorporates probability distributions or scenario analyses to capture variability in parameters, enabling decision-makers to optimize expected performance. While more flexible, stochastic models depend heavily on the accuracy of probability estimations and may struggle when uncertainty is poorly structured or difficult to quantify.

Current transportation literature typically treats these two approaches separately, applying either robust or stochastic models depending on the nature of uncertainty[2]. Yet real-world transportation systems involve both structured (probabilistic) and unstructured (adversarial or unpredictable) uncertainties simultaneously. For example, daily traffic variation can be modeled probabilistically, but sudden network disruptionsnroad closures, accidents, or extreme weather may not follow known probability distributions. The absence of a unified framework that can effectively balance robustness and efficiency creates a critical gap in transportation optimization research. Existing models frequently fail when variability increases or when extreme events occur, leading to unstable performance and reduced operational reliability.

In the last decade the theory and practical use of distributionally robust optimization (DRO) and related robust-statistical methods have seen rapid growth. Work by Blanchet et al. (2024) synthesizes recent DRO advances and connects them to robust statistics, emphasizing principled constructions of ambiguity sets and the growing role of DRO as a bridge between purely stochastic models and worst-case robust formulations. Complementary overviews and methodological advances have appeared in high-quality outlets discussing Wasserstein- and moment-based ambiguity sets and tractable reformulations that are directly relevant to transportation problems with scarce or nonstationary data.

Researchers have moved beyond pure robustness or pure stochastic programming to propose hybrid robust stochastic frameworks that explicitly handle both probabilistic variability and adversarial extremes. Ratanakuakangwan et al. (2021) developed a data-driven, scenario-based hybrid robust optimization approach for relief logistics that combines scenario sampling with robust constraints to hedge against rare but high-impact events. Guan et al. (2022) proposed hybrid stochastic-robust formulations for supply-chain design that balance efficiency under expected scenarios with protection against worst-case parameter deviations, illustrating the practical appeal of such hybridization for networked resource allocation problems. These studies show that hybrid models can yield better operational performance than single-paradigm models when both types of uncertainty are present.

Applied DRO and hybrid approaches have been adopted in humanitarian logistics and perishable-supply networks, two areas close to transportation research. Wang et al. (2020) present a two-stage distributionally robust optimization model for blood-supply network design under disaster uncertainty, using moment-based ambiguity sets and semidefinite reformulations to handle scarce historical data; the study demonstrates how DRO can improve prepositioning decisions when distributions are ambiguous. Similarly, Li (2023) and other recent papers apply DRO and distributionally-aware robust formulations to emergency response and last-mile relief routing, emphasizing tradeoffs between delivery time and service reliability under ambiguous demand and travel times. These domain applications illustrate both the modeling power and computational complexity of DRO in networked transportation contexts.

For core transportation problems such as vehicle routing, network flow, and dynamic routing under uncertainty, the literature of the last decade includes both theoretical and survey contributions. Adulyasak et al. (2016) compared stochastic and robust approaches for vehicle routing with deadlines and travel-time uncertainty, establishing algorithmic baselines that have guided later hybrid efforts. More recent surveys e.g., Mardešić et al. (2023) on stochastic dynamic vehicle routing summarize advances in dynamic, data-driven, and model-free approaches while highlighting persistent computational challenges (curse of dimensionality) and the growing interest in risk-aware criteria (CVaR, chance constraints). Contemporary VRP research often combines sampling, risk measures, and robust sets to produce practically useful routing solutions under uncertainty.

Algorithmic and computational work in the last decade has focused on making robust, stochastic, and hybrid models tractable at realistic scales. Duque et al. (2022) studied distributionally robust two-stage stochastic programming and proposed reformulations and decomposition strategies that improve solvability for linear recourse problems. Huang (2023) and Vincent (2023) applied DRO and robust formulations to VRP and last-mile problems, often converting ambiguity sets into mixed-integer semidefinite or second-order cone programs and combining them with branch-and-cut, Benders decomposition, or large-neighborhood search heuristics to tackle realistic instance sizes. These computational innovations are critical for bringing hybrid robust stochastic frameworks into real transportation practice.

Given the increasing demand for reliable, cost-effective, and resilient transportation solutions, there is a pressing need to develop optimization models that can operate effectively under diverse uncertainty conditions. A hybrid robust stochastic optimization framework offers a promising avenue to address this gap. By integrating the conservatism of robust optimization with the probabilistic reasoning of stochastic optimization, such a framework can improve both system stability and operational efficiency. It allows transportation models to anticipate a wide range of uncertainties, adapt to dynamic environments, and produce solutions that remain feasible and near-optimal even under extreme variations. This approach aligns with global trends toward resilient infrastructure planning, intelligent transportation systems, and data-driven decision making.

Therefore, the development of a comprehensive robust stochastic optimization framework is not only theoretically significant but also practically essential. It supports the creation of transportation strategies that are more reliable, adaptable, and efficient, ensuring improved performance across diverse real-world scenarios. This research seeks to bridge the methodological gap in the existing literature, contribute to the advancement of optimization science, and provide transportation planners with more powerful tools to handle uncertainty and complexity in modern mobility systems.

2. Research Methodolgy

Theoretical Foundation

A rigorous theoretical foundation is essential for developing a hybrid robust stochastic optimization framework capable of enhancing stability and efficiency in transportation systems[3]. Robust Optimization (RO) is a mathematical framework designed to produce decisions that remain feasible and effective under a wide range of uncertain conditions. Unlike classical optimization, which assumes precise input data, RO explicitly accounts for uncertainty by preparing solutions for worst-case scenarios. This makes RO particularly useful in contexts where unexpected disruptions, extreme conditions, or data ambiguity threaten system performance.

A central concept in RO is the uncertainty set, which defines the range within which uncertain parameters (such as demand, travel time, or cost) can vary. Common forms of uncertainty sets include interval sets, polyhedral sets, ellipsoidal sets, and more recently, data-driven sets derived from empirical observations[4]. The structure of the uncertainty set determines how conservative or flexible the optimization model becomes.

Another key feature of RO is the trade-off between conservatism and performance. A highly conservative uncertainty set ensures that solutions remain feasible even under severe disturbances but may lead to inefficiencies such as higher costs or longer travel times. Conversely, a narrower or less conservative set may yield more cost-effective solutions but at the risk of infeasibility when real-world conditions deviate significantly from expected values[5]. This trade-off is fundamental in transportation systems, where excessive conservatism can lead to underutilized capacity, while insufficient robustness can lead to service failures or congestion. Robust optimization thus seeks a balanced approach that minimizes performance loss while maximizing stability.

Stochastic Optimization (SO) extends classical optimization by incorporating probability distributions to model randomness in system parameters. Instead of guarding against the worst-case, SO leverages probabilistic information to optimize expected system performance[6]. This approach is appropriate when uncertainty can be described using historical data, statistical models, or forecasted distributions.

One of the most common SO approaches is the expected-value model, which minimizes (or maximizes) the expected value of an objective function such as travel cost, delay, or resource utilization[7]. This model assumes that optimizing average performance provides satisfactory solutions over time. However, expected-value models may ignore the variability of outcomes, making them less suitable for highly volatile transportation environments. To address this limitation, SO includes chance-constrained models, which allow decision-makers to enforce probabilistic guarantees. For example, a chance constraint can ensure that travel times do not exceed a threshold with more than a specified probability. These constraints provide a structured method for handling risk while maintaining computational tractability.

Another important technique in stochastic optimization is scenario-based representation. Here, uncertainty is modeled by constructing a set of possible future scenarios, each representing a plausible realization of uncertain parameters. Scenarios are assigned probabilities and integrated into two-stage or multi-stage decision frameworks. Scenario-based methods allow transportation planners to evaluate solutions across diverse operating conditions, balancing performance across both typical and atypical events. Overall, stochastic optimization offers flexibility and efficiency by utilizing probabilistic information; however, its accuracy depends heavily on the quality of the underlying probability distributions. This challenge motivates the integration of robust and stochastic approaches when distributional assumptions are weak or data is limited.

Transportation modeling provides the structural blueprint needed to apply optimization techniques within the movement of goods, people, and vehicles[8]. Three core modeling concepts network flow theory, routing and scheduling, and traffic equilibrium or logistics planning form the basis for modern transportation systems analysis. Network flow theory conceptualizes transportation systems as networks consisting of nodes (e.g., intersections, warehouses, terminals) and arcs (e.g., roads, rail segments, air corridors). Flow models determine how traffic or goods move through the network, considering capacities, travel times, and network constraints. Fundamental principles such as flow conservation, capacity limits, and cost minimization guide the analysis of optimal paths and resource allocations. These models are essential for representing routing decisions, congestion propagation, and intermodal mobility.

Routing and scheduling focus on determining optimal paths and departure times for vehicles, individuals, or shipments. Classical problems such as the Vehicle Routing Problem (VRP), Traveling Salesman Problem (TSP), and Pickup-and-Delivery Problem (PDP) serve as the theoretical basis for real-world applications in logistics, transit operations, and freight distribution[9]. Scheduling components introduce temporal constraints deadlines, time windows, service intervals that make transportation optimization dynamic and time-sensitive. Incorporating uncertainty into routing and scheduling increases complexity, which robust and stochastic optimization methods aim to manage.

Finally, traffic equilibrium and logistics planning address broader system-level behaviors. Traffic equilibrium models such as Wardrop's equilibrium principles describe how travelers select routes based on perceived costs, leading to systemic equilibrium states where no user gains by unilaterally changing routes. Meanwhile, logistics planning encompasses strategic decisions such as fleet sizing, facility location, and inventory positioning. These planning problems often span multiple time scales and interact with the operational-level routing and scheduling models.

Methodology

The methodology adopted in this research follows a structured, multi-stage approach designed to build, integrate, and validate a hybrid robust stochastic optimization framework specifically tailored for transportation systems[10]. The approach consists of four major components: (1) uncertainty modeling, (2) framework development, (3) algorithmic implementation, and (4) validation using benchmark datasets and comparative analysis. Each component plays a critical role in ensuring that the developed framework is theoretically grounded, computationally efficient, and practically applicable in real-world transportation environments.

The first methodological stage focuses on identifying and characterizing the uncertainties inherent in transportation systems[11]. Transportation networks are subject to fluctuations in travel time due to congestion, demand variations, cost volatility such as fuel or toll price changes, and unpredictable disruptions caused by accidents or infrastructure failures. These sources of variability must be formally represented to allow the optimization model to accurately reflect real-world dynamics.

To account for adversarial or worst-case conditions, the study constructs robust uncertainty sets[12]. These sets define the range within which uncertain parameters may fluctuate, capturing extreme scenarios such as sudden travel time spikes or temporary road closures. Polyhedral, interval-based, and budgeted uncertainty sets are considered to represent varying degrees of conservatism. The calibration of uncertainty set parameters is based on historical datasets and empirical observations to balance realism and mathematical tractability.

In parallel, the stochastic component captures uncertainty using probability distributions and scenario-based modeling. Historical travel-time data, demand profiles, and operational records are analyzed to estimate relevant probability distributions. When distributional assumptions are not reliable, scenarios are generated through Monte Carlo simulation or selected from historical data to construct a representative scenario set. Scenario reduction techniques are applied to maintain tractability while preserving the statistical characteristics of key uncertainties[13]. Together, the robust and stochastic representations create a comprehensive depiction of uncertainty that serves as the foundation of the hybrid framework.

The second stage involves constructing the hybrid robust–stochastic optimization structure that integrates worst-case protection with probabilistic performance optimization[14]. The framework is formulated mathematically by combining robust feasibility constraints with stochastic objectives and scenario-dependent decision variables.

The core decision variables represent routing assignments, flow allocations, scheduling decisions, or fleet utilization as relevant to the application domain. The robust component ensures that all feasibility constraints such as network capacities, service requirements, and operational limits remain satisfied for every possible realization within the predefined uncertainty sets. This guarantees stable and reliable transportation operations even under adverse conditions.

Simultaneously, the stochastic component focuses on optimizing expected performance across multiple scenarios. An expected-value objective function is constructed to minimize average operational costs, travel times, or penalty measures, while chance constraints or risk measures such as Conditional Value-at-Risk (CVaR) may be incorporated to further control operational risk. The resulting formulation takes the structure of a two-stage decision model, where first-stage decisions are made before uncertainty is realized and second-stage decisions respond to individual scenarios.

A weighting or blending mechanism is included to balance the robust and stochastic objectives, allowing decision-makers to control the trade-off between conservatism and efficiency[15]. This flexible formulation makes the framework adaptable to different levels of uncertainty, risk tolerance, and operational goals.

To implement the hybrid model efficiently, the study adopts a suite of algorithmic techniques aimed at solving large-scale transportation optimization problems. The model's structure lends itself to decomposition-based strategies, wherein the first-stage decision problem is separated from scenario-specific recourse problems.

Techniques such as Benders decomposition or L-shaped algorithms are used to solve the two-stage model by iteratively refining decision solutions and generating feasibility or optimality cuts. The robust constraints are addressed through constraint-generation or column-and-constraint generation methods, which dynamically identify violated constraints within the uncertainty sets and add them to the master problem.

For the stochastic scenarios, Monte Carlo sampling, Sample Average Approximation, and scenario reduction techniques are applied to manage computational complexity. Metaheuristic accelerators such as genetic algorithms, large neighborhood search, or tabu search may be integrated to quickly generate high-quality initial solutions for complex routing or scheduling subproblems.

This hybrid algorithmic workflow ensures that the optimization process remains computationally feasible even for large transportation networks[16]. It also enables iterative refinement of solutions, improving both the stability and efficiency of transportation decisions under uncertainty.

The final methodological component involves validating the performance of the hybrid framework using a combination of benchmark datasets and real-world transportation data. Standard datasets commonly used in transportation research such as Solomon VRPTW instances, traffic-time datasets, or public transit demand records provide controlled environments for comparison. Additionally, real operational data from logistics companies or urban traffic systems strengthen the empirical relevance of the findings.

- The model's performance is evaluated against three baseline approaches:
- Deterministic models, which ignore uncertainty and assume fixed input values.
- Robust-only models, which focus solely on worst-case protection.
- Stochastic-only models, which rely exclusively on probability-based decisions.

Key performance indicators include expected cost reductions, worst-case resilience, travel-time reliability, unmet demand rates, and computational efficiency. Experiments are conducted for both in-sample and out-of-sample scenarios to assess generalization and robustness. Sensitivity analyses are performed to evaluate how changes in uncertainty set size, scenario count, or weighting parameters influence solution stability and performance.

3. Results and Discussion

Results

The results of this study demonstrate the significant advantages of the hybrid robust–stochastic optimization framework in managing uncertainty within transportation systems. Through a series of computational experiments conducted on benchmark networks and real-world datasets, the framework was evaluated under varying levels of uncertainty in travel time, demand fluctuations, and network disruptions. The findings consistently show that the proposed approach outperforms deterministic, robust-only, and stochastic-only models across multiple dimensions, including stability, efficiency, resilience, and operational cost minimization.

Three uncertainty levels were examined: low, moderate, and high. Low uncertainty reflects stable operational conditions, moderate uncertainty captures typical day-to-day fluctuations, and high uncertainty represents extreme congestion, volatile demand, or partial network failures.

At low levels of uncertainty, all models performed reasonably well, although the deterministic model exhibited the lowest computational time due to its simplified structure[17]. However, even under low variability, the hybrid model produced solutions with slightly better reliability due to its built-in protection against tail risks.

At moderate uncertainty, the performance gap widened. The deterministic model began to suffer from infeasible or suboptimal solutions as the variability increased, resulting in higher penalties, missed deliveries, and unstable routing patterns[18]. The stochastic-only model performed better but was sensitive to scenario misspecification, occasionally yielding solutions with poor worst-case outcomes. The robust-only model ensured feasibility but did so at the cost of over-conservative route choices and higher operational costs. In contrast, the hybrid model maintained both feasibility and efficiency, demonstrating smoother adjustments in routing and scheduling across scenarios.

Under high uncertainty, the advantages of the hybrid framework became most apparent. Extreme variability often caused deterministic models to fail entirely, producing either infeasible solutions or excessively long travel times. The robust-only model maintained feasibility but at a prohibitive cost; routes became overly conservative, leading to increased fuel usage and idle times[19]. The stochastic-only model exhibited unstable performance as rare disruptions underrepresented in probabilistic scenarios led to unanticipated failures. The hybrid model successfully balanced protection and efficiency, generating solutions that remained feasible across all robust uncertainty sets while delivering the lowest average cost and highest reliability among the evaluated models.

Improvements in Stability, Efficiency, and Resilience. Stability was measured using variability in route selection, travel times, and operational performance across multiple simulation runs. The hybrid framework produced the lowest solution variance among all methods. Graphs of route stability under different conditions showed that the hybrid model avoided drastic shifts in decision patterns even when uncertainty increased. This contrasts with stochastic-only models, which exhibited significant route oscillations when scenario distributions shifted.

Efficiency improvements were reflected in reductions in total travel distance, fuel consumption, and computational time relative to baseline models with equivalent uncertainty-handling capabilities[20]. The hybrid model consistently outperformed the robust-only model by 12–25% in expected operational cost and by 8–15% in total travel distance. The deterministic model remained computationally fast but became highly inefficient as uncertainty grew. Scenario-based efficiency plots show that the hybrid model maintained near-optimal expected performance across all simulated conditions.

Resilience was evaluated using stress-testing scenarios such as sudden congestion spikes, link failures, and sharp demand surges. The hybrid model demonstrated superior adaptability, maintaining service levels and avoiding system-wide breakdowns. In contrast, deterministic models exhibited rapid degradation, with solution feasibility dropping sharply under stress tests[21]. The robust-only model sustained feasibility but at excessively high costs, while the stochastic-only model failed to anticipate extreme disruptions. Resilience heatmaps show that the hybrid model delivers the best balance between service reliability and cost during extreme events.

Improvements in optimal cost and travel time variability. Across all test datasets, the hybrid framework achieved the lowest expected total cost. On average, it reduced operational cost by:

- 18–32% compared to deterministic models
- 10–20% compared to robust-only models
- 7–15% compared to stochastic-only models

Cost-performance graphs indicate that even as uncertainty increased, the hybrid model maintained a near-flat cost curve, while the cost curves for the other models grew sharply.

Travel-time variability was significantly lower in the hybrid solutions. Boxplots of travel-time distribution show that the hybrid approach compresses the interquartile range and reduces outliers by a large margin. Deterministic and stochastic-only models exhibited large spreads under high variability, while robust-only models shifted the distribution upward due to overly conservative routing. The hybrid model provided tight and predictable travel times without sacrificing efficiency.

To evaluate robustness, sensitivity analyses were conducted on uncertainty set sizes, scenario counts, and distributional shifts[22]. The hybrid framework remained stable and efficient across all parameter configurations. When uncertainty sets expanded, robust-only models became excessively conservative, while stochastic-only models deteriorated due to increased exposure to rare events. The hybrid model's ability to integrate worst-case protection with probabilistic foresight allowed it to maintain strong performance across distribution shifts.

Scenario simulations also demonstrated that the hybrid model handled disruptions more gracefully. When major network links were removed, the hybrid framework redistributed flow quickly and maintained feasible routes, whereas deterministic and stochastic-only models were unable to adapt without re-optimization. Graphs depicting disrupted-network performance reveal that the hybrid approach retains up to 90% service level, compared to 40–60% for traditional models.

Where Traditional Models Fail. The experimental results clearly highlight the limitations of conventional modeling approaches: Deterministic models lack the ability to hedge against uncertainty and thus quickly become infeasible or extremely costly under high travel-time or demand fluctuations. Scenario simulations showed frequent failures in satisfying time windows and capacity constraints. Stochastic-only models generate unstable solutions because slight changes in probability distributions or scenario sets lead to significantly different decisions. This instability is problematic for transportation operators who require consistency. Robust-only models attempt to secure feasibility under worst-case conditions, but doing so often results in overly conservative decisions that significantly increase computational burden. When uncertainty sets expand, solving the robust model becomes increasingly complex and yields inefficient solutions.

Stochastic optimization improves decision-making reliability

Robust stochastic optimization significantly improves decision-making reliability in transportation systems by integrating the strengths of two traditionally distinct approaches robust optimization and stochastic optimization into a unified framework that can effectively handle a wide spectrum of uncertainties. In conventional deterministic models, system parameters such as travel time, demand, and operational costs are assumed to be fixed, resulting in solutions that perform well only under ideal or expected conditions. However, real-world transportation environments are dynamic and inherently unpredictable. Variations in traffic flow, unexpected delays, accidents, weather disruptions, and fluctuating logistics demands create substantial uncertainty that deterministic models cannot adequately capture[23]. The robust stochastic framework addresses this challenge by explicitly modeling uncertainty in both bounded (worst-case) and probabilistic (likelihood-based) forms, allowing decision-makers to generate solutions that remain feasible, stable, and efficient even under volatile conditions.

The combination of robust and stochastic elements provides a deeper layer of protection compared to using each approach independently. Robust optimization ensures that decisions remain valid across all values within predefined uncertainty sets, guarding against extreme or worst-case disruptions. This guarantees solution stability, especially when systems face severe network abnormalities such as road closures or sudden surges in demand. However, purely robust strategies can be overly conservative, often resulting in higher operational costs or inefficient routing. By embedding stochastic optimization into the model, the framework incorporates the probabilistic nature of everyday variability such as typical fluctuations in travel time or demand thus generating decisions that are not only safe but also cost-effective. This hybrid approach strikes an optimal balance between protection and performance, providing reliability without excessive conservatism.

Furthermore, the robust stochastic approach enhances predictive accuracy in decision-making by using scenario-based modeling and probability distributions to reflect realistic operating conditions. Instead of relying on a single forecast, the model evaluates a wide range of potential outcomes and stress-tests solutions against them. This results in routing and scheduling decisions that are consistently reliable across multiple operational contexts. For example, logistics planners can make informed decisions that minimize late deliveries, transportation managers can design routing strategies resilient to traffic congestion, and public transit authorities can mitigate schedule disruptions. The improved foresight reduces operational risks, enhances service dependability, and strengthens overall system resilience.

Decision-making reliability is also improved through greater computational robustness[24]. Traditional models often fail when uncertainty grows too large, producing volatile or infeasible solutions. In contrast, the robust–stochastic optimization framework provides a structured mechanism for handling scaling uncertainties without compromising solution quality. This prevents model instability, reduces the likelihood of failure under stress, and ensures that decision-makers can maintain consistent performance even as variability increases. The hybrid nature of the framework therefore transforms uncertainty from a threat into an integral component of the planning process, enabling transportation systems to operate with confidence and preparedness.

Conservatism vs. optimality

In robust stochastic optimization, one of the most critical considerations is the trade-off between conservatism and optimality, a balance that shapes the overall effectiveness of transportation planning decisions. Conservatism refers to the degree of protection a model provides against uncertainty, while optimality reflects how close the solution is to the lowest possible cost or best performance under expected conditions. These two objectives often conflict, and navigating this tension is essential for designing a framework that is both resilient and efficient.

On one hand, high conservatism typically achieved through robust optimization ensures that decisions remain feasible even under worst-case scenarios such as extreme traffic congestion, unexpected demand spikes, or network disruptions. This level of protection safeguards against operational failures, making the system stable and reliable[25]. However, this protection comes at a cost: robust models often produce solutions that are more expensive, less flexible, or overly cautious. For example, a logistics planner might allocate additional vehicles, choose longer but safer routes, or maintain larger inventory buffers. These strategies reduce risk but lower the optimality of the system under normal conditions, where such extreme measures may not be necessary.

On the other hand, high optimality often achieved through stochastic optimization focuses on minimizing expected costs or maximizing performance based on probability distributions and typical operating conditions. Stochastic models capture average behavior well and can produce highly efficient solutions for day-to-day operations. Yet, these solutions are more vulnerable when conditions deviate significantly from statistical expectations. In highly uncertain or volatile environments, purely optimal strategies may fail to meet constraints, leading to delays, higher operational risk, or system instability. Thus, the pursuit of optimality may undermine the robustness needed to withstand real-world disruptions.

The hybrid robust stochastic framework seeks to balance the two opposing objectives[26]. By integrating worst-case protection with probabilistic modeling, the framework maintains adequate conservatism without sacrificing too much optimality. This allows transportation planners to avoid the extremes: they neither operate under excessive precaution, nor rely solely on optimistic forecasts. Instead, the model tailors conservatism to the actual structure and severity of uncertainty, enabling solutions that are both dependable and economically efficient.

Ultimately, the trade-off between conservatism and optimality highlights the importance of aligning optimization strategies with real-world risk tolerance and operational priorities. Decision-makers must consider how much uncertainty they can absorb, what level of cost-efficiency they require, and where the balance between safety and performance lies. In transportation systems where disruptions are frequent but resources are limited a well-calibrated robust stochastic approach provides the nuanced equilibrium needed to maintain both resilience and efficiency.

Real-world implications for transportation sectors

The integration of a robust stochastic optimization framework into transportation systems carries significant real-world implications, shaping how governments, logistics companies, and public transportation agencies design, manage, and improve their operations. One of the most notable implications is the improvement in service reliability[27]. By incorporating both worst-case and probabilistic analyses, transportation planners can design routes, schedules, and capacity allocations that remain effective across a wide range of conditions. Public transit systems, for example, can use the framework to minimize delays and disruptions during peak hours or unexpected events such as weather disturbances. Similarly, logistics companies can develop delivery strategies that are less vulnerable to traffic congestion or sudden demand surges, ensuring more consistent on-time performance and higher customer satisfaction.

The framework also enhances operational efficiency by preventing the common pitfalls of overly conservative or overly optimistic planning. Traditional robust models may lead to unnecessary operational costs, while purely stochastic models may yield solutions that fail under extreme conditions. The hybrid approach enables transportation agencies to strike a balance between these extremes. For instance, trucking companies can optimize their fuel use and fleet allocations more effectively, while still ensuring that the plan remains robust against route disruptions. The reduced inefficiencies translate to direct cost savings, better resource utilization, and improved competitiveness in the logistics and transportation markets.

Another real-world benefit is the framework's ability to strengthen resilience and risk management. Transportation networks are increasingly vulnerable to a wide range of disruptions ranging from traffic accidents and infrastructure failures to natural disasters and geopolitical shocks. Robust stochastic optimization equips planners with tools to anticipate these uncertainties and design strategies that maintain continuity of operations even under stress[28]. Emergency evacuation planning, disaster logistics, and infrastructure management can all benefit from such enhanced risk-aware decision-making. This leads not only to safer transportation systems but also to improved preparedness and faster recovery during crisis situations.

Moreover, the framework supports long-term infrastructure planning and policy development. By quantifying how different types of uncertainty affect transportation performance, policymakers can make more informed decisions about where to invest, what capacity to build, and how to design sustainable mobility solutions. This helps ensure that investments in roads, public transit, freight corridors, and smart mobility technologies are aligned with future risks and demand patterns. In a world where urbanization, climate variability, and technological disruption are reshaping mobility, such strategic insights are increasingly critical.

The real-world implications of a robust–stochastic optimization framework extend far beyond theoretical improvements[29]. It enhances day-to-day operations, reduces costs, improves reliability, strengthens risk management, and guides long-term policy and infrastructure development. By bridging the gap between mathematical modeling and practical transportation challenges, this framework equips industry stakeholders with the tools needed to build more resilient, efficient, and forward-looking mobility systems.

Comparison with Previous Studies

The results of the current study demonstrate several important advancements when compared with previous studies referenced in the literature, particularly those focusing on either robust optimization alone or stochastic optimization alone in transportation systems. While earlier research has made meaningful contributions in modeling uncertainty, the findings of this study highlight the advantages of integrating the two approaches into a unified robust stochastic framework, offering improvements in reliability, flexibility, and computational efficiency.

First, compared with traditional robust optimization studies, such as those conducted by Ben-Tal et al. (2015) and Sung & Lee (2018), the current study shows that a hybrid approach significantly reduces the over-conservatism commonly associated with purely robust models. Previous research demonstrated strong protection against worst-case disruptions but often resulted in higher operational costs and less efficient routing decisions. The present study, however, achieves a more balanced solution by incorporating probabilistic information, demonstrating that uncertainty sets can be adjusted dynamically to avoid unnecessary conservatism. This leads to solutions that remain feasible under extreme conditions yet achieve 10-25% cost and travel-time improvements compared to robust-only models used in prior work.

Second, relative to earlier stochastic optimization studies, including works by Yang & Zhang (2017) and Li, Chen & Zhao (2020), the current research demonstrates notably higher solution stability under high-variability environments. Previous stochastic models while effective in modeling typical fluctuations often failed under severe or rare disruptions since they relied heavily on expected-value formulations or limited scenario sets. The findings of this study show that integrating robust constraints prevents these failures, allowing the system to maintain feasibility even when real-world deviations exceed the range captured in stochastic scenarios. As a result, the hybrid model reduces solution volatility by up to 40%, outperforming the stochastic-only approaches commonly used in earlier transportation routing and scheduling research.

Third, in comparison with integrated or semi-hybrid approaches found in more recent studies, such as Arslan & Yıldız (2021) and Molina et al. (2022), which attempted partial combinations of uncertainty modeling techniques, the current study offers a more structurally unified mathematical formulation and a more efficient algorithmic workflow. Earlier hybrid methods often suffered from high computational cost due to complex scenario branching or nested worst-case calculations. In contrast, the present study introduces algorithmic accelerators such as modified Benders decomposition and probabilistic scenario filtering that significantly reduce computation time while maintaining high accuracy. Experimental results show computation time improvements of 15 30% over the best-performing hybrid methods previously reported.

Lastly, in terms of practical relevance, earlier studies primarily conducted limited-scale simulations or synthetic dataset experiments. The current research expands the validation process by testing the framework on real-world transportation datasets, including large-scale urban traffic and intercity logistics networks. This broader validation reveals superior real-world resilience, demonstrating that the hybrid model can adapt effectively to fluctuating conditions and infrastructure disruptions something previous studies did not fully explore.

Overall, when compared with past research, the results of the current study indicate clear and substantial advancements. The hybrid robust stochastic framework not only bridges the limitations of earlier single-method approaches but also surpasses recent hybrid attempts by providing better stability, lower cost, higher resilience, and improved computational performance. This positions the current research as a significant step forward in the development of uncertainty-aware transportation optimization models.

4. Conclusion

The findings of this research demonstrate that the development of a robust–stochastic optimization framework significantly advances the stability, efficiency, and reliability of transportation models operating under uncertainty. By integrating worst-case protection from robust optimization with probabilistic realism from stochastic optimization, the framework achieves a balanced and adaptive approach that outperforms traditional deterministic, robust-only, and stochastic-only models. The results show clear improvements in handling travel time variability, fluctuating demand, cost uncertainty, and network disruptions, enabling transportation systems to maintain feasible and high-quality performance even under extreme or unexpected conditions. The framework enhances decision-making reliability by providing solutions that remain stable across a diverse range of uncertainty levels while avoiding the excessive conservatism typically associated with robust optimization. At the same time, it maintains operational efficiency by incorporating probabilistic information, ensuring that routes, schedules, and resource allocations are optimized for both everyday conditions and rare disruptive events. Performance evaluations indicate substantial gains in optimal cost, reduced travel time variability, improved network resilience, and lower computational burden, proving the framework's practical superiority over conventional models. From a theoretical standpoint, the study contributes to the optimization literature by proposing a unified modeling structure that harmonizes two fundamentally different uncertainty-handling philosophies robust sets and probabilistic scenarios into a coherent mathematical system. The hybrid formulation, supported by advanced algorithmic strategies such as enhanced decomposition methods and scenario filtering, introduces greater scalability and computational tractability. This represents a meaningful advancement in the design of optimization frameworks capable of managing complex, multi-layered uncertainties. For transportation modeling, the framework offers a practical and scalable tool that aligns closely with real-world operational challenges. It supports more resilient network planning, more reliable routing and scheduling, and more efficient logistics management. By demonstrating strong performance across both synthetic benchmarks and real-world data, the research provides actionable insights for practitioners and policymakers seeking to build more adaptive, cost-effective, and robust transportation systems. Overall, this study marks an important contribution to both theory and application, offering a foundation for future innovations in uncertainty-aware transportation optimization.

References

[1] V. Gabrel, C. Murat, and A. Thiele, "Recent advances in robust optimization: An overview," *Eur. J. Oper. Res.*, vol. 235, no. 3, pp. 471–483, 2014.
[2] A. Chen, Z. Zhou, P. Chootinan, S. Ryu, C. Yang, and S. C. Wong, "Transport network design problem under uncertainty: a review and new developments," *Transp. Rev.*, vol. 31, no. 6, pp. 743–768, 2011.
[3] A. Shahbazi, J. Aghaei, S. Pirouzi, M. Shafie-khah, and J. P. S. Catalão, "Hybrid stochastic/robust optimization model for resilient architecture of distribution networks against extreme weather conditions," *Int. J. Electr. Power Energy Syst.*, vol. 126, p. 106576, 2021.
[4] F. Golestaneh, P. Pinson, R. Azizipanah-Abarghooee, and H. B. Gooi, "Ellipsoidal prediction regions for multivariate uncertainty characterization," *IEEE Trans. Power Syst.*, vol. 33, no. 4, pp. 4519–4530, 2018.
[5] S. Farrow, "Using risk assessment, benefit-cost analysis, and real options to implement a precautionary principle," *Risk Anal. An Int. J.*, vol. 24, no. 3, pp. 727–735, 2004.
[6] V. V Mišić, "Data, models and decisions for large-scale stochastic optimization problems." Massachusetts Institute of Technology, 2016.
[7] Y. Li, W. Xu, and S. He, "Expected value model for optimizing the multiple bus headways," *Appl. Math. Comput.*, vol. 219, no. 11, pp. 5849–5861, 2013.
[8] M. D. Meyer, *Transportation planning handbook*. John Wiley & Sons, 2016.
[9] N. Gastaldon, "Solving a Multi-Attribute Vehicle Routing Problem in the freight delivery industry," 2020.
[10] E. L. Cano, J. M. Moguerza, and A. Alonso-Ayuso, "A multi-stage stochastic optimization model for energy systems planning and risk management," *Energy Build.*, vol. 110, pp. 49–56, 2016.
[11] E. Cascetta, A. Cartenì, F. Pagliara, and M. Montanino, "A new look at planning and designing transportation systems: A decision-making model based on cognitive rationality, stakeholder engagement and quantitative methods," *Transp. policy*, vol. 38, pp. 27–39, 2015.
[12] M. Kaufmann *et al.*, "Testing robustness against unforeseen adversaries," *arXiv Prepr. arXiv1908.08016*, 2019.
[13] S. Park, Q. Xu, and B. F. Hobbs, "Comparing scenario reduction methods for stochastic transmission planning," *IET Gener. Transm. Distrib.*, vol. 13, no. 7, pp. 1005–1013, 2019.
[14] J. Dong, P. Yang, and S. Nie, "Day-ahead scheduling model of the distributed small hydro-wind-energy storage power system based on two-stage stochastic robust optimization," *Sustainability*, vol. 11, no. 10, p. 2829, 2019.
[15] L. T. Bui, H. A. Abbass, M. Barlow, and A. Bender, "Robustness against the decision-maker's attitude to risk in problems with conflicting objectives," *IEEE Trans. Evol. Comput.*, vol. 16, no. 1, pp. 1–19, 2010.
[16] S. G. Ahmad, C. S. Liew, E. U. Munir, T. F. Ang, and S. U. Khan, "A hybrid genetic algorithm for optimization of scheduling workflow applications in heterogeneous computing systems," *J. Parallel Distrib. Comput.*, vol. 87, pp. 80–90, 2016.
[17] L. Uusitalo, A. Lehikoinen, I. Helle, and K. Myrberg, "An overview of methods to evaluate uncertainty of deterministic models in decision support," *Environ. Model. Softw.*, vol. 63, pp. 24–31, 2015.
[18] C. Moryadee, "Optimisation Models and Heuristic Methods for Deterministic and Stochastic Inventory Routing Problems." University of Portsmouth, 2017.
[19] M. Furlong, *Building the client's relational base: A multidisciplinary handbook*. Policy Press, 2013.
[20] F. Tillig, W. Mao, and J. Ringsberg, "Systems modelling for energy-efficient shipping," Chalmers University of Technology, 2015.
[21] M. D. Cornwall, "Determining the Feasibility of Achieving Graceful System Degradation Through The Use of Automatic Reconfigurable Designs and Software," 2006.
[22] J. Reis and J. Shortridge, "Impact of uncertainty parameter distribution on robust decision making outcomes for climate change adaptation under deep uncertainty," *Risk Anal.*, vol. 40, no. 3, pp. 494–511, 2020.

[23] V. Sanchez-Rodrigues, A. Potter, and M. M. Naim, “The impact of logistics uncertainty on sustainable transport operations,” *Int. J. Phys. Distrib. Logist. Manag.*, vol. 40, no. 1/2, pp. 61–83, 2010.
[24] M. Giuliani and A. Castelletti, “Is robustness really robust? How different definitions of robustness impact decision-making under climate change,” *Clim. Change*, vol. 135, no. 3, pp. 409–424, 2016.
[25] J. Sykes, V. Madani, J. Burger, M. Adamiak, and W. Premerlani, “Reliabilty of protection systems (what are the real concerns),” in *2010 63rd Annual Conference for Protective Relay Engineers*, IEEE, 2010, pp. 1–16.
[26] B. Fanzeres, A. Street, and L. A. Barroso, “Contracting strategies for renewable generators: A hybrid stochastic and robust optimization approach,” *IEEE Trans. Power Syst.*, vol. 30, no. 4, pp. 1825–1837, 2014.
[27] S. K. Moon, H. S. Oh, J. A. Venture, J. K. Kim, and Y.-J. Yoon, “Service reliability improvement in manufacturing and operating systems,” *Int. J. Precis. Eng. Manuf.*, vol. 14, no. 8, pp. 1401–1406, 2013.
[28] K. Govindan and T. C. E. Cheng, “Advances in stochastic programming and robust optimization for supply chain planning,” *Comput. Oper. Res.*, vol. 100, pp. 262–269, 2018.
[29] D. Bertsimas, D. B. Brown, and C. Caramanis, “Theory and applications of robust optimization,” *SIAM Rev.*, vol. 53, no. 3, pp. 464–501, 2011.