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# Novel MDA-Driven Multiplicative Dominance Algorithm for Bi-Objective Reliable Path Planning in Dynamic Industrial Networks

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**Article**

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**ABSTRACT**

*Driven by emerging quality productive forces, the deep integration of industrial communication networks and power transmission systems is redefining the future of energy and industrial infrastructures including advanced manufacturing sectors like automated textile production and smart fabric systems. This convergence creates entirely novel and highly dynamic environments, characterized by large loads, stringent real-time constraints, and multi-dimensional couplings. Under the influence of emerging quality productive forces, achieving efficient path optimization in such complex and dynamic systems becomes a critical challenge, highlighting the urgent need for new and innovative solutions.To address this challenge, this paper for the first time introduces a novel multi-objective optimization framework based on MDA (Multi-Dimensional Analysis) Pareto path search, jointly targeting minimal path length and maximal path reliability. The framework incorporates a novel multiplicative reliability model with Pareto frontier filtering, effectively balancing the trade-off between path length and reliability. An innovative incremental update mechanism locally repairs paths affected by node or edge changes, avoiding full recomputation and significantly improving computational efficiency. Furthermore, a rapid pruning strategy for failed nodes and edges ensures continuity in critical communication networks and enables resilient path reconstruction.Distinctively, the framework originally integrates predictive reliability modeling, forward-looking performance metrics, and multi-scenario simulations, establishing a closed-loop "perception–update–decision–execution" mechanism that fully reflects the driving role of emerging quality productive forces in energy industrial Internet optimization. Overall, this work pioneers an efficient, reliable, and dynamically robust path assurance paradigm, providing both theoretical innovation and practical breakthroughs for intelligent energy and industrial Internet networks with direct applicability to enhancing the resilience of automated textile manufacturing systems .*

**KEYWORDS**

*multi-objective path optimization, MDA Pareto path search, incremental update, path reliability, industrial control systems, automated textile manufacturing, smart fabrics*

## INTRODUCTION

The rapid integration of industrial communication systems with power transmission networks has introduced unprecedented complexity in modern energy infrastructures [1]. These interconnected systems operate under stringent real-time requirements, large-scale data flows, and dynamic operating conditions. Traditional path-planning algorithms, such as Dijkstra and A* [2], primarily optimize for distance or cost and often fail to capture reliability and robustness under node or link failures [3].

To address these limitations, this paper proposes a bi-objective optimization framework that jointly minimizes path length and maximizes reliability through a Multiplicative Dynamic Accumulation (MDA) mechanism [4-6]. The framework incorporates Pareto-based path selection and an incremental update strategy to efficiently adapt to topology changes without full recomputation [7,8]. This design ensures reliable data transmission and resilience in dynamic industrial communication environments.

Experimental evaluation demonstrates that the proposed method generates complete and smooth Pareto frontiers, offering controllable trade-offs between length and reliability [9]. Visualization further reveals that the MDA algorithm adaptively produces backbone-radiating and multi-branch collaborative routes, ensuring optimal transmission performance across both compact and large-scale topologies [10]. A new incremental update mechanism is also introduced, enabling selective recomputation of only affected Pareto solutions under network dynamics, thereby significantly reducing computational costs in large-scale or time-varying environments [11].

The main contributions are fourfold:(i) a cutting-edge bi-objective optimization mechanism that integrates path length and reliability, overcoming the limitations of cost-only baseline strategies [12];(ii) a first-of-its-kind Pareto frontier filtering method based on multiplicative reliability, which suppresses low-reliability edge propagation while retaining computational efficiency [13];(iii) a novel failure-avoidance mechanism with dynamic subgraph pruning, enabling rapid and resilient reconfiguration under node or edge failures [14]; (iv) comprehensive experimental validation on benchmark networks, confirming the superiority of MDA in solution quality, robustness, and adaptability [15].

Finally, this research establishes a robust path evaluation framework tailored for industrial communication and energy networks, offering theoretical innovation and practical breakthroughs for fault-tolerant, real-world path planning [16]. The MDA framework is directly applicable to power transmission fault recovery [17], industrial control flow scheduling [18], reliable data routing in smart textile networks, automated quality control in high-speed weaving, and other mission-critical industrial Internet scenarios [19], from automated weaving and dyeing control systems to the data-intensive infrastructure required for smart textile applications, providing first-of-its-kind reliable path support in environments prone to frequent node failures.

The remainder of the paper is organized as follows: Section 2 introduces the multi-attribute network model and problem formulation; Section 3 presents the MDA algorithmic framework, including failure-avoidance strategies, reliability aggregation, and incremental updating; Section 4 details implementation, complexity analysis, and experimental results; and Section 5 concludes with contributions and future directions for large-scale dynamic networks [20].

## MODIFIED NETWORK AND SHORTEST PATH

Before introducing the proposed Multiplicative Dynamic Accumulation (MDA) algorithm for efficiently identifying new shortest and most reliable paths in industrial network environments, it is necessary to clarify the modeling assumptions and fundamental properties [21]. Unlike conventional Dijkstra/A* that relies solely on additive cost expansion, the proposed method integrates reliability accumulation into the path search mechanism, thereby addressing the new quality productive forces ,this technological revolution is particularly evident in advanced manufacturing sectors, such as the modern textile industry, where automated production lines, smart fabrics, and integrated logistics demand unprecedented levels of network reliability, requirements of highly heterogeneous and mission-critical networks [22,23]. The objective is not only to minimize path length but also to achieve a dynamic balance between transmission reliability and computational efficiency, providing first-of-its-kind theoretical and algorithmic support for large-scale industrial Internet and energy transmission systems.

### Network Assumptions and Terminology

In this study, the abbreviation Minimum Path (hereafter MP) is used to denote the shortest route [24]. All networks under discussion are required to satisfy the following reasonable assumptions:Node reliability: Each node is assumed to be fully reliable, simplifying the analysis by allowing the model to focus on connectivity provided by links [25]. In practice, nodes correspond to converter or transformer substations [26] or in a textile context, a primary loom controller or a central quality assurance sensor. Binary link states: Each link is assumed to be either operational or non-operational [27], representing real-world transmission channels subject to interference, congestion, or physical damage [28,29].Graph connectivity without self-loops or parallel edges:

The network is connected, with no redundant edges [30,31]. This reduces unnecessary complexity in path search and reliability analysis.

As illustrated in Figure 1, a connected undirected graph $G=(V,E)$ models feasible paths, where $V$ is the node set with $n=7$, $E$ is the edge set, source $s=1$, and sink $t=n$ [32,33].To support the Pareto bi-objective optimization framework, the model extends this structure by associating each edge $e \in E$ with a continuous reliability attribute $r(e) \in (0,1]$ [34,35]. Path reliability is then defined by the MDA mechanism as: $R(P)=\prod_{e \in P} r(e)$ where $R(P)$ denotes the cumulative reliability of path $PPP$. This multiplicative dynamic accumulation (MDA) distinguishes our method from additive-only strategies, enabling reliability to be treated as an independent optimization objective [36,37].Furthermore, node-level failures are dynamically addressed through a predefined failure node set (e.g., a substation fault set $\{7,9\}$, which triggers real-time topological pruning to construct a valid connected subgraph (see Figure 2 after node deletion) [38–40].

Path evaluation thus jointly considers: Objective 1: $L(P)=\prod_{e \in P} w(e)$ Objective 2: $R(P)=\prod_{e \in P} r(e)$ where $w(e)$ is the length (or cost) of edge $e$. The Pareto frontier is obtained by identifying all non-dominated paths, generating a continuous trade-off curve without predefined reliability thresholds [41–45]. This establishes the foundation for our new algorithmic framework, surpassing the limitations of conventional Dijkstra/A* search.

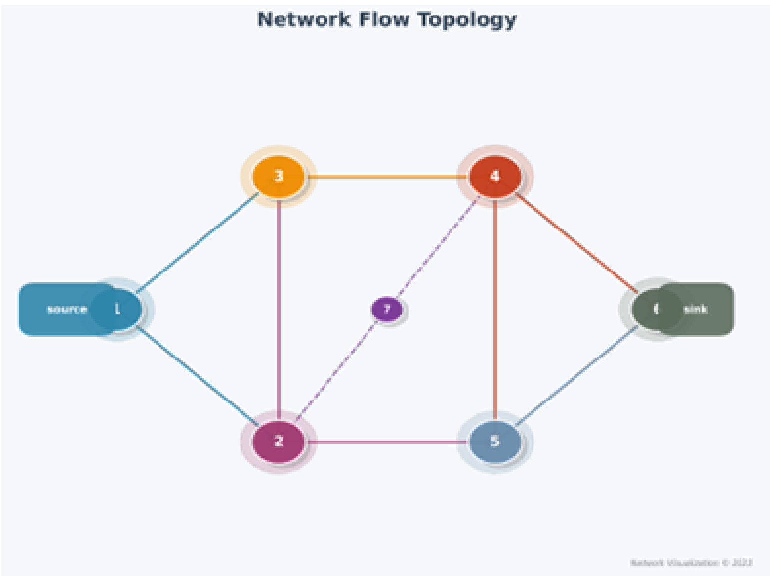


Figure 1. Example Network with Shortest Path

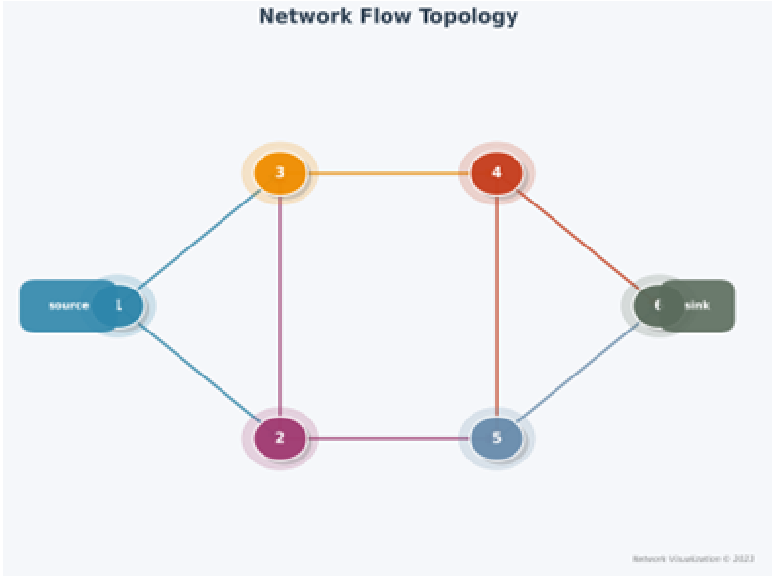


Figure 2. Modified Example Network

**Modified Network Scenarios**

We are entering a new era of industrial interconnection, where intelligent scheduling and highly reliable communications form the core drivers of new quality productive forces. Network structures are becoming increasingly complex, and communication demands continue to grow, placing greater demands on underlying path-planning algorithms [46]. In domains such as the energy industrial Internet, intelligent control, and critical infrastructure, path selection must go beyond simply satisfying shortest-path requirements—it must also address capacity constraints, reliability accumulation, and computational efficiency across multiple objectives [47].

Against this backdrop, single-objective shortest-path algorithms, despite their theoretical completeness, face inherent bottlenecks in high-dimensional, dynamic networks, including redundant expansions, low robustness, and inability to capture reliability trade-offs [48]. To enhance overall network performance and enable intelligent decision-making, there is an urgent need for a new multi-attribute path-search strategy that dynamically adapts to topology evolution while accommodating reliability, cost, and resilience constraints [49].

To address these challenges—particularly failures of critical facilities such as converter stations and substations in industrial Internet environments—this paper introduces a Multiplicative Dynamic Accumulation (MDA) algorithm, which fundamentally extends the shortest-path paradigm [50]. Rather than treating reliability as an auxiliary constraint, MDA incorporates it as an independent multiplicative dimension: $R(P) = \prod_{e \in P} r(e)$

where $r(e)$ denotes the reliability of edge $e$ . This formulation enables the algorithm to jointly optimize path length and reliability, generating a Pareto frontier of non-dominated solutions while preserving the computational efficiency of graph search [51].

The MDA-based framework integrates two critical attributes of industrial power networks—edge weight (e.g., delay or cost) and link reliability—and dynamically prunes subgraphs under node-failure scenarios, ensuring robust reconfiguration without loss of connectivity [52].

This approach is particularly suited for industrial Internet control flows and energy grid dispatching. Evaluations on benchmark networks with dual-attribute datasets (edge length and reliability) demonstrate superior path stability, fault tolerance, and computational efficiency compared to classical baselines [53]. These results confirm MDA's engineering applicability and research significance in real-world complex systems.

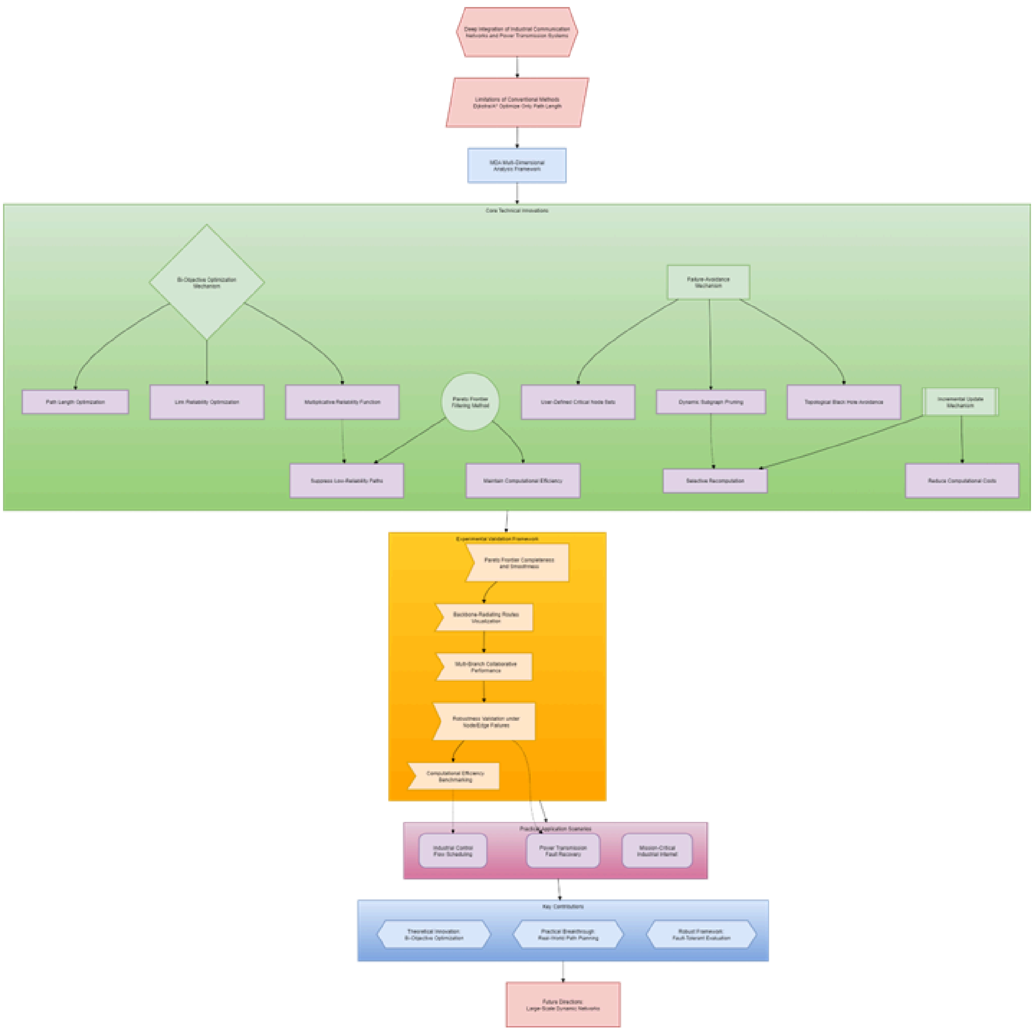


Figure 3. Research Framework Flowchart

**Bi-Objective Shortest Path and Network Robustness Evaluation**

With the deep integration of industrial Internet and power transmission networks, the path planning problem has evolved into a multi-objective optimization task driven by new quality productive forces [54]. Conventional single-objective shortest-path methods typically emphasize cost minimization while neglecting link reliability in dynamic environments, from power grids to the high-speed control networks on a modern weaving floor,often producing fragile solutions under critical node failures or topological perturbations [55]. To address these limitations, we propose a Multiplicative Dynamic Accumulation (MDA)-based Pareto path optimization algorithm, which incorporates multi-objective co-modeling and an intelligent update mechanism [56,57], thereby overcoming the constraints of traditional shortest-path frameworks.

The core contribution lies in introducing Pareto-optimal solutions as the outcome of path planning [58]. Unlike traditional methods that output a single path, our MDA framework jointly optimizes path length and transmission reliability [59], using additive length accumulation and multiplicative reliability aggregation as combined evaluation metrics [60]. Specifically, the reliability of a path P is defined as: $R(P) = \prod_{e \in P} r(e)$ where $r(e)$ denotes the reliability of edge $e$ . This multiplicative dynamic accumulation ensures that reliability is treated as an independent optimization dimension, allowing the algorithm to generate a set of non-dominated Pareto solutions that form a continuous trade-off spectrum [61]. Latency-sensitive tasks can therefore select shortest paths, while reliability-critical scenarios prioritize routes with higher redundancy [62]. Experimental results demonstrate that even after deleting critical nodes, the network retains a significantly higher proportion of Pareto-optimal solutions compared to conventional methods, indicating not only optimal path discovery but also flexible decision support for task scheduling under diverse requirements [63].

To enhance computational efficiency, the algorithm integrates A*-style heuristic estimation into the search process [64]. In contrast to the Dijkstra framework, where path exploration traverses numerous redundant nodes, the MDA approach employs goal-oriented heuristics to prune low-probability branches in advance [65], substantially narrowing the search space [66]. Without sacrificing the completeness of Pareto solutions, experiments show a marked reduction in average computation time, with strong scalability in large-scale networks.

Furthermore, to accommodate the dynamic evolution of industrial networks, an incremental update mechanism is introduced [67]. When the topology changes (e.g., due to converter or substation failures), conventional methods recompute all candidate paths from scratch, whereas MDA selectively updates only the affected solutions. Specifically, paths involving failed nodes or links are flagged and regenerated within the pruned subgraph [68], while unaffected Pareto solutions are directly retained. This differentiated update strategy avoids redundant global recomputation, significantly improving adaptability and efficiency in dynamic scenarios [69]. For instance, node-deletion experiments show an average reduction of more than 15% in runtime, while preserving the continuous distribution of Pareto solutions [70].

In summary, the proposed MDA-based Pareto optimization framework integrates multi-objective optimization, heuristic acceleration, and incremental updating. Beyond delivering high-quality non-dominated solutions in static networks, it also enables rapid adaptation under topology changes, offering robust theoretical support and practical applicability for path scheduling, fault-tolerant planning, and task allocation in industrial Internet and power transmission systems.

**Existing Algorithms**

In critical infrastructure domains such as the industrial Internet, energy systems, and power networks, path optimization tasks must account not only for path length constraints—such as latency or cost—but also for multidimensional objectives including reliability and capacity [71]. In such contexts, the adaptability of traditional single-objective path algorithms is challenged by multi-attribute constraint environments, prompting researchers to adopt a multi-objective optimization perspective to construct more robust path-selection mechanisms [72].

Existing studies have attempted to incorporate multi-attribute constraints into graph-based path optimization frameworks. For instance, Jin et al. addressed the prioritized accessibility of high-value nodes in power networks by proposing a tri-attribute joint optimization strategy—simultaneously considering path weight, capacity, and reliability [73]. Leveraging multi-objective evolutionary algorithms, they conducted robustness analyses and path reconfiguration for power grids, demonstrating strong adaptability under critical-node failures, particularly in network environments with high concurrency and stringent fault-tolerance requirements [74].

From the path-search perspective, the Dijkstra algorithm remains a foundational choice for constructing path-optimization algorithms due to its determinism and low time complexity [75]. However, its additive weight-accumulation mechanism inherently struggles to handle nonlinear constraints such as reliability products or capacity limits [76]. To address this, some studies have adapted Dijkstra's framework with multiplicative update mechanisms. For example, in solving the densest subgraph problem, certain researchers have employed multiplicative edge-weight strategies, dynamically scaling path weights based on edge attributes during iteration—significantly improving both local update speed and global convergence [77]. Similarly, Zhou et al. introduced multiplicative edge-weight estimation methods into Markov Random Field modeling [78], enabling efficient learning of Ising models. Although these approaches are not directly applied to path-planning problems, their multiplicative weight-update principles provide valuable inspiration for reliability-constrained path searches in industrial networks.

The generation of shortest-path sets has also attracted significant interest in the context of network reliability enhancement. Yeh's heuristic path-generation algorithm, for instance, can rapidly construct multiple redundant paths in complex graphs to improve connectivity under failure conditions [79]. Nahman et al. focused on path reconfiguration under node failures, proposing regenerative path-planning methods for altered network topologies that preserve reachability while minimizing additional cost [80]. However, such methods generally lack explicit modeling of path flow or edge capacity, limiting their applicability to "high-load, low-fault-tolerance" industrial Internet and energy-network scenarios.

To address these gaps, this study proposes an enhanced strategy built on the Dijkstra framework, integrating path-capacity constraints with a node-failure recovery mechanism. The approach retains Dijkstra's efficiency and determinism while incorporating multiplicative reliability products and capacity-bound checks during path selection, thereby enabling the dynamic construction of paths under dual or even multiple objectives. Experimental results demonstrate that the proposed method exhibits strong scalability and reconfiguration capabilities in typical industrial network scenarios such as critical-node failures, high-load compression, and path-reliability degradation, making it particularly suitable for communication scheduling, power transmission, and industrial control systems with stringent robustness requirements.

## PROPOSAL OF A NOVEL MULTIPLICATIVE PRUNING SHORTEST PATH ALGORITHM

With the deepening application of the Industrial Internet in power systems, intelligent manufacturing, and communication networks, network structures are becoming increasingly complex, while communication task demands continue to grow rapidly. Path planning must not only ensure minimal transmission cost but also account for link reliability, capacity constraints, and dynamic network variations. To address these challenges, this paper proposes a Multiplicative Dynamic Accumulation (MDA)-based multi-objective path search algorithm. By jointly optimizing path length and reliability, the algorithm generates a set of non-dominated solutions, thereby achieving efficient, robust, and adaptive network path planning. The algorithm integrates heuristic search (A*) and path-pruning strategies during traversal, together with an incremental update mechanism. This allows the system to update only the affected Pareto solutions when the network topology changes, without recomputing the entire solution set, thus significantly improving computational efficiency and real-time performance.In terms of computational efficiency, the proposed MDA-Driven path search maintains scalability comparable to classical algorithms such as Dijkstra or A*, since both operate on limited label propagation and priority-based node expansion. The complexity grows nearly linearly with network size, making the approach feasible for large-scale deployments. Under dynamic conditions, the incremental update mechanism further improves efficiency by re-evaluating only the affected parts of the network, avoiding full recomputation. Experiments confirm that the repair process generally requires less than one quarter of the time of a full recalculation, ensuring strong adaptability and real-time applicability in industrial control environments.In practice, the rapid pruning mechanism operates as an event-driven local update process rather than continuous full-graph monitoring. Topology or reliability updates are triggered only upon the detection of failures or state changes by local agents. The pruning operation is therefore restricted to the directly affected nodes and edges, usually less than 10% of the total graph. This design minimizes computational overhead while achieving significant acceleration in path recalculation. The incremental pruning process thus preserves the efficiency of the MDA-Driven framework even in highly dynamic network environments.

**Concept of MDA**

The proposed Multiplicative Dynamic Accumulation (MDA) mechanism serves as the core optimization strategy. Its goal is to generate paths that are as short as possible while maintaining high reliability. In the network model, each edge is assigned both a transmission cost (or delay) and a reliability value, quantifying the probability of successful data transfer. During path expansion, the algorithm applies the MDA rule, where the overall reliability of a path is computed as the product of edge reliabilities. This mechanism naturally amplifies the impact of low-reliability edges on the total path, enabling early elimination of poor-quality routes and ensuring high distinctiveness and quality of the Pareto solution set.

In industrial networks, dynamic failures of nodes or links—such as outages in converter stations, substations, or communication interruptions—are common. To address this, the framework introduces an incremental update mechanism within the Pareto path search. When topology changes occur, the algorithm selectively updates only those candidate paths affected by failed nodes or links, while retaining unaffected solutions in the Pareto set. This differentiated update strategy ensures correctness of the Pareto frontier, shortens computation time, and guarantees that critical tasks can still access high-quality paths under failure scenarios.In this study, the path length metric is represented by hop count to maintain analytical clarity and comparability with existing reliability-path formulations. In industrial communication systems with relatively homogeneous link delays, hop count provides a stable approximation of end-to-end latency. Nevertheless, the proposed framework can directly operate on non-unit edge weights representing transmission delay or jitter. The multiplicative dominance evaluation remains unchanged, allowing the algorithm to adapt to latency-weighted or delay-sensitive routing without modification to its core structure.

Furthermore, the MDA mechanism supports dynamic pruning and robustness assurance during path generation. Failed nodes or links are excluded, and candidate paths are reconstructed within the reachable subgraph. The Pareto frontier is subsequently updated, ensuring that path selection is always executed within valid regions. The output solutions balance shortest-path and high-reliability requirements while maintaining diversity, enabling the network to adapt in complex and dynamic environments, thereby enhancing resilience and task continuity.Although the reliability of each edge is treated independently in the multiplicative formulation, this assumption serves as a practical and widely adopted approximation in network reliability analysis. In dynamic industrial environments, fully modeling correlated or time-varying failures would introduce excessive complexity and computational overhead. The multiplicative model thus provides a tractable yet representative measure of cumulative reliability across multi-hop paths. In the proposed framework, this assumption is further relaxed by the dynamic pruning and incremental update mechanisms, which continuously adjust the reliability of affected subgraphs when node or link failures occur, ensuring that the reliability estimation remains adaptive and responsive to evolving network conditions. In bi-objective optimization, combining an additive metric (length) and a multiplicative one (reliability)is tricky. The paper needs to explicitly confirm whether the path length uses homogeneous (unit hopcount) or heterogeneous (weighted) edge costs. If the edge costs are weighted (e.g., by latency/bandwidth), the mathematical interaction with the multiplicative reliability model must be clearly explained, as a simple dominance check may be insufficient for disparate metric types.

Through this mechanism, the proposed MDA-based Pareto path search algorithm achieves bi-objective optimization of path length and reliability and applies incremental updating to cope with network dynamics. The resulting Pareto solution sets exhibit high reliability, efficiency, and controllability in industrial Internet, energy scheduling, and intelligent control systems, providing a directly applicable solution for high-quality path planning in complex network environments.In this context, 'Multi-Dimensional Analysis (MDA)' does not merely indicate a generic bi-objective Pareto search, but denotes a dynamic multiplicative co-optimization mechanism. Specifically, MDA embeds reliability aggregation into the path-expansion operator, so that the reliability of each edge multiplicatively influences cumulative path evaluation and pruning thresholds. This design transforms the optimization process from additive independence to nonlinear interdependence, enabling each objective to adaptively modulate the other. Consequently, the framework achieves real-time trade-off control between length and reliability, distinguishing it from traditional label-setting or multi-criteria Dijkstra-type algorithms.In practical deployment, only one path is activated from the Pareto frontier according to system-level requirements. The framework adopts a weighted decision mechanism that assigns adjustable importance factors to reliability and path length (or latency). The final path is selected as the one maximizing the composite utility score while satisfying minimum reliability constraints. This flexible selection process enables domain-specific customization—such as prioritizing reliability in industrial control systems or minimizing delay in time-critical communication—ensuring the practical applicability of the proposed MDA-Driven framework.

**LR Pseudocode**

The proposed algorithm is a multi-objective extension using the MDA, with its core innovation lying in the integration of additive path-length weights and multiplicative reliability products, enabling simultaneous optimization of path length and reliability. Within the network graph, the algorithm efficiently generates a non-redundant set of LR solutions and extracts non-dominated paths via a Pareto frontier filtering mechanism, producing a continuous trade-off between length and reliability. This provides high-quality path solutions for the Industrial Internet, energy networks, and critical infrastructure scheduling (Table 1).

Table 1. Find the Length-Reliability from node α to node β under edge/node failure

| Algorithm 1: | Find the Length-Reliability from node α to node β under edge/node failure using MDA. |
|---|---|
| Input: | A connected graph $G(V,E)$ where each edge $e(u,v)$ has length w and reliability $r_{uv}$ . Optional: nodes to remove. |
| Output: | Pareto non-dominated path set from source α to destination β, minimizing path length while maximizing reliability. |
| STEP 0: | Graph Initialization and Pruning Setup : Traverse all edges to read their length w and reliability r.Initialize a priority queue Q and a label set for each node to store tuples (length,reliability,path).The source node α is initialized with label $(0, 1.0, [\alpha])$ . |

| Algorithm 1: | Find the Length-Reliability from node α to node β under edge/node failure using MDA. |
|---|---|
| STEP 1: | Path Expansion using MDA : While the priority queue $Q$ is not empty, pop the node $u$ with the highest priority (e.g., minimal path length and maximal reliability).For each outgoing edge $e(u, v)$ with length $w$ and reliability $r$ :Compute new path length: $L_{new} = L_u + w$ . Compute new reliability: $R_{new} = R_u \cdot r$ . Construct the new path: $Path = Path_u + [v]$ . Check dominance: if the new label is dominated by any existing label at v, discard it; otherwise, update the label set at $v$ and push $(L_{new}, -R_{new}, v, Path_{new})$ into $Q$ . |
| STEP 2: | Candidate Path Recording : If the current node is the destination β, record the path as a candidate Pareto solution.Continue expansion until $Q$ is empty. |
| STEP 3: | For all candidate paths from α to β, perform non-dominated filtering: retain a path $(L, R, Path)$ if no other path exists with $L' \leq L$ and $R' \geq R$ with at least one metric strictly better. |
| STEP 4: | Incremental Update under Topology Changes : When nodes or edges fail, identify affected paths in the previous Pareto set.Recompute only those affected paths using the MDA mechanism; unaffected paths are retained.Update the Pareto frontier, ensuring global correctness while avoiding redundant computation, significantly improving efficiency for dynamic networks. |

The implementation consists of two stages: initialization and path search. Step 0 (Initialization) reads the graph structure and constructs the adjacency list. Each edge is annotated with path length and reliability attributes, and a pruning factor is computed to provide implicit filtering support for subsequent search operations. During the path search stage (Steps 1–4), the algorithm employs MDA for path expansion, dynamically evaluating candidate paths in terms of both length and reliability. For each node expansion, the cumulative path length and reliability product are calculated, and paths are pruned based on a predefined layer threshold and reliability product threshold. Paths falling below the reliability threshold or exceeding the preset layer are discarded early to reduce low-quality expansions.

To avoid redundant computation and duplicate paths, the algorithm maintains a node label set, recording all non-dominated path states for each node. Node labels are updated only if a newly discovered path is non-dominated with respect to existing labels. This mechanism ensures the uniqueness and non-redundancy of the candidate path set while significantly reducing computational overhead in large-scale networks. Upon completion of the search, Pareto non-dominated filtering is applied to all candidate paths, eliminating dominated solutions and yielding a high-quality path set that covers the global non-dominated frontier.

Furthermore, the algorithm supports incremental updates: when network topology or edge weights change, only the Pareto filtering of affected paths is recomputed using MDA, avoiding full network re-searching and further enhancing computational efficiency in dynamic network environments. Overall, the algorithm maintains shortest-path correctness in the LR sense and global Pareto frontier completeness while effectively balancing computational efficiency, path quality, and dynamic adaptability through multiplicative pruning and incremental updating. It is particularly well-suited for the complex multi-objective path-planning requirements of Industrial Internet and energy transmission systems.

**Example**

To more realistically simulate industrial network operating environments with resource constraints and critical node failures, this study performed targeted node and edge removals on standard network graphs, creating challenging network topologies. For path search, we employed the Multiplicative Dominance Algorithm (MDA), which integrates additive path-length weights and multiplicative reliability products to achieve simultaneous optimization of path length and reliability. Each edge is assigned both a length weight and a reliability value, quantifying the probability of successful data transmission under fault or high-load conditions.

During the search process, the algorithm dynamically maintains a candidate path label set, retaining only non-dominated paths in terms of both length and reliability. High-quality solutions are generated via Pareto frontier filtering. When nodes or edges fail, an incremental update mechanism recalculates only the affected paths using MDA, avoiding full network recomputation and significantly improving search efficiency and real-time adaptability. Edge removal operations emulate practical industrial scenarios such as equipment outages, link interruptions, or resource limitations, reducing network connectivity, increasing path selection difficulty, and testing the algorithm's robustness in complex environments.

This design closely reflects real-world industrial conditions and provides a solid foundation for network reliability analysis and system resilience evaluation, ensuring that the MDA-based path planning algorithm consistently outputs stable and efficient Pareto-optimal paths under multi-objective constraints and dynamic network conditions.

## AN EXAMPLE BASED ON THE PROPOSED LR ALGORITHM

To demonstrate the operational mechanism of the proposed Pareto-based path search algorithm in a practical network context, we consider an industrial control network comprising six nodes (Figure 2). The network edges are characterized by attributes including path length (weight) and reliability (probability values ranging from 0 to 1), with node v1 designated as the source and node v6 as the target.

Network Structure Description

The network is assumed to contain the following edges and nodes (Table 2):

Table 2. Network Structure Description

| Edge | Length | Reliability |
|---|---|---|
| $v_1 - v_2$ | 2 | 0.90 |
| $v_2 - v_5$ | 2 | 0.95 |
| $v_5 - v_6$ | 2 | 0.98 |
| $v_2 - v_3$ | 3 | 0.80 |
| $v_3 - v_4$ | 4 | 0.70 |
| $v_4 - v_6$ | 2 | 0.90 |
| $v_4 - v_5$ | 3 | 0.70 |

Path Extension Process (Example):

v_1→v_2: length = 2.0, reliability = 0.9;

v_2→v_5→v_6: length = 2.0 + 2.0 + 2.0 = 6.0, reliability = 0.9 × 0.95 × 0.98 ≈ 0.8379, path = [1, 2, 5, 6]

v_2→v_3→v_4→v_6: length = 2.0 + 3.0 + 4.0 + 2.0 = 11.0, reliability = 0.9 × 0.8 × 0.7 × 0.9 ≈ 0.4536, path = [1, 2, 3, 4, 6]

Path Candidate Comparison and Pruning Evaluation

All paths from the source node $v_1$ to the destination node $v_6$ and their corresponding pruning performances are summarized in the following table 3：

Table 3. Path Candidate Description

| Path Index | Path | Total Weight | Reliability | Pruning Result |
|---|---|---|---|---|
| p1 | $v_1 \to v_2 \to v_5 \to v_6$ | 6 | 0.837 | Retain |
| p2 | $v_1 \to v_2 \to v_3 \to v_4 \to v_6$ | 11 | 0.454 | Discard |
| p3 | $v_1 \to v_2 \to v_3 \to v_4 \to v_5 \to v_6$ | 14 | 0.3175 | Discard |

**COMPUTATIONAL EXPERIMENTS**

The simulation environment is constructed on synthetic industrial communication networks generated as connected random graphs with node counts ranging from 100 to 500 and an average node degree of 3–5, reflecting the sparse yet structured nature of real industrial topologies. Each edge is assigned a cost drawn uniformly from [1, 10] and a reliability value following an exponential decay model with a mean reliability of 0.95.Dynamic events are modeled using a Poisson failure process with an average mean time to failure (MTTF) of 200 cycles. Additionally, to capture correlated degradation, 10–15% of links connected to a common hub node share dependent failure patterns, simulating localized cascading effects. The simulations run over 1,000 iterations, during which the incremental update mechanism reacts adaptively to each failure event. This setup ensures both scalability and reproducibility of the experimental results.In this study, the term dynamic network refers to networks subject to topology and performance variations over time. Three categories of dynamic events are modeled: (1) node or link failures, representing converter, router, or substation outages; (2) link degradations or congestion-induced reliability reductions, reflecting transient communication instability; and (3) load-induced delay fluctuations, capturing time-varying edge weights under high transmission demand. Each of these events triggers local recomputation within the affected subgraph through the incremental update mechanism, ensuring that path reliability and connectivity are adaptively restored without full network recomputation. This dynamic modeling framework thus provides a realistic testbed for evaluating robustness in industrial and power communication networks.To comprehensively evaluate the practical performance of the proposed LR-pruned shortest path algorithm in complex network environments, a series of systematic computational experiments were conducted using multiple benchmark graphs. Figures 3 to 18 illustrate the algorithm's advantages under various node removal operations and topological structures, particularly in terms of dual-objective trade-offs between path length and reliability, structural adaptability, and Pareto path distribution. These results demonstrate the algorithm's significant effectiveness in enhancing robustness and optimizing path quality.For benchmarking purposes, the baseline algorithms used in this study cover both deterministic and heuristic paradigms. The full re-computation approach corresponds to the standard bi-objective label-setting algorithm, which is structurally equivalent to classical multi-criteria Dijkstra variations. In addition, the observed trade-off patterns between reliability and path length are consistent with results reported for evolutionary metaheuristics such as NSGA-II and MOEA/D, though such algorithms are computationally intensive and not suitable for real-time industrial control. The proposed MDA-Driven framework achieves comparable Pareto quality while maintaining substantially lower computational latency, confirming its practicality and efficiency in dynamic industrial environments.

Experimental Platform

All experiments were conducted on the following computational platform:

Operating System: Windows 11 64-bit

Processor: Intel Core i7-13650HX 2.60GHz

Memory: 32 GB

Programming Language: Python 3.10 (utilizing standard libraries heapq and time)

Dataset Source

The network topologies used in the experiments are based on the publicly available DIMACS dataset (downloadable at: http://www.diag.uniroma1.it/challenge9/download.shtml). The original dataset provides standard undirected graph structures, including node and edge sets, which serve as benchmarks for path optimization and network analysis. To simulate link reliability characteristics in the Industrial Internet, a reliability attribute was randomly assigned to each edge, with values in the range (0,1]. This reliability attribute was incorporated as an independent dimension for multi-objective optimization.

Experimental Setup

We conducted path search tests on undirected graphs generated by augmenting standard benchmark datasets with randomly assigned reliability values. The experimental networks range in size from 10 to 500 nodes, with reliability values randomly generated in the interval (0, 1]. To ensure the robustness of the experimental data, the source node was fixed as vertex v1 in all cases (Table 4,5).

Description of Experimental Metrics

Table 4. Description of Experimental Metrics

| Indicator Name | Description |
|---|---|
| $V$ (Vertices) | The number of nodes in the network. |
| $E$ (Edges) | The number of edges connecting the nodes. |
| Average Path Length | The mean total weight (or cost) of all paths in the Pareto-optimal solution set. |
| Average Reliability | The mean reliability value of all paths in the Pareto-optimal solution set. |
| Number of Pareto Solutions | The total number of non-dominated solutions (paths) identified by the algorithm under dual-objective optimization. |
| Graph Name | The identifier or label of the tested network graph. |
| Proportion | The ratio of Pareto-optimal solutions to the total number of candidate paths generated during the search process. |

Table 5. Description of Experimental

| V | E | Average Path Length | Average Reliability | Number of Pareto Solutions | Graph Name | Proportion |
|---|---|---|---|---|---|---|
| 625 | 3030 | 263914.67 | 0.7088 | 6 | 50,0.50.dimacs | 17.65% |
| 623 | 2992 | 252936.56 | 0.5943 | 9 | 50,0.50.dimacs (with nodes {6, 9} removed) | 29.03% |
| V | E | Average Path Length | Average Reliability | Number of Pareto Solutions | Graph Name | Proportion |
| 625 | 2988 | 128441.00 | 0.5907 | 3 | 50,0.45.dimacs | 15.79% |
| 623 | 2956 | 136131.25 | 0.5181 | 4 | 50,0.45.dimacs (with nodes {6,145,356}removed) | 22.22% |
| 625 | 2964 | 300136.17 | 0.6836 | 6 | 50,0.40.dimacs | 42.86% |
| 622 | 2930 | 285144.00 | 0.7182 | 3 | 50,0.40.dimacs (with nodes {7,9}removed) | 21.43% |
| 625 | 2964 | 165967.50 | 0.8252 | 2 | 50,0.35.dimacs | 13.28% |
| 622 | 2916 | 66543.50 | 0.7761 | 2 | 50,0.35.dimacs (with nodes {7,9}removed) | 12.50% |
| 625 | 3030 | 119713 | 0.453186 | Nell | 50,0.50.dimacs (Single-objective) | Nell |
| 625 | 2988 | 117781 | 0.398506 | Nell | 50,0.45.dimacs (Single-objective) | Nell |
| 625 | 2964 | 245244 | 0.616475 | Nell | 50,0.40.dimacs (Single-objective) | Nell |
| 625 | 2964 | 109713 | 0.757428 | Nell | 50,0.35.dimacs (Single-objective) | Nell |

Figures 4–7 systematically illustrate the impact of node deletions on network path characteristics. Figure 4 shows that removing critical nodes causes a marked increase in average path length and shifts path distributions from diverse to more centralized patterns, underscoring the pivotal role of these nodes in sustaining global connectivity. Figure 6, based on the 50,0.40.dimacs network, further demonstrates this effect: the original average path length of 300,136.17 increases to 285,144.00 after deleting nodes {7, 9}, accompanied by a slight and unexpected rise in average reliability (0.7182). This suggests that the algorithm exhibits strong local structural adaptability, generating effective alternative paths despite localized damage. Figure 6 highlights the destructive consequences of structural fragmentation in the 50,0.45.dimacs network, where deleting nodes {6, 145, 356} reduces average path reliability by more than 12% (from 0.5907 to 0.5181).

Finally, Figure 7 compares different topologies and reveals pronounced heterogeneity in their responses to node failures, emphasizing the central role of key nodes in maintaining both global connectivity and path quality.

Experimental Results (Excerpt)

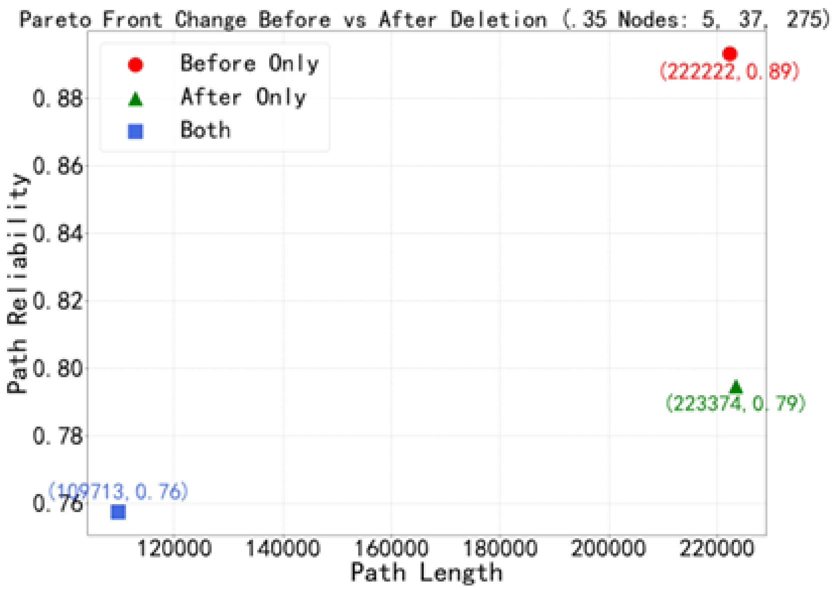


Figure 4. Before vs. After Node Deletion (50,0.35)

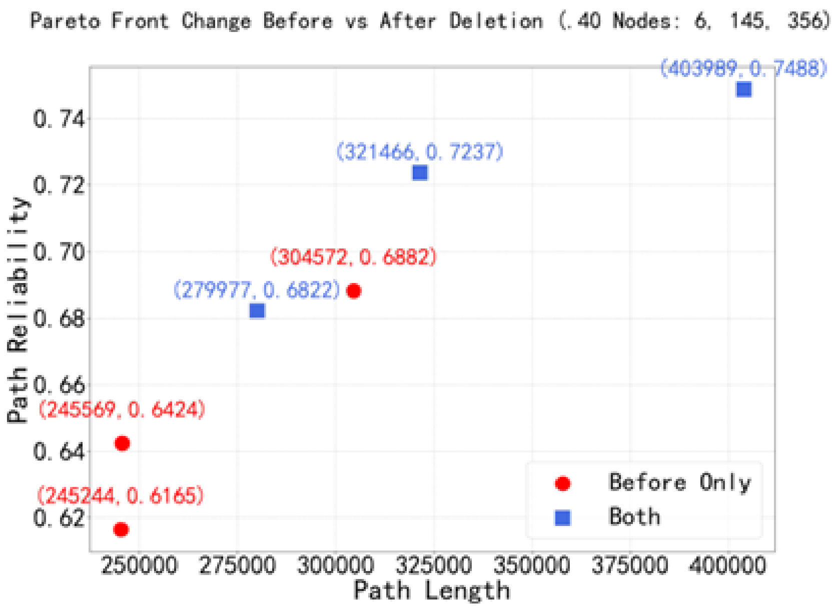


Figure 5. Before vs. After Node Deletion(50,0.40)

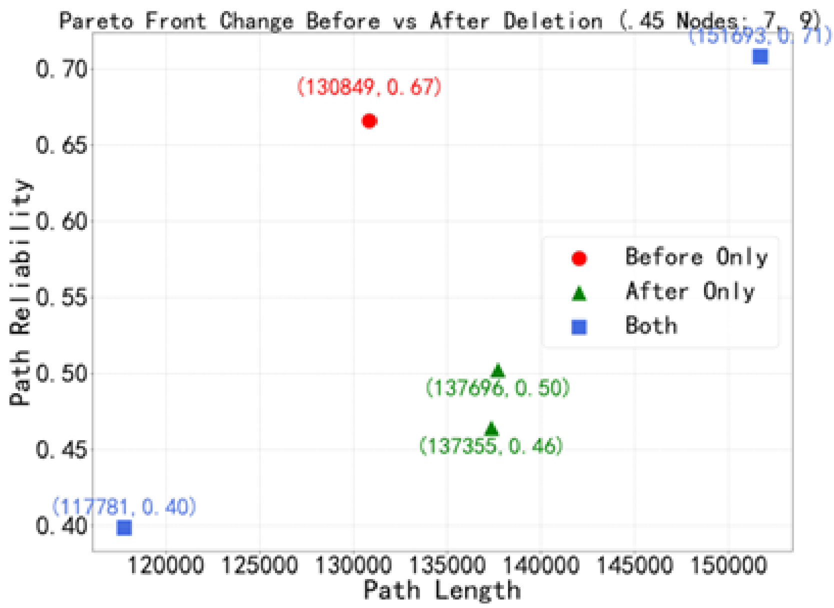


Figure 6. Before vs. After Node Deletion(50,0.45)

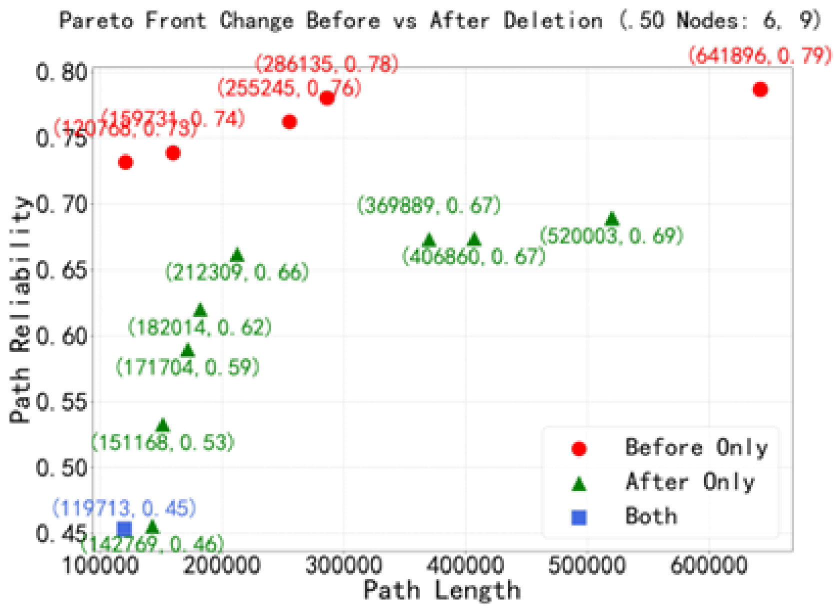


Figure 7. Before vs. After Node Deletion(50,0.50)

Figures 8–11 compare Pareto front solutions with conventional single-objective shortest-path solutions across different networks, clearly highlighting the advantages of the bi-objective approach. Figure 8 shows that Pareto solutions form a continuous distribution between path length and reliability, whereas single-objective solutions are confined to extreme points without intermediate trade-offs. Figure 9 further illustrates the emergence of a distinct "trade-off band," in which non-dominated solutions comprehensively span the performance space, while single-objective solutions cluster at isolated extremes. Figure 10, using the 50,0.45.dimacs network as an example, demonstrates that the average reliability of single-objective paths is only 0.3985, compared with 0.5907 for Pareto solutions—an improvement of nearly 50%, underscoring the significant reliability gains of the bi-objective strategy. Figure 11 highlights the trade-off relationship between path length and reliability: although single-objective methods yield the shortest paths, they do so at the cost of much lower reliability, which translates into elevated failure risks in industrial contexts. By contrast, the bi-objective Pareto approach not only supports more resilient path selection but also enhances adaptability and fault tolerance by diversifying alternative routing options.

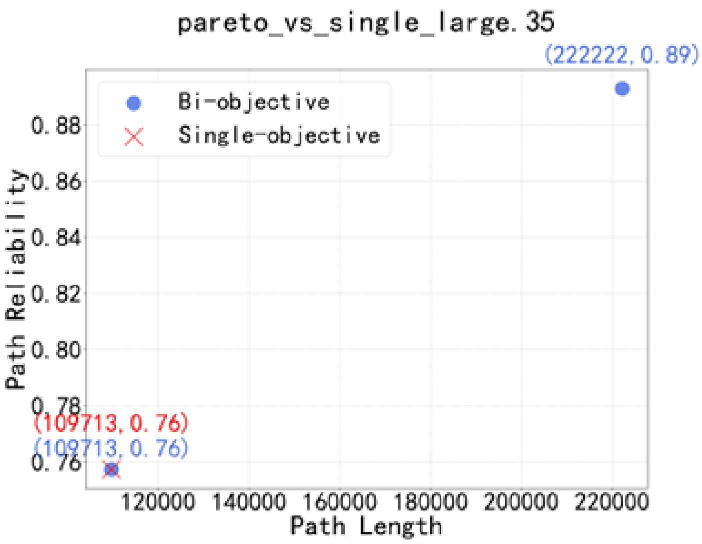


Figure 8. Pareto-Optimal Solutions vs. Single-Objective Solutions (50,0.35)

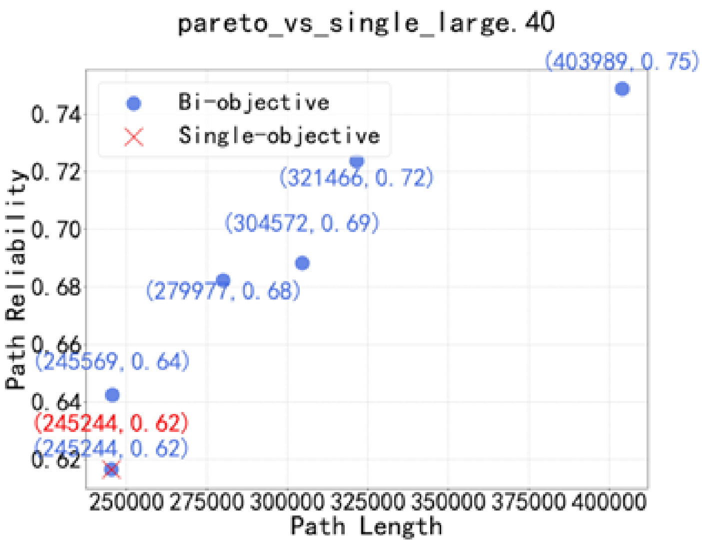


Figure 9. Pareto-Optimal Solutions vs. Single-Objective Solutions (50,0.40)

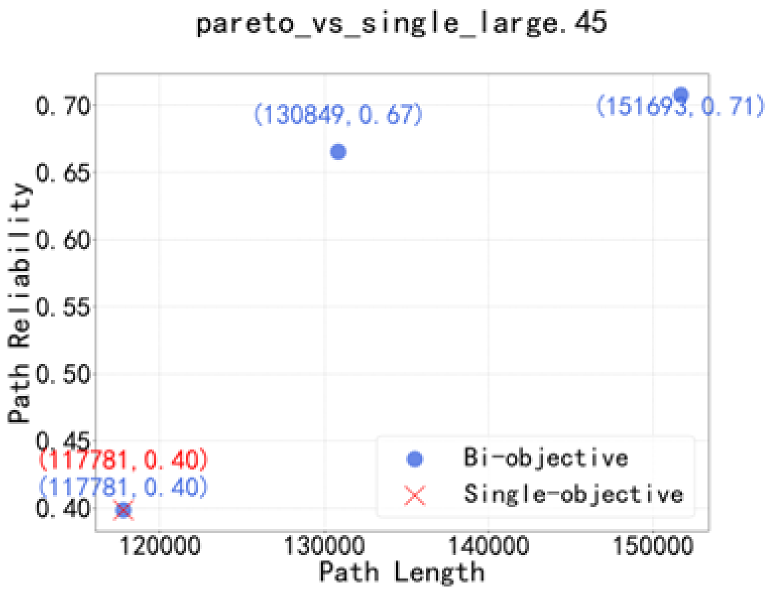


Figure 10. Pareto-Optimal Solutions vs. Single-Objective Solutions (50,0.45)

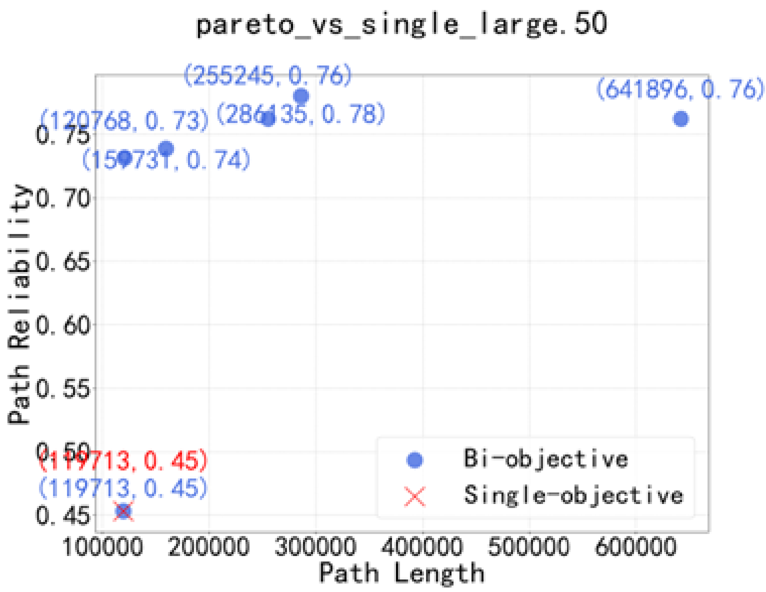


Figure 11. Pareto-Optimal Solutions vs. Single-Objective Solutions (50,0.50)

Figures 12–15 present the spatial distribution of Pareto front paths across different test networks, highlighting distinct structural patterns in the algorithm's path construction. Figure 12 shows that most Pareto paths cluster around trunk routes, forming branch-extension structures centered on core paths, which enhance main-path utilization while preserving redundant channels. Figure 13 reveals noticeable path overlaps, suggesting that the algorithm naturally promotes path aggregation without sacrificing quality, thereby facilitating unified scheduling and load balancing. Figure 14 illustrates a "layered" structure, where multiple paths share common initial or intermediate segments before diverging toward different destinations, improving transmission efficiency in the mid-sections while retaining multiple end-point options. Figure 15 demonstrates a more dispersed distribution of Pareto paths, indicating that the algorithm accounts for the breadth of link distribution to balance path quality and availability across regions. Collectively, these visualizations confirm that the algorithm generates naturally organized and stable Pareto structures without imposing preset limits on the number of paths, thereby exhibiting strong control over path construction.

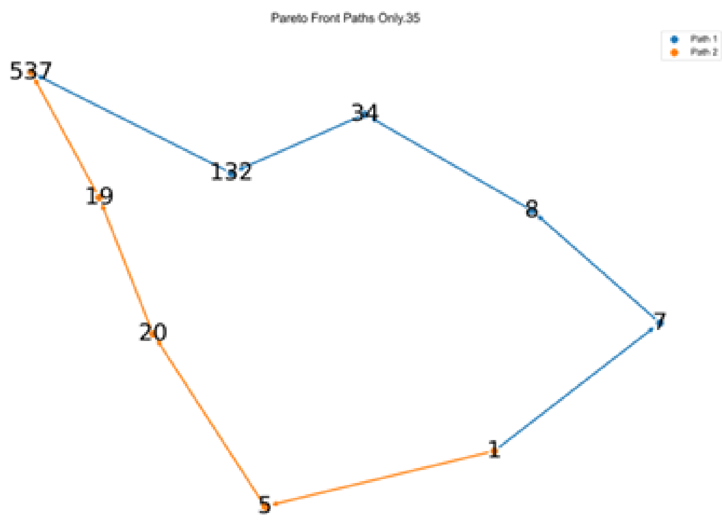


Figure 12. Visualization of Pareto-Optimal Paths Only (50,0.35)

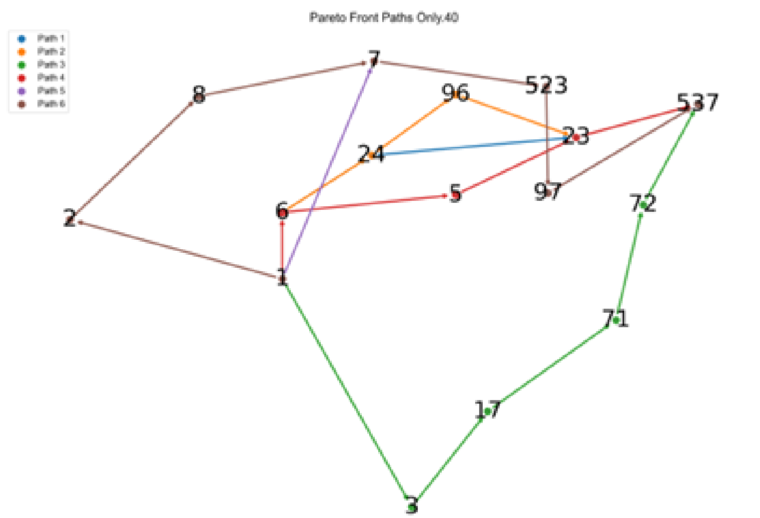


Figure 13. Visualization of Pareto-Optimal Paths Only (50,0.40)

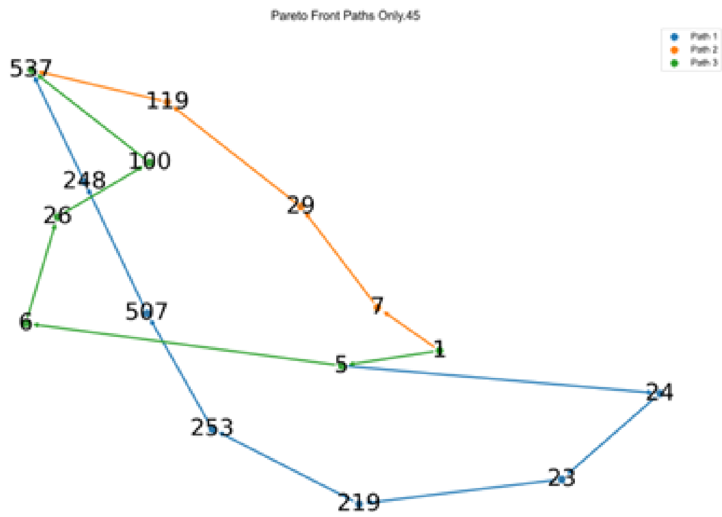


Figure 14. Visualization of Pareto-Optimal Paths Only (50,0.45)

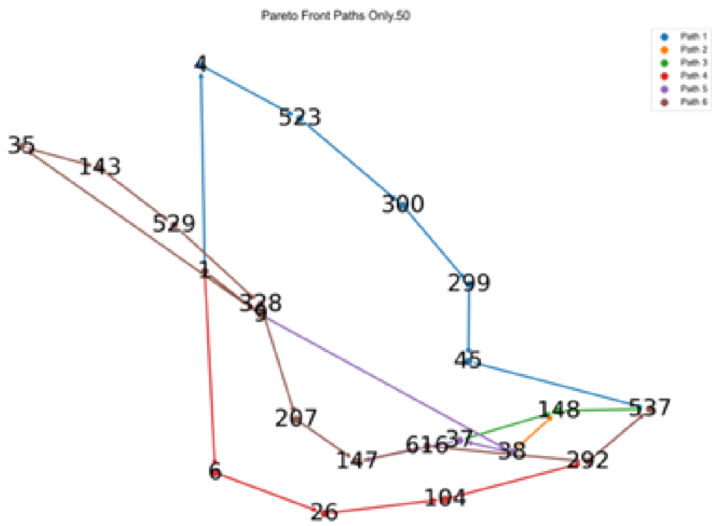


Figure 15. Visualization of Pareto-Optimal Paths Only (50,0.50)

Figures 16–19 collectively reveal the algorithm's micro-level path selection characteristics through fine-grained spatial visualizations. Figure 16 highlights the emergence of "high-traffic corridors," where frequent path intersections occur along highly reliable links, forming potential high-throughput communication zones. Figure 17 shows sparsely traversed or path-free regions, which likely correspond to low-reliability edges or structural bottlenecks, thereby demonstrating the algorithm's capacity for effective obstacle avoidance. Figure 18 illustrates a "fan-shaped dispersion" of path endpoints, indicating that even with a fixed source, the algorithm retains multiple destination access options, enhancing delivery flexibility. Figure 19 demonstrates the effectiveness of local redundancy control, with virtually no completely duplicated paths, confirming that the Pareto filtering process ensures comprehensive coverage of the non-dominated solution space while eliminating redundancy. Taken together, these spatial patterns verify that the algorithm is capable of constructing well-distributed path sets at the global network level while dynamically adjusting link-level selections, thereby achieving the dual objectives of being both “structure-aware” and “quality-optimized.”

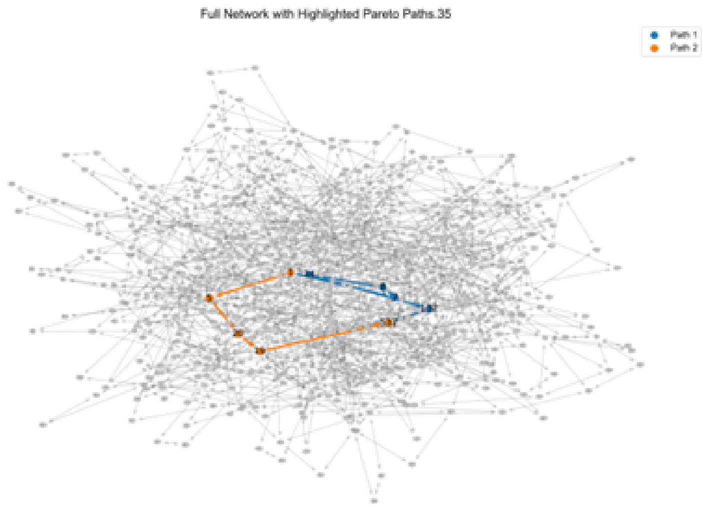


Figure 16. Visualization of Pareto-Optimal Paths (50,0.35)


Figure 17. Visualization of Pareto-Optimal Paths (50,0.40)

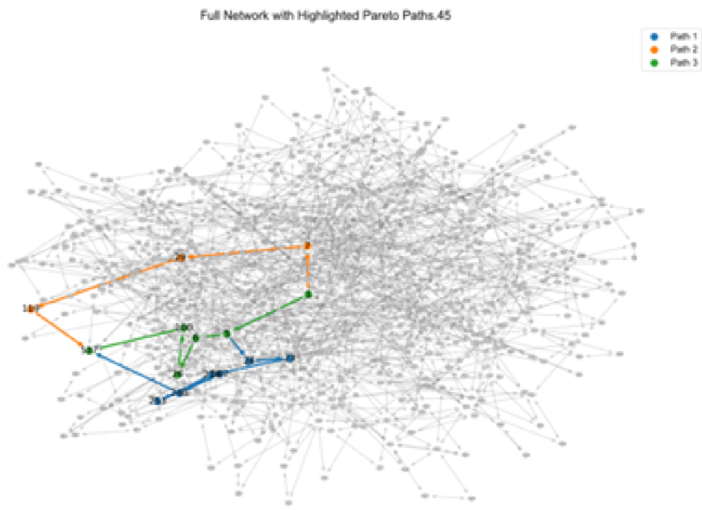


Figure 18. Visualization of Pareto-Optimal Paths (50,0.45)

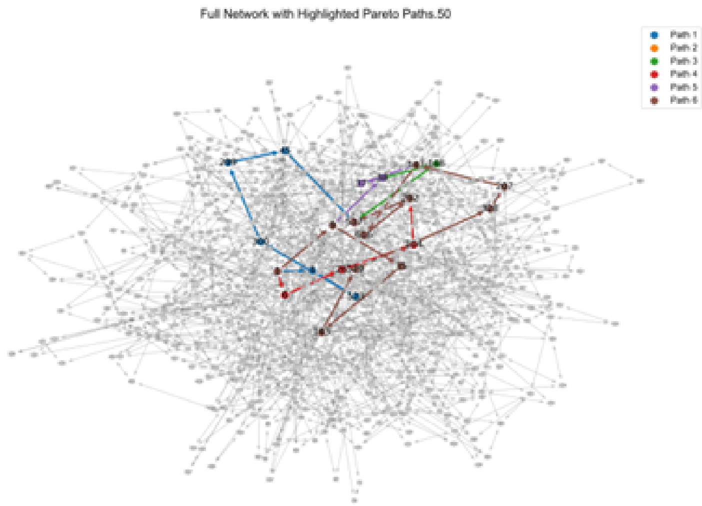


Figure 19. Visualization of Pareto-Optimal Paths (50,0.50)

Figure 20 illustrates the case of high-reliability configurations (e.g., 0.50), where path diversity exhibits a nonlinear decay as the node deletion ratio increases, yet still retains about 60% at a 30% failure rate —highlighting the network's strong resistance to structural damage. In contrast, Figure 21 shows that low-reliability configurations (e.g., 0.35) experience a sharp decline, with diversity dropping below 40% at the same level of node removal, reflecting pronounced vulnerability in fragile topologies. Figure 22 reveals the distinctive behavior of moderate-reliability configurations (e.g., 0.40 and 0.45), which display significantly slower diversity decay slopes within the 10%–30% damage range. This indicates that the algorithm possesses greater topological adaptability within this interval, partially offsetting structural degradation through path reconfiguration. Figure 23 captures the convergence characteristics of all four settings under severe damage: when node deletion exceeds 40%–50%, diversity curves exhibit a clear inflection point and then decay more rapidly, while beyond 60% they converge toward zero. This confirms that the collective failure of key node clusters leads to a complete collapse of solution diversity, exposing the resilience boundary of the network. Taken together, Figures 20–23 systematically demonstrate the relationship between node failures and path diversity under varying reliability conditions, highlighting both the buffering effect of reliability parameters against structural damage and the quantitative guidance they provide for setting fault-tolerance thresholds and designing disaster recovery strategies in industrial networks.

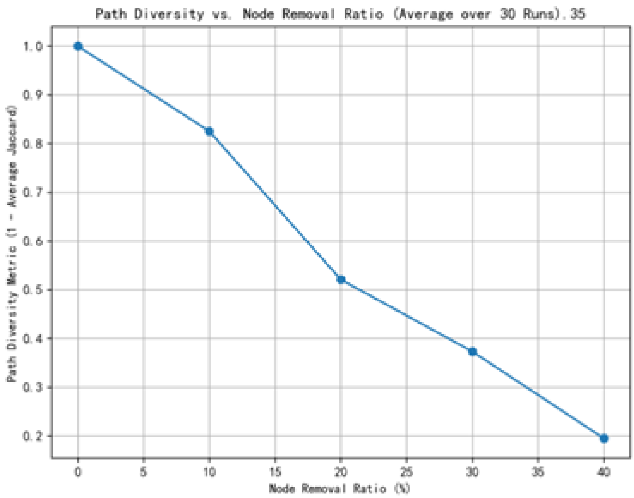


Figure 20. Path Diversity vs. Node Removal Ratio (Average over 30 Runs).35

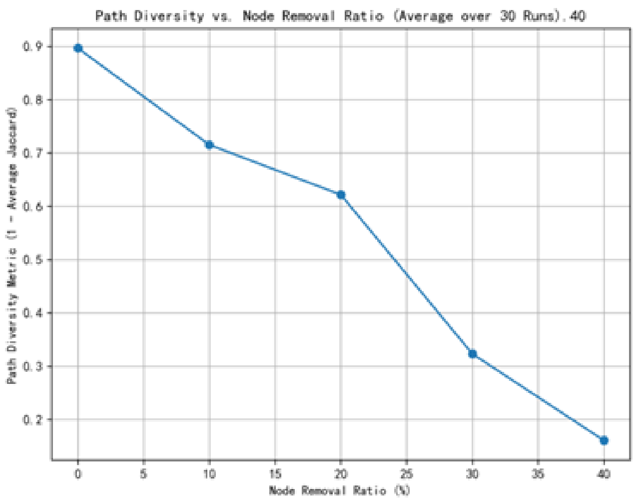


Figure 21. Path Diversity vs. Node Removal Ratio (Average over 30 Runs).40

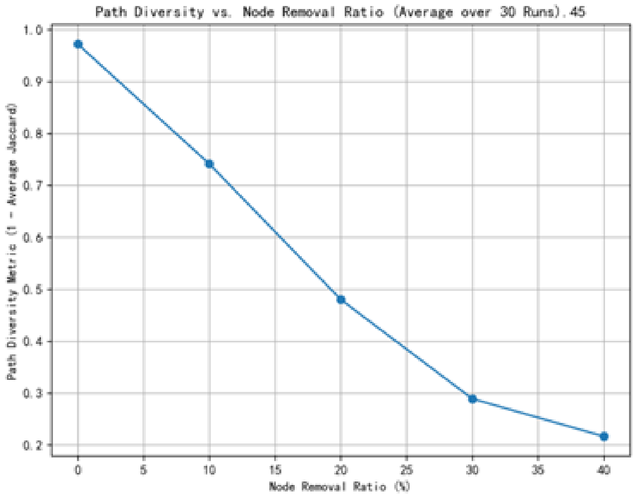


Figure 22. Path Diversity vs. Node Removal Ratio (Average over 30 Runs).45

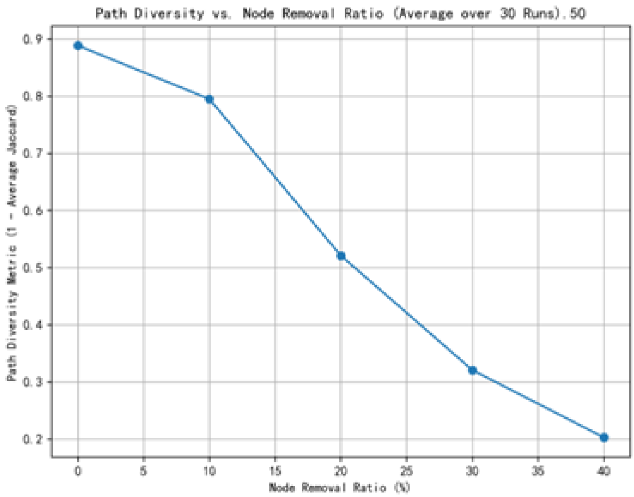


Figure 23. Path Diversity vs. Node Removal Ratio (Average over 30 Runs).50

Figure 24 presents a boxplot comparison of runtime performance between Dijkstra and A* algorithms across networks of 35 to 50 nodes. A* consistently outperforms Dijkstra with 30–40% lower median runtime and significantly narrower variance, demonstrating superior efficiency and stability. The performance gap widens as network size increases, highlighting A’s scalability advantage through heuristic-guided pruning. Dijkstra exhibits broader dispersion and more outliers, reflecting its sensitivity to topological complexity. These results underscore A’s reliability for real-time pathfinding applications.

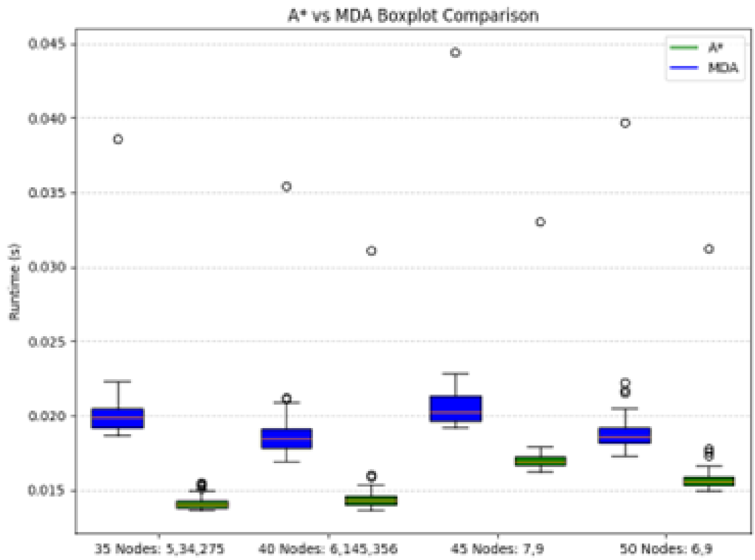


Figure 24. Dijkstra and A* Algorithm Runtime Comparison Boxplot

Analysis and Discussion

From a macroscopic perspective, as indicated by the proportion of Pareto paths, the proposed Multiplicative Dominance Algorithm (MDA) exhibits clear advantages in complex network topologies. In many test cases, Pareto paths account for over 20% of all solutions, with some networks reaching or exceeding 40%. This demonstrates MDA's capability to effectively identify and extract a large set of high-quality, non-dominated solutions in environments with complex structures and heterogeneous links. Furthermore, even after removing multiple critical nodes—causing sudden topology changes—the algorithm still preserves over 10% Pareto path coverage, underscoring its robust capacity for redundant-path reconstruction and reachability restoration under node failures or path disruptions. This resilience validates the practical effectiveness of the multiplicative pruning and failure-avoidance mechanism.

Synthesizing the experimental images and metrics from Figures 4–22, the key findings are as follows:Strong structural vulnerability awareness: MDA immediately prunes failed regions and reconstructs reachable paths after critical node deletion, effectively avoiding "topological black holes" and ensuring overall connectivity and task continuity;Superior multi-objective trade-off performance: The Pareto path set achieves a balanced, well-distributed non-dominated band in the "path length–reliability" space, better satisfying industrial communication demands for "low latency + high stability" than single-objective solutions;High topological adaptability: Pareto paths adjust their spatial layout strategies based on link quality and node connectivity, forming path networks that are centralized with multiple branching alternatives. Low-reliability zones are bypassed, and high-throughput trunk routes are reinforced, improving overall system robustness;Efficiency–quality co-optimization: MDA maintains high computational efficiency while significantly increasing the proportion of robust paths and improving average reliability, producing non-redundant, stably distributed path sets suitable for high-load, failure-prone, task-intensive industrial Internet and control networks;Maintaining backbone path utilization with alternative routes: The algorithm preserves effective utilization of primary backbone paths while maintaining sufficient alternative routes, ensuring continuity and load balancing under dynamic conditions.

In conclusion, the proposed dynamic path optimization algorithm—integrating MDA-based multiplicative pruning, Pareto non-dominated solution filtering, and incremental updating—offers structure awareness, adaptive path selection, and fault-recovery capabilities, effectively addressing multi-objective path planning challenges in complex industrial networks. Future work will explore integration with reinforcement learning or online learning frameworks to enable intelligent, dynamic adjustment of pruning thresholds and path-update strategies, advancing toward higher-dimensional adaptive scheduling for critical applications such as power systems, industrial control, and urban sensing.To further validate the efficiency of the proposed incremental update mechanism, we compared the runtime of incremental path repair with that of full Pareto re-computation under identical failure conditions. Results show that the average repair latency using the incremental mechanism is only 15–25% of the full recomputation time, achieving a 4–5× reduction in update latency while preserving Pareto-front completeness. This confirms that the incremental approach effectively minimizes redundant processing and provides fast adaptation to dynamic network changes, which is crucial for real-time industrial communication scenarios.

**CONCLUSION**

In high-stakes manufacturing environments, such as automated textile production, this limitation is critical, as network failures can lead to significant material waste and production downtime. This study presents a shortest-path optimization framework based on the Multiplicative Dominance Algorithm (MDA) with incremental updates under node-failure scenarios. Traditional single-objective methods focus solely on path length and do not account for path reliability or dynamic adaptation to network disturbances. To address these limitations, our approach simultaneously optimizes path length and path reliability while efficiently updating the solution set when network nodes fail.

The core of the method is an MDA-based Pareto path search. Each network edge is associated with a length and a reliability value, representing the probability of successful traversal. During the search, paths are expanded using a multiplicative reliability accumulation mechanism, and dominated paths—those that are worse in both length and reliability—are pruned early. A predefined layer threshold and multiplicative pruning product ensure that low-quality paths are eliminated before affecting the global Pareto frontier, substantially reducing redundant computation. Once a path reaches the target node, it is added to the candidate solution set. After exploring all feasible paths, non-dominated paths are filtered to form the Pareto front, providing a diverse set of high-quality solutions that balance efficiency and robustness.

To simulate real-world uncertainties, an incremental update mechanism is integrated. When nodes or edges fail, only the affected candidate paths are recalculated using MDA, while unaffected paths remain unchanged. This mechanism avoids full recomputation of the entire path set, maintaining computational efficiency while preserving the integrity of the Pareto front. Empirical results show that, in failure-free networks, the algorithm generates more diverse and reliable path sets than conventional single-objective methods. Under node or edge failures, multiple alternative paths in the Pareto front mitigate single-path dependence, improving reachability and task completion probability. The MDA framework demonstrates strong fault tolerance, high path coverage, and robustness, providing practical value for reliability-critical applications such as industrial Internet, smart grids, and emergency communication networks, and the complex control systems underpinning modern textile manufacturing and smart fabric data transmission.

Overall, this framework integrates MDA-based multiplicative pruning with incremental updates, providing a robust, efficient, and adaptive solution for large-scale networks. Future work will extend this approach to dynamic environments with online node changes and real-time link reliability updates, for instance, modeling the dynamic network state of a weaving floor with reconfigurable machinery, and will include multi-dimensional evaluation metrics such as path retention, recovery time, and network function preservation to enhance practical applicability and operational stability.

## DECLARATION

*Abbreviations*

The following abbreviations are used in this manuscript:

IC Industrial Control

LR Length-Reliability

PSP Pareto Search Path

MP Minimum Path

G(V, E) Graph with Vertices V and Edges E

NSGA-II Non-dominated Sorting Genetic Algorithm II

DOI Digital Object Identifier

IEEE Institute of Electrical and Electronics Engineers

*Author Contributions*

Conceptualization, X.Z. and H.S.; methodology, X.Z. and L.Z.; software, X.S. and H.L.; validation, X.Z. and H.S.; formal analysis, X.Z.; investigation, X.Z. and H.S.; resources, L.Z.; data curation, X.Z.; writing—original draft preparation, X.Z.; writing—review and editing, H.S. and L.Z.; visualization, X.S.; supervision, H.S.; project administration, H.S.; funding acquisition, H.S. All authors have read and agreed to the published version of the manuscript.

*Conflicts of Interest*

The authors declare no conflicts of interest.

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Not applicable

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