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Evaluation of Optimal Turns Configuration at Intersections in Urban Roads Network Based on Safety and Congestion indices using Non-dominated Sorting Genetic Algorithm-2

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A B S T R A C T

Optimal turns configuration at intersections is a fundamental strategy in the pursuit of transportation network design problems. Most interventions implemented at intersections to manage traffic are typically assessed based on their localized impact at the specific node. However, a critical question arises: can any intervention at a single node be truly independent of the conditions and performance of other nodes within the transportation network? While point-based evaluation methods often produce limited and isolated outcomes, traffic dynamics within a network context evolve in a markedly different manner, where interdependencies render optimal solutions inherently multidimensional, and sensitive to broader system-wide interactions. This study proposes three novel approaches to address this challenge: (1) the development of a comprehensive, network-based decision-making framework for managing turn movements; (2) a conceptual shift from conventional link-based methodologies to node-centric patterns in network design; and (3) the adoption of conflict indices as surrogate safety measures in place of traditional crash data, thereby facilitating a more integrated, proactive, and safety-oriented approach to urban transportation network planning. To operationalize these methodologies, a bi-level, multi-objective optimization framework is developed, integrating the NSGA-2 algorithm for generating Pareto-optimal solutions and the TOPSIS method for decision-making support. The model formulation and optimization processes are grounded in empirical data collected from the urban road network of Dezful, Iran. The findings yield a diverse spectrum of optimal solutions, offering valuable insights for enhancing existing transportation systems and informing the strategic planning and design of future urban networks.

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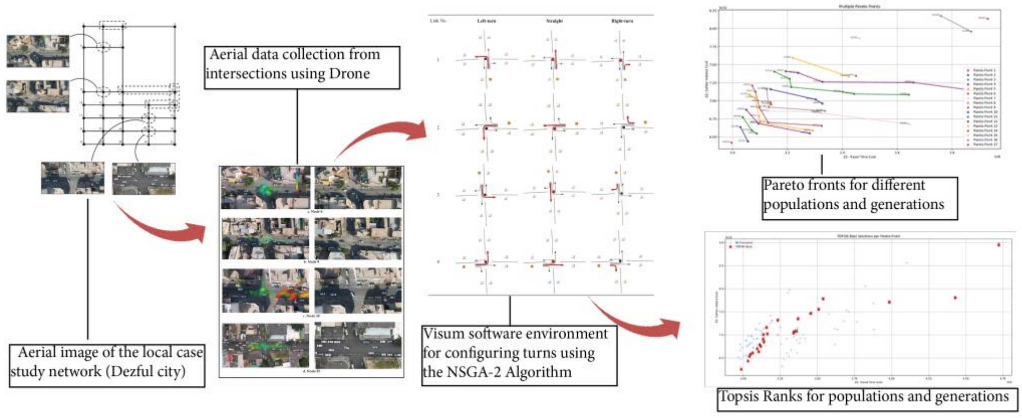
Graphical Abstract



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1. INTRODUCTION

In recent years, the effective design of traffic movements at urban intersections has emerged as a critical strategy for optimizing traffic flow and enhancing road safety. While interventions aimed at regulating turn movements can significantly improve the operational performance of individual intersections, a fundamental question arises: do these localized treatments operate independently of the broader transportation network? The interconnected and dynamic nature of urban road systems implies that interventions at a single node can propagate through the network, potentially influencing the performance of adjacent intersections and overall network functionality. Although such networked systems offer considerable operational advantages, they also introduce vulnerabilities, as disruptions or adjustments at one location may trigger ripple effects, thereby affecting the stability and efficiency of the entire network (1). It appears that enhancing the performance of an intersection, in terms of indices such as travel time, yields different outcomes when evaluated through a network-level perspective compared to a point-based approach. In this context, each intersection should be considered as a node within the interconnected system of the transportation network, and its performance assessed in relation to the overall network dynamics. Such an integrated perspective transforms the problem into a form of the Transportation Network Design Problem (NDP), where localized interventions must be evaluated based on their broader, system-wide implications.

In the transportation network design literature, an urban transportation network is typically defined as a system comprising intersections (nodes) and streets (links), generally planned with the main objective of minimizing travel time for users. The optimization of such network configurations is conventionally formulated as a bi-level optimization problem, wherein upper-level decisions guide network design strategies while lower-level models capture traffic assignment and user equilibrium behaviors (2). On the other hand, much of the existing literature on transportation network design has centered on the development of algorithms (3) focused primarily on minimizing travel time across networks. The optimal allocation of resources to reduce user travel costs has long constituted the principal objective of related studies. However, users in transportation systems are exposed not only to the costs associated with travel delays but also to the substantial risks and consequences stemming from safety deficiencies within the network. Although travel time metrics have traditionally dominated decision-making frameworks in network design problems, most objective functions have concentrated on link configurations while often overlooking the critical influence of nodes. Yet, intersections and nodes play a pivotal role in shaping the overall safety performance of transportation systems. Moreover, a review of the existing literature reveals that investigations into the relationship between road networks and safety have predominantly addressed the correlation between overall network structure and historical indices such as crash frequency. In contrast, safety-centered approaches to network design remain limited and underexplored.

This study seeks to integrate surrogate safety measures (SSMs), which has garnered growing attention in recent years (4), into the analysis of safety outcomes within network design. To this end, a bi-level modeling framework is employed to assess traffic and movement control strategies from a network-wide perspective, underscoring that the outcomes of network-based node management differ fundamentally from those derived through conventional point-based approaches. The analysis is supported by conflict models developed using empirical data from a real-world case study. Drawing upon these findings, a bi-level, multi-objective model is introduced, offering a comprehensive framework for evaluating the optimal configuration of traffic operations within a safety-focused network design paradigm. The main objective of this study is to examine various scenarios involving permissible and non-permissible movements at selected urban intersections and to identify their optimal combination based on multiple criteria using the Non-dominated Sorting Genetic Algorithm 2 (NSGA-2) algorithm. Given the multi-objective nature of the problem and the vast solution space, the application of this algorithm effectively guides the optimization process. The problem is addressed under different population sizes and generation numbers, and a reliable optimization framework is developed to identify and present superior scenarios within the studied network.

The literature review highlights that most studies on turn control at intersections have primarily adopted point-based approaches, with limited consideration of network-wide perspectives. This underscores the necessity of embedding such concepts within the broader framework of network design problems. Furthermore, decision-making in this field has traditionally relied on travel time indices; however, the integration of safety indices substantially expands the solution space. The findings of this study, discussed in detail below, confirm that within the framework of multi-objective, two-level optimization methods, a wide spectrum of solutions can be generated and evaluated for network design.

2. LITERATURE REVIEW

Numerous studies have explored the impacts of control strategies at intersections, providing valuable insights for modeling and analysis in this domain. Chen and Jia (5) proposed a traffic management platform centered on the design of left-turn lanes within the framework of sustainable urban development. Their study employed the NSGA-2 algorithm, incorporating both air pollution indices and traffic delay metrics at urban intersections to guide optimization decisions. Moinuddin et al. (6) employed machine learning models to predict driver behavior in selecting turn maneuvers and demonstrated that algorithms such as K-Nearest Neighbors (KNN) exhibit high predictive accuracy in forecasting route choice decisions. Their findings underscore the potential of behavior prediction models to inform the optimization of permissible turn combinations at intersections, thereby enhancing network performance and safety outcomes. In the domain of congestion analysis at turn movements, Kan et al. (7) utilized spatial trajectory data from taxis to identify congestion hotspots specifically at turning points. Their findings revealed that turn-level analyses offer substantially higher precision compared to intersection-level evaluations, providing a more reliable foundation for traffic management policies concerning the operational status of turns. Similarly, Fan et al. (8) investigated the environmental impacts associated with left-turn movements in mixed traffic streams and reported that optimizing left-turn lane configurations resulted in a 30% reduction in pollutant emissions, alongside significant decreases in queue lengths and vehicular delays. These outcomes highlight the critical importance of incorporating environmental considerations into traffic control and decision-making frameworks.

In the field of traffic safety, Autey et al. (9) the safety implications of geometric modifications to right-turn lanes and demonstrated that the implementation of smart right-turn significantly reduced traffic collisions and enhanced safety. These findings indicate that the operational status of right-turn lanes at specific intersections can have a direct and measurable impact on overall intersection safety performance. Foulaadvand and Belbasi (10) demonstrated that signal timing parameters and turn probabilities exert a significant influence on intersection capacity and congestion levels. Their findings highlight the importance of accounting for the combined effects of various open and closed turn scenarios on overall network flow dynamics. Hu et al. (11) proposed an integrated design combining U-turn and advanced left-turn movements, demonstrating that the separation of these flows effectively reduces conflicts and alleviates congestion at intersections. In the context of turn optimization interacting with rail transit, Currie and Reynolds (12) examined the impact of the Hook Turn maneuver on tram operations, concluding that under specific conditions, this strategy can improve intersection capacity and reduce delays. These findings underscore the critical role of turn management decisions — particularly the regulation of right- and left-turn movements — in optimizing multimodal network performance. Additionally, the operational efficiency of U-turns and driver behavioral responses to various turn management scenarios have been investigated, with particular attention to their implications for network delays and safety outcomes (13, 14).

Collectively, these studies highlight that targeted management of traffic flows at urban nodes — through scenario development and multi-objective optimization incorporating both delay and safety indices — can substantially enhance overall network performance. In this context, algorithms such as NSGA-2, with their capability to effectively navigate multi-objective solution spaces and generate efficient Pareto-optimal fronts, present a particularly suitable approach for addressing such complex, multi-criteria decision problems. This research builds upon these insights by applying the NSGA-2 algorithm to optimize turn management scenarios within an urban road network. Most studies in the area of turns and movements have primarily concentrated on lane design, driver behavior, operational control, conflict analysis, and the development of various algorithms for left-turn (15, 16), right-turn (17-19), and other maneuvers at intersections. However, despite the existence of comprehensive and diverse works in these areas, relatively limited attention has been given to adopting a network-wide approach to junction design.

A review of network-based approaches further reveals that most studies in the field of network design have predominantly concentrated on algorithm development and the formulation of mathematical models (20). Within the discrete network design literature, a wide range of algorithmic strategies has been employed, including ant colony optimization (21), linearization and approximation techniques (22), support function frameworks (23), genetic algorithms (24), combinatorial methods (25), and quasi-optimization decomposition approaches (26). For continuous network design problems, a diverse array of methodologies has also been explored, including simulated annealing (27), the Hooke-Jeeves algorithm (28), iterative optimal assignment techniques (29), and mixed-integer linear programming for fundamental path routing problems (30). In the domain of mixed network design, research has introduced various optimization strategies, ranging from mixed-integer linear programming (31) and genetic algorithms (32) to other advanced metaheuristic and combinatorial approaches. A significant portion of these studies has predominantly focused on minimizing travel time (33-37) or reducing travel time-related costs for both operators and users (38-40), whereas the incorporation of safety indices within road network frameworks has received comparatively limited and less explicit attention in the existing literature (41).

Studies addressing network safety have also primarily aimed to investigate the relationship between network topology and crash frequency, frequently employing crash prediction models as the foundational framework for developing safety rankings (42). For instance, Fancello et al. (43) introduced an advanced model for assessing safety parameters within urban transportation networks, offering valuable insights into the mechanisms of safety evaluation and risk analysis in traffic systems. In a similar vein, Gomez et al. (44), through an applied case study, systematically evaluated the safety performance index of an urban network, providing critical insights into safety assessment methodologies within the network context. Ewing and Dumbaugh (45) undertook a rigorous investigation into the influence of urban structure on transportation safety, utilizing regression analysis to probe the complex interplay between network configuration and safety outcomes. Moeinaddini et al. (46) conducted a comprehensive assessment of urban road networks, revealing a strong positive correlation between improved safety performance and network characteristics such as a lower number of nodes within a given area, shorter average highway lengths, and longer urban road segments. Additionally, analyses of network configurations have indicated that limited-access designs are associated with a decreased incidence of crashes involving vulnerable road users, particularly when compared to traditional network patterns and alternative topological layouts (47). In a related study, Marshall and Garrick (48) demonstrated that increasing road network density — notably through a higher number of intersections — is significantly associated with reductions in overall crash frequency.

A comprehensive review of the literature reveals a notable gap in understanding the relationship between safety indices and network design problems, accompanied by insufficient attention to the costs associated with safety deficiencies. This oversight implies that many evaluations, which predominantly emphasize increasing route capacity or expanding network links, often neglect the broader spectrum of related costs. By prioritizing travel time reduction, such assessments frequently fail to account for the substantial economic and social consequences stemming from compromised safety conditions. In network design problems, modeling efforts typically emphasize the relationship between travel time and traffic volume. To address safety considerations within such frameworks, surrogate safety measures (SSMs) have been employed as alternative indices, particularly in cases where reliable crash data are unavailable, incomplete, or insufficiently accurate (49). The application of surrogate safety measures in traffic safety analysis can be traced back to the early 1970s (50). A key advantage of SSMs over traditional crash data lies in their ability to capture the sequence of events preceding a collision, thereby offering valuable insights into the underlying causes of traffic conflicts (51). SSMs are generally categorized into three primary groups: time-based, energy-based, and acceleration-based indices. In the present study, a time-based metric — specifically, Time to Collision (TTC) — is employed, as it remains one of the most widely adopted and extensively validated indices in the field of traffic safety research (52).

The literature review highlights several essential dimensions in addressing the challenges of node network design. First, while prior research has explored complex issues such as network stability and operational uncertainties, comparatively limited attention has been devoted to achieving a meaningful paradigm shift through the integration of safety indices within network design frameworks. Second, existing studies on network safety have largely concentrated on structural and configurational attributes, overlooking localized operational dynamics. Third, the growing application of surrogate safety measures (SSMs), including conflict-based indices, underscores their emerging significance as practical alternatives to crash-based assessments. Finally, most investigations addressing the optimization of permissible turn and movement scenarios at intersections have relied on point-based methodologies, with fewer studies adopting comprehensive network-based perspectives.

To address these identified gaps, the present study proposes a comprehensive framework that simultaneously incorporates both safety and delay indices to determine the optimal configuration of movement scenarios within an urban road network. Following the introduction and review of existing literature, the structure of this research is organized into four subsequent sections. Section 3 details the methodological approach and problem formulation, encompassing the development of the optimization framework, the definition of decision variables and model parameters, the data acquisition procedures, and the formulation of the principal modeling functions. Section 4 presents the results derived from the implemented models, including validation outcomes and a thorough analysis of the network design scenarios. Section 5 offers an in-depth discussion of the key findings, articulating their theoretical contributions and practical implications for urban traffic management. Finally, section 6 concludes the study by summarizing the principal conclusions and proposing avenues for future research and practical application.

3. METHODOLOGY

Given that this study addresses a network design problem by integrating safety indices alongside traditional delay-based performance measures, the initial phase involves developing appropriate safety performance functions and extending them to incorporate conflict indices as a central component of the analysis. In the subsequent phase, the problem is structured within a two-level bi-objective optimization framework, wherein the fundamental safety performance functions of the network are evaluated through an empirical case study. Concurrently, a customized two-level bi-objective optimization algorithm is employed to solve the problem. It is important to underscore that the simultaneous integration of safety indices with delay-based criteria, within a multi-objective optimization structure, substantially increases the computational complexity and analytical demands of the solution process, necessitating carefully designed modeling strategies and solution procedures.

This complexity is further exacerbated when surrogate safety measures are employed in place of traditional crash-based indices, as these measures require more intricate modeling and interpretation within the optimization framework. In this study, to optimize decisions concerning the operational status of left-turn, right-turn, and through movements at intersections within an urban road network, a combined two-level bi-objective optimization model was formulated. The NSGA-2 metaheuristic algorithm was utilized to address the multi-objective nature of the problem and to generate an efficient set of Pareto-optimal solutions. Subsequently, the TOPSIS multi-criteria decision-making method was applied to rank and prioritize the non-dominated solutions, thereby facilitating the selection of optimal scenarios for practical implementation.

The core structure of the problem was conceptualized as a two-level model. In the first level, decisions are made regarding the permissibility of straight, right-turn, and left-turn movements at designated nodes within the network. The second level subsequently addresses the traffic assignment problem based on the configuration of permitted movements established in the first level.

3. 1. Node Safety Performance Functions In network design problems, the primary objective is typically the minimization of travel time for users. This relationship is conventionally modeled using a travel time function, as shown in Equation 1, which defines the dependence of travel time on traffic flow. Similarly, the development of a safety performance function requires formulating a relational model that associates safety (denoted as s_{ij}) with traffic flow. This relationship is expressed through Equation 2.

$$t_{ij} = f(x_{ij}) \tag{1}$$

$$s_{ij} = g(x_{ij}) \tag{2}$$

This model is based on the Time to Collision (TTC) index as a surrogate safety measure. To support the modeling process, empirical data were collected from four unsignalized intersections within the urban road network of Dezful city. The relationship between traffic flow and safety performance was modeled using a linear regression approach, formally expressed in Equation 3. Table 1 provides a summary of the key features and statistical parameters of the linear regression model structure. Subsequently, the specific safety-traffic model developed for this study is presented in Equation 4.

$$Y = \beta_0 + \beta_1(X_1) + \beta_2(X_2) + \cdots + \beta_i(X_i) \tag{3}$$

$$Conflict\ Index = \beta_0 + \beta_1(Traffic\ Flow) \tag{4}$$

The delay function applied is presented in detail in Equation 5 (53). In this equation, V denotes the traffic flow volume, while C represents the intersection capacity. The parameters α, β, and γ serve as key coefficients within the model, with their corresponding values provided in Table 2.

$$D_m = 9.6 \times (\alpha + \beta \times (\frac{V}{7 \times C})^{\gamma}) \tag{5}$$

3. 2. Designing the Problem Structure The main objective of the Network Design Problem (NDP) is to determine an optimal solution under imposed constraints. It is typically addressed through a two-level framework, where the leader level solves the network design problem and the follower level handles the traffic allocation. The primary goal of the NDP is to optimize the assignment of limited resources by selecting the most efficient links from predefined candidates to enhance overall network performance. The structure of this two-level problem is presented in Equation 6, with key variables and parameters summarized in Table 3.

$$\begin{gathered} \min_{m \in M, n \in N} F(m,n) \\ subject\ to: G_i(m,n) \le 0\ for\ i \in \{1,2,\dots,I\} \\ n \in argmin\left\{f(m,v): g_j(m,v) \le 0, j \in \{1,2,\dots,J\}\right\} \end{gathered} \tag{6}$$

TABLE 1. Linear Regression Model Structure

Y	Dependent Variable
X_i	Independent Variables
β_i	Model Parameters

TABLE 2. Delay model parameters (53)

	Intersection
α	3.5
β	4.53
γ	1.35

The main problem follows Equation 7.

$$\underset{y}{Min} \sum_{i,j\in(A\cup A_y)} x_{ij}{}^{*} t_{ij}(x_{ij}^{*})$$

$$s.t: y_{ij} = 0 \; or \; 1 \quad \forall \, (i,j) \in A_y \tag{7}$$

$$\sum_{i,j\in A_y} c_{ij} y_{ij} \leq B$$

x_{ij}^{*}: Represents the user's equilibrium flow obtained by solving the low-level problem (Equation 8) in N (V, $A \cup A_y$). given the vector of projects y:

$$\underset{x}{Min} \sum_{i,j\in(A\cup A_y)} \int_0^{x_{ij}} t_{ij}\,(u) du$$

$$s.t.: \quad \sum_{P\in P_{ks}} x_P^{ks} = d^{ks}, \; \forall \, (k,s) \in P$$

$$x_P^{ks} \geq 0, \; \forall \, p \in p_{ks}\,, \; \forall \, (k,s) \in P \tag{8}$$

$$x_{ij} = \sum \; \sum \; x_P^{ks}.\delta_{ij,p}^{ks} \quad \forall \, (i,j) \in A_y$$

The complete formulation of the two-level optimization problem is presented in Table 4. At the upper level (leader level), the decision variable concerns the configuration of turns at network nodes. The problem simultaneously minimizes two objective functions: a congestion-related index (travel time), and a safety-related index (time-to-collision conflict measure). To solve the lower-level assignment problem, the full capabilities of Visum software were utilized, given its efficiency and accuracy in network assignment modeling. The formulation incorporates three primary constraints:

1) **Flow conservation** – the total demand between an origin-destination pair must equal the sum of flows assigned to the corresponding paths.
2) **Non-negativity** – demand values and flow volumes must remain non-negative.
3) **Link demand assignment** – if a link is shared among multiple O–D paths, the total link flow must equal the aggregate demand distributed across all relevant paths.

Furthermore, in the Python implementation of the model, the **win32com library** was used to establish a dynamic interface between Python and the **Visum environment**. This connection enabled intelligent exchange of network data and results, thereby allowing seamless integration of Visum's computational power with the optimization algorithm coded in Python.

This study adopts a similar framework, where the follower-level task follows the conventional assignment problem formulation with two key modifications: a node-oriented problem structure and the integration of a safety index into the objective function. In the model structure of this study, the upper level simultaneously minimizes two objective functions — the conflict index and the delay index — both dependent on the flow volume at the node.

TABLE 3. Variables and Parameters of Network Design Problem

$N(V, A)$	The network consists of a set of arcs (A) and nodes (V).
(k, s)	origin (k)-destination (s), O/D, pair;(k, s) ϵ P, where P is the set of O/D pairs, $P \subseteq V \times V$
y_{ij}	Project decision variable, taking values 0 or 1 depending on rejection or acceptance of project link (*i,j*), (*i,j*) ϵ A_y, where A_y is the set of project links.
y	vector of y_{ij}'s with dimension equal to the number of the elements of A_y.
d^{ks}	Demand from k to s, (k, s) ϵ P, assumed to be constant.
x_{ij}	Link flow (*i,j*), (*i,j*) ϵ A.
x_p^{ks}	path flow p from origin k to destination s, p ϵ p_{ks}, where p_{ks} is the set of paths from k to s, (*k,s*) ϵ P.
x	vector of x_{ij}'s with dimension equal to the number of elements of $A \cup A_y$
$t_{ij}(x_{ij})$	volume- delay function of link (*i,j*), (*i,j*) ϵ $A \cup A_y$, representing average travel time , which is assumed to be only a function of flow in link (*i,j*), continuous, differentiable, Riemann integrable, and convex, defined for $x_{ij} \geq 0$
B	Budget level.
c_{ij}	Construction cost of link (*i,j*), (*i,j*) ϵ A_y

3. 3. Solution Algorithm

To solve the proposed two-level model and extract the Pareto fronts, the NSGA-2 algorithm was employed. Recognized as one of the most widely used metaheuristic algorithms for multi-objective problems, it operates by ranking Pareto fronts and preserving population diversity through a crowding distance mechanism. For each individual in the population, the number of decision variables was set

TABLE 4. Formulation of the two-level optimization problem

$\underset{y}{Min} \sum_{i,j\in(A)} x_{ij}{}^{*} t_{ij}(x_{ij}^{*})$	First Objective (Congestion)	**Leader level**
$\underset{y}{Min} \sum_{i(V_Y)} TTC_i(x_{ij}^{*})$	Second Objective (Conflict Index)	**Follower level**
$\underset{x}{Min} \sum_{i,j\in(A\cup A_y)} \int_0^{x_{ij}} t_{ij}\,(u) du$	Objective Function of Follower level	
$s.t.: \sum_{P\in P_{ks}} x_P^{ks} = d^{ks}, \forall (k,s) \in P$	Constraint. 1	
$x_P^{ks} \geq 0, \forall \, p \in p_{ks}\,, \forall \, (k,s) \in P$	Constraint. 2	
$x_{ij} = \sum \sum x_P^{ks}.\delta_{ij,p}^{ks} \; \forall \, (i,j) \in A_y$	Constraint. 3	

equal to the number of movement-related decisions at the network nodes. Then, the FitnessMulti and Individual classes were defined using the DEAP library, with each individual represented as a binary list. The initial population was generated using random binary values (0 and 1) with varying population sizes of 50, 100, and 150 individuals.

In this study, the Two-Point Crossover operator and Bit Flip Mutation with a mutation probability of 5% for each decision variable were applied. Parent selection for the next generation was performed using the selNSGA2 method, which ranks individuals based on Pareto front order and crowding distance. For each individual, after determining the combination of access status decisions, the traffic allocation model was executed in VISUM, and the resulting network traffic volumes were extracted and incorporated into the high-level problem. To investigate the model's behavior and assess the effect of population size and number of generations on result quality, various combinations of population sizes (50, 100, and 150) and generation counts (10, 15, 20, 25, 30, 35, 40, 45, and 50) were tested. In total, 27 combination cases were examined, and for each, the Pareto fronts and optimization indices were extracted and analyzed. Figure 1 shows the left, straight, and right movements for each node in VISUM. Each movement is encoded as a string of 0s and 1s, representing whether it is open or closed at the node location. Within a Python loop, each configuration is parsed, the assignment model is executed in VISUM for every case, and the results are recorded for use in the higher-level model.

The NSGA-II algorithm is well-suited for addressing large-scale optimization problems, owing to its combined use of metaheuristic search techniques and Pareto front analysis. A distinctive feature of this study is the integration of NSGA-II with the specialized traffic

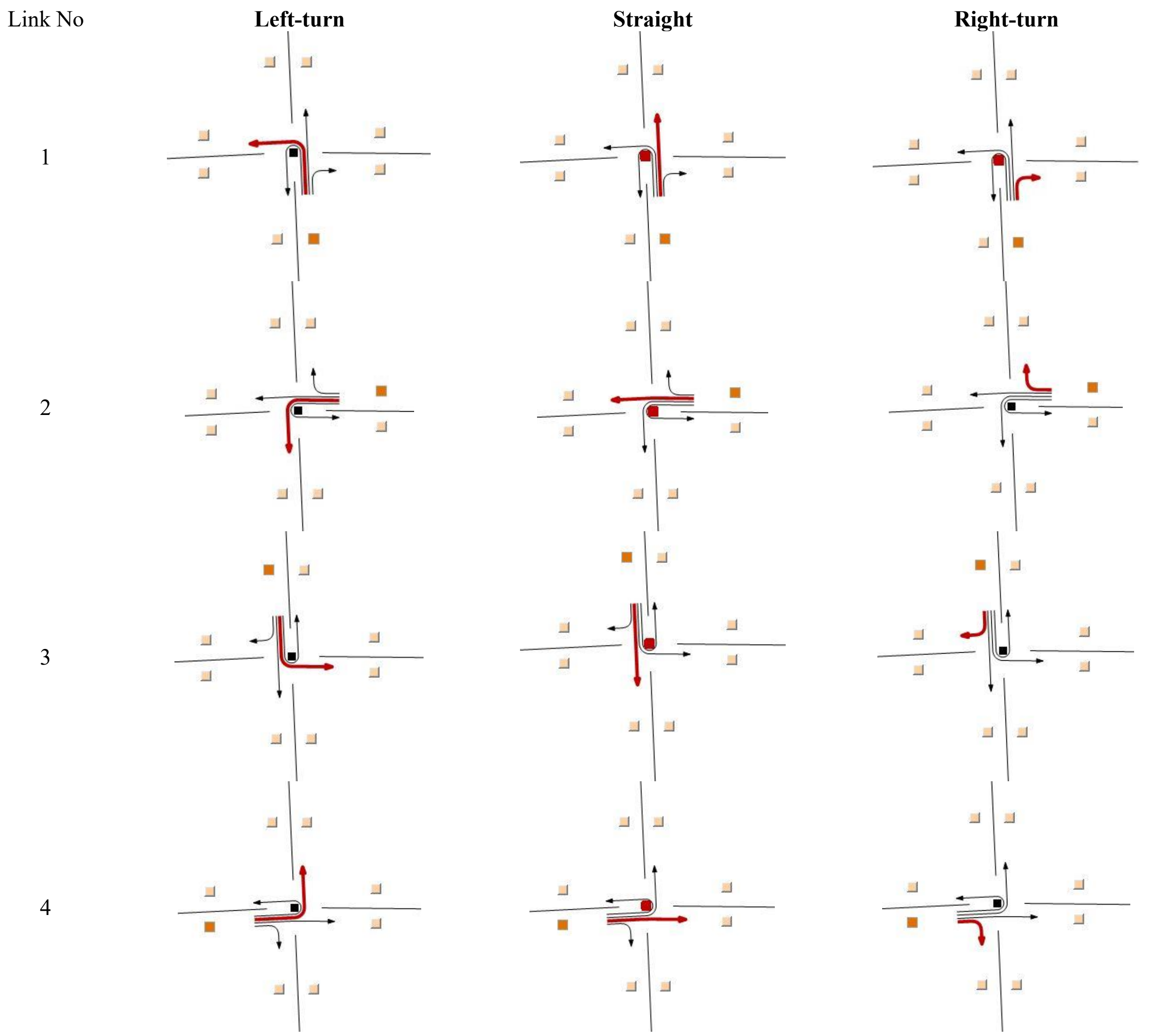


Figure 1. Left-turn, straight, and right-turn movements in Visum software

generation and evaluation was implemented in Python, enabling automated interaction with Visum through built-in connectivity functions. This setup allowed for seamless execution of assignment models and the direct transfer of results into the optimization framework, thereby ensuring both computational efficiency and methodological rigor. The logic of Pareto fronts is based on representing alternative scenarios in the coordinate system of two objective functions. When the horizontal axis is defined as the first objective function and the vertical axis as the second, the relative distribution of scenarios forms the basis for identifying dominant and non-dominated solutions. In a minimization problem, if the origin is defined as the point of reference, scenarios located in the first quadrant are considered non-dominated, those in the second and fourth quadrants are equivalent, and those in the third quadrant are dominated. A key feature of the NSGA-II algorithm lies in its reliance on evolutionary search principles. Similar to other metaheuristic algorithms, it begins by generating an initial set of solutions and iteratively progresses toward the global optimum, thereby reducing the risk of entrapment in local optima. The evolutionary operators form the core of this mechanism: the crossover operator combines chromosomes (scenarios) to explore promising solution spaces, while the mutation operator introduces variability, enabling the algorithm to escape local optima and preserve diversity across generations.

To address the lower-level assignment problem, Visum PTV 2023 software was employed, while the comprehensive solution algorithm was developed in Python 3.9.9. The main Python libraries utilized for writing and executing the algorithm are listed in Table 5. The overall workflow of the algorithm implementation is illustrated in Figure 2.

For the evolutionary operators, the two-point crossover (cxTwoPoint) was adopted for recombination, while the bit-flip mutation (mutFlipBit) was applied to introduce variability (54). Both operators are widely recognized in the genetic algorithm literature and are readily available through standard Python libraries, making them effective and reliable choices for this problem. Figure 3 show the a part of code written in Python.

3. 4. Scenario Analysis After generating the Pareto fronts, the TOPSIS method was applied to identify the best combination of decisions from the set of non-dominated solutions. In this method, the decision matrix

TABLE 5. Python libraries utilized for writing and executing the algorithm

No.	Library
1	win32com
2	numpy
3	pandas
4	random
5	time
6	pickle
7	matplotlib
8	deep

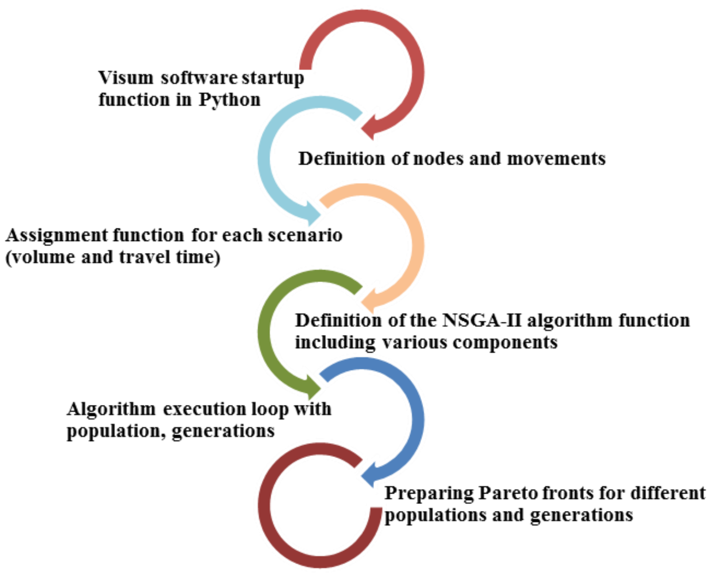


Figure 2. The overall workflow of the algorithm implementation

```python
def run_assignment(individual):
    index = 0
    binary_representation = ""
    for node, turns in turn_movements.items():
        for turn in turns:
            fromNode, toNode, _ = turn
            turn_obj = visum.Net.Turns.ItemByKey(fromNode, node, toNode)
            if turn_obj is not None:
                turn_obj.SetAttValue("TSysSet", "C" if individual[index] == 1 else "B")
            binary_representation += str(individual[index])
            index += 1

    visum.Procedures.Execute()

    results = []
    for link in visum.Net.Links:
        results.append({
            "FromNode": link.AttValue("FromNodeNo"),
            "ToNode": link.AttValue("ToNodeNo"),
            "Volume": link.AttValue("VolVehPrT(AP)"),
            "TravelTime": link.AttValue("TCur_PrTSys(C)"),
        })
```

Figure 3. A part of code written in Python

containing the Z1 and Z2 values for each solution was first extracted and normalized. Subsequently, the distance of each solution from the positive and negative ideal points was calculated, and a proximity index to the ideal solution was determined. The solution with the highest proximity index was selected as the optimal solution. Pareto front diagrams were plotted for all 27 combination cases, and the corresponding TOPSIS results were reported for each case.

It is important to emphasize that the Relevance Estimation and Value Calibration (REVAC) method—one of the fundamental approaches in parameter tuning—was employed to calibrate the parameters of the proposed problem (55, 56). This method not only determines the optimal parameter values but also evaluates the relative importance of each parameter. The REVAC procedure begins by assigning a probability distribution over the feasible range of each parameter.

The process is then iteratively updated by applying an evaluation function, selecting elite solutions, and shifting the distributions (bin distribution) toward regions associated with improved performance. The evolution of parameter distributions is further assessed using an entropy index, which captures the degree of concentration of parameter values. To refine the selection of optimal intervals, the differential entropy index was applied. The interpretation of this method is straightforward: A narrow, concentrated distribution (low entropy) indicates high parameter importance, as specific parameter values strongly enhance algorithmic performance. A wide distribution (high entropy) suggests low parameter importance, as variations in that parameter do not significantly influence outcomes. A notable strength of REVAC lies in its emphasis on identifying an optimal probabilistic model for parameters, rather than a single deterministic value, thereby offering a more robust foundation for algorithm tuning.

Unlike explicit intervalization, the REVAC method employs probability density models to identify a probability distribution centered within a subset of the initial parameter range. Over the course of the process, the mean of the distribution shifts toward the optimal region, while the variance decreases, thereby concentrating the search around the most promising parameter values. The iterative process of optimization and parameter tuning is illustrated in Figure 4.

4. CASE STUDY CHARACTERISTICS

The general layout of the Dezful case study network is illustrated in Figure 5. The data derived from this network form the foundation for developing the models in the design problem. Conflict indices were derived from a meticulous analysis of video data captured via drone surveillance, enabling the accurate identification and classification of potential traffic conflicts at each intersection. Data collection was performed on weekdays between 8:00 AM and 6:00 PM using a Phantom 4 Pro drone equipped with a 1-inch, 20-megapixel sensor, capable of recording ultra-high-definition 4K (4096×2160) video at 60 frames per second, stabilized by a 3-axis gimbal to ensure high-precision data acquisition.

Each drone flight session lasted approximately 30 minutes and maintained a minimum altitude of 150 meters to prevent any influence on driver behavior due to the drone's presence. The recorded video data were subsequently processed and analyzed using the DFS (Drone Footage Analysis System) and SSAM (Surrogate Safety Assessment Model) software tools. Within the modeling framework, the number of observed traffic conflicts served as the dependent variable, while the corresponding intersection flow rate was treated as the independent variable. Figure 6 illustrates the empirical data collected from the four observed intersections, providing a visual representation of traffic volumes and conflict occurrences during the study period.

An important feature of the geometric configuration of the study area is that each intersection node is connected to exactly four links, providing a uniform structural foundation for the analysis (Table 6). The study concentrates on a set of unsignalized urban intersections, whose geometric and operational characteristics were derived from field data. The intersections were selected according to specific criteria, including geometric similarity, comparable traffic conditions, and the absence of traffic signals, thereby enabling a focused examination of the influence of geometric factors on both safety and traffic flow. The intersections analyzed in this study were all four-legged, unsignalized junctions without physical dividers. In all cases, the intersection angles were approximately 90 degrees, representing a near-perpendicular geometry. Lane widths on the secondary roads were measured at 10–12 meters, while those on the main roads ranged between 13 and 15 meters. This variation in main road width is particularly noteworthy, as it may reflect differences in traffic capacity and could influence driver behavior in maneuver selection. In total, four intersections were examined under field conditions, each selected to ensure broadly similar characteristics while maintaining slight geometric variations.

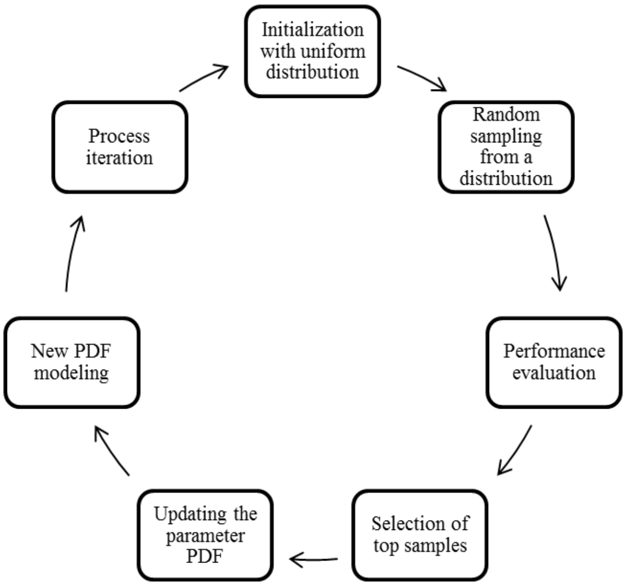


Figure 4. Iterative process of optimization and parameter tuning

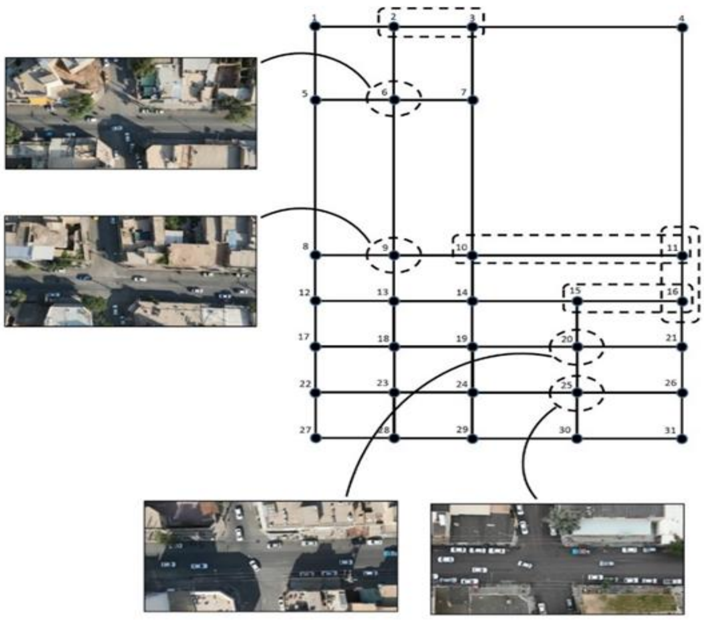
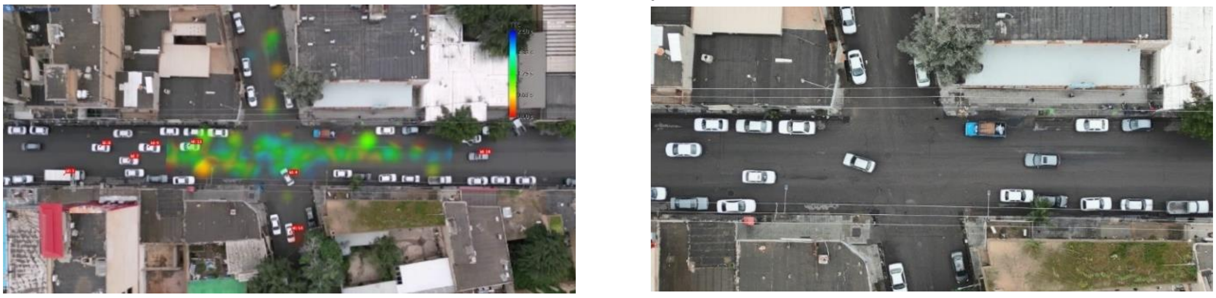


Figure 5. Overview of the study intersections within the Dezful city roads network

a. Node 6

b. Node 9

c. Node 20



d. Node 25

Figure 6. Data collection process at intersections and extraction of conflict indices

Specifically, Intersection No. 6 had a main road width of 15 meters, Intersection No. 9 measured 14 meters, and Intersections Nos. 20 and 25 measured 14 and 13 meters, respectively. The combination of comparable baseline conditions and modest geometric differences provides a valuable context for analyzing the influence of main road width on both safety outcomes and traffic performance at unsignalized intersections.

TABLE 6. Unsignalized urban intersections characteristics

node	Number of Legs	Type	Lane width (m)		Divider
			Major	Minor	
6	4-leg	Unsignalized	15	12	Undivided
9	4-leg	Unsignalized	14	12	Undivided
20	4-leg	Unsignalized	14	10	Undivided
25	4-leg	Unsignalized	13	10	Undivided

4. RESULTS

This section presents the results of implementing a two-level optimization model for the optimal management of turn movements at selected nodes within an urban network. The primary objective was to identify optimal configurations for opening or closing turn movements at nodes, aiming to simultaneously minimize travel time cost (Z1) and safety-related cost (Z2). The multi-objective NSGA-2 algorithm was employed to solve the model, followed by the application of the TOPSIS multi-criteria decision-making method to analyze and select the most suitable scenarios. A key feature of this solution approach is its emphasis on the diversity of optimal responses, in contrast to the single-solution focus of previous network design studies.

In line with the node-based network design framework outlined in the preceding sections, the results of the proposed safety models for network configuration are presented. Table 7 summarizes the estimated parameters of the linear regression model developed for the network's nodes. Among the independent variables, traffic volume and speed were identified as statistically significant factors influencing safety outcomes. The corresponding t-values for traffic volume and speed were 16.387 and -1.542, respectively. The model demonstrated an R-squared value of 0.64, indicating a satisfactory level of explanatory power. As illustrated in Figure 7, the descriptive plots confirm a positive association between increasing traffic volume and the number of conflicts. Moreover, diagnostic plots validate that the assumptions underpinning linear regression are reasonably satisfied in this model.

By developing conflict-based safety models, the two-level problem was solved using the NSGA-2 algorithm. The main problem model was implemented across 27 different cases, comprising three population groups of 50, 100, and 150 individuals, each tested over 10, 15, 20, 25, 30, 35, 40, 45, and 50 generations. The resulting Pareto front diagrams for populations of 50, 100, and 150 are shown in Figures 8 to 10, respectively. The number of optimal fronts identified for these populations was 17, 25, and 31, respectively. For the population size of 50, both the first and last fronts contained a single solution, while the middle fronts included multiple optimal solutions. In the case of a population of 100, the first front

TABLE 7. Conflict-Traffic Model Estimated Parameters

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.904	4.126		0.461	0.645
Traffic Volume	1.033	.063	.798	16.387	0.000
Speed	-.258	.167	-.075	-1.542	0.125
R-square: 0.64					

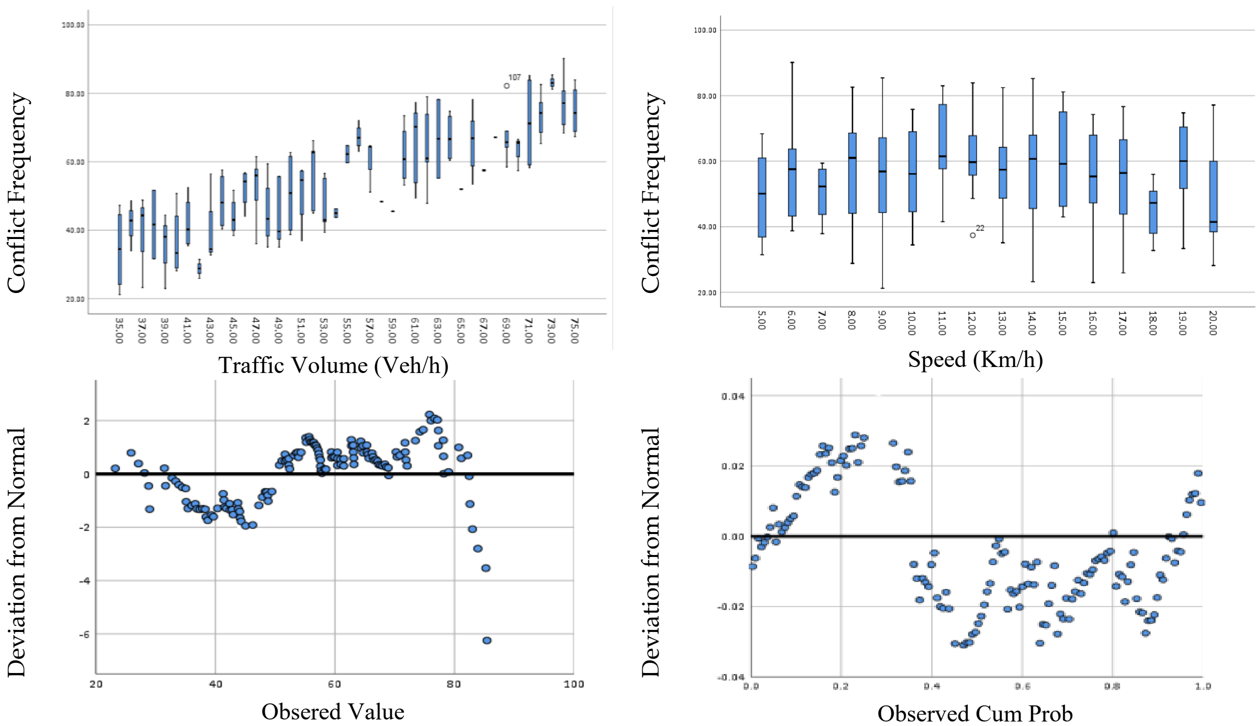


Figure 7. Descriptive statistics of Conflicts-volume models

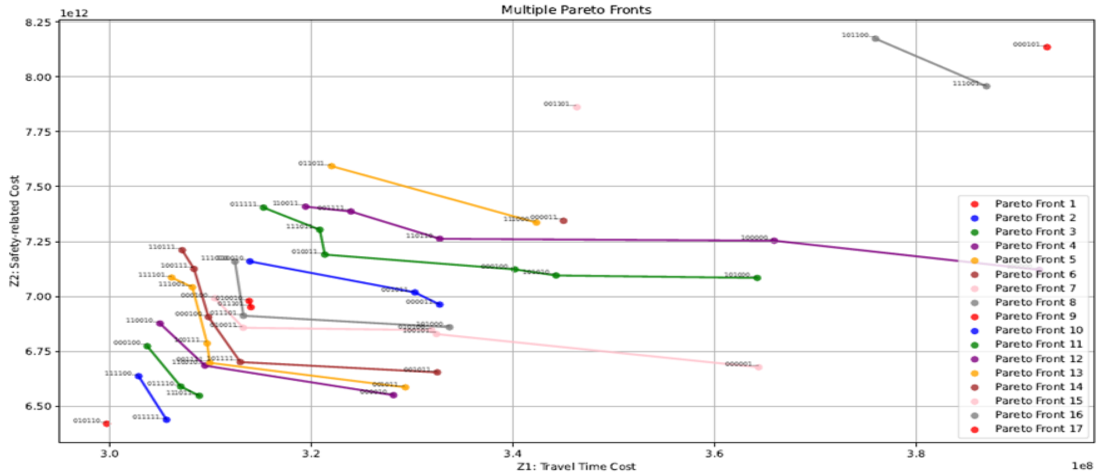


Figure 8. Pareto fronts diagram for a population size of 50 individuals

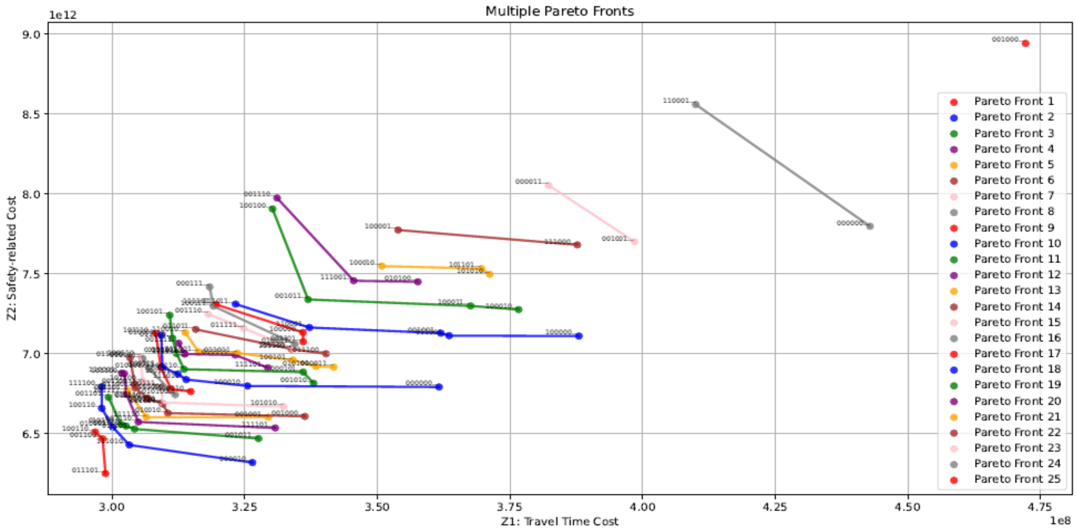


Figure 9. Pareto fronts diagram for a population size of 100 individuals

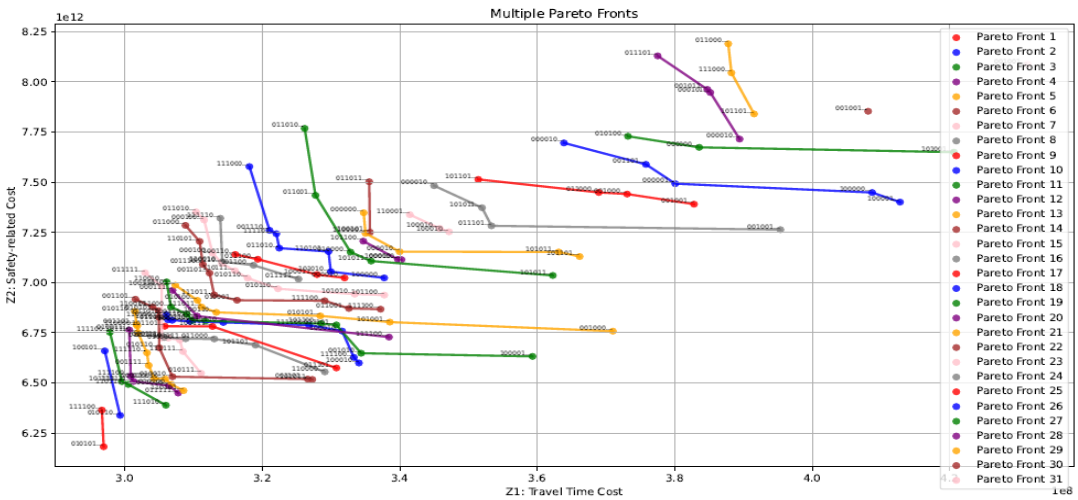


Figure 10. Pareto fronts diagram for a population size of 150 individuals

consisted of three solutions and the last front contained one. As the population increased to 150, the number of Pareto fronts rose accordingly; here, the first front contained two solutions, and the last front again contained a single solution.

Figure 11, for example, illustrates the distribution of Pareto fronts for a population size of 100 across generations 15 to 50. The number of fronts obtained in these nine cases is 26, 29, 26, 26, 25, 25, 24, and 24, respectively. To further assess the performance of the

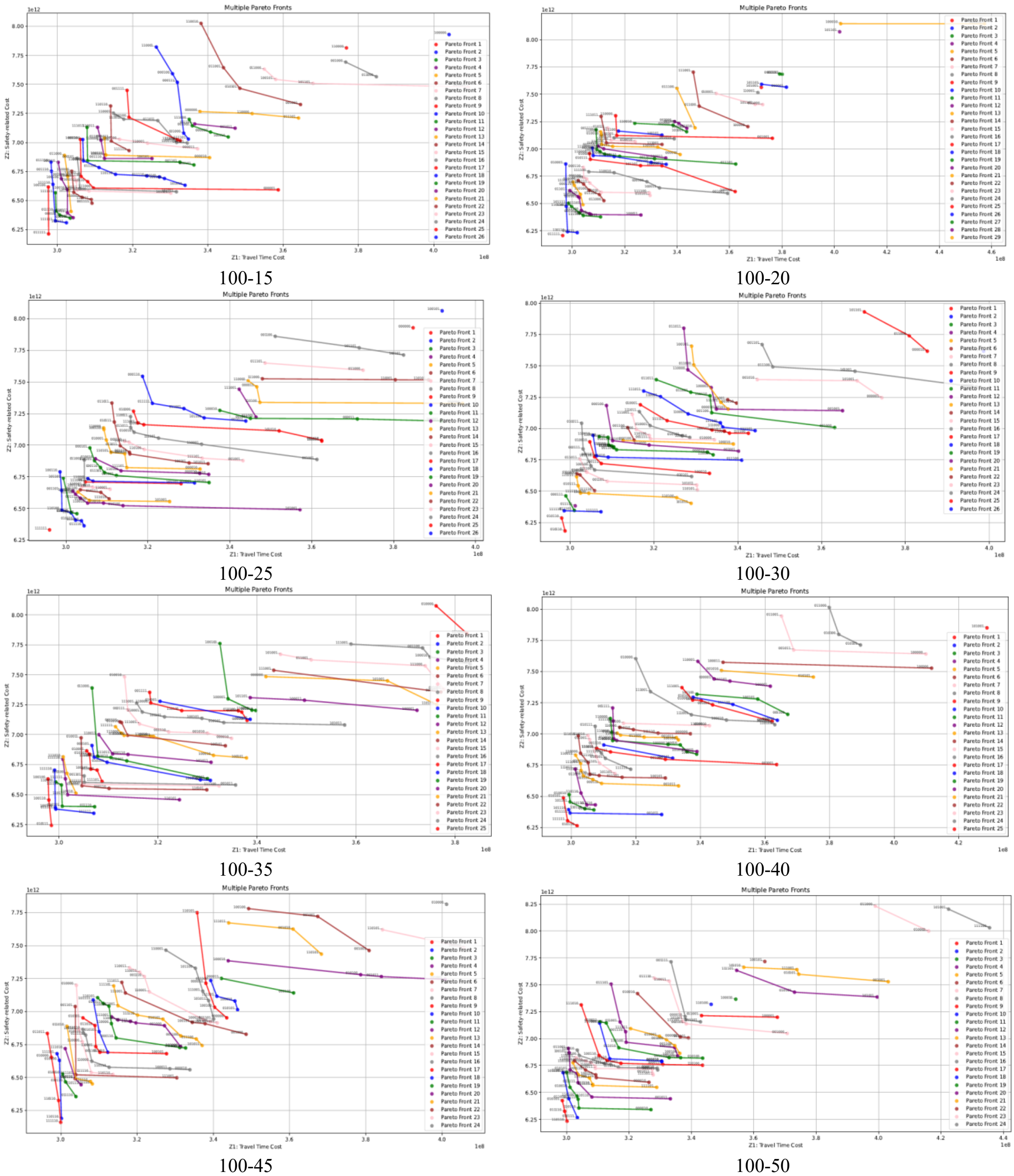


Figure 11. Distribution of Pareto fronts for a population size of 100 across generations 15 to 50.

TABLE 8. Running time and number of Pareto fronts for different populations and generations

Population	Generation	Fronts Frequency	1st front solutions	Last front solutions	Running time (s)
	10	25	3	1	6234
	15	26	2	1	9336
	20	29	1	2	12455
	25	26	1	1	15563
100	30	26	2	1	18675
	35	25	3	2	21777
	40	25	3	1	24895
	45	24	4	1	28001
	50	24	3	2	31108
	10	31	2	1	9357
	15	33	6	1	13990
	20	32	2	1	18667
	25	32	1	1	23328
150	30	29	3	2	27991
	35	31	4	1	32655
	40	34	4	1	37326
	45	31	3	1	42010
	50	29	3	1	46673

NSGA-2 algorithm, a sensitivity analysis was conducted based on two primary parameters: the initial population size and the number of generations. Three population sizes (50, 100, and 150) and nine generation counts (10, 15, 20, 25, 30, 35, 40, 45, and 50) were tested, resulting in a total of 27 different algorithm runs. The results indicate that increasing the population size has a negligible impact on enhancing the quality of the Pareto fronts. The fronts generated for population sizes of 100 and 150 show little difference compared to those obtained with a population of 50. In contrast, increasing the number of generations produced a gradual and modest improvement in the results. For each of the 27 runs, a corresponding Pareto front diagram was plotted, illustrating the trade-off relationship between the model's two primary objective functions (Z1 and Z2).

Selected figures from these 27 graphs illustrate the progression and enhancement in the dispersion and quality of solutions across higher generations. A summary of the model's running details for two population sizes — 100 and 150 — is provided in Table 8, where the running time for each scenario is also reported. The model's running time is primarily influenced by population size. Given the computational capabilities of the system used (Processor with 11th Gen Intel(R) Core (TM) i7 & 16 GB RAM), the average running time for a population of 100 — involving the generation of 100 scenarios and solving the assignment model 100 times — was approximately 622 seconds, equating to 6.22 seconds per assignment. For a population of 150, this time increased by roughly 1.5 times, with each assignment taking about 9.34 seconds. Based on the analysis results; achieving satisfactory optimal fronts appears feasible with a medium-sized population (around 100) and a generation count of at least 30. Additionally, the application of the TOPSIS method in the final decision-making phase proved valuable in clarifying the selection of the most suitable scenarios from the obtained Pareto points.

Subsequently, for a more detailed evaluation of each Pareto front, the TOPSIS method was applied to identify the most favorable scenario within each front. By calculating the TOPSIS score for each scenario, corresponding graphs were generated, highlighting the top-performing scenario in each front (marked in red). This approach facilitated multi-criteria decision-making even among non-dominated (Pareto optimal) solutions. Figure 12 illustrates the graph depicting the best scenario selection within each front for a population size of 100, evaluated up to the tenth generation, where the number of Pareto fronts reached 25. Detailed TOPSIS scores and their corresponding ranks are provided in Table 9. Furthermore, Figures 12 and 13 present the distribution of the TOPSIS-selected optimal scenarios across different generations of the model for a population of 100.

TABLE 9. TOPSIS scores and their ranks for different Pareto fronts

Pareto Front	Topsis Score	Topsis Rank	Pareto Front	Topsis Score	Topsis Rank
1	0.99	1	14	0.76	63
2	0.95	2	15	0.75	68
3	0.92	6	16	0.74	70
4	0.91	9	17	0.73	73
5	0.90	10	18	0.71	77
6	0.89	12	19	0.68	81
7	0.87	17	20	0.63	84
8	0.86	25	21	0.60	87
9	0.85	28	22	0.55	94
10	0.83	36	23	0.44	96
11	0.82	42	24	0.31	98
12	0.80	49	25	0.00	100
13	0.79	51			

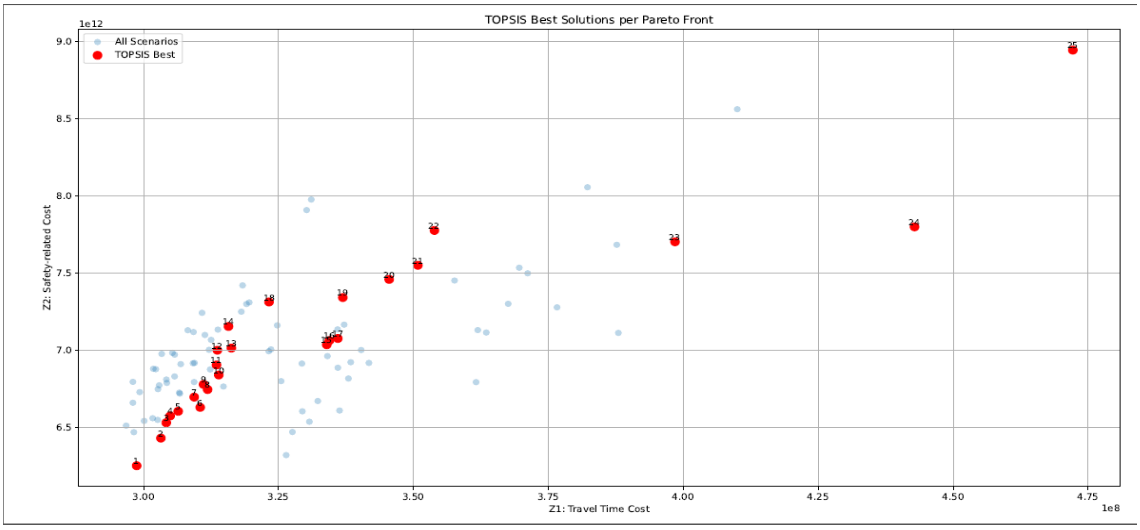


Figure 12. Distribution of TOPSIS-Selected Optimal Scenarios across Pareto Fronts for Generation 10 with a Population Size of 100

The graphs presented in Figures 12 and 13 are based on TOPSIS scores calculated using equal weights for the two objective functions (0.5–0.5). However, in practice, policymakers may assign different priorities to each objective depending on specific conditions. In such cases, the weights of the objective functions can be dynamically adjusted within the TOPSIS framework to reflect these priorities. Figures 14a and 14b illustrate the TOPSIS results under two extreme weighting scenarios: in Figure 14a, a weight of 1 is assigned to the safety cost objective and 0 to the travel time objective, causing the optimal solutions to cluster towards the horizontal axis, representing lower safety costs. Conversely, Figure 14b depicts the scenario where the travel time objective is fully prioritized (weight of 1), resulting in the optimal solutions shifting towards the vertical axis, indicating lower travel time costs.

According to the methodology described for algorithm parameter tuning, the REVAC process begins with a uniform distribution. For tuning the population size parameter, the initial search interval was set between 50 and 150. Assuming this range as the parameter space of the uniform distribution, the initial variance was calculated as 833, with corresponding differential entropy values of 6.89 (bit) and 4.78 (nat). The rationale for using a uniform distribution lies in ensuring complete neutrality and maximum coverage of the search space.

However, this approach inherently results in high variance, elevated entropy, and instability during the early search process, which in turn leads to a sharp decline in efficiency (Figure 15). To address this limitation, a truncated normal distribution, centered at the median with a controlled variance, was applied to refine the process (Figure 16). The rationale for using a uniform distribution lies in ensuring complete neutrality and maximum coverage of the search space. However, this approach inherently results in high variance, elevated entropy, and instability during the early search process,

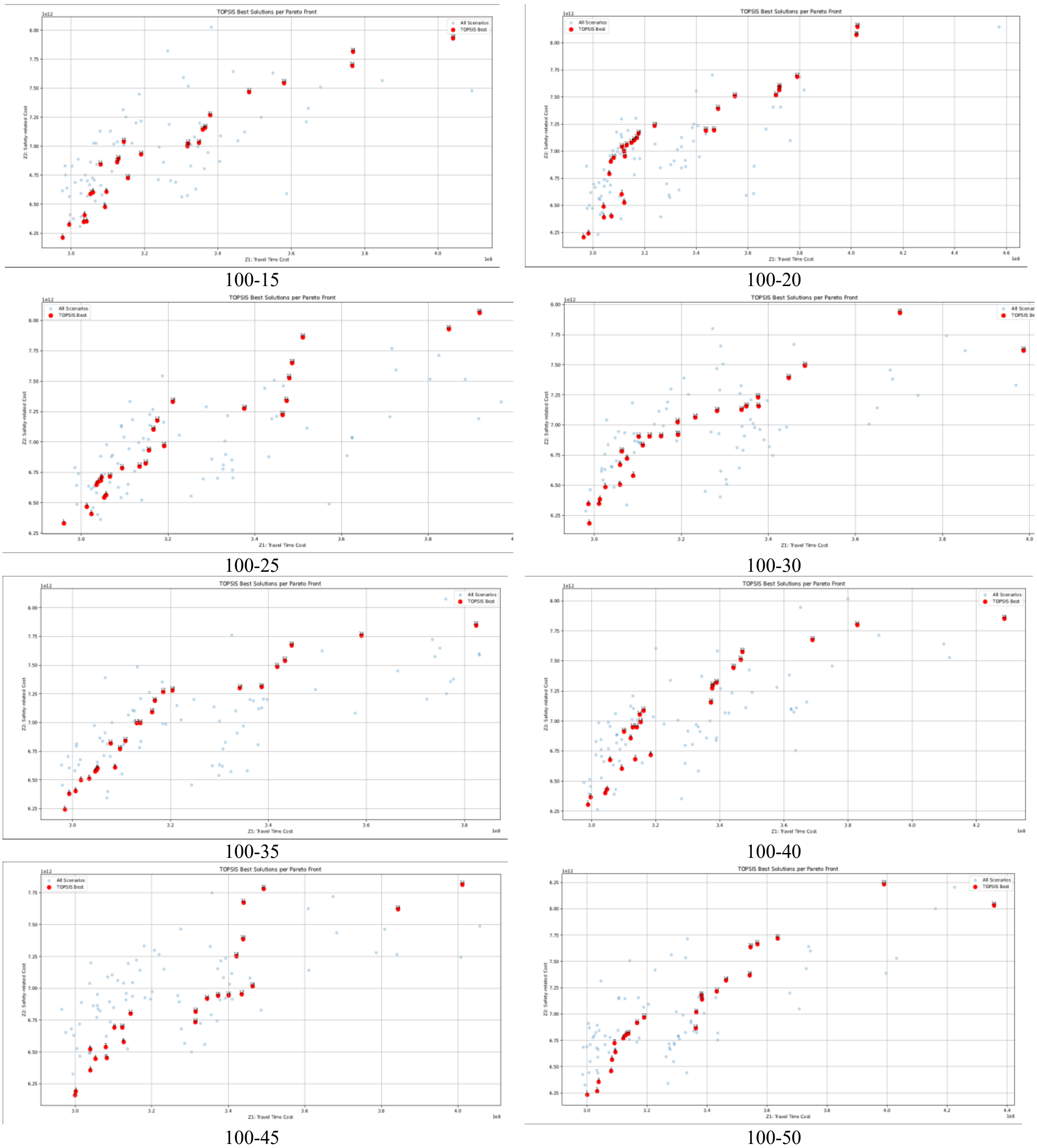


Figure 13. Distribution of TOPSIS-Selected Optimal Scenarios across Pareto Fronts for Generations 15 to 50 with a Population Size of 100

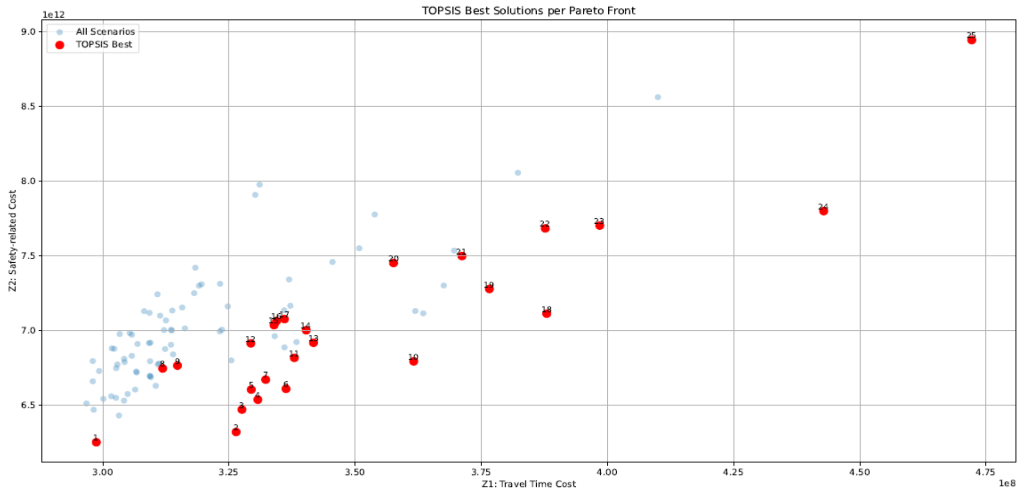


Figure 14a. TOPSIS-optimal scenarios with a weighting factor of 1 for safety and 0 for travel time

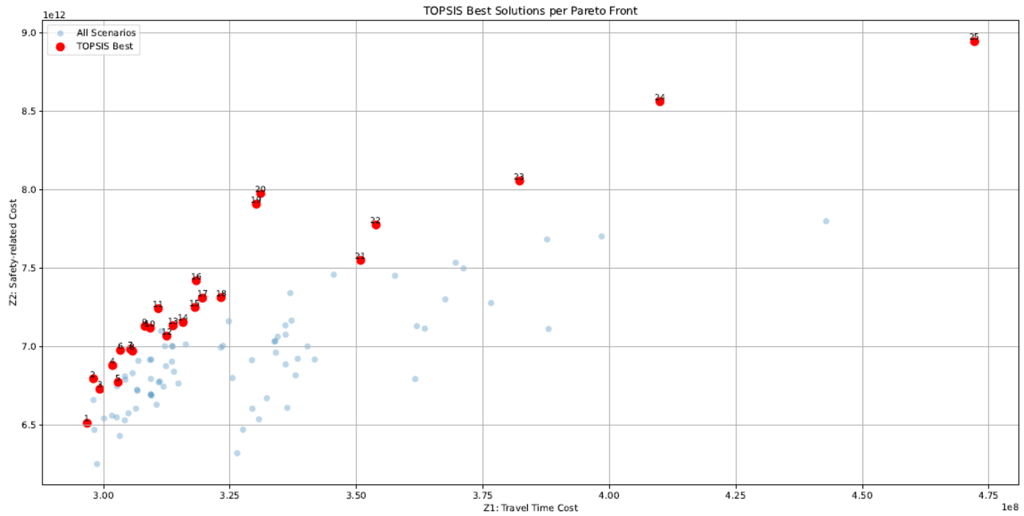


Figure 14b. TOPSIS-optimal scenarios with a weighting factor of 0 for safety and 1 for travel time

Figure 14. Distribution of TOPSIS-selected optimal scenarios across Pareto fronts under different weighting schemes for safety and travel time (delay) objectives

which in turn leads to a sharp decline in efficiency. To address this limitation, a truncated normal distribution, centered at the median with a controlled variance, was applied to refine the process (Figure 17).

5. DISCUSSION

The findings of this study underscore two pivotal dimensions in the context of network design problems. The first pertains to the explicit integration of safety considerations within the optimization framework—an aspect largely overlooked in previous studies, which predominantly prioritized congestion-related objectives through single-objective approaches. By embedding a safety performance function alongside congestion measures, and conducting a sensitivity analysis on the relative weighting of these objectives, this research advances a multi-objective perspective that offers a diverse set of optimal solutions. This stands in contrast to traditional methodologies, which typically culminate in a single recommended configuration, thereby limiting strategic insight for policymakers. The second significant contribution lies in the paradigm shift from link-based optimization strategies to a node-oriented network design approach. Rather than concentrating solely on the optimization of link capacities or configurations, this study emphasizes the strategic management of node-level movements (left, straight, and right turns) to influence overall network performance. This approach not only introduces greater flexibility in managing urban traffic systems but also enables more localized and safety-conscious interventions in critical network locations.

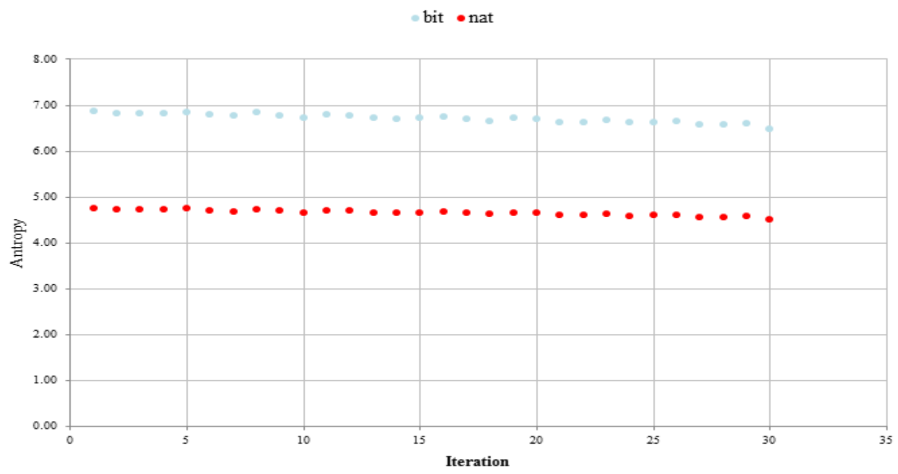


Figure 15. The dispersion of entropy values related to a population parameter with an initial uniform distribution

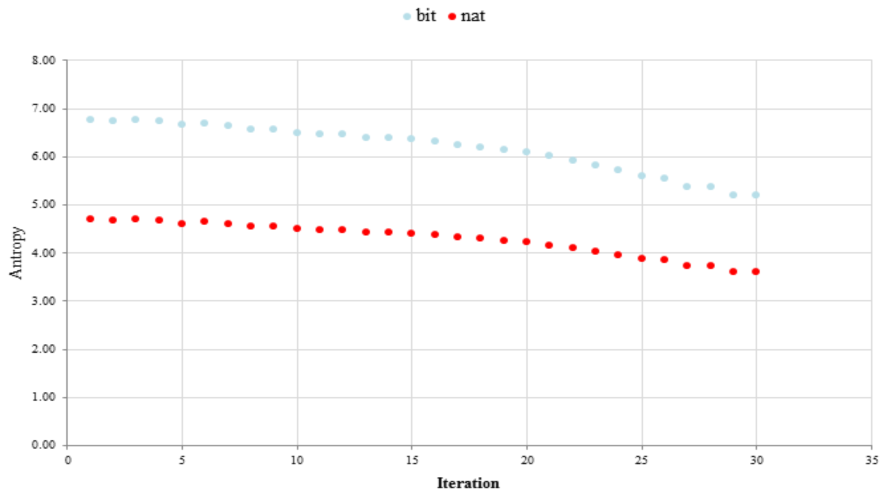


Figure 16. The dispersion of entropy values related to a population parameter with an initial truncated normal distribution

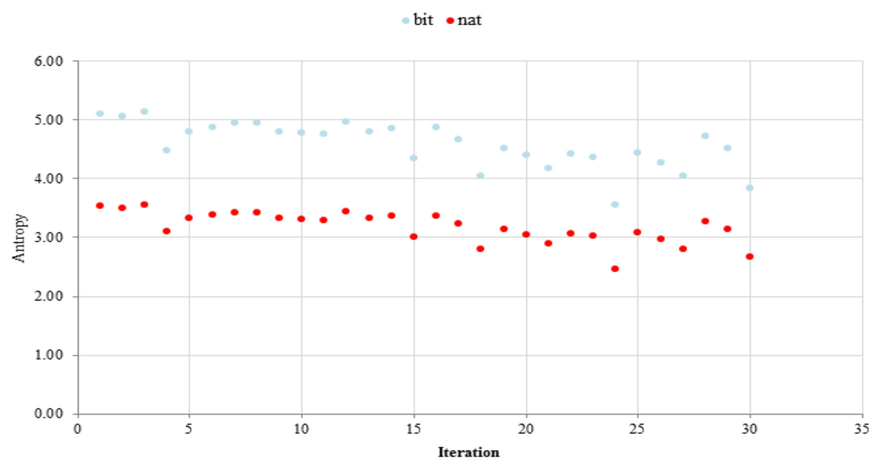


Figure 17. The dispersion of entropy values related to a generation parameter with an initial truncated normal distribution

Previous studies in the field of network design have predominantly adopted link-based optimization approaches, seeking to identify the most efficient set of links to enhance network performance. A classic example is the seminal work of LeBlanc (57) on the Sioux Falls network, comprising 24 nodes and 76 links, which employed a congestion-based, single-objective framework and ultimately recommended a single optimal solution—scenario 10110—for implementation. In his study, five candidate improvement projects were evaluated, with the first, third, and fourth projects selected based on their impact on network congestion. Gao et al. (23) also arrived at the identical solution of 10110 using the same network structure, as did Luathep et al. (31) in their analysis. With a developmental approach, the present study introduces a methodological advancement by shifting the focus from link-based interventions to node-level decision-making within the network design problem.

A second key innovation of this study lies in the explicit integration of a safety component into the network design problem. The detailed findings presented in the preceding sections demonstrate that a diverse set of optimal solutions can be identified, providing decision-makers with the flexibility to select configurations based on varying trade-offs between safety and congestion. This is particularly important in contexts where users may not consistently prioritize either safety or congestion reduction. Zhu et al. (58) highlighted this dilemma by illustrating that, from the users' perspective, the minimization of travel time delays often takes precedence over potential safety risks. This observation underscores the necessity for network planners and decision-makers to move beyond purely technical or optimization-based frameworks and incorporate behavioral insights into their strategies. The findings of this study emphasize the necessity of adopting a network-centric perspective in the analysis of node-level interventions, as opposed to a localized, point-specific approach. This research demonstrates that operational treatments implemented at a given node cannot be regarded as isolated adjustments, since their influence inevitably permeates through interconnected nodes within the network. Despite this, the majority of prior studies have predominantly concentrated on evaluating isolated node-specific treatments, often neglecting their broader systemic implications. For instance, Sun (59) examined vehicle interaction dynamics for right-turn maneuvers at individual intersections using conflict indices. Similarly, performance measures such as the Post Encroachment Time (PET) index have been employed to assess turning operations exclusively at singular node locations (60). Guo et al. (61) extended this line of inquiry by analyzing intersection safety based on specific treatments at node locations, relying on interaction indices for right-turning vehicles to gauge operational outcomes. Furthermore, a range of optimization models has been proposed to enhance turn control strategies, including the development of a mixed-integer linear programming model for optimizing left-turn geometries (62). Distinguishing itself from these conventional approaches, the present study integrates the Time to Collision (TTC) conflict index—a widely recognized time-based surrogate safety measure —within a comprehensive network optimization framework. This methodology enables the simultaneous evaluation of individual node performance and its interrelations with the operational states of other nodes across the network, thereby offering a more holistic and interconnected perspective on network safety and efficiency optimization.

Finally, it is essential to underscore the broader applicability of this study's findings to other transportation modes, including public transit and bus networks, positioning it as a foundational framework for addressing complex network design challenges. For instance, Loder et al. (63) introduced the Multimodal Urban Network Design Problem (MMNDP), a comprehensive framework aimed at supporting policymakers in formulating optimal pricing strategies and infrastructure investment decisions within multimodal transport networks. Their research demonstrated that increasing the cost of private vehicle usage and reallocating road space in favor of public transport can substantially reduce network-wide travel times. In the context of such multimodal optimization problems, incorporating node-based safety performance indices—an innovation advanced in the present study—can meaningfully influence decision-making processes in public transit network design by accounting for safety considerations alongside operational efficiency. Similarly, Canca et al. (64) proposed an integrated model combining strategic and tactical decision-making layers to optimize railway network design problem (RWNDP) and minimize associated costs. When integrated with the node-centric, safety-informed approach introduced in this study, such frameworks have the potential to enhance decision-support systems for railway and other multimodal networks, offering a more holistic and safety-conscious methodology for contemporary transportation network planning.

The findings of this study highlight that in the domains of policy-making, planning, and decision-making for improving urban indicators—particularly traffic infrastructure—traditional one-dimensional approaches may not only fail to deliver sustainable improvements but may, in some cases, result in the deterioration of key indicators despite substantial financial investment. Conventional approaches, which rely primarily on single performance measures such as travel time (congestion), often produce solutions that diverge from those identified through the advanced, multi-dimensional framework employed in this study. For instance, an urban decision-maker may initially observe improvements in local travel time following the implementation of a treatment at a node; however, over time, safety indicators may deteriorate, or the travel time index itself may regress to pre-treatment congestion levels due to network-wide interactions.

6. CONCLUSIONS

This study demonstrates that the integration of safety considerations exerts a substantial influence on the design, configuration, and operational performance of transportation networks. The findings clearly indicate that a one-dimensional approach—centered exclusively on minimizing travel time as a proxy for congestion—is fundamentally insufficient for addressing the complexities of network design. By incorporating safety as a critical objective alongside travel time, the network design process transitions from producing singular, efficiency-driven solutions to generating a diverse set of balanced configurations. This underscores the necessity of adopting a holistic, multi-objective framework in which trade-offs between safety and travel time are systematically evaluated, ultimately yielding more robust, and operationally effective network designs.

In contrast to conventional network design problems, which are predominantly single-objective and congestion-focused, typically producing a singular optimal solution, this study demonstrates that the resulting solutions vary considerably depending on the relative prioritization of safety and congestion criteria. Addressing a critical gap in the literature, this research shifts the focus from traditional link-based decision-making—where optimization efforts have largely concentrated on identifying efficient link configurations within budgetary constraints—to a node-based network design framework. The study advances the methodological landscape by seeking the optimal configuration of flows at node locations, thereby capturing the interactive and system-wide effects of node-level interventions on overall network performance. Adopting a network-level perspective on node interventions enables decision-makers to enhance traffic capacity without necessarily compromising safety or exacerbating congestion, despite the potential associated costs. This finding underscores the notion that optimizing travel time improvements across a network does not inherently translate to enhanced safety outcomes. Conversely, interventions that improve safety or travel time at an individual node may fail to yield system-wide benefits. Additionally, the substitution of traditional crash data with conflict-based surrogate safety measures offers a valuable opportunity to develop multi-objective, two-level safety performance functions capable of balancing safety and travel time objectives within network design frameworks. Future research is encouraged to explore this potential by examining a broader array of conflict indices to refine these multi-criteria models.

The findings of this study hold significant implications for both the enhancement of existing transportation networks and the planning of future urban developments. Integrating safety considerations into network design necessitates a proactive, forward-looking strategy that not only aims to optimize travel times but also prioritizes the substantial reduction of crash risks and their associated consequences. This approach positions safety as a foundational criterion in network planning and design, rather than as a secondary outcome. Future research is encouraged to expand upon this proactive framework, applying it to the optimization of existing networks and embedding safety as a central principle in the design and adaptation of both current and emerging urban transportation systems.

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Persian Abstract

چکیده

پیکربندی بهینه حرکات گردشی در تقاطع‌ها، یک راهبرد اساسی در حوزه مسائل طراحی شبکه حمل و نقل است. اکثر مداخلاتی که در تقاطع‌ها برای مدیریت ترافیک دنبال می‌گردد، معمولاً بر اساس تأثیر موضعی آنها در گره خاص ارزیابی می‌شوند. با این حال، یک سوال اساسی مطرح می‌شود: آیا هرگونه مداخله‌ای در یک گره واحد می‌تواند مستقل از شرایط و عملکرد سایر گره‌ها در شبکه حمل و نقل باشد؟ در حالی که روش‌های ارزیابی نقطه‌ای، اغلب نتایج محدود و جداگانه‌ای ارایه می‌کنند، پویایی ترافیک در رویکرد شبکه‌ای به شیوه‌ای کاملاً متفاوت تکامل می‌یابد، و در یک چهارچوب تعادلی و چند معیاره، راه‌حل‌های بهینه را پیشرفته‌تر و چندبعدی می‌کنند. این مطالعه سه رویکرد جدید برای پرداختن به این چالش پیشنهاد می‌کند: (۱) توسعه یک چهارچوب تصمیم‌گیری جامع مبتنی بر شبکه برای مدیریت حرکات گردشی؛ (۲) تغییر مفهومی از روش‌های مرسوم مبتنی بر لینک به الگوهای گره محور در طراحی شبکه؛ و (۳) اتخاذ شاخص‌های تداخل به عنوان اقدامات ایمنی جایگزین به جای داده‌های سنتی تصادف، که در نتیجه یک رویکرد یکپارچه‌تر، پیشگیرانه‌تر و ایمنی‌محورتر را برای برنامه‌ریزی شبکه حمل و نقل شهری تسهیل می‌کند. برای عملیاتی کردن این روش‌ها، یک چهارچوب بهینه‌سازی دو سطحی و چند هدفه توسعه داده شده است که الگوریتم NSGA-2 را برای تولید راه‌حل‌های بهینه پارتو و روش TOPSIS را برای پشتیبانی از تصمیم‌گیری ادغام می‌کند. فرمول‌بندی مدل و فرآیندهای بهینه‌سازی بر اساس داده‌های تجربی جمع‌آوری‌شده از شبکه جاده‌ای شهری دزفول، ایران، بنا شده‌اند. یافته‌ها طیف متنوعی از راه‌حل‌های بهینه را ارائه می‌دهند که بینش‌های ارزشمندی را برای بهبود سیستم‌های حمل‌ونقل موجود و اطلاع‌رسانی در برنامه‌ریزی راهبردی و طراحی شبکه‌های شهری آینده ارائه می‌دهند.