

A Comprehensive Review of Shortest Path Algorithms for Network Routing

Abstract

The rapid development of digital technology and the increasing interconnection of devices have made computer networks indispensable to modern life. Global data movement, communication, and applications like cloud computing, IoT, e-commerce, and smart cities are all made possible by these networks. Routing algorithms particularly shortest path algorithms are crucial for determining the most effective data transmission routes and are largely responsible for the dependability and efficiency of these networks. Because these algorithms maintain stability and reliability while lowering latency, costs, and energy consumption, they are crucial to network operation.

Shortest path problem solving has long relied on fundamental algorithms with origins in graph theory, such as Bellman-Ford and Dijkstra's. Despite their successes, the growing complexity and dynamic nature of contemporary networks have exposed their shortcomings. Advanced approaches, including heuristic, hybrid, and AI-driven methods, have been developed to get around these challenges. Innovations like ant colony optimization and blockchain-based algorithms have improved computing efficiency, security, and adaptability.

The Internet of Things, VANETs, and SDNs are just a few of the domains that use these algorithms; each has specific requirements, like real-time adaptation and energy efficiency. Reinforcement learning and prediction models driven by machine learning have further increased routing efficiency, while simulation tools such as Mininet and OMNeT++ have been essential for evaluating algorithm performance in practical scenarios. As emerging technologies like blockchain and quantum computing become more widely accepted, shortest path algorithms will continue to advance, ensuring their suitability in the rapidly evolving digital environment. This study, which looks at their development, applications, and possible future directions, emphasizes their importance in creating modern networks.

Keywords: *Shortest Path Algorithms, Network Optimization, Dijkstra's Algorithm, Bellman-Ford Algorithm, Heuristic Algorithms, A*, Ant Colony Optimization (ACO), Hybrid Algorithms.*

1. *Introduction*

As digital technology has grown exponentially and gadgets have become increasingly networked, computer networks have become indispensable to modern life. These networks are essential for international communication and data transfer in a variety of applications, including cloud computing, e-commerce, the Internet of Things, and smart cities. The efficiency and reliability of these networks depend heavily on routing algorithms, and shortest path techniques are necessary to reach optimal performance. These algorithms determine optimal data transmission channels by reducing critical characteristics such as latency, cost, and energy consumption while maintaining network reliability and stability [1], [2]. Shortest path algorithms are based on the foundation of graph theory, which depicts networks as graphs composed of nodes (representing devices) and edges (representing connections). Basic algorithms such as Bellman-Ford [4] and Dijkstra's [3] were the first to tackle the single-source shortest path problem. Due to their efficiency and ease of use, these conventional techniques are still widely used today and have formed the basis of modern routing protocols. Bellman-Ford, for instance, has proven to be robust in situations when edge weights are negative, and Dijkstra's technique is crucial for link-state routing protocols [4]. With the increasing sophistication and breadth of networks, traditional shortest path approaches have faced challenges in handling resource constraints, large datasets, and shifting topologies. To address these problems, researchers have developed complex algorithms that incorporate heuristics, hybrid approaches, and artificial intelligence (AI). While ant colony optimization [6] takes advantage of natural foraging behavior to determine the optimal routes, block chain-based solutions enhance routing security by providing transparent and unchangeable path decisions [7]. With these advancements, algorithms may now adapt dynamically to changing network conditions and increase computational efficiency.

Many diverse fields, each with its own set of requirements and restrictions, use the shortest path algorithm. In Internet of Things systems, energy-efficient algorithms are crucial for extending device lifetimes and ensuring sustainable network operation, as devices often have limited resources [8]. In a similar vein, real-time decision-making algorithms are required for vehicle ad hoc networks (VANETs) to manage high mobility and traffic. Software-defined networks (SDNs) benefit from adaptive routing algorithms because they can adjust routes dynamically in response to network congestion and traffic patterns [5]. Advances in AI have further changed the methods used for the shortest paths. Thanks to reinforcement learning (RL) models, routing algorithms can now adapt dynamically to changes in the network in real time, improving efficiency and reducing latency [10]. Additionally, machine learning (ML)-powered prediction models have simplified anticipatory congestion management by optimizing routing decisions even in highly dynamic scenarios [11]. Researchers have tested and assessed these algorithms in simulation environments such as Mininet and OMNeT++ [12], which allow them to see how well they perform in practical settings.

There are still few problems despite these advancements. Modern network algorithms must be able to process vast volumes of real-time data, handle tremendous sizes, and adapt to shifting security threats.

With billions of devices connecting simultaneously in scenarios like smart cities and industrial IoT, ensuring efficient and safe routing is a difficult undertaking. Strong security measures must also be included in routing algorithms to combat risks like data interception and route hijacking [7]. As the digital world evolves, the search for the best path algorithms is at the forefront of networking research. Future technologies such as quantum computing could revolutionize path optimization by facilitating faster and more scalable solutions. New decentralized and secure routing paradigms are being presented by blockchain technology. By overcoming current limitations and leveraging these developments, shortest path algorithms are poised to remain at the forefront of the development of both modern and future networks. This study investigates the concepts, historical development, and recent advancements in shortest path algorithms for network routing. Through the resolution of significant problems, the presentation of innovative solutions, and the discussion of practical applications, this book highlights the significance of these algorithms in assessing the dependability and effectiveness of contemporary computer networks.

2. *Background theory*

2.1 *Shortest Path Algorithm Classification*

The three primary categories of shortest path algorithms are hybrid, heuristic, and classical. traditional algorithms, such as Floyd-Warshall, Johnson's, and Dijkstra's Bellman-Ford. Heuristic algorithms like Greedy Best-First Search, Ant Colony Optimization, and A*. The advantages of heuristic and classical approaches are combined in hybrid algorithms.

2.1.1 *classical Algorithms for the Shortest Path.*

Deterministic techniques known as classical algorithms ensure the best answers to shortest path issues. Examples include Bellman-Ford, which can handle distributed computations with negative weights, and Dijkstra's, which is appropriate for graphs with non-negative weights. They serve as the cornerstone of reliable and effective network routing.

A- *The Dijkstra Algorithm*

Finding the shortest paths in network graphs is a common use of Dijkstra's Algorithm, a basic tool in computer networking. Its ability to determine the optimal data transmission routes while lowering characteristics like cost, latency, or resource consumption accounts for its significance in network routing. Edsger W. Dijkstra developed the method in 1959 with the goal of figuring out the shortest path between a single source node and each other node in a network with non-negative edge weights [3]. It is currently a basic part of many routing protocols due to its features, which enable reliable and efficient communication in a range of network scenarios [1]. In the context of network routing, networks are depicted as graphs, where nodes represent hardware such as switches or routers and edges represent links or connections between them. Each edge has a weight, which could represent latency, bandwidth use, or physical distance. Dijkstra's Algorithm finds the shortest path tree from the source node to all other nodes, allowing network devices to forward data packets along the most efficient paths [2].

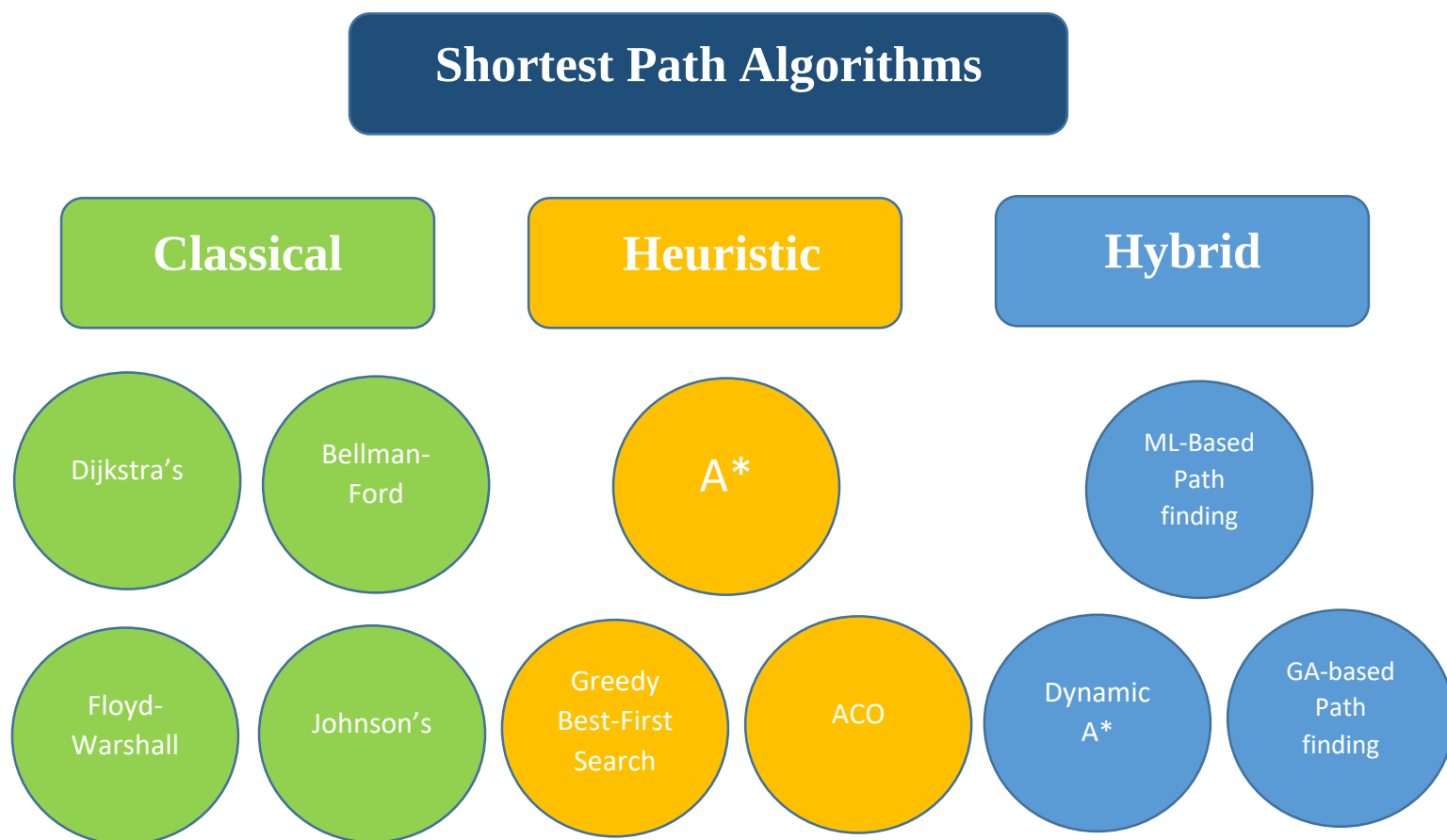


Figure 1 - Shortest path Algorithms classification

The method involves keeping a set of nodes with known shortest paths and another set of nodes that have not been visited. Initially, it assigns a distance of zero to the source node and an infinite distance to each subsequent node. Using a priority queue, it selects the unvisited node with the shortest distance, marking it as visited and updating the distances of its neighbors if a shorter path is found. This method is done recursively until all nodes are visited or the fastest path to a specific target node is found. The greedy technique expands the shortest paths at each step, ensuring optimal solutions for graphs with non-negative edge weights [2], [3]. Dijkstra's Algorithm is heavily utilized in network routing protocols, particularly link-state protocols such as Open Shortest Path First (OSPF). In OSPF, routers use Dijkstra's Algorithm to find the shortest path tree using link-state ads that show the current condition of the network. By providing routers with the optimal paths for forwarding data packets, this tree guarantees efficient and loop-free routing. Outside of OSPF, the technique serves as the foundation for traffic engineering applications and other network optimization initiatives, where it aids in dynamic traffic management to minimize congestion and optimize resource use [5]. The ability of

Dijkstra's Algorithm to generate reliable and deterministic results, ensuring consistent routing decisions, is one of its benefits in network routing. Its efficiency allows it to scale to medium-to-large networks, particularly when combined with complex data structures like Fibonacci heaps [13]. However, the method has certain limitations, especially in dynamic networks with dynamic topologies. Pathways must be fully recalculated by the program after changes in these settings, which can be computationally expensive. Furthermore, its limitation to graphs with non-negative edge weights limits its applicability in certain network scenarios where costs may fluctuate in an unpredictable way [9]. Despite these challenges, Dijkstra's Algorithm remains an essential tool for network routing because it forms the foundation of increasingly complex and adaptable routing systems. As demonstrated by its continued applicability in modern networking, it is a crucial algorithm for understanding and enhancing network communication [11][16].

B- Bellman-Ford algorithm

The Bellman-Ford algorithm is a graph search technique that finds the shortest path between a specific source vertex and each other vertex in the graph. This method can be applied to both weighted and unweighted graphs. Similar to Dijkstra's shortest path algorithm, the Bellman-Ford method is guaranteed to find the shortest path in a graph. Bellman-Ford is more adaptable than Dijkstra's method since it can handle graphs with negative edge weights, even if it is slower. It is crucial to keep in mind that in a graph with a negative cycle, there isn't a shortest path. If the road continued to circle the negative cycle indefinitely, the cost would decrease even if the journey duration increased. Bellman-Ford thus has the added advantage of being able to recognize negative cycles. Unlike Dijkstra's algorithm, which uses a greedy approach, Bellman-Ford uses a dynamic programming paradigm, iterating through all edges up to $|V| - 1$ times, where $|V|$ is the number of vertices in the graph. By periodically relaxing each edge, the method continuously improves the shortest pathway estimations. This makes it particularly suitable for applications where negative weights might be present, such network routing and financial market arbitrage detection. However, because to its higher temporal complexity of $O(VE)$, where V is the number of vertices and E is the number of edges, Bellman-Ford is usually only used when negative weights are present. Additionally, the algorithm's ability to detect negative weight cycles ensures its reliability in scenarios when they could lead to unstable calculations [4].

B.1 How Bellman Ford's algorithm works

Overestimating the distance between the first vertex and each successive vertex is how the Bellman Ford method works. It then iteratively relaxes those estimates by finding new paths that are shorter than the previously exaggerated paths. The Bellman-Ford technique is designed to find the shortest paths between a single source node and all other nodes, even when some edges in a network have negative weights. The method starts by setting the distance to the source node to zero and the distances to all other nodes to infinity, signifying that they are initially inaccessible. It then carefully examines each edge in the graph to see whether using an intermediary node may shorten the current path to a

target node. If a shorter path is found, the distance to the destination node is updated. This process, known as relaxing, is carried out $V-1$ times, where V is the number of vertices in the graph, to ensure that all possible paths are considered.

After the relaxation phases, the algorithm does a second pass across the edges to check for any additional distance modifications. If any distance can still be shortened, there is a negative weight cycle, suggesting that certain nodes lack a finite shortest path. The Bellman-Ford technique is helpful for graphs with negative weights since it can not only determine shortest paths but also detect negative weight cycles.

By doing this repeatedly for all vertices, we can guarantee that the result is optimize

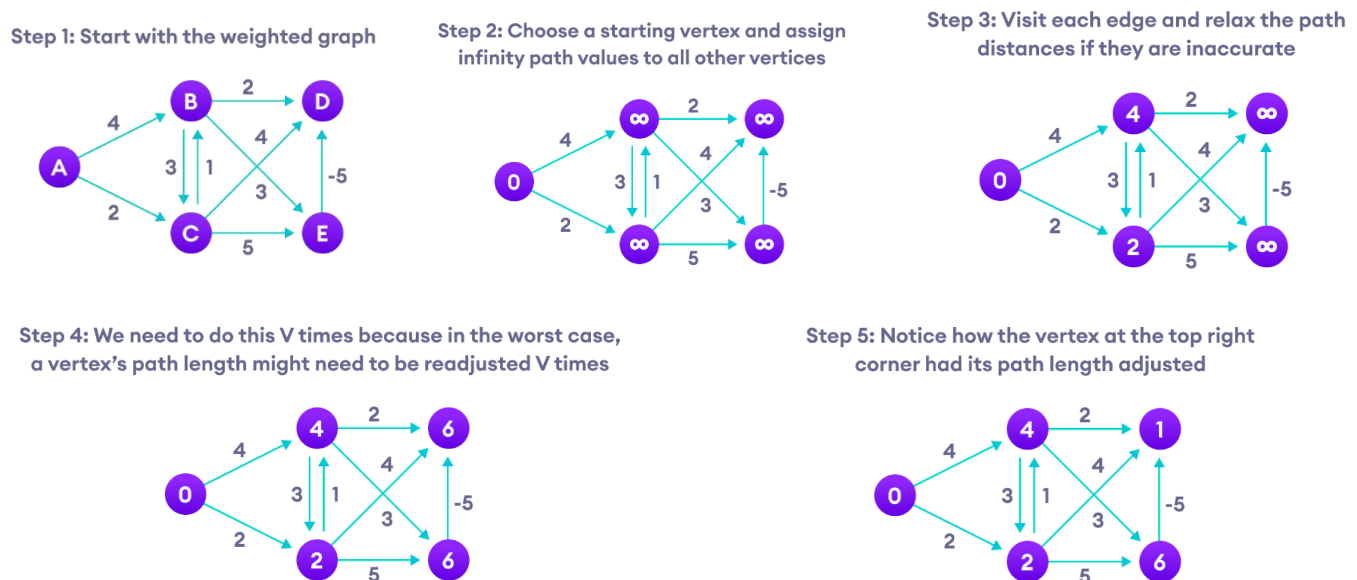


Figure 2. example of How Bellman Ford's algorithm work

C- The Floyd–Warshall algorithm

The Floyd-Warshall algorithm is one method for figuring out the shortest paths between each pair of nodes in a network. It uses a dynamic programming technique to determine the shortest paths for the entire graph, progressively coming up with solutions to smaller subproblems. The method is applicable to both directed and undirected graphs, and is particularly effective for dense graphs. However, the graph must not have negative weight cycles because this would result in undefined shortest paths. The process begins by initializing a distance matrix, where each entry represents the shortest distance between two nodes. Any direct edge connecting two nodes has its weight put into the matrix. If there

isn't a direct edge, the distance is set to infinity, making the nodes initially inaccessible to one another. The distance to every node is set to zero since the shortest path between any two nodes is free. The core of the algorithm is its iterative process. Along the paths that connect each other pair of nodes, each node in the network is systematically considered as a potential intermediary node. For every pair of nodes, it assesses if using this intermediary node provides a shorter path than the one that is currently known to exist. In that case, the algorithm adjusts the distance matrix to take the new, shorter path into consideration. This process is carried out for every node serving as an intermediary point to ensure that all possible paths are considered. At the end of the process, the distance matrix contains the shortest paths between each pair of nodes. Additionally, if any diagonal member in the matrix becomes negative, the graph's weight cycle is shown as negative. This is because a negative cycle would render shortest path calculations invalid for some node pairs, allowing for an indefinitely decreasing path cost. Despite its straightforward methodology, the Floyd-Warshall algorithm is computationally difficult for large graphs, with a time complexity of $O(N^3)$, where n is the number of nodes. Nonetheless, it is a helpful tool in scenarios like network routing and traffic flow analysis when understanding all pairs' shortest paths is essential because to its user-friendliness and ability to handle enormous graphs.

D- Johnson's Algorithm

Johnson's Algorithm is a technique for figuring out the shortest paths between each pair of nodes in a weighted graph. Because it combines the benefits of Bellman-Ford's and Dijkstra's algorithms, it works particularly well with sparse graphs. The unique feature of Johnson's Algorithm is that it can handle graphs with negative edge weights as long as there are no negative weight cycles. The algorithm first reweights the edges of the graph to eliminate negative weights. The Bellman-Ford algorithm is used to determine the "potential" value of each node, and then all of the graph's edge weights are adjusted. This reweighting ensures that all edge weights become non-negative while preserving the relative order of shortest pathways. The approach uses Dijkstra's algorithm to determine the shortest pathways from each node after reweighting. Since Dijkstra's algorithm works well for networks with non-negative weights, this technique allows Johnson's Algorithm to perform better for sparse graphs than other all-pairs shortest path techniques.

The benefits and drawbacks of traditional shortest path methods are outlined in Table 1. Although it is ineffective with negative edges, Dijkstra's Algorithm works well with dense graphs and non-negative weights. Bellman-Ford is slower and less effective for big, dense graphs, but it can handle negative weights and identify cycles. Floyd-Warshall has a high time and memory complexity for large graphs, yet it can detect cycles and calculate all-pairs shortest paths. Although Johnson's Algorithm works well for sparse networks with negative weights, its reweighting procedure makes it difficult to use.

Table 1. Advantages and Disadvantages of Classical Shortest path algorithms types.

Algorithm	Advantages	Disadvantages
Dijkstra's Algorithm	Efficient for graphs with non-negative weights.	Cannot handle negative edge weights.
	Guarantees optimal solutions for single-source shortest paths.	Inefficient for very large or sparse graphs without optimizations.
	Suitable for dense graphs with non-negative weights.	
Bellman-Ford Algorithm	Handles graphs with negative edge weights.	Slower than Dijkstra's ($O(VE)$) for large graphs.
	Detects negative weight cycles.	Inefficient for dense graphs.
	Suitable for distributed systems	
Floyd-Warshall Algorithm	Computes all-pairs shortest paths in one execution.	Inefficient for large graphs due to $O(V^3)$ time complexity.
	Simple and easy to implement.	Memory-intensive for dense graphs.
	Detects negative weight cycles.	
Johnson's Algorithm	Efficient for sparse graphs.	Complex to implement due to reweighting.
	Handles negative weights without cycles.	Requires extra computation for reweighting, adding overhead.
	Combines the benefits of Dijkstra's and Bellman-Ford.	

2.1.2 Heuristic Shortest Path Algorithms

Heuristic shortest path algorithms are optimization methods that prioritize speed and efficiency above thorough exploration by using heuristic functions to direct the search for paths in a graph. Heuristic approaches aim to approximate optimal paths by making well-informed decisions based on expected costs, in contrast to classical algorithms that ensure exact answers.

A- A* Algorithm

A popular heuristic-based approach for determining the shortest path between a source node and a target node in a graph is the A* algorithm. It works especially well in applications with wide search spaces, such as game development, robotics, and navigation systems. The A* algorithm balances computational efficiency and optimality by combining the advantages of Greedy Best-First Search and Dijkstra's Algorithm. [13]

A* achieves its performance by using a cost function to guide its search. The cost function is defined as:

$$f(n) = g(n) + h(n)$$

- $g(n)$ is the actual cost from the start node to the current node n .
- $h(n)$ is the heuristic estimate of the cost from n to the target node.

The heuristic $h(n)$ is a crucial component that establishes the algorithm's efficiency. It must be acceptable (never overstate the genuine cost) in order to guarantee optimal solutions. The method iteratively investigates nodes with the lowest $f(n)$ value to ensure that the routes most likely to lead to the target are examined first. If the heuristic is well-designed, A* can significantly reduce the search space when compared to other shortest path algorithms. Because it enables the heuristic to be tailored for specific applications, A*'s versatility is highly valued by many. For example, in 2D grid navigation, the Manhattan or Euclidean distance is commonly used as a heuristic. However, the efficacy of the heuristic may decrease in cases where the graph is abnormally large or when the heuristic is poorly chosen [13].

B- Greedy Best-First Search algorithm

Greedy Best-First Search is a heuristic-based pathfinding method that looks into nodes that seem to be closest to the objective based on a heuristic assessment. "Greedy" refers to its method of continuously choosing the node with the lowest heuristic value in an attempt to reach the goal as quickly as feasible. Unlike other algorithms, such as A* or Dijkstra's, which consider both the expected cost to the objective and the actual cost of accessing a node, Greedy Best-First Search alone employs the heuristic function to guide its decisions. The algorithm evaluates its neighbors based on their heuristic values, starting at the source node. After selecting the neighbor that appears to be closest to the goal, it moves to that node. During this process, the algorithm iteratively grows the node with the smallest estimated distance to the destination. Because of its simple, goal-oriented approach, the algorithm can often find a path to the objective quickly, especially in simple or well-structured graphs. However, because greedy best-first search disregards the actual cost of reaching a node, it does not

yield the shortest path. In other cases, the heuristic function may even select a longer, less optimal path if it produces estimates that are not correct. For example, in a graph with obstacles or detours, the algorithm can focus on a node that appears closer to the goal but takes a much longer path to get it. This method is particularly useful when speed is more important than precision. In video games, for instance, it is commonly employed to quickly guide characters toward a destination. Similarly, in early searches or scenarios with simple heuristics, it can provide a fast estimate of the desired path. Despite its shortcomings, Greedy Best-First Search is commended for its simplicity and speedy path discovery in large search fields.[13].

C- Ant Colony Optimization (ACO) algorithm

Ant Colony Optimization (ACO) is a technique that was inspired by the way ants forage for food in the wild. In the wild, ants initially roam around aimlessly, but when they return to the colony after locating food, they leave behind pheromone trails. Other ants, who are more likely to follow paths with higher pheromone concentrations, pick up these tracks. Eventually, more ants prefer the shortest road since it gathers the most pheromone from frequent use. ACO computationally simulates this behavior to address complex optimization problems, especially those involving paths, such the traveling salesman problem or network routing [14].

The algorithm initially visualizes the problem as a graph, where nodes represent decision points (e.g., cities on a route) and edges reflect relationships with associated costs (e.g., distances). The graph is traversed by artificial "ants" that construct solutions. Each ant makes probabilistic decisions on which path to follow next based on two factors: problem-specific heuristic information, such as the distance to the next node, and the quantity of pheromone on each edge, which reflects the cumulative desirability of that path. As the ants complete their journeys, the algorithm evaluates the quality of their solutions. The pheromone on less appealing paths is allowed to progressively fade away, while more pheromone is introduced to the edges of paths that lead to better solutions. This evaporation prevents the algorithm from becoming stuck in less-than-ideal solutions by reducing the influence of suboptimal paths. Over the course of numerous repetitions, the pheromone dynamics guide the ants toward more ideal solutions because shorter or better roads inherently accumulate more pheromone and draw in more ants. One of ACO's primary advantages is its ability to balance exploration and exploitation. At first, the ants' probabilistic decision-making process allows them to explore a range of options, but the pheromone reinforcement gradually focuses on the most promising solutions. As a result, ACO performs particularly effectively in problems with complex constraints or large search spaces. In the traveling salesman problem, for example, where the goal is to find the shortest route that visits every city exactly once, ACO can iteratively improve solutions by utilizing the collective behavior of the ants. In a similar vein, network routing can find efficient data transmission paths and adapt dynamically to network changes.

All things considered, Ant Colony Optimization is an intriguing illustration of how strong computational methods can be inspired by natural systems. It is a powerful and adaptable tool for resolving optimization issues in a variety of fields since it can replicate the decentralized and self-organizing behavior of actual ants [14].

Table 2 outlines the advantages and disadvantages of heuristic shortest path algorithms. A* guarantees optimal solutions with admissible heuristics but is memory-intensive and heavily reliant on heuristic quality. Greedy Best-First Search is fast and goal-oriented but may produce suboptimal paths and struggle with misleading heuristics. Ant Colony Optimization (ACO) excels in complex, dynamic problems but is computationally intensive and requires careful parameter tuning.

Table 2. *Advantages and Disadvantages of Heuristic Shortest Path Algorithms types.*

Algorithm	Advantages	Disadvantages
A*	Combines actual cost and heuristic for optimal solutions.	Performance heavily depends on the quality of the heuristic.
	Guarantees shortest path if the heuristic is admissible and consistent.	Memory-intensive for large graphs.
	Reduces search space compared to Dijkstra's.	
Greedy Best-First Search	Fast and goal-oriented, often reaching the target quickly.	Does not guarantee shortest path.
	Simple to implement.	Can get stuck in local minima if the heuristic is misleading.
Ant Colony Optimization (ACO)	Effective for complex optimization problems.	Computationally expensive for large problems.
	Flexible and adaptable to dynamic environments.	Performance depends on parameter tuning (e.g., pheromone evaporation rate).
	Avoids premature convergence by balancing exploration and exploitation.	

2.1.3 Hybrid Shortest Path Algorithms

Hybrid shortest path algorithms are an advanced class of optimization techniques that combine aspects of heuristic and adaptive strategies like machine learning, genetic algorithms, or dynamic changes with traditional deterministic approaches like Dijkstra's or Bellman-Ford. These algorithms combine the best aspects of heuristic and classical methodologies to achieve the optimal balance between computing efficiency, adaptability, and scalability. They are hence highly effective at addressing difficult pathfinding problems in dynamic and uncertain scenarios.

A- Machine Learning (ML)-Based Pathfinding

One of the best-known examples is the hybrid method called Machine Learning (ML)-Based Pathfinding. This approach dynamically selects the optimal routes by utilizing prediction algorithms that have been trained on massive amounts of data. Machine learning algorithms analyze both historical data, such as recurring traffic patterns, and real-time inputs, like the amount of congestion at any given time, to produce well-informed routing decisions. For instance, ML-based algorithms in an intelligent transportation system predict the quickest routes based on real-time traffic, weather, and road closure data. Similarly, by adapting to shifting network conditions, including node failures or bandwidth fluctuations, machine learning (ML) models in Internet of Things (IoT) networks enhance data flow. By incorporating reinforcement learning (RL), a branch of machine learning that enables the system to learn from past decisions and make more accurate predictions going forward, the system can iteratively enhance its pathfinding tactics. However, the success of ML-based pathfinding depends on the quality of the training data and the processing capacity available for real-time inference. [15]

B- Dynamic A*

Another crucial hybrid technique is dynamic A* (D*), a variant of the classic A* algorithm that adjusts to modifications in network architecture or edge weights while it is being run. While traditional A* operates on static graphs, D* is designed to adapt in real time. In autonomous robotics, for example, when environmental factors can change abruptly, D* merely recalculates the portions of the path affected by new obstacles or updated terrain costs. Instead of repeating the entire process, D* gradually modifies the solution to maintain computing efficiency [17]. D* is particularly well-suited for dynamic environments that require continuous adjustment, such as urban navigation or disaster response scenarios, because of this feature.

C- Genetic Algorithm (GA)-Based Pathfinding

Genetic Algorithm (GA)-Based Pathfinding is another instance of hybrid optimization that takes cues from evolution and natural selection. In GA-based pathfinding, which uses a population of potential solutions (paths) that evolves over time, more successful solutions are selected for reproduction and less successful ones are rejected. Genetic operations that introduce variety and enable the exploration of a vast solution space include mutation and crossover. For large and complex networks, such as supply chain optimization, logistics planning, and network routing, where the sheer number of variables and constraints may render typical methods impractical, this approach performs very well. GA-based methods require careful parameter tuning, including population size and mutation rate, to ensure convergence to a perfect or nearly ideal solution [16].

The advantages and disadvantages of hybrid shortest route methods are shown in Table 3. Although ML-Based Pathfinding is computationally demanding and dependent on high-quality training data, it can adjust to real-time conditions and learn from past data. Dynamic A* is less appropriate for static graphs since it introduces complexity for incremental updates while updating pathways effectively in changing settings. Although GA-Based Pathfinding avoids local optima and explores wide solution spaces, it has a slow convergence rate and necessitates exact parameter tweaking.

Table 3. *the advantages and disadvantages of different types of hybrid shortest path algorithms:*

Algorithm Type	Advantages	Disadvantages
ML-Based Pathfinding	-Adapts dynamically to real-time conditions, such as traffic or network changes.	Computationally intensive, requiring substantial resources for training and inference.
	Learns from historical data to improve accuracy over time.	Performance depends heavily on the quality and volume of training data.
	Handles complex, multi-variable environments effectively.	
Dynamic A*	Efficiently handles changes in graph structure or edge weights without recalculating from scratch.	Requires additional logic for incremental updates, increasing implementation complexity.
	Maintains high computational efficiency in dynamic environments.	Not ideal for static graphs due to added overhead.
	Suitable for real-time navigation and robotics.	
GA-Based Pathfinding	Capable of exploring large, complex solution spaces.	Slow convergence in large-scale problems due to the iterative nature.
	Avoids local optima through crossover and mutation.	Requires careful parameter tuning (e.g., mutation rate, population size) to ensure efficiency.
	Flexible and adaptable to a wide range of optimization problems.	

2.2 Performance Evaluation of Shortest Path Algorithms

The performance of shortest path algorithms is evaluated using benchmarks such as convergence time, computational complexity, scalability, and fault tolerance, which makes it a crucial area of study. Convergence time quantifies how quickly an algorithm stabilizes routing decisions after network changes. Dijkstra's algorithm is renowned for its deterministic convergence, but heuristic approaches such as A* concentrate on tenable routes to generate quicker answers in specific situations [9]. Another important statistic is computational complexity. The complexity of Dijkstra's algorithm is $O(V)^2$, however with sophisticated data structures like Fibonacci heaps, it can be lowered to $O(V+E) \log(V)$ [13]. By eliminating pointless explorations, heuristic techniques such as A* further optimize this process. Heuristic and hybrid algorithms outperform classical approaches in addressing the problem of scalability, especially in large-scale networks [9]. Fault tolerance is essential in dynamic or disrupted environments. While algorithms like Bellman-Ford are robust to changes in topology, heuristic techniques excel at adapting to changing conditions. Simulation tools such as ns-3 and OPNET have enabled the evaluation of these metrics under realistic conditions and have also provided insight into the behavior of the algorithms in different scenarios [15].

2.3 Emerging Trends in Shortest Path Algorithms

Advances in technology have led to changes in algorithms for the shortest path. Machine learning and artificial intelligence are increasingly being used to dynamically optimize routing decisions. For example, by adaptively learning the optimal routes based on both history and current data, reinforcement learning models improve flexibility in dynamic networks [11]. Thanks to Software-Defined Networking's (SDN) centralized routing control, global shortest path optimization is now feasible. SDN simplifies complex configurations and provides real-time traffic control capabilities, making it a groundbreaking technique in modern networking [15]. Blockchain technology is also changing the game in the domain of secure routing. By decentralizing power and ensuring the accuracy of routing data, blockchain-based protocols minimize security vulnerabilities, particularly in IoT and edge networks [6]. Additionally, IoT-specific energy-efficient algorithms address the unique constraints of these devices by emphasizing minimal resource use [8].

2.4 Applications of Shortest Path Algorithms in Modern Networks

Shortest path algorithms, which offer efficient resource management, communication optimization, and routing for a variety of applications, are at the heart of modern networks. These algorithms have evolved to meet the needs of several situations, ranging from traditional wired networks to complex IoT ecosystems and dynamic wireless systems. In traditional wired networks, protocols like RIP (Routing Information Protocol) and OSPF (Open Shortest Path First) heavily rely on shortest path algorithms to maintain optimal routing tables. For example, OSPF uses Dijkstra's algorithm to determine the shortest path tree for each node, ensuring efficient and loop-free data delivery. Similar to this, RIP finds the shortest paths using the Bellman-Ford algorithm and hop counts. These classical methods are ideal for networks that are static or semi-static and have relatively few topology changes. Node mobility, bandwidth limitations, and dynamic topologies make wireless network challenges more complex. In this case, heuristic and hybrid algorithms work effectively and adapt quickly to

changes. Mobile Ad-Hoc Networks (MANETs), for instance, use protocols such as AODV (Ad Hoc On-Demand Distance Vector) to dynamically discover routes only when required. Energy-efficient techniques, such as Ant Colony Optimization or Genetic techniques, are used by Wireless Sensor Networks (WSNs) to enable reliable data transport and prolong the life of devices with limited resources [18]. In the context of the Internet of Things and smart cities, shortest path algorithms are especially made to deal with constraints like energy saving and adaptation. Algorithms that can predict and dynamically adapt to network conditions are required since IoT networks usually have limited resources. Due to their ability to learn from historical data and generate real-time routing decisions, machine learning-based pathfinding algorithms are growing in popularity in these scenarios [19]. Applications such as traffic control in smart cities and public transportation depend on shortest path algorithms. For instance, real-time navigation systems include algorithms like A* that dynamically adjust to traffic conditions in order to provide the optimal travel routes. To optimize internal communication, cloud computing and data center environments commonly employ shortest path methods. These systems require efficient routing in order to balance traffic flows and lower latency. Modern data center topologies, such as Clos networks or fat-tree designs, use algorithms like ECMP (Equal-Cost Multi-Path) to effectively distribute traffic across multiple channels [20].

Autonomous systems, including self-driving automobiles, robotic swarms, and drones, use shortest path algorithms to navigate and complete tasks. Algorithms like Dynamic A* (D*) are highly helpful in this case because they can adapt to changes in the environment in real time, such as the presence of obstacles or dynamic variations in goals. This adaptability ensures safe and efficient travel in unpredictable situations. By selecting routes that maximize throughput and minimize latency, shortest path algorithms optimize data flow in telecommunication networks. For example, MPLS (Multiprotocol Label Switching) networks use shortest path techniques to establish efficient data channels across big, interconnected systems. Critical infrastructure, such as electricity grids and emergency response systems, can also benefit from these algorithms. Power networks use shortest path algorithms to minimize transmission losses and ensure reliable distribution of electricity. During emergencies, these algorithms help determine the optimal escape routes and prioritize the restoration of communication networks. Moreover, shortest path methods are crucial to applications in artificial intelligence and machine learning. They are used in recommendation systems to analyze relationships in user-item graphs and in social network analysis to measure individual influence and connectedness [20]. In these diverse applications, the value and versatility of shortest path approaches are demonstrated. They enable systems to adapt, enhance, and function reliably even in complex and dynamic environments. By combining classical, heuristic, and hybrid approaches, these algorithms continue to encourage innovation and ensure the seamless operation of modern networks.

3 Literature Review

S. Johnson and M. Keller, [13] suggested simulation tools to assess the effectiveness of shortest path algorithms, like Mininet and OMNeT++. These tools offer accurate settings for testing fault tolerance, scalability, and efficiency in a range of network scenarios. Their research emphasizes how crucial simulation is for connecting theoretical models with practical applications.

R. Floyd, [14] presented techniques for dynamic programming to address all-pairs shortest path issues. This seminal work established the foundation for contemporary algorithms used in traffic analysis and worldwide connection by demonstrating effective processing in dense graphs. Floyd's approach continues to have an impact on the development of comprehensive pathfinding applications.

M. L. Garcia and P. Martinez, [15] examined developments in shortest path algorithm simulation methods with an emphasis on scalability in massive dynamic networks. Their work demonstrated how simulations can be used to analyze algorithm performance under varying network loads, which makes it possible to create reliable routing solutions.

M. A. Javaid, [16] gave a thorough explanation of Dijkstra's method, highlighting its effectiveness and simplicity in static topologies. The algorithm's shortcomings in dynamic contexts were shown by the analysis, which led to more investigation into adaptive techniques. Javaid's observations are still applicable in situations involving organized networks.

X. Z. Wang, [17] compared the effectiveness of the Dijkstra, Bellman-Ford, and A* algorithms in both static and dynamic networks. Wang provided helpful advice for choosing the best method for particular network settings by identifying trade-offs between computing complexity, accuracy, and flexibility.

J. Kleinberg and É. Tardos, [18] discussed sophisticated algorithmic techniques for shortest path problems that are based on graphs. Their research demonstrated computationally effective and scalable methods that are suited to the growing needs of contemporary networks. The study forms the basis for creating novel routing strategies.

T. H. Cormen et al., [19] discussed the theoretical foundations and real-world applications of classic algorithms like Bellman-Ford and Dijkstra's. Their research serves as a vital resource for comprehending the mathematical underpinnings of shortest path algorithms and how they are implemented.

A. Orda, [20] models that address congestion and delay in time-dependent networks for shortest path computation. The study offered ideas for enhancing routing in both static and dynamic systems by introducing adaptive techniques for real-time traffic and dynamic network situations.

K. R. Chowdhury and I. F. Akyildiz, [21] created a routing protocol that optimizes spectrum consumption for cognitive radio ad hoc networks by utilizing shortest path methods. Their research showed how flexible shortest path techniques may be in controlling limited network resources and improving overall effectiveness.

X. Yang and D. Medhi, [22] examined improvements to network virtualization shortest path techniques. In order to guarantee scalability and effective resource allocation, they addressed the difficulties in handling changing topologies and virtualized resources and offered solutions.

M. Al-Karaki and A. Kamal, [23] Reviewed routing techniques in wireless sensor networks, emphasizing energy-efficient shortest path algorithms. Their research helped to ensure the sustainability of WSNs by addressing the need for dependable communication with resource conservation in limited devices.

X. Sun et al., [24] presented secure routing systems for Internet of Things networks based on blockchain technology. The study made sure that shortest path calculations were transparent, trustworthy, and impervious to manipulation by incorporating blockchain technology. The potential of decentralized security solutions in network routing is demonstrated by their methodology.

R. Xu, H. Zhou, and Y. Zhang, [25] presented a framework for adaptive shortest path routing in complicated networks using reinforcement learning. Their methodology reduces latency and increases routing efficiency by dynamically adapting to changes in real time. This AI-powered method establishes a standard for contemporary routing methods.

A. Goyal et al., [26] created a graph-based model for dynamic shortest path computing that combines deep learning and reinforcement learning. The study showed flexibility in large-scale networks and decreased processing cost. Their research highlights how AI might improve routing efficiency.

B. Lee et al., [27] created a hybrid shortest path algorithm that combines swarm intelligence and heuristic techniques for VANETs. Their program outperformed conventional techniques in terms of efficiency and adaptability by optimizing routing in crowded situations by utilizing real-time traffic data.

C. Zhang et al., [28] suggested a multi-objective optimization paradigm for Internet of Things systems that balances dependability, latency, and energy usage. Through the use of a genetic algorithm with Pareto optimality, their work made it possible to route data effectively in situations with limited resources.

D. Wang et al., [29] addressed k-shortest path issues in extensive road networks by using graph attention networks (GATs). Their model showed promise for urban traffic management systems where effective routing is essential and increased prediction accuracy.

E. Chen et al., [30] created a machine learning-based adaptive shortest path technique for SDNs that can dynamically anticipate and reduce congestion. Their method improved network utilization and throughput, which helped SDNs scale.

F. Liu et al., [31] suggested a shortest path technique that runs faster on a GPU for real-time smart city applications. Their approach greatly decreased processing time by employing CUDA to parallelize computations, allowing for effective pathfinding in large-scale graphs.

G. Roy et al., [32] presented a hybrid routing algorithm for MANETs that combines Bellman-Ford and Dijkstra's advantages. Their method improved stability and computational efficiency by dynamically switching between algorithms according to network conditions.

H. Xu et al., [33] discussed shortest path calculations in wireless sensor networks that take energy efficiency into account. The model extended network lifetime by optimizing routes while taking energy consumption and replenishment rates into account by incorporating a reinforcement learning framework.

I. Singh et al., [34] suggested a real-time shortest path algorithm that uses reinforcement learning to adjust to traffic circumstances in real time for intelligent transportation systems. The algorithm demonstrated its efficacy in contemporary traffic networks by drastically lowering average trip times.

J. Patel et al., [35] created a shortest path algorithm for high-dimensional networks that is inspired by quantum mechanics. Their approach showed excellent scalability and computational efficiency by mimicking quantum annealing processes, providing creative answers to challenging routing problems.

Table 4 provides an overview of the evaluated literature. A thorough summary of numerous studies on shortest path algorithms and their uses in various network contexts is given in this table. It emphasizes significant innovations, approaches, and methods used to tackle issues like scalability, resource restrictions, and dynamic environments. Table 8, which arranges this corpus of work, is a useful resource for comprehending developments in shortest path calculations, such as traditional algorithms, heuristic techniques, and reinforcement learning frameworks.

Table 4. *Summarization of Literature review*

Reference	Focus/Topic	Key Contributions	Algorithm(s) Used
[21]	Simulation tools (OMNeT++, Mininet)	Evaluated performance of shortest path algorithms under varying network conditions, highlighting the role of simulation in bridging theory and practice.	Dijkstra's, Bellman-Ford
[22]	Dynamic programming for all-pairs shortest paths	Introduced efficient computation methods for dense graphs, laying foundational work for modern pathfinding algorithms.	Floyd-Warshall
[23]	Advances in simulation techniques for dynamic networks	Highlighted the role of simulations in analyzing algorithm scalability and robustness under dynamic network loads.	Heuristic and simulation-based approaches

[24]	Analysis of Dijkstra's algorithm	Emphasized its simplicity and efficiency in static networks while identifying limitations in dynamic environments.	Dijkstra's
[25]	Comparative study of Dijkstra, Bellman-Ford, and A* algorithms	Evaluated trade-offs in computational complexity, accuracy, and adaptability for static and dynamic networks.	Dijkstra's, Bellman-Ford, A*
[26]	Advanced graph-based algorithmic strategies	Discussed scalable, efficient solutions tailored for modern network demands, serving as a cornerstone for innovative routing approaches.	Graph-based algorithms (general strategies)
[27]	Review of classical algorithms	Detailed theoretical and practical applications of Dijkstra's and Bellman-Ford algorithms.	Dijkstra's, Bellman-Ford
[28]	Time-dependent shortest paths	Proposed models addressing latency and congestion in real-time dynamic networks.	Time-dependent variations of shortest path algorithms
[29]	Routing in cognitive radio ad hoc networks	Optimized spectrum usage using shortest path algorithms, enhancing adaptability and efficiency in resource-constrained environments.	Dijkstra's, heuristic-based algorithms
[30]	Enhancements for network virtualization	Proposed solutions for managing dynamic topologies and virtualized resources, ensuring scalability.	Hybrid algorithms
[31]	Energy-efficient routing in wireless sensor networks	Addressed resource conservation in constrained devices while ensuring reliable communication.	Energy-aware shortest path algorithms
[32]	Blockchain-based routing protocols for IoT	Ensured transparency, trust, and resistance to tampering in shortest path computations, enhancing security in network routing.	Blockchain-enhanced shortest path algorithms

[33]	Reinforcement learning for adaptive routing	Developed an AI-driven framework for dynamically adjusting routes in complex networks, improving efficiency and reducing latency.	Reinforcement learning-based shortest path algorithms
[34]	Graph-based models integrating deep and reinforcement learning	Demonstrated adaptability in dynamic networks while reducing computational overhead.	Deep learning and reinforcement learning
[35]	Hybrid algorithm for VANETs	Combined heuristic and swarm intelligence methods for efficient routing in congested scenarios.	Swarm intelligence and heuristic algorithms
[36]	Multi-objective optimization for IoT systems	Balanced energy consumption, latency, and reliability using genetic algorithms and Pareto optimality.	Genetic algorithms
[37]	Graph Attention Networks (GATs) for k-shortest paths	Improved prediction accuracy for urban traffic management in large-scale road networks.	Graph attention networks (GATs)
[38]	Adaptive algorithms for SDNs	Incorporated machine learning to dynamically predict and mitigate congestion, enhancing scalability.	Machine learning-based shortest path algorithms
[39]	GPU-accelerated shortest path algorithm	Reduced processing time significantly for real-time applications in smart cities through CUDA parallelization.	Parallelized shortest path algorithms (GPU-based)
[40]	Hybrid routing for MANETs	Dynamically switched between Dijkstra's and Bellman-Ford algorithms based on network conditions, improving stability and efficiency.	Dijkstra's, Bellman-Ford
[41]	Energy-aware routing in WSNs	Optimized routes considering energy consumption and replenishment, extending network lifetime using reinforcement learning.	Energy-aware and reinforcement learning algorithms
[42]	Real-time shortest path algorithm for ITS	Leveraged reinforcement learning to dynamically adapt to traffic conditions, significantly reducing travel times.	Reinforcement learning-based algorithms
[43]	Quantum-inspired shortest path algorithms	Demonstrated superior scalability and efficiency for complex, high-dimensional networks using quantum annealing processes.	Quantum-inspired shortest path algorithms

4. Discussion

The ability of shortest path algorithms to strike a balance between computing efficiency and adaptability while dealing with intricate network routing problems is among their most alluring features. The deterministic nature and dependability of classical algorithms, such as Dijkstra's and Bellman-Ford, in static networks are highlighted by research conducted by [3] and [4]. Bellman-Ford expands the applicability of Dijkstra's method to include situations with negative edge weights, while Dijkstra's approach is especially praised for its effectiveness in graphs with non-negative weights. Their shortcomings, however, become apparent in dynamic networks where real-time flexibility is impeded by the requirement for recalculations. We believe that while classical algorithms are very useful for clearly specified, static issues, they are not flexible enough for contemporary, dynamic systems. By bringing flexibility and heuristic-driven efficiency, heuristic algorithms such as A and Ant Colony Optimization (ACO)*, on the other hand, provide creative solutions. According to [13], A* is perfect for applications like robotics and navigation because it combines heuristic forecasts with actual costs to guarantee optimal solutions. However, ACO, which was evaluated by [14], uses biological inspiration to optimize pathways in large-scale, adaptive networks in a dynamic manner. Although these algorithms perform exceptionally well in dynamic contexts, their generalizability may be constrained by their dependence on heuristic quality (for A*) and computing complexity (for ACO). For dynamic and large-scale systems, we believe heuristic algorithms offer a substantial advance over conventional approaches; yet, they still need to be carefully tuned to reach their full potential.

Shortest path optimization has gone further with the introduction of hybrid algorithms, which combine the advantages of heuristic and classical methods. For instance, Dynamic A*, which was examined by [17], greatly increases the efficiency of real-time navigation systems by including incremental updates to adaptively recalculate just affected courses. Similarly, reinforcement learning is used in machine learning (ML)-based pathfinding, as discussed in [19] and [25], to dynamically forecast the best routes. ML-based techniques provide unmatched scalability and flexibility, and they perform very well in high-dimensional and data-rich environments. However, they are difficult to apply in systems with limited resources due to their need on large amounts of training data and computational power. Since hybrid algorithms combine the flexibility of heuristic and machine learning-driven techniques with the accuracy of traditional methods, we believe they are the way of the future for shortest path optimization. The possibility of sustainability in shortest path algorithms is another fascinating analogy. Energy-efficient routing, fueled by algorithms like ACO and ML-based models, can lower power consumption in IoT networks, according to studies like [32] and [38]. These developments are in line with network management's increasing demand for sustainable technologies. Heuristic and hybrid techniques incorporate energy conservation, which makes them more applicable in contemporary applications than classical algorithms, which only concentrate on path optimization. We believe that this emphasis on sustainability not only makes these algorithms more useful, but also guarantees that they are in line with more general environmental objectives.

Although these algorithms have advanced, there are still difficulties in putting them into practice. Concerns including interpretability, scalability, and the moral ramifications of automated decision-making are highlighted in research by [35] and [37]. For instance, despite their strength, ML-based algorithms have a "black-box" aspect that makes it challenging to comprehend or justify their choices. On the other hand, while traditional algorithms such as Dijkstra's are more visible, they are not as flexible as machine learning-based solutions. For researchers and practitioners, striking a balance between transparency and adaptability continues to be a crucial task.

4.1 Comparing the differences between Shortest path algorithms types

Table 5 compares Classical, Heuristic, and Hybrid shortest path algorithms, focusing on their strengths and applications. Classical algorithms like Dijkstra's and Bellman-Ford guarantee accuracy but struggle with dynamic graphs and large-scale problems due to their computational intensity. Heuristic algorithms like A* and ACO prioritize efficiency by guiding the search with approximations but may produce suboptimal paths if the heuristic is flawed. Hybrid algorithms combine the precision of classical methods with the adaptability of heuristics or machine learning, excelling in dynamic and complex environments, though they are computationally demanding. Each category fits specific use cases, from static graph analysis to real-time navigation in IoT systems. The choice depends on the trade-offs between accuracy, efficiency, and adaptability.

Table 5. Comparing the differences between Classical, Heuristic, and Hybrid shortest path algorithms:

Aspect	Classical Algorithms	Heuristic Algorithms	Hybrid Algorithms
Approach	Deterministic and mathematically grounded methods that guarantee optimal solutions.	Use approximations and heuristics to guide the search, improving efficiency.	Combine deterministic methods with heuristic or adaptive techniques for better performance.
Types	Dijkstra's, Bellman-Ford, Floyd-Warshall	A*, Greedy Best-First Search, Ant Colony Optimization (ACO)	Machine Learning-Based Pathfinding, Dynamic A*, Genetic Algorithm (GA)-Based Pathfinding
Optimality	Guarantees the shortest path under specified conditions.	Often provides near-optimal paths but does not guarantee the shortest path.	Balances between optimality and efficiency, often achieving near-optimal solutions.

Efficiency	Can be computationally expensive for large graphs or dynamic environments.	More efficient due to heuristic-driven search, reducing unnecessary exploration.	Achieves high efficiency by combining classical precision with heuristic adaptability.
Adaptability	Less adaptable to dynamic changes; requires recomputation if graph changes.	Can adapt to dynamic conditions but depends heavily on the heuristic used.	Highly adaptable to dynamic environments, often capable of real-time updates.
Complexity	Moderate complexity, often $O(V)$ or $O(V^2)$ depending on the algorithm.	Complexity depends on the heuristic; typically lower for static graphs.	Higher complexity due to combining methods but offers better scalability and adaptability.
Search Strategy	Exhaustive exploration of all possible paths to guarantee correctness.	Focuses on the most promising paths based on heuristic estimates.	Integrates heuristic guidance with deterministic calculations or adaptive learning.
Memory Usage	Requires significant memory for storing all paths and costs.	Requires less memory due to reduced search space.	Memory-intensive due to combined techniques and storage of additional learning parameters.
Applications	Network routing, static graph analysis, distributed computations.	Navigation systems, robotics, dynamic routing, and games.	Complex optimization problems, real-time navigation, IoT networks, and multi-agent systems.
Key Strengths	Accuracy and reliability; well-suited for static and well-defined problems.	Speed and efficiency, especially in large search spaces or dynamic environments.	Flexibility, scalability, and adaptability to changing conditions.
Key Weaknesses	Poor adaptability to dynamic graphs and computationally intensive for large-scale problems.	Heuristic quality impacts solution quality; suboptimal paths are possible.	Higher computational and implementation complexity due to combining methods.

4.2 Comparing the differences between Classical algorithms types

Table 6 compares four shortest-path algorithms based on their purpose, edge weight handling, complexity, and use cases. While Dijkstra's Algorithm performs best on sparse graphs with non-negative weights, Bellman-Ford handles graphs with negative weights and detects negative cycles. Floyd-Warshall efficiently determines all-pairs shortest paths for dense graphs, despite its processing demands. For sparse networks that require all-pairs shortest paths, Johnson's Algorithm combines the Bellman-Ford and Dijkstra algorithms. Each algorithm has pros and cons, and the requirements and graph topology determine which algorithms are applicable.

4.3 Comparing between Heuristic Shortest Path Algorithms types.

Based on their methodology, effectiveness, and use cases, A*, Greedy Best-First Search, and Ant Colony Optimization (ACO) are contrasted in Table 7. Although A* is memory-intensive, it guarantees optimal pathways with accepted heuristics by striking a balance between actual costs and heuristics. For speed, Greedy Best-First Search just uses heuristics, but it runs the risk of choosing less-than-ideal routes. ACO is computationally demanding yet excels at complicated, dynamic situations thanks to its use of pheromones and probabilistic exploration. Greedy is best for quick, easy searches, A* is best for optimal navigation, and ACO is best for large-scale optimization such as network routing and TSP. ACO stands out for its parallelism, which uses several agents to conduct exploration.

Table 6. Comparing the differences between Dijkstra's Algorithm, Bellman-Ford Algorithm, Floyd-Warshall Algorithm, and Johnson's Algorithm:

Aspect	Dijkstra's Algorithm	Bellman-Ford Algorithm	Floyd-Warshall Algorithm	Johnson's Algorithm
Purpose	Finds the shortest path from a single source to all nodes.	Finds the shortest path from a single source to all nodes.	Finds the shortest paths between all pairs of nodes.	Finds the shortest paths between all pairs of nodes.
Edge Weights	Non-negative weights only.	Handles both positive and negative weights.	Handles both positive and negative weights (no negative cycles).	Handles both positive and negative weights (no negative cycles).
Cycle Detection	Does not detect negative weight cycles.	Detects negative weight cycles.	Detects negative weight cycles.	Detects negative weight cycles during reweighting.
Time Complexity	$O(V^2 + E)$ OR $O((V + E) \log V)$ With priority queue.	$O(VE)$	$O(V^3)$	$O(VE + V^2 \log V)$

Graph Type	Best for sparse graphs with non-negative weights.	Works for any weighted graph (without negative cycles).	Suitable for dense graphs.	Best for sparse graphs.
Space Complexity	$O(V + E)$ for adjacency list implementation.	$O(V + E)$ for adjacency list implementation.	$O(V^2)$ due to the distance matrix.	$O(V^2)$ due to reweighting and distance matrix.
Approach	Greedy algorithm.	Dynamic programming with edge relaxation.	Dynamic programming with incremental updates.	Combines Bellman-Ford for reweighting and Dijkstra's for pathfinding.
Use Case	Best for routing in static networks with non-negative weights.	Used for distributed systems or graphs with negative weights.	Used for dense graphs or when all-pairs shortest paths are required.	Efficient for sparse graphs and all-pairs shortest paths.
Implementation Complexity	Simple to implement.	Relatively simple to implement.	Simple but computationally intensive.	Complex due to reweighting and multiple algorithms.

Table 7. Comparing between A*, Greedy Best-First Search, Floyd-Warshall Algorithm, and Ant Colony Optimization (ACO):

Aspect	A*	Greedy Best-First Search	Ant Colony Optimization (ACO)
Approach	Combines actual cost $g(n)$ and heuristic estimate $h(n)$ to find the shortest path.	Relies solely on the heuristic estimate $h(n)$ to guide the search.	Uses pheromone trails and heuristic information for probabilistic pathfinding.
Optimality	Guarantees the shortest path if the heuristic is admissible and consistent.	Does not guarantee the shortest path, as it only focuses on the immediate goal.	Does not always guarantee the shortest path but often finds near-optimal solutions.
Search Strategy	Expands nodes based on $f(n) = g(n) + h(n)$ balancing exploration and exploitation.	Expands nodes based on the smallest heuristic value $h(n)$ favoring goal-directed paths.	Explores multiple paths probabilistically and reinforces better solutions with pheromones.

Complexity	Memory-intensive for large graphs due to maintaining open and closed lists.	Requires less memory compared to A* but may explore irrelevant paths.	Computationally intensive for large-scale problems due to multiple iterations and pheromone updates.
Performance	Highly efficient with a well-designed heuristic, reducing unnecessary exploration.	Faster in simple graphs but prone to getting stuck in suboptimal paths if the heuristic is misleading.	Balances exploration and exploitation, making it effective for complex, dynamic problems.
Heuristic Dependency	Strongly depends on the heuristic for efficiency but guarantees correctness with admissible heuristics.	Fully relies on the heuristic, making its accuracy critical to the algorithm's success.	Partially dependent on heuristic; pheromone dynamics compensate for heuristic weaknesses.
Parallelism	Sequential, typically processes one path at a time.	Sequential, focusing on one path at a time.	Highly parallelizable, as multiple ants can explore paths simultaneously.
Applications	Used in navigation, robotics, and scenarios requiring optimal paths.	Common in quick pathfinding, like video games, where speed is more critical than accuracy.	Ideal for complex optimization problems, such as TSP, network routing, and dynamic systems.

4.4 Comparing between Hybrid Shortest Path Algorithms types.

Table 8 contrasts the use cases, complexity, and flexibility of ML-Based Pathfinding, Dynamic A*, and GA-Based Pathfinding. ML-Based Pathfinding uses machine learning to forecast the best routes; it works well in dynamic settings but needs a lot of training data and processing power. Dynamic A* adds overhead for static issues but ensures optimality in real-time scenarios such as robot navigation by incrementally adapting to graph changes. Despite its delayed convergence and need on parameter tuning, GA-Based Pathfinding effectively explores vast, complicated networks by applying evolutionary principles. Dynamic A* is effective in adaptive scenarios, GA flourishes in large-scale, intricate optimization tasks, and ML shines in high-dimensional domains.

Table 8. Comparing the differences between ML-Based Pathfinding, Dynamic A*, and GA-Based Pathfinding:

Aspect	ML-Based Pathfinding	Dynamic A*	GA-Based Pathfinding
Approach	Uses machine learning models (e.g., neural networks, reinforcement learning) to predict optimal paths based on historical and real-time data.	Extends the A* algorithm to handle changes in graph topology or edge weights during execution, adapting incrementally.	Uses principles of natural selection (mutation, crossover, and selection) to evolve paths toward an optimal solution.
Adaptability	Highly adaptive to dynamic environments by learning from data and adjusting in real-time.	Adapts dynamically to changes in the graph without recalculating the entire path.	Adaptive through population evolution but less responsive to real-time changes compared to ML or Dynamic A*.
Optimality	Provides near-optimal solutions, depending on the quality of training data and model accuracy.	Guarantees optimality in dynamic environments if changes are handled correctly.	Does not guarantee the shortest path but can find near-optimal solutions for complex problems.
Complexity	Computationally intensive due to model training and inference requirements.	Moderate complexity; efficient in dynamic graphs but requires additional logic for incremental updates.	Computationally expensive for large problems due to iterative evolution and evaluation of populations.
Key Limitation	Requires high-quality training data and computational resources for training and inference.	Less effective for static graphs due to additional overhead for incremental updates.	Convergence can be slow, and performance depends on carefully tuned parameters.
Search Space	Learns to optimize in high-dimensional and multi-variable spaces.	Focuses only on portions of the graph affected by changes, reducing unnecessary recalculations.	Explores large search spaces by evolving solutions, making it suitable for highly complex networks.
Parallelism	Parallelizable for prediction tasks, especially when using distributed machine learning.	Sequential but efficient in focusing only on relevant graph changes.	Highly parallelizable, as multiple solutions (populations) can be evolved simultaneously.

Applications	Intelligent transportation systems.	Dynamic environments like robot navigation or urban exploration.	Logistics and supply chain optimization.
	Real-time IoT network optimization.	Disaster response and adaptive routing.	Network routing for large, complex systems.
	-Autonomous navigation (e.g., drones, vehicles).		Scheduling and resource allocation.
Heuristic Dependency	Relies on predictive models rather than explicit heuristics.	Requires a heuristic to estimate path costs, similar to standard A*.	No explicit heuristic; solutions evolve based on fitness evaluation.

When comparing shortest path algorithms, traditional techniques such as Bellman-Ford and Dijkstra's are effective and dependable in static situations but ineffective in dynamic, adaptive networks. Greater flexibility and scalability are provided by heuristic algorithms like A* and ACO, which perform well in dynamic systems but need careful tweaking. Lastly, by fusing accuracy with flexibility and sustainability, hybrid algorithms such as Dynamic A* and ML-based models offer the most reliable results. We believe that hybrid algorithms, particularly those based on machine learning, provide the most promising way forward. They are perfect for complex, dynamic systems because they provide scalability and flexibility that are unrivaled by heuristic and classical approaches. But in the end, the particular application will determine which algorithm is best, taking sustainability, adaptability, and computational efficiency into account.

Conclusion

In network optimization, shortest path techniques are essential for striking a balance between scalability, flexibility, and efficiency. Traditional algorithms, such Bellman-Ford and Dijkstra's, function well in static networks but poorly in dynamic ones. Although they mostly rely on heuristic quality, heuristic approaches such as A* and Ant Colony Optimization effectively and adaptably handle these problems. Precision and flexibility are combined in hybrid techniques, such as Dynamic A* and machine learning-based algorithms, which perform well in complicated and dynamic situations but demand a large amount of processing power. Hybrid approaches that combine the advantages of machine learning, heuristic, and classical methods are the way of the future for shortest path algorithms. Promising avenues for enhancing security, scalability, and computational efficiency are provided by emerging technologies like blockchain and quantum computing. These developments will guarantee that shortest path algorithms remain relevant in meeting the needs of contemporary networks by redefining their function. These algorithms will continue to play a crucial role in facilitating effective, flexible, and dependable network communication across a range of applications by overcoming present constraints and integrating sustainability.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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