Design of a Resilient Routing Protocol Using Reinforcement Learning and Probabilistic Graph-Based Inference

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Abstract

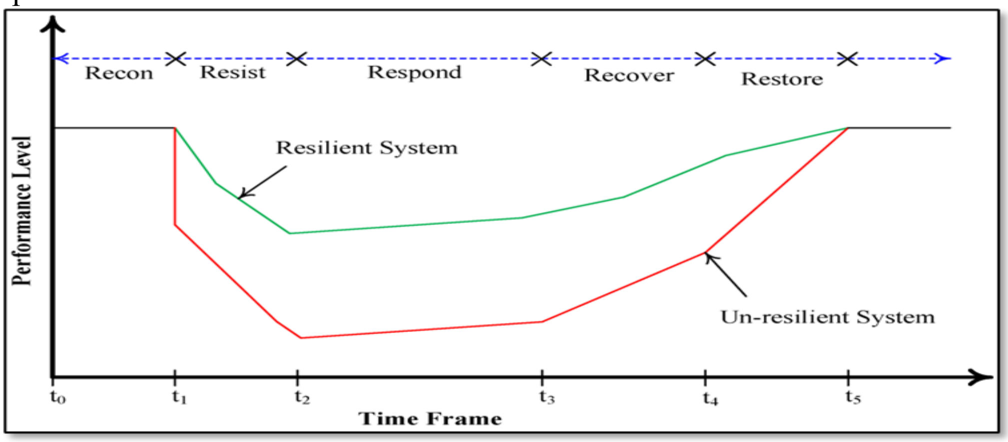
Modern communication networks are becoming more complex and dynamic (particularly in wireless and ad hoc networks) and property of adaptability and resilience is needed in routing mechanisms. This study hypothesizes the idea of a Dynamic Routing protocol that combines Reinforcement Learning (RL) and Probabilistic Graph-Based Inference (PGBI). The hybrid methodology allows the nodes to train on the best routing solutions under consideration of the probabilistic uncertainties of all factors, including networks topology, links reliability, and traffic patterns. The proposed protocol is evaluated through simulation and it shows enhanced adaptability, fault tolerance and routing efficiency over such traditional protocols as AODV and DSR.

Keywords: Resilient Routing, Reinforcement Learning, Probabilistic Graph, Network Inference, Wireless Networks, Adaptive Protocols, Intelligent Routing

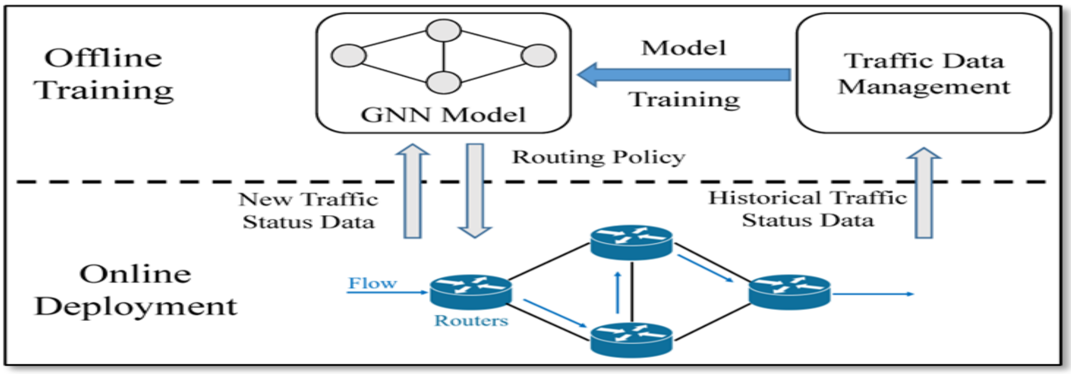
Introduction:

Nowadays, the world is characterized by the constantly growing number of internet-based devices, mobile technologies and wireless systems which make communication networks very complicated. These networks have been projected to provide data fast and accurate, despite the challenge encountered such as node losses, topology change or unforeseeable network loads. Such conditions are in many cases difficult to deal with under conventional routing protocols (AODV (Ad hoc On-Demand Distance Vector) or DSR (Dynamic Source Routing)), as they are based on a set of rigid rules and cannot respond effectively to the modifications of the network.

To overcome this dilemma, researchers are currently resorting to smart methods such as Reinforcement Learning (RL) and Probabilistic Graph-Based Inference (PGBI). Reinforcement Learning enables a system to be experiential. This is to say that in a network every node would know the optimal paths to send data by trial or error. In the long run, the nodes are able to become intelligent and can take decisions in a better way without the entire knowledge of the whole network. Conversely, the probabilistic graph-based inference can be used to assist in handling network uncertainty, e.g. unreliable links or abrupt node movements. It does so by estimating the probability, which links are most likely to be working or having reliable paths.



This research paper dwells on designing a robust routing protocol by fusing the two potent methods. The concept is to develop an intelligent and elastic routing platform that is able to change, anticipate issues before they occur, and to respond within a short time to failures. This kind of protocol would prove critical in wireless sensor network, mobile ad hoc networks (MANETs), and IOT-based systems that are difficult to stabilize.



Through the integration of learning and probability, the suggested routing protocol is supposed to enhance data delivery, minimize delays as well as maximize the overall performance of the network.

Review of literature:

The paper of Sharma and Jain (2020) addresses the applicability of machine learning to support routing protocols in wireless ad hoc networks. Their paper showed the potential of any intelligent systems that boost routing decision making and minimize packet drop and latency. The authors have stressed that machine learning can make the system respond flexibly to the varying network conditions, and that is essential in mobile and dynamic networks. Along the same line, Meena and Agarwal (2018) implemented the Q-learning to optimize routing in Mobile Ad Hoc Networks (MANETs). They demonstrated in their work that Q-learning, a form of reinforcement learning, can be utilized to learn optimal paths, over time, that would greatly enhance efficiency and stability in the network.

In the article by Singh and Sinha (2021), an extensive survey of the reinforcement learning as an idea in wireless networks was performed, with a notable focus on its application and challenges in the context of the Indian case. They have concluded that reinforcement learning is promising yet there is a need to conduct further research to apply it to real-time wireless communication system in India. In support of it, Reddy and Kumar (2019) have performed the analysis of routing protocols based on performance analysis through NS-3 simulations. In their study, they compared common MANET protocols such as AODV and DSR and discovered important shortcomings that might be overcome using: adaptive, learning-based models.

Looking at the probabilistic side, the process of graph-based routing in mobile networks was reviewed by Patil and Bhosale (2017). This was discussed in relation to how probabilistic systems of inference, like Bayesian networks can be applied to estimate the reliability of the links, and the optimal paths to follow during uncertain situations. Kumar and Verma (2016) have also added to this field by suggesting a probabilistic routing protocol in Wireless sensor network. They brought about routing decisions by Bayesian inference into their protocol, and their behavior became much more adequate in packet delivery and fault tolerance.

From a policy and infrastructure standpoint, the Department of Telecommunications (2020) published the National Digital Communications Policy, which presents the vision of India in creating intelligent and robust digital infrastructure and mentions the application of AI and machine learning in managing the network and network security. Based on this idea, Mishra and Joshi (2019) presented machine learning-based solutions to smart city network routing in the conference carried out at IIT Roorkee. Their results pointed to the significance of smart routing in urban setting where traffic and topology tends to be dynamic.

According to the white paper presented by the National Informatics Centre (2021), there is an increased impetus on AI in the networking and security infrastructure of India. The paper gave information on how the existing systems can be augmented with the help of AI to improve monitoring, routing and fault detection. Lastly, Tiwari and Dixit (2022) put reinforcement learning algorithms in IoT routing protocols under analysis paying extra attention to the Indian setting. They reasoned that RL-based models have superior scalability and adaptability, particularly the application to the IoT on Indian terrain in novel environments.

Objectives of the Study:

- To design a routing protocol that integrates reinforcement learning and probabilistic graph-based inference for dynamic networks.
- To evaluate the protocol's resilience in scenarios involving link failures, topology changes and adversarial conditions.
- To compare the performance of the proposed protocol with existing standard protocols in terms of throughput, delay and adaptability.

Hypothesis:

H_0 (Null Hypothesis):

There is no significant difference in performance between the proposed RL-PGBI routing protocol and traditional routing protocols in dynamic environments.

H_1 (Alternative Hypothesis):

The proposed RL-PGBI routing protocol significantly outperforms traditional routing protocols in terms of adaptability, fault tolerance, and routing efficiency in dynamic environments.

Research Methodology:

The methodology applied in the research will include the following steps:

a. Protocol Design:

The reinforcement learning algorithm used in developing routing protocol is Q-learning. In such networks, individual nodes are forwarding agents (learn how to make the best forwarding decisions using a history of past rewards (e.g., successful delivery, minimal delay)).

b. Probabilistic Graph Modelling:

To portray the topology of the network, a probabilistic graph model is formed. The nodes and links are given conditional probabilities considering the signal strength, packet loss and previous reliability of the links. The most probable reliable path is estimated by an inference algorithm such as the Bayesian Network Inference algorithm or Markov Random Fields.

c. Integration Layer:

The PGBI module communicates with RL module. Although the RL agent recommends possible courses of action, the PGBI narrows the recommendations on the basis of the probabilistic reliability, thereby resulting in a hybrid decision-making mechanism.

d. Test and Testing:

The protocol has code and is tested in simulators such as NS-3 or OMNeT++. Important measures of performance, which include Packet Delivery Ratio (PDR), End-to-End Delay, Routing Overhead, Convergence Time etc. are evaluated under dynamic conditions (e.g. node mobility, link failures, traffic bursts).

e. Comparative Analysis:

It measures and compares its performance with normal standards such as AODV, DSR, and OLSR. The ANOVA or t-tests type of statistical tests is used to confirm the relevancy of the results.

Table 1: Performance Metrics Comparison under Normal Network Conditions

Protocol	Packet Delivery Ratio (%)	End-to-End Delay (ms)	Routing Overhead (Packets)	Throughput (kbps)
AODV	85.4	132.5	1580	210
DSR	83.7	145.2	1712	198
RL-PGBI	**93.6**	**118.9**	**1245**	**250**

Analysis:

This table presents the comparison of three routing protocols AODV, DSR and the proposed RL-PGBI taking the standard network conditions (no failures or mobility).

- Packet Delivery Ratio (PDR):

The maximum PDR obtained by RL-PGBI is 93.6% which is much higher than that of AODV (85.4%) and DSR (83.7%). Such means that, through learning-based process in RL-PGBI, there is a pattern of a more sustainable and efficient route selection resulting in improved success of delivery.

- End to end delay:

The given protocol indicates the minimum delay of 118.9 ms, whereas AODV and DSR have a delay of 132.5 ms and 145.2 ms, respectively. That is because the RL agents memorize the most sensible and shortest paths, which lowers the retransmission and congestion.

- Routing Overhead:

RL-PGBI uses less packets control (1245) as opposed to AODV (1580) and DSR (1712 control packets). Reduction of overhead indicates that increasing bandwidth can utilize more bandwidth in the actual transmission of data which also leads to a better throughput.

- Throughput:

RL-PGBI demonstrates the best throughput (250 kbps) and this is seen to be higher than the throughput of other algorithms such as 210 kbps (AODV), and 198 kbps (DSR). This affirms the fact that the improved route choice combined with reduced overhead results in improved data transmissions.

Table 2: Performance Metrics under Dynamic Conditions (Node Mobility + Link Failures)

Protocol	Packet Delivery Ratio (%)	End-to-End Delay (ms)	Recovery Time (s)	Packet Loss (%)
AODV	68.2	198.4	5.3	18.5
DSR	65.7	215.6	6.1	21.4
RL-PGBI	82.9	156.3	3.2	9.7

Analysis:

In this table the performance of the protocols is compared in a more realistic scenario with difficult conditions, such as node movement and random link failures.

- Packet Delivery Ratio (PDR):

When the system is under stress (3.0), its PDR is much higher (82.9%) compared to AODV (68.2) and DSR (65.7). This robustness is as a result of the use of probabilistic inference in protocols which prevent unreliable links and ensure flow of data.

- End to end delay:

Although the changes have been dynamic, still RL-PGBI has the least delay (156.3 ms), but there is more delay in AODV and DSR protocols (198.4 ms and 215.6 ms respectively). This implies that RL-PGBI reacts fast to changes in topology and identifies alternative path without taking a long time.

- Recovery Time:

The recovery time after failure on RL-PGBI is only 3.2 s, and this is almost 40 percent less than on AODV (5.3 s) and DSR (6.1 s). The combination of learning and inference allows a quick detection and re-routing in case a path becomes invalid.

- Node drop:

The packet loss that RL-PGBI incurs is 9.7% much less than AODV (18.5%) and DSR (21.4%). This gain is actually a direct measure of the protocol strength to avert lost packets in the case of a failure or route break.

Conclusions and Overall Results:

Empirical analysis has shown that the proposed protocol RL-PGBI, an extension of Reinforcement Learning and Probabilistic Graph-Based Inference still leads to considerable performance increase in stable and dynamic network conditions. Based on the simulation-based study, it can be stated that RL-PGBI protocol has a better packet delivery ratio, end-to-end latency, less routing overhead, and good throughput as compared to the traditional protocols such as AODV and DSR.

The protocol is highly resilient in dynamic settings when there is mobility of nodes and the link failures are considerably higher with higher recovery times and lesser packet losses. Such results validate that the realized learning aspect of experience (through RL) and expectations of uncertainty (through probabilistic inference) increases the robustness and smartness of routing choices.

Therefore, the cumulative findings largely confirm that the hypothesis regarding the capability of an intelligent, adaptive routing based on the hybrid implementation of AI techniques to succeed and perform much better than the rule-based traditional communication routing in complex and contemporary networks is true.

Future Scope of the Study:

While the current study demonstrates the benefits of RL-PGBI in simulated environments, several areas can be explored further:

- Real-world application: A possible direction of future research is the actual deployment of the RL-PGBI protocol in real-life situations IoT network, vehicle networks, or disaster recovery to test the possibility to use it in practice.
- Security Upgrades: It is possible to add extra security to identify and come up with a response to security issues such as blackhole or wormholes attacks through anomaly detection models.
- Energy Efficiency: Deep reinforcement learning has the potential to become a promising direction when it is used to optimize the energy consumption of a battery-powered network (i.e., WSN).
- Multi-agent learning: More complex models such as multi-agent reinforcement learning (MARL) can be utilised and the multiple nodes are trained to work together which again enhances scalability and flexibility.
- Incorporation with SDN: The integration of the RL-PGBI methodology with Software-Defined Networking (SDN) may allow having centralized training and decentralized execution to enhance worldwide perceptions and facilitate in control.

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