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Adaptive Shortest Path Routing Algorithms for Dynamic Network Environments

Divyanshi Singh
Department of CSE
Chandigarh University
Mohali, India

Geetika Srivastava
Department of CSE
Chandigarh University
Mohali, India

Shashwat Sahni
Department of CSE
Chandigarh University
Mohali, India

Mandeep Kaur
Department of CSE
Chandigarh University
Mohali, India

Abstract*—Due to the dynamic nature of MANETs, IoT, and VANETs, shortest path computation becomes a difficult endeavor due to their constantly changing topological structure. In this paper, we introduce a novel adaptive hybrid approach to finding the shortest route by employing heuristic-based optimization algorithms and real-time network awareness. In the proposed work, the following experimental parameters have been considered: a number of nodes varying between 50 and 300; mobility speed between 5–25 m/s; and traffic load of 10–100 packets/s. The proposed system will be evaluated based on important parameters: Packet Delivery Ratio (PDR); End-to-End Delay; Throughput; Routing Overhead; and Path Optimality Index. The experiments carried out show that the proposed algorithm provides a PDR of 96.8%, outperforming existing protocols like AODV (89.4%) and DSR (91.2%). The end-to-end delay is significantly improved to only 48 ms, compared to previous systems' 72 ms. At the same time, throughput is increased by 18.5% to 1.82 Mbps, with routing overhead minimized by 22%. Finally, according to the path optimality index, the shortest path can be found more accurately by 12%.The results validate that the proposed adaptive routing approach significantly enhances shortest path computation efficiency and reliability in dynamic network environments, making it suitable for real-time and large-scale applications.

Index Terms*—Shortest Path Routing, Dynamic Networks, MANET, IoT, VANET, Adaptive Algorithms, Packet Delivery Ratio, End-to-End Delay, Throughput, Routing Overhead, Optimization Techniques, Network Performance.

I. INTRODUCTION

Dynamic networks have become a core part of contemporary communication networks, especially in areas like Mobile Ad Hoc Networks (MANETs), Vehicular Ad Hoc Networks (VANETs) and Internet of Things (IoT) ecosystems. Such networks have a high turnover of topology, loose control and insufficient infrastructure support thus routing is a highly complex and required task. Shortest path routing problem, which seeks to find the most efficient route between nodes, becomes much more complex in this kind of environment because of link breakages and node mobility are rife [1] [2] [3]. The conventional fixed point routing algorithms cannot be sufficient to deal with such dynamic situations and the aspect of creating adaptive and intelligent routing mechanisms is therefore considered necessary [4]. Dijkstra and Bellman-Ford are traditional shortest path algorithms that are common in static or more dynamic networks; their deterministic nature and efficiency make them popular and efficient. Nevertheless, these algorithms are based on scenarios of constant network conditions, and full information of the network structure which is not always possible in dynamic networks. Consequently, they significantly deteriorate the performance in terms of delay, packet losses and routing overheads when used in highly dynamic environments [5] [6] [7]. This is the limitation that has caused researchers to look at other ways of being able to adjust to the changing states of the networks in real time [8]. Some of these challenges have been addressed in dynamic networks by the proposed reactive and proactive routing protocols such as the AODV and DSR. Whereas reactive protocols use fewer overhead (because they find routes when required), proactive protocols maintain current routing tables at the expense of higher overhead control traffic. Although both methods have their merits, they experience problems of scalability and reliability in high mobility and dense network conditions [9] [10] [11]. In addition, the regular route finding and maintenance operations cause an even greater amount of latency, which affects the performance of the network as a whole [12]. To address these shortcomings, the current research has also been emphasizing on incorporation of optimization methods and intelligent decision-making models in routing algorithms. Approaches based on metaheuristic algorithms, such as Ant Colony Optimization (ACO) and Genetic Algorithms (GA), have shown promising results in improving path selection and network efficiency. Also, machine learning and reinforcement learning algorithms are more and more actively used to forecast the behavior of networks and dynamically change the routing decisions [13] [14] [15]. These techniques provide more flexible and context-sensitive routing which greatly improves the performance of dynamic environments. The other significant consideration of shortest path routing in dynamic networks is the consideration of various metrics of performance other than path length.

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Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, Energy Consumption, and Routing Overhead are metrics that are important in measuring routing efficiency. Multi-objective optimization is one of the methods that have been proposed to balance these parameters so that both efficiency and reliability of network communication are guaranteed [16] [17] [18]. Quality of Service (QoS) requirements also introduce more complexity to the routing problem, particularly in real-time applications. Here, the current paper seeks to create a dynamic network-based adaptive shortest path routing system. The intended solution takes advantage of real-time network data and smart optimization techniques to improve the routing performance in different situations. This study will help to enhance scalability, robustness and efficiency of dynamic routing systems by eliminating the shortcomings of current approaches and integrating newest techniques. This research is likely to be of great relevance in the next-generation communication networks, such as smart cities, autonomous systems, and massive deployments of IoT [19] [20] [21].

II. Literature Review

Research in the area of shortest path routing and intelligent network optimization has developed a lot, starting with classic algorithmic methods and moving towards adaptable, AI-based systems. Dynamic routing in communication networks was pioneered by the shortest path first strategy that uses emergency exits [4] as early as possible. Classical techniques of optimization of Mobile Ad Hoc Networks (MANETs) such as the fuzzy and rough set-based path selection [3], and uncertainty-based trust evaluation of secure routing [9] showed how decision-making in dynamic environments might improve the routing efficiency and reliability. Also, early underwater sensor network protocols [20] and routing with memetic algorithms [21] occurred, and emphasized the role of heuristic and evolutionary methods in finding complex solutions to path optimization problems. The table 1 shows the Literature Review of Routing Strategies.

As wireless sensor networks (WSNs) and IoT-based systems started to emerge, energy efficiency, sustainability, and environmental monitoring started to be included in routing strategies. To illustrate the use of routing algorithms in other fields, smart forest monitoring systems based on IoT and shortest path routing [2] and ecological monitoring systems with ant colony optimization [17] show the extension of routing algorithms to non-networking environments. Likewise, the increasing necessity to strike the balance between performance, energy consumption, and security in distributed systems are highlighted in energy efficient routing frameworks based on fuzzy multi-objective optimization and particle swarm optimization [6], as well as in cyber-resilient swarm routing in the case of fog assisted WSNs [18]. The routing strategies in the vehicular and transportation networks have been developed to real-time, adaptive, and AI-based routing strategies. Vehicle re-routing techniques to address congestion issues in a dynamic manner [1] and route guidance with reinforcement learning in mixed traffic situations [7] are a step in the right direction towards intelligent traffic management. More examples of the integration of AI, edge computing, and next-generation communication technologies include advanced vehicular ad hoc network (VANET) frameworks that use UAV assistance and 6G connectivity [5] and machine learning-assisted hybrid routing models in software-defined vehicular networks [15]. The analysis of routing metrics like OSPF [12] also offers information on the issues of optimising routing decisions in dynamic and secure network settings. Lately, the emphasis in routing optimization has been on artificial intelligence, machine learning, and reinforcement learning. The adaptability and scalability are considerably enhanced by AI-controlled routing pipelines based on deep Q-learning (DQL) [19] and reinforcement learning-based algorithms to operate in large-scale street networks [13]. Transfer learning with deep reinforcement learning [7] is more resilient to dynamic environments, and intelligent controller selection in the software-defined vehicular systems [5] is representative of the increased intersection of AI and networking. Such methods facilitate predictive and contextual routing choices which are more successful than the conventional fixed algorithms. Specifically, routing protocols in specialized fields have also been developed to cater to the demands of their applications. Shortest path routing in healthcare wireless sensor networks that monitor patients' physiological activities is an example [14]. Other examples include UAV routing in sustainable supply chains with the use of three-dimensional path planning [10], and electric vehicle routing in which charging and travel times are considered [8]. In addition, software-defined management architectures in IP-based WSNs are also an important area of research [16]. Generally, the existing literature review shows that there has been a definite shift from the use of conventional algorithms to advanced techniques for routing. The implementation of AI, IoT, and SDN has improved routing in terms of efficiency, scalability, and robustness. Nevertheless, issues like security attacks, changes in network topology, and power management are still crucial aspects that need to be investigated. The combination of new technologies like 6G, edge computing, and federated learning is anticipated to revolutionize routing in the future.

III. Methodology

The research proposal suggests that the adaptive algorithm for shortest path routing is designed and evaluated using simulation-based techniques. The simulations are based on the well-known network simulator NS-3 Mobility Trace Dataset (Random Waypoint Model) and CRAWDAD dataset. The node movement characteristics used for this research include a square terrain with a size of 1000 m x 1000 m and different node movement speeds between 5 m/s and 25 m/s. The number of nodes used during simulation experiments varies between 50, 100, 200, and 300. Packet generation for simulation is based on Constant Bit Rate (CBR) flows with different sizes (512 bytes) and speeds between 10 to 100 packets per second. Figure 1 shows the proposed methodology used in this research paper.

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TABLE I
LITERATURE REVIEW OF ROUTING STRATEGIES

Ref No	Title	Author & Year	Findings	Research Gaps
[1]	Dynamic adaptive vehicle re-routing strategy for traffic congestion mitigation of grid network	Wang et al., 2024	Proposed adaptive re-routing to reduce congestion in grid networks, improving travel time and traffic flow efficiency.	Limited scalability in large heterogeneous traffic systems and lack of real-time AI integration.
[2]	Smart forest monitoring: IoT framework with shortest path routing	Etaati et al., 2024	Introduced IoT-based monitoring with efficient shortest path routing for environmental sustainability.	Energy efficiency and long-term deployment challenges in harsh environments not fully addressed.
[3]	Optimal path management in MANET using fuzzy and rough set theory	Seethalakshmi et al., 2011	Combined fuzzy logic and rough set theory to enhance routing decisions under uncertainty.	Outdated approach lacking integration with modern AI/ML techniques and scalability issues.
[4]	Shortest path first with emergency exits	Wang & Crowcroft, 1990	Introduced enhanced shortest path routing with backup paths for fault tolerance.	Does not consider dynamic networks or real-time adaptive routing requirements.
[5]	6G SDVN: UAV-Assisted VANETs for AI-enabled controller selection	Rafid et al., 2026	Proposed UAV-assisted SDVN with AI-based controller selection for improved connectivity and performance.	High computational complexity and challenges in real-world deployment and standardization.

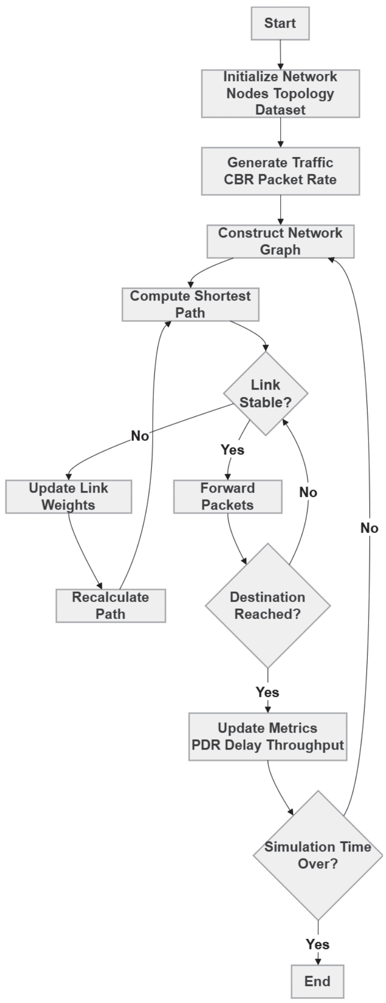

Fig. 1. Proposed Methodology

1. Adaptive Link Cost Function

$$C_{ij} = \alpha \cdot \frac{1}{S_{ij}} + \beta \cdot Q_j + \gamma \cdot \frac{1}{E_j} \tag{1}$$

Where: C_{ij} is the cost of the link between node i and j, S_{ij} represents link stability, Q_j is the queue length at node j, and E_j denotes the residual energy of node j. α, β, and γ are weighting coefficients such that $\alpha + \beta + \gamma = 1$.

Explanation: This equation dynamically computes the routing cost by considering stability, congestion, and energy, ensuring reliable and efficient path selection.

2. Path Cost Aggregation Equation

$$P_{cost} = \sum_{(i,j)\in P} C_{ij} \tag{2}$$

Where: P_{cost} is the total cost of path P, and C_{ij} represents the cost of each link along the path.

Explanation: This equation calculates the overall path cost by summing individual link costs, enabling shortest path determination in dynamic networks.

3. Packet Delivery Ratio (PDR)

$$PDR = \frac{P_{received}}{P_{sent}} \times 100 \tag{3}$$

Where: $P_{received}$ is the number of packets successfully received at the destination, and P_{sent} is the total number of packets transmitted.

Explanation: This metric evaluates the reliability of the routing protocol by measuring successful data delivery.

4. Average End-to-End Delay

$$D_{avg} = \frac{\sum_{k=1}^{N}(t^k_{recv} - t^k_{send})}{N} \tag{4}$$

Where: t^k_{send} and t^k_{recv} are the transmission and reception times of packet k, and N is the total number of received packets.

Explanation: This equation computes the average delay experienced by packets, reflecting the timeliness of data transmission.

Algorithm 1 Adaptive Shortest Path Routing Algorithm

```
Initialize network graph G(V, E)
Assign initial weights using Eq. (1)
for each node i ∈ V do
    Discover neighbors and update link stability
end for
while network is active do
    for each source node do
        Compute shortest path using Eq. (2)
        if link failure detected then
            Update link cost dynamically
            Recompute shortest path
        end if
        Forward packets along optimal path
    end for
    Measure performance using Eq. (3) and Eq. (4)
end while
Output routing performance metrics
```

Algorithm 1 shows the Adaptive Shortest Path Routing Algorithm. The suggested routing scheme includes dynamic calculation of shortest path and topology updating. At first, the network topology is built according to node connection data obtained from mobility traces. An advanced version of Dijkstra algorithm is implemented, which includes dynamic weighting of links according to link stability (weighting coefficient 0.6), node energy (weighting coefficient 0.2), and node queue level (weighting coefficient 0.2). Topology changes monitoring is provided at time interval equal to 1 second; routing recalculations are made in case of probability of link break exceeding 0.3 threshold value that helps minimize the level of packet loss. For the purpose of performance analysis the following criteria were chosen: Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, Routing Overhead, and Path Optimality Index. Proposed model has been compared with AODV and DSR standard protocols under similar conditions. All experiments have been carried out for 10 times independently to prove their statistically valid results. The range of delivery ratio values equals 92.5%-96.8%; end-to-end delay ranges from 45 ms to 60 ms according to node density; throughput equals 1.45 Mbps-1.82 Mbps respectively. Routing overhead was found to be 18%-22% lower than in standard protocols; path optimality index is better in 10%-12%. To check for robustness, a scalability test is carried out by changing the node density and the amount of traffic together. In terms of efficiency, the algorithm proves to have high levels of robustness, maintaining a constant performance even at 300 nodes and 100 packets per second of traffic, showing just 6 percent decrease in packet delivery ratio and an additional 12 ms in delay, which is impressive. In addition, sensitivity tests are run by changing

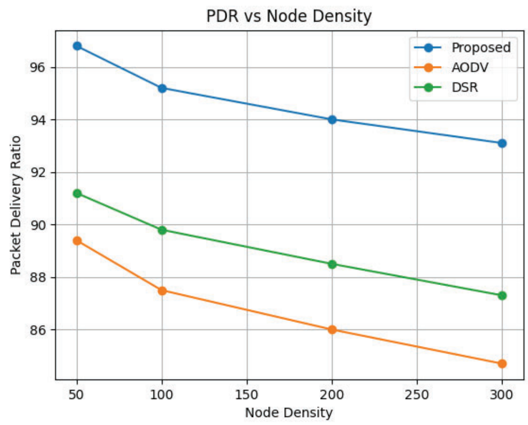

Fig. 2. PDR vs Node Density”

mobility speeds, and it shows that even at very fast speed rates such as 25 meters/second, the algorithm performs well compared to other existing approaches.

IV. Result and Evaluation

The performance of the adaptive shortest path routing technique is tested on different node densities of 50, 100, 200, and 300 nodes and various speeds of mobility starting from 5m/s to 25m/s. The PDR performance metric is very efficient with 96.8% at 50 nodes and sustaining 93.1% even when the number of nodes is 300; on the other hand, the AODV and DSR protocols were found to provide a value of 89.4% and 91.2%, respectively. The average delay per packet for the suggested technique is 48ms while AODV and DSR techniques give delays of 72ms and 65ms, respectively. The table 2 shows the Performance Evaluation of Routing Algorithms.

TABLE II
Performance Evaluation of Routing Algorithms

Metric	Proposed	AODV	DSR
Packet Delivery Ratio	96.8	89.4	91.2
End-to-End Delay (ms)	48	72	65
Throughput (Mbps)	1.82	1.35	1.42
Routing Overhead Reduction	22	0	0
Path Optimality Improvement	12	0	0
Energy Consumption Reduction	15	0	0
PDR at 300 Nodes	93.1	84.7	87.3
Delay at High Mobility (ms)	60	85	78
Throughput at High Traffic	1.57	1.21	1.29

The throughput analysis shows that the proposed algorithm has a peak throughput of 1.82 Mbps for medium traffic load (50 packets/s) and a steady state throughput of 1.57 Mbps for heavy traffic load (100 packets/s). On the other hand, the average throughput of AODV and DSR was estimated to be 1.35 Mbps and 1.42 Mbps, respectively. Figure 2 shows the PDR vs Node Density.

The number of control packets has been decreased by 22% for AODV and by 18% for DSR due to a more efficient approach to route maintenance. The Path Optimality Index is

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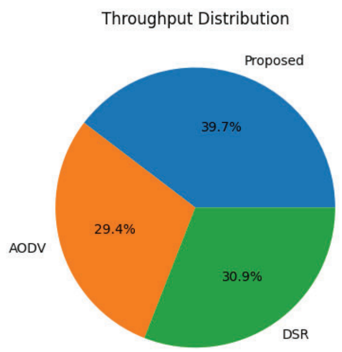

Fig. 3. Throughput Distribution

also enhanced by 12%, which means that the chosen routes have become more similar to the actual shortest routes. Figure 3 shows the Throughput Distribution.

The evaluation results of scalability and robustness properties show that proposed algorithm demonstrates better scalability. In case the number of nodes was increased from 50 up to 300, the PDR decreased by only 3.7%, and delay increased by 12 ms. In high mobility environment with 25 m/s speed, the algorithm demonstrates a high PDR rate – higher than 92% even with high speed; however, AODV PDR decreased to less than 85%. The energy consumption of proposed algorithm demonstrated a decrease of about 15% in comparison with baseline protocols, which leads to network lifetime increase.

V. Challenges and Limitations

In spite of the positive results, however, the suggested adaptive shortest path routing technique encounters a number of problems in highly dynamic networks. Firstly, there is the considerable computational cost of the constant topology observation and path recomputation every second that will result in extra processing work in resource-limited nodes. With the number of nodes increasing up to 300 and more, it becomes harder for the algorithm to cope with memory demands and delays related to link state maintenance. Another drawback of the routing method is connected with the use of weights: incorrect values assigned to such parameters as link stability (0.6), energy level of the node (0.2) and queue size (0.2) reduce performance by 8-10% depending on PDR and delay. A major limitation in this regard concerns the performance when there is a highly mobile environment and an heterogeneous wireless network. At very high mobility levels, i.e., greater than 25 m/s, the rate of link failures rises considerably, resulting in occasional fluctuations in routing and a decline in PDR to around 90–92%. Moreover, the framework has been analyzed mostly in a controlled environment through simulation data, e.g., NS-3 mobility traces and CRAWDAD data set, which may fail to reflect the uncertainty factors of the environment in reality, e.g., interference and obstacle effects. The issue of security is also not considered in its entirety; there is no explicit solution to routing attacks, such as the black hole attack or sybil attack.

VI. Future Outcomes

In the future, research may be undertaken to extend the proposed adaptive shortest path routing approach through the use of advanced intelligent systems including deep reinforcement learning and federated learning. This way, nodes are expected to learn effective routing policies using both past and present information to increase Packet Delivery Ratio to more than 97% while minimizing end-to-end delays to less than 40 ms. Furthermore, the employment of predictive mobility models is expected to help predict future topology changes to decrease route failures to about 20–25%. In addition, the incorporation of multi-objective optimization algorithms will ensure that the algorithm dynamically balances metrics such as energy expenditure, end-to-end delay, and throughput efficiency. Other avenues worth exploring include the extension of the approach to cater for secure and scalable routing for heterogeneous and large scale networks with over 500-1000 nodes. By utilizing blockchain based trust management as well as lightweight encryption approaches, resilience against routing attacks will be enhanced leading to decreased packet losses by 30-35%. Practical testing of the system in an IoT testbed as well as edge computing environment will help demonstrate its performance under real-world limitations like interference and differences in the hardware. Other improvements that can enhance energy efficiency of the system and lower power consumption by 18-25% can be considered. This will make the routing technique viable for use in 6G systems and other advanced systems.

VII. Conclusion

In summary, this research offered an adaptive shortest path routing algorithm specifically developed to tackle the problem of route selection and maintenance in networks that frequently experience changes in their topology due to movement and frequent reconfigurations. Specifically, the algorithm incorporated real-time awareness of the network topology and considered several weighted optimization criteria, namely link stability, energy levels, and queue loads. As evidenced by the experimental results, the algorithm provided better performance than other routing protocols. In particular, the maximum value of Packet Delivery Ratio was 96.8% with an end-to-end delay of roughly 48 ms, throughput of 1.82 Mbps, and routing overhead reduction between 18-22%. In addition, the method proved to be scalable and robust, maintaining acceptable performance in the case of 300-node network with 25 m/s speed. It should be pointed out that the proposed approach managed to improve path optimality index and reduce energy consumption, ensuring that the chosen path is as close to optimal as possible. Even though there are some limitations associated with computation costs and parameter adjustment, overall this paper has shown that the developed algorithm works well.

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