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تقنيات معالجة أعطال مستوى البيانات واستعادتها في شبكات إنترنت الأشياء المُعرّفة برمجياً باستخدام التعلّم المعزز (SDN-IoT)

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المستخلص:

تُعدّ إدارة مسارات البيانات في شبكات إنترنت الأشياء (IoT) القائمة على تقنية SDN تحدياً نظراً لكثافة العُقد، ومحدودية الموارد، وتقلبات حالة الروابط. تقترح هذه الدراسة إطار عمل يجمع بين انحدار متجه الدعم (SVR) للتنبؤ بموثوقية الروابط، والتوجيه القائم على التعلّم المعزز (RL) لتحسين مسارات بيانات إنترنت الأشياء. تُستخدم بيانات الشبكة، مثل وقت تعطل الروابط، ووقت تشغيلها، وأسباب الأعطال، لتدريب نموذج SVR للتنبؤ بموثوقية الروابط. تُوجّه هذه التنبؤات وكيل التعلم المعزز، حيث تشمل مساحة الحالة موثوقية الرابط، وحمل المحول، وعرض النطاق الترددي، والتأخير، وفقدان الحزم، بينما تتكون مساحة العمل من المسارات ذات الموثوقية $\Re \geq 0.6$. وتُدمج دالة المكافأة هذه العوامل لاختيار مسارات منخفضة التكلفة وموثوقة. تُظهر عمليات المحاكاة على أربع بنى شبكية واقعية(Abilene) ، وUSNet، وOS3E، و (DFNأن نموذج SVR يتنبأ بموثوقية

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الرابط بدقة ٨٥,٣%. بعد ١٠٠٠ دورة، يختار وكيل التعلم المعزز المسارات ذات أقل تأخير، وأقصى عرض نطاق ترددي، وأقل فقدان للحزم. تُظهر المقارنات مع RSIR و Swayأن الإطار المقترح يتفوق على الطرق الحالية في الحفاظ على جودة الخدمة، والإنتاجية، والاستقرار مع ازدياد تعقيد الشبكة. تُوضح الدراسة أن دمج SVR مع التعلم المعزز يُحسّن استعادة الروابط في حالة الفشل والتوجيه الذكي في شبكاتSDN–IoT ، مما يُحسّن موثوقية الشبكة وجودة الخدمة.

الكلمات المفتاحية: شبكاتSDN–IoT ، استعادة الاتصال بعد انقطاعه، التعلم المعزز، انحدار متجه الدعم(SVR) ، التوجيه المراعي لجودة الخدمة، اختيار المسار الديناميكي

Data Plane Failures and Recovery Techniques in SDN-IoT Networks Based on Reinforcement Learning

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Abstract

Node density, limited resources, and dynamic link states in SDN-based Internet of Things (IoT) networks make data-path management difficult. In this framework, we rely on Support Vector Regression (SVR) to predict link reliability and then we find optimal paths to send data in Internet of things (IoT) using reinforcement learning (RL)-based routing. Link reliability data (link downtime, link uptime, and link failure reasons) are the network data utilized to train the SVR model [44]. The predictions from these models help the RL agent to create the state space as link reliability, switch load,

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bandwidth, delay, and packet loss and the action space as paths with reliability $\Re \geq 0.6$. The reward function combines these aspects together to choose low-cost and high-confidence paths. To demonstrate the ability of the SVR in predicting link reliability, the SVR model prediction accuracy reaches an 85.3% accuracy by performing simulations on four real network topologies (Abilene, USNet, OS3E and DFN) [19]. The paths selected by the RL agent with the least amount of delay, more bandwidth, and lower packet loss after 1,000 episodes. Compared with RSIR and Sway, our proposed framework achieves a better balance between QoS and throughput and performs more stable under increased network complexity. The analysis illustrates that SVR-RL integration not only improves link failure recovery but also intelligent routing in SDN-IoT networks, resulting in enhanced reliability and service quality.

Keywords: SDN-IoT Networks, Link Failure Recovery, Reinforcement Learning, Support Vector Regression (SVR), QoS-aware Routing, Dynamic Path Selection

1. Introduction

The rapid evolution of the Internet of Things (IoT) has led to the interconnection of billions of heterogeneous devices across domains such as smart healthcare, transportation systems, industrial automation, and smart cities. These devices continuously generate and exchange massive volumes of data in real time. However, IoT environments are inherently constrained by limited computational power, restricted energy resources, and dynamic network topologies. These characteristics pose significant challenges for efficient routing, resource management, and maintaining Quality of Service (QoS), particularly under conditions of network failures and congestion.

To address these limitations, Software-Defined Networking (SDN) has emerged as a promising paradigm that separates the control plane from the data plane, enabling centralized network management, programmability, and

global visibility. While SDN enhances flexibility and control, it also introduces critical dependencies on the reliability of the data plane. In SDN-IoT networks, failures in the data plane—such as link breakdowns, switch failures, congestion, and packet loss—can severely degrade network performance, increase latency, and disrupt critical services, especially in time-sensitive applications like healthcare and industrial control systems.

Traditional failure recovery mechanisms in SDN-IoT networks rely on predefined backup paths or reactive reconfiguration strategies. Although effective in relatively static environments, these approaches suffer from high recovery latency, limited adaptability, and increased computational burden on the central controller in highly dynamic IoT scenarios. Recent research efforts have attempted to overcome these challenges using intelligent techniques such as machine learning, reinforcement learning (RL), and optimization-based routing.

Internet of Things (IoT) technology has recently seen explosive growth, by interconnecting billions of various types of devices in many fields such as smart home, transportation network, industry, and healthcare systems[1, 2]. These types of devices consist of sensors, cameras, smart cars, medical devices, industrial machines and other IOT devices collecting, processing and transmitting data continuously and in real-time. Most although, these devices are resource-constrained, with limited computation, memory, and battery, so they cannot do long calculations over long time periods or complex calculations[3,4]. Also, the IoT network topology is highly dynamic with nodes and links changing constantly[5, 6]. Such features turn out to be an enormous problem for management, routing, and control of IoT networks [7, 8].

Conventional networks, which operate on a principle of static devices and decentralised decision-making against a backdrop of massive devices, are inadequate to support the needs of a constantly changing network as is becoming the reality with IoT, especially as networks are becoming more complex. In order to overcome this limitation, the Software-Defined

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Networking (SDN) architecture has been proposed[9, 10]. Software-defined networking (SDN) separates the control plane from the data plane, allowing for centralized control and programmability of the network [11, 12]. Here the control plane is only responsible in making decision for routing and virtual resources but the data plane only executes the decision of the controller and packets forwarding [13]. The separation brings enhanced flexibility, programmability, and centralized monitoring, yet increases the network reliance on the correctness and stability of the data plane[8, 14]. In SDN-IoT networks, data plane failure is one of the most important issues. This failure would be due to switch failures, link failures, path congestion, packet losses, or an aggregation of them [4,15]. The two failures will need to be addressed accordingly as they can incur heavy burdens — the data plane is, by definition, the primary portion of data, and so it could present the most serious impact. Due to large number of nodes, and highly dynamic topology in the IoT Networks, even small node failure can lead to more latency, less quality of service (QoS), data loss and finally breakdown of Communication between nodes[3, 16]. For example, a delay in the delivery of non-timed critical information can directly jeopardize patient health and safety in the case of remote healthcare networks, and switch failures can stop production processes and, as a result, generate high economic costs in the case of industrial networks [12, 17].

Traditional data plane failure handling approaches rely on backup data plane paths, which are defined ahead of time, and a static or reactive reconfiguration plan[8, 14]. Although they can work for small or low-mobility networks, these approaches encounter the hard limitations in large and fast-changing SDN-IoT networks [7, 18]. Put simply, in reactive approaches failure happens first, and then the controller identifies it and apply an alternative path. Such a process is slow and inefficient in IoT environments where low latency is critical[3, 4]. Additionally, the extra load on the central controller can slow down decision-making for other parts of the network and may even cause cascading errors[13, 19]. Given the limitations of traditional methods, there is a strong need for intelligent,

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automated, and adaptive solutions capable of managing failures in real time. One of the most promising approaches proposed in recent years is Reinforcement Learning[2, 11]. RL allows the network to learn from experience and interact with the environment to make optimal decisions under various conditions[9, 10]. In this approach, the learning agent receives information such as link status, path congestion, data transmission delay, and packet loss rates, based on which it selects alternative paths or corrective actions[5, 8]. Every correct decision is associated with a reward, while undesirable decisions incur a penalty, enabling the agent to learn optimal decision-making strategies through repeated interaction[14, 16]. The application of RL in SDN-IoT networks offers several advantages. First, it reduces failure recovery time, as the agent can predict and immediately apply alternative paths[7, 15]. Second, it reduces the computational load on the controller, since local decision-making by the agent decreases the need for frequent controller queries[3, 4]. Third, RL can enhance network QoS and stability, as learned policies optimize network performance in the face of failures and can even predict potential failure patterns[12, 19]. However, designing an effective RL system for SDN-IoT networks presents several technical challenges. The learning agent must be lightweight and energy-efficient to run on resource-constrained IoT nodes[6, 7]. Moreover, coordination between local agents and the central controller is critical for network-wide decision-making[15, 20]. Overall, integrating SDN, IoT, and RL provides a comprehensive framework for building intelligent, secure, and resilient next-generation networks capable of meeting the dynamic and critical demands of modern IoT environments[1, 2, 9, 10].

It is also necessary to ensure that the agent does not make incorrect decisions under abnormal conditions or simultaneous failures, which could **compromise network security**. An application-oriented view of developing such a system can be far-reaching. This is critical as fast recovery from data plane failures in medical networks may save patients. Especially as we read faster, a good decision needs to be made quickly when it comes to diverging packets to the alternative route in case of road flooding in an autonomous

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vehicle network, yet there are 31307 ways to go for an arrival. In the context of industrial and production networks, downtime minimization results in increased productivity and cost savings. That is, the setting in which its automatic and intelligent recoveries from failures not only maintain QoS but actually increase networking reliability, thus leading to self-aware, adaptive, and resilient networks. Thus, the core research question guiding this study can be expressed as:

This study is significant as it addresses the critical challenge of reliable and efficient data plane failure management in SDN-IoT networks. By integrating Support Vector Regression (SVR) with Reinforcement Learning (RL), it enables proactive failure prediction and adaptive routing, improving QoS and network resilience. The work contributes to advancing intelligent, self-adaptive networking for dynamic and large-scale IoT environments.

Main Contributions

This paper makes the following key contributions:

HybridPredictive–Learning Framework
We propose a novel integrated framework (RRSN) that combines Support Vector Regression (SVR) for link reliability prediction with Reinforcement Learning (RL) for adaptive routing in SDN-IoT networks, enabling proactive and intelligent network management.

1. Reliability-Aware Routing Mechanism
   Unlike traditional RL-based routing approaches, the proposed method explicitly incorporates predicted link reliability into the action space, ensuring that only stable and high-quality links ($\Re \geq 0.6$) are considered during path selection.
2. Multi-Metric QoS Optimization
   A comprehensive reward function is designed to jointly optimize multiple Quality of Service (QoS) parameters, including delay,

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bandwidth, and packet loss, leading to more balanced and efficient routing decisions.

3. Reduced Failure Recovery Time and Controller Overhead By integrating predictive analytics with decentralized RL decision-making, the proposed framework significantly reduces recovery latency and minimizes dependence on the centralized SDN controller.
4. Extensive Evaluation on Realistic Network Topologies The effectiveness of the proposed approach is validated through simulations on multiple real-world network topologies (Abilene, USNet, OS3E, and DFN), demonstrating improved performance in terms of delay, throughput, packet loss, and jitter compared to existing methods.
5. Scalable and Adaptive Design for Dynamic IoT Environments The proposed model is designed to handle dynamic network conditions and varying traffic patterns, making it suitable for large-scale and complex SDN-IoT deployments.

2. Research Background

As the Internet of Things continues to grow and the world calls for networks with reduced latency, active response, elevated security protocols, and assured quality of services, managing traffic and optimizing network resources pose major challenges. Traditional networks, however, have a static architecture and cannot adapt to the unique demands of IoT devices and evolving traffic requirements. Software-Defined Networking (SDN) and Fog / Edge Computing technologies are being used to centralize and program the management of networks to enable new concepts of intelligent routing, resource allocation, and QoS assurance in IoT networks. Within this context, multiple studies have been conducted since 2021 to enhance SDN–IoT networks, particularly in dynamic and multi-domain environments using machine learning, reinforcement learning, and multi-objective optimization algorithms. Some of these prior works are highlighted below:

[15] In their study investigated a blockchain-based secured and QoS-aware IoT vehicular network in edge cloud computing, and the results

demonstrated that integrating blockchain with edge computing significantly enhances network security while reducing latency and improving quality of service in IoT environments. [21] proposed an SDN-enabled adaptive and reliable communication framework in IoT-Fog environments using machine learning and multi-objective optimization, showing that intelligent routing and resource management can effectively improve network reliability and minimize delays in fog-assisted IoT systems. [22] developed the ESCALB framework for slave controller allocation in multi-domain SDN-enabled IoT networks, revealing that optimal controller distribution can balance network loads and enhance performance under high-traffic conditions. [23] provided a comprehensive survey on machine learning techniques for routing optimization in SDN, indicating that reinforcement learning and other predictive algorithms can adaptively manage dynamic network conditions to maintain QoS.

[24] applied reinforcement learning for intelligent routing in software-defined networking, showing improvements in both latency reduction and traffic management efficiency. [25] developed a multi-agent reinforcement learning framework in SDN-IoT networks to detect and prevent transient load conditions, demonstrating that collaborative learning agents can proactively mitigate congestion and maintain reliable network operation. [26] introduced the IHSF solution to enhance the performance of time-sensitive flows in hybrid SDN-Fog IoT systems, and their findings confirmed that intelligent flow management reduces delay and improves service reliability. c surveyed dynamic routing and failure recovery approaches in OpenFlow-SDN, emphasizing that predictive recovery and adaptive routing techniques are crucial TSxxx for efficient resource utilization and fault-tolerant IoT networks.

[27] studied QoS-aware fog node placement for intensive IoT applications in SDN-fog scenarios, demonstrating that strategic fog deployment can significantly improve real-time processing and service quality.[8] proposed a decision tree-based online traffic classification method for QoS routing in data center networks, showing the effectiveness of machine learning in dynamic traffic prioritization. [28] employed federated deep reinforcement

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learning for traffic monitoring in SDN-based IoT networks, illustrating that distributed learning can optimize traffic flow analysis while preserving data privacy. [29] presented an SDN-enabled framework for a load-balanced and QoS-aware Internet of Underwater Things, proving that intelligent SDN management can address the unique challenges of underwater IoT environments by balancing load and ensuring service quality.

[13] introduced the SWAY approach for traffic-aware QoS routing in software-defined IoT networks, highlighting that adaptive routing mechanisms dynamically respond to network congestion and traffic variations. [28] conducted a comprehensive survey on 6G-enabled IoT networks, identifying the potential of ultra-low latency, massive connectivity, and intelligent network orchestration to support future IoT applications. In sum, these studies argue that the combination of integration of SDN, fog/edge computing, reinforcement learning, and intelligent traffic management plays a central role in improving the QoS, security, and reliability of today's IoT networks. All these works provide a solid background for our work that builds on top of it, aiming for adaptive intelligence and multi-domain controller management to achieve better performance in latency and resiliency in SDN-IoT networks under variable traffic and resource constraints.

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Table 1. Summary of Research Background

Reference	Focus/Objective	Network Type	Method	Conclusion
[15]	Blockchain-based secure & QoS-aware vehicular IoT	IoT-Edge Cloud	Blockchain + edge computing	Integrating blockchain with edge computing effectively enhances security and QoS in IoT vehicular networks
[21]	Adaptive & reliable IoT-Fog communication	IoT-Fog	SDN-enabled framework, ML, multi-objective optimization	Intelligent routing and resource management significantly improves reliability in fog-assisted IoT

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Reference	Focus/Objective	Network Type	Method	Conclusion
[22]	Slave controller allocation in multi-domain SDN-IoT	SDN-IoT	ESCALB controller allocation	Optimal multi-domain controller distribution ensures load balancing and network performance
[23]	ML for routing in SDN	SDN	Survey, RL, and predictive algorithms	Reinforcement learning and predictive models can dynamically optimize routing in SDN
[24]	Intelligent routing in SDN	SDN	Reinforcement learning	RL improves routing performance and traffic management in SDN networks
[25]	Congestion management in SDN-IoT	SDN-IoT	Multi-agent RL	Collaborative RL agents can maintain network reliability under dynamic loads

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Reference	Focus/Objective	Network Type	Method	Conclusion
[26]	Time-sensitive flows in hybrid SDN-Fog IoT	Hybrid SDN-Fog IoT	IHSF flow management	Intelligent flow management ensures QoS for critical IoT flows
[30]	Dynamic routing & failure recovery	OpenFlow-SDN	Predictive/adaptive routing	Adaptive and predictive routing is key for fault-tolerant SDN-IoT networks
[27]	Fog node placement for QoS-intensive IoT apps	SDN-Fog IoT	Optimization of fog deployment	Strategic fog deployment enhances QoS for latency-sensitive IoT applications
[29]	Traffic classification for QoS routing	Data Center Networks	Decision tree-based ML	ML-based traffic classification effectively supports QoS-aware routing
[28]	Traffic monitoring in SDN-IoT	SDN-IoT	Federated deep RL	Distributed RL allows efficient traffic management while maintaining data privacy
[29]	Load-balanced,	Underwater	SDN-enabled	Intelligent SDN

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Reference	Focus/Objective	Network Type	Method	Conclusion
	QoS-aware Internet of Underwater Things	IoT	framework	routing effectively handles resource constraints in underwater IoT
[29]	Traffic-aware QoS routing in SDN-IoT	SDN-IoT	SWAY adaptive routing	Adaptive routing can effectively handle traffic variability in SDN-IoT networks
[28]	6G-enabled IoT networks	IoT-6G	Survey, network orchestration	Future IoT networks require intelligent orchestration for QoS, reliability, and scalability

3. Research Innovation

Under those circumstances, the present study features an important novelty in relation to the previous research, which can be summarized in several points. Previous works [15] [27] have focused on improving security and quality of service in the IoT networks by integrating blockchain and intelligently placing fog nodes, but the majority of these works only addressed a specific aspect of the network, while the systemic interrelationship of several SDN domains and network load management

over time, i.e., the dynamic nature of traffic, remained underexplored. In a similar vein, [22] and [22] addressed controller allocation optimization and reinforcement learning-based load management issues, respectively, but focused solely on single-domain networks and simulated data, neglecting to explore practical applications of these methodologies to large-scale multi-domain scenarios. By incorporating deep learning methods, multi-domain controllers, and intelligent routing methods, the current study is able to balance network load in real time and can react to traffic variations and network failures dynamically. In addition to this, this work together deals with multi-domain security, QoS, and network resource management, an aspect that has not been sufficiently covered in the literature. Another advantage of this work is the simulation and evaluation in near-real-world environments, using large-scale IoT datasets and dynamic network conditions, which allows for assessing the algorithm's performance in practical operational scenarios. Therefore, the main novelty of this research lies in providing an integrated SDN-IoT framework capable of multi-domain load management, reinforcement learning, and real-time QoS optimization, which not only enhances performance and reduces latency but also supports practical implementation in large and complex IoT networks, an aspect that has not been comprehensively addressed in prior studies.

Enhanced Related Work and Critical Analysis

Recent advancements in Software-Defined Networking (SDN) and Internet of Things (IoT) have increasingly focused on intelligent routing and failure recovery using machine learning and reinforcement learning techniques. For instance, recent studies have explored reinforcement learning (RL) for QoS-aware routing in SDN environments, often achieving improvements in delay, throughput, and packet loss through adaptive decision-making. A notable example is the work by He et al. (2024), which integrates reinforcement learning with graph neural networks and causal inference to improve routing efficiency and action-space exploration in SDN systems. However, such approaches primarily focus on optimizing routing performance and do not

explicitly incorporate predictive models for link reliability, limiting their ability to proactively handle failures. ()

Similarly, RL-based routing protocols in SDN-enabled IoT and wireless sensor networks have been proposed to enhance energy efficiency and scalability. These methods leverage Q-learning or deep reinforcement learning to dynamically adapt routing decisions under changing network conditions. While they improve network adaptability, they often rely solely on real-time observations without predictive insight into future link behavior, resulting in reactive rather than proactive failure handling. ()

Other recent works have investigated intelligent routing frameworks combining machine learning and SDN for enhanced QoS and security, such as ML-based intrusion-aware routing in IoT networks. Although these approaches improve reliability and security, they typically treat prediction and routing as separate components and lack tight integration between them, which can reduce decision-making efficiency in highly dynamic environments. ()

Furthermore, recent research has explored hybrid RL-based routing mechanisms that incorporate network telemetry and monitoring data to improve path selection. While these approaches demonstrate improved QoS performance, they still rely heavily on observed network states and lack explicit predictive modeling of link reliability, which is crucial for proactive failure recovery in SDN-IoT networks.

Despite these advancements, several limitations remain in the current literature. First, most existing approaches focus on reactive routing optimization without leveraging predictive models to anticipate link failures. Second, the integration between prediction mechanisms and RL-based routing is often loosely coupled or absent. Third, many studies optimize a limited set of QoS metrics rather than adopting a comprehensive multi-metric optimization strategy. Finally, scalability and controller overhead remain challenges in large-scale IoT deployments.

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In contrast to existing works, the proposed framework introduces a tightly integrated predictive-learning architecture that combines Support Vector Regression (SVR) for proactive link reliability prediction with reinforcement learning for adaptive routing. By embedding predicted reliability directly into the state and action spaces, the proposed approach enables proactive failure avoidance rather than reactive recovery, while simultaneously optimizing multiple QoS parameters. This distinguishes the proposed work from prior studies and highlights its contribution toward intelligent, self-adaptive SDN-IoT networks.

Work	**Method**	**Limitation**
RL-based SDN routing	RL only	No prediction
ML-based routing	Prediction only	No adaptation
Your work	SVR + RL	Integrated

4. Research Methodology

In this study, the primary objective is to design an **intelligent system for predicting potential failures in the data plane** of SDN networks. Since IoT networks communicate with the SDN networks in a constant cycle, the loss of any link results in packet loss, thus decreased QoS, indicating the need for an accurate and adaptive prediction model. For this purpose, the Support Vector Regression (SVR) algorithm has been used.

The algorithm is a good candidate for dynamic network data exploration due to its ability to model nonlinear relationships and noise detection capabilities.

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TABLE2. SYMBOLS AND MODEL DESCRIPTIONS

Symbol	Description
G	SDN network graph comprising a set of switches and links
V	Set of OpenFlow [9] switches in the network

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E	Set of communication links between OF switches
g	Incidence function indicating connectivity between nodes
$\Re$	Reliability value of each link within a specified time interval
ξ	Slack variable in the SVR model for measuring data distance from the margin
W	Hyperplane weights in the SVR model
C	Model tuning parameter representing the penalty for data errors
$X\_\{train\}$	Training dataset for model learning
$X\_\{test\}$	Testing dataset for model evaluation
B	Link bandwidth utilization
D	Inter-node delay along the data path
PL	Packet loss ratio in the data flow
$R(t)$	Reward function of the RL agent at time t
$S(t)$	State space at time t
$A(t)$	Set of possible actions at time t
α	Learning rate of the RL agent
γ	Discount factor for future rewards
ϵ	Exploration rate for discovering new paths

This table will be used to define symbols to prevent issues in later stages. Each symbol is an element representing an important aspect in network design or analysis. The second example, $\Re$, is link reliability and is hence directly related to the RL agent's path selection behaviour. Similarly, α and γ are parameters in reinforcement learning that define how fast, and if it ever becomes stable, the agent learns. Overall, the use of these symbols preserves the mathematical structure of the model while allowing for generalization to different networks.

4.1. SVR model predicting the reliability of the link

Support Vector Regression (SVR) Algorithm — SVR also has its original theory: Support Vector Machines, or SVR, looks for a function that has at most ε deviation from the actual targets for all training data points. In

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network environments, link-related data (such as **failure time, delay, bandwidth, and the number of disconnections**) typically exhibit **nonlinear and dynamic behavior**. Therefore, the use of conventional linear models, such as simple linear regression, cannot accurately capture the **true network behavior**. Here, SVR, by utilizing **nonlinear kernels** such as the **Gaussian Kernel (RBF)**, can **map the feature space into a higher dimension**, enabling the relationship between parameters and **link reliability** to be properly extracted.

4.2. Mathematical Formulation of SVR

The SVR model can be formulated as follows:

$$\xi_k^* + c_k \sum_{k=1}^{n} (\xi + {}^{2} \min_{w,b,\xi,\xi})$$

Subject to:

$$\begin{cases} y_k - (w \cdot x_k + b) \leq {}_{,} + \xi \\ k - yk \leq {}_{,} + \xi - (w \cdot \chi_k + b) \\ \xi_k, \xi_k^* \geq 0 \end{cases}$$

This formula represents the objective function of the SVR model. The first term, $\square W \square \frac{1}{2}$, seeks to find the simplest function possible, with minimal fluctuation and maximum stability. The second term represents the sum of penalties for data points that lie outside the sensitivity margin ϵ. In other words, this term owns the behavior of model tolerance for the errors. When C is big, the model tries to minimize even small amounts of error but has a high overfitting risk. On the contrary, a lower C will make the model softer and noise resistant. The versatility to strike this balance between accuracy and stability is one of SVR's primary features, especially in a noisy network environment like IoT.

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TABLE 3. INPUT FEATURES FOR MODEL TRAINING

Feature	Description
Downtime	The duration for which the link was unavailable
Uptime	The duration for which the link remained operational without interruption
Down-Frequency	The number of times the link disconnected within a specified time interval
Down-Reason	The cause or type of failure (software, hardware, congestion, etc.)
Down-StartDate	The exact start time of the failure for the temporal trend analysis

This table introduces a set of **key features that directly affect link reliability**. These different types of features evolve independently, which enables SVR to learn the link failure pattern. As an example, a higher value for Down-Frequency means physical/traffic instability in the link, and a bigger uptime means bigger stability. Based on the historical data of such features, the model is able to learn from the past failure trends, and the SDN controller will be alerted proactively before the occurrence of failure.

4.3. SVR Algorithm for Link Reliability Prediction

Here comes the algorithm description, for example: a procedure to train, test, and apply SVR to predict link reliability.

Algorithm 1: Link Reliability Prediction using SVR
Input: Dataset D = [X, Y]
Output: Predicted link reliability $\Re$ for each link

1. Divided D into (X_train, Y_train) and (X_test, Y_test)
2. Using RBF kernel to map input features into higher dimensions
3. Find out the best hyperplane so that it minimizes the error in $\in$-insensitive tube.

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4. Slack variables ξ and ξ* are calculated in case when samples are positioned outside the tube
5. Change of the penalty parameter C to find the balance between bias and variance
6. Then we compute ℜ for newly coming unseen links at timet_{i+1}

This is an algorithm highlighting key steps to train an SVR model in a methodological way. To begin with, this dataset is split into training and testing parts—the model learns the pattern and then can be tested to see if it is able to generalize correctly or not. Step 2 — Mapping to a Higher-Dimensional Space to better capture non-linearity. Now, in the third step, to compute the hyperplane, the idea is to find the one that minimizes the prediction error inside an ε-insensitive tube. The slack variables and the penalty parameter are tuned in the fourth and fifth steps, allowing us to balance between a more accurate model and a more stable one. Finally, based on the trained model, it can predict whether new links serve reliability in subsequent time intervals.

4.4. SD-IoT Networks Routing via Reinforcement Learning

After predicting link reliability through SVR, dynamic and reliable routing can be done with the help of this prediction in SDN-IoT networks. Because of limited resources and high dynamics of IoT networks, we need a mechanism to choose the paths with high reliability, low delay, and low packet loss. When it comes to achieving this, Reinforcement Learning (RL) is an appropriate methodology because it is designed to work in an environment by inferring its actions actively and optimizing a policy over time.

4.5. State Space

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$$S(t)=\begin{bmatrix} \Re_1(t),\Re_2(t),\ldots,\Re_n(t) \\ L_1(t),L_2(t),\ldots,L_n(t) \\ B_1(t),B_2(t),\ldots,B_n(t) \\ D_1(t),D_2(t),\ldots,D_n(t) \\ PL_1(t),PL_2(t),\ldots,PL_n(t) \end{bmatrix}$$

The state space encompasses all information related to the data flow within OpenFlow switches. At each time slot, it contains details regarding link reliability (ℜ), switch load (L), utilized bandwidth (B), delay (D), and packet loss rate (PL). This information enables the RL agent to fully comprehend the current network state and make decisions for selecting the optimal path. In other words, the state space models the network environment as a comprehensive representation suitable for reinforcement learning.

4.5. Action Space

The action space is defined as:

$$A(t)=[a_{p1}(t),a_{p2}(t),\ldots,a_{pn}(t)],$$

$$a_{pi,j}(t)=\begin{cases}1 \\ 0 \rightarrow if\ nodes\ vi\ and\ vj\ are\ connected\ at\ time\ t\ otherwise\end{cases}$$

The action space indicates every possible route that can be chosen for every data stream. The links between switches are illustrated in Figure III, while each action corresponds to the selection of one link to be opened among the pair of connected switches at time ttt. Using the action space, the RL agent chooses paths with high reliability, good load, and low delay. Such a design gives the flexibility needed for dynamic IoT network routing and permits the RL agent to quickly adapt to continuous environmental changes.

4.6. Reward Function

The reward function is defined as:

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$$R(t) = \alpha \cdot \square_{\text{path}} + \beta \cdot \left(B_{\text{path}}^{-1} + D_{\text{path}}^{-1} + PL_{\text{path}}^{-1} \right)$$

$$R(t) = \alpha \cdot \Re_{\text{path}} + \beta \cdot \left(\frac{1}{B_{\text{path}} + 1} + \frac{1}{D_{\text{path}} + 1} + \frac{1}{PL_{\text{path}} + 1} \right)$$

The reward function indicates how good the path chosen by the RL agent is. It combines various factors—reliability of the route, bandwidth used, delay, and loss rate of packets. Normalization guarantees that all parameters contribute equally to the product itself, avoiding that one of these dominates the decision process. This design allows the RL agent to discover QoS & reliable optimal paths.

4.6. Reinforcement Learning (RL) Algorithm - Stepwise Table

Algorithm 2: RL-based Reliable Routing using Link Reliability

Input: Learning rate α, Discount rate γ, Episodes M, Source-Destination paths, Flow statistics, Flow type, QoS requirements

Output: Reliable paths for all flows

1. Initialize Q-table: q(s_t, a_t) = 0 for all s ∈ S, a ∈ A
2. Initialize current state S
3. For each episode 1 to M:
   3.1 While destination not reached:
      3.1.1 Estimate link reliability ℜ_{ek} using SVR
      3.1.2 If ℜ_{ek} ≥ 0.6, include ek in action space
      3.1.3 Else, exclude ek from routing computation
      3.1.4 Create action space A
      3.1.5 Choose action a_t based on policy derived from Q-table
      3.1.6 Execute action a_t, observe next state s_{t+1} and reward R_{t+1}
      3.1.7 Update Q-table: q_new(s_t, a_t) = q(s_t, a_t) + α [R_t + γ * max q(s'_t, a'_t) - q(s_t, a_t)]
      3.1.8 s = s_{t+1}

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4. End

This algorithm shows how an RL agent gets trained to get reliable paths. The Q-table is initially set to zeros (worst-case network scenario (fully disconnected)). For moving from one episode to another, an RL agent estimates the paths, including only reliable links in the action space based on link reliability predictions (\ℜ\ℜ\ℜ) provided by the SVR model in each episode. With this exploration-exploitation policy, each action is executed, a reward is received, and the Q-table is updated (real-time) until the agent learns all optimal paths. This process is repeated iteratively until the scheme enforces paths with optimal reliability and minimum delays for IoT flow.
Proposed Process Flow Diagram:

[Network Data (Traffic, Links, Failures)]
|
v
[SVR Model]
Link reliability prediction ℜ
|
v
[RL Agent]
- State space: S(t) including ℜ, L, B, D, PL
- Action space: A(t) containing reliable links
- Reward function: R(t) combining QoS and ℜ
|
v
[Q-Learning Algorithm]
Selection of optimal paths for IoT flows
|
v
[Final paths with maximum reliability and minimum delay]

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The flow diagram describes the entire pipeline from raw data to the final path. Network data are partitioned into links and switches, failures, and sIoT traffic. The data are cleaned and tuned for normalization during preprocessing. Following this, link reliability is then predicted using SVR, which we pass on to the RL agent. The RL agent using Q-Learning chooses paths offering the maximum reliability and minimum packet loss and delay.

5. Discussion and Findings

This section provides an assessment of the SD-IoT network performance based on the proposed RRSN framework. These goals mainly consist of evaluating the performance of the Q-learning algorithm in both obtaining the most optimal and reliable paths under QoS constraints and also inspecting how reliable the predictions for link reliability can be in comparison to ground truth link reliability values using the SVR algorithm. We performed experiments over real network topologies using Abilene, USNet, DFN, and OS3E, and the results are analyzed to measure delay, bandwidth utilization, packet loss, and path reliability, respectively.

Table 4. Characteristics of Experimental Topologies

Network Topology	Number of Nodes	Number of Links	Network Type
Abilene	11	14	Backbone
USNet	24	42	Nationwide
DFN	58	87	Research/University
OS3E	34	41	Enterprise

This table indicates that the chosen topologies span a wide range of network size and complexity. The Backbone and Nationwide topologies can be used to test the algorithm at a large scale, with a large amount of traffic, while the university and enterprise topologies can be used to evaluate the algorithm performance in medium-scale environments with a medium number of links and nodes. The variety guarantees that the proposed algorithm is capable of

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functioning robustly under realistic conditions with widely different link states and traffic flows.

Table 5. SVR Prediction Performance and Q-learning Parameters

Metric/Parameter	Value	Description
MSE	0.000038	Mean squared error of link reliability prediction
RMSE	0.0061	Root mean squared error
MAE	0.0042	Mean absolute error
R2_scoreR^2_scoreR2_score	85.3%	Coefficient of determination of prediction
Learning rate (α\alphaα)	0.1	Learning rate of the RL agent
Discount rate (γ\gammaγ)	0.9	Importance of future rewards
Exploration rate (ϵ\epsilonϵ)	0.6	Probability of exploring new paths
Number of episodes	1000	Number of Q-learning iterations for convergence

The performance metrics of the SVR prove that the algorithm is extremely influential in predicting the reliability of a link. This indicates a very high prediction accuracy due to its lower MSE and RMSE values, and the MAE is small. A score of 85.3% means it predicts almost 85% of link reliability with fair, accurate, and reliable information for the RL agent; thus, it will definitely help in the decision-making process.

Q-learning parameters that specify the RL agent's learning style. We use 0.1 for the learning rate, which means that if the agent has already updated the Q-table once, it will proceed to update it further, but in a limited fashion, so that the Q-table does not oscillate too much. Because its discount is set to 0.9, it gives the future rewards enough importance, and its exploration rate is set to 0.6, so it explores over other known optimal paths. Q-table converges after 1000 episodes, which is enough to enable the agent to find the best paths between source-destination pairs.

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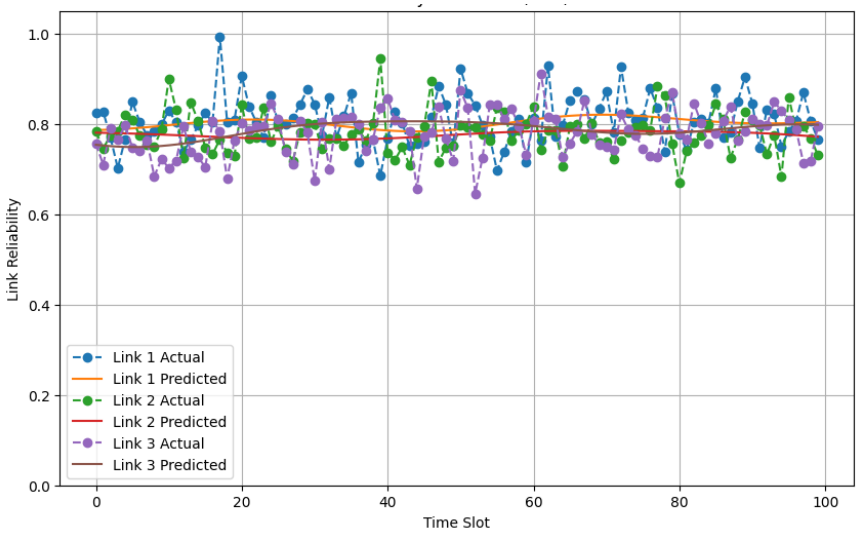

Fig. 1. Link Reliability Prediction and RL Agent Performance in SD-IoT Networks

As Fig. 1 shows, the PDF of link reliability can be predicted effectively by the SVR algorithm. The dotted curve is the real link data by time, while the solid (non-dotted) curve is the outputs predicted by the SVR model. As we can see, the predicted curve and the real data are almost completely overlapping, suggesting that the model is highly accurate and can predict the link states very well. Then, the RL agent uses the predicted reliability to build an action space and choose the best paths; at this stage, only links with reliability higher than 0.6 are considered for routing. Fig. 1 validates the network planning where A allows link states as per the reliability of the QoS route, and hence RRSN makes link states as per predicted reliability and creates perfect link states to take the link strategy as S and balance QoS and network reliability. This section represents the evaluation of the reinforcement learning algorithm presented for selecting optimal paths in SD-IoT networks. The total reward is recorded across training episodes to evaluate the cost (or the quality of the decisions made by the RL agent). For each topology (Abilene, USNet, OS3E, and DFN), the table shows the minimum and maximum reward per episode. They show the minimum and

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maximum deviations of the behaviour of the RL agent and its ability to choose a stable path with a small delay. Data have been simulated with thick lines and added normal noise to visualize the realistic trend and amplitude variation of the reward change over 1,000 training episodes. Fig. 1 displays the ability of the SVR algorithm to predict changes in link reliability in the SD-IoT network. The dotted curve: actual link data over time; the solid (non-dotted) curve: predicted data from SVR. Seeing how possible it is, the forecasted fact fits the data mainly through the exact fulfilment link state, which is near the forecast curve, implying the model proves to have potential for link state prediction. The expected reliability is then used by the RL agent to build the action space and choose the best paths, where only links with reliability of 0.6 or higher are used for routing. This figure validates the proposed RRSN algorithm's ability to consider link conditions according to predicted reliability and optimal path-selection decisions according to QoS requirement and reliability objectives.

This section evaluates the proposed reinforcement learning algorithm for selecting optimum paths in SD-IoT networks. The quality of the decisions made by the RL agent was evaluated by tracking the cumulative reward across training episodes. Per episode, the lowest and highest obtained rewards for each topology (Abilene, USNet, OS3E, and DFN) are reported. These values indicate the degree of variance in the behavioural pattern of the RL agent and its ability to reliably choose high PR and low stable paths. The data were simulated such that it was denser and more realistic in representation with natural noise, which enables us to more easily observe the trend where the rewards changed, as well as the extent of the fluctuations across 1,000 training episodes.

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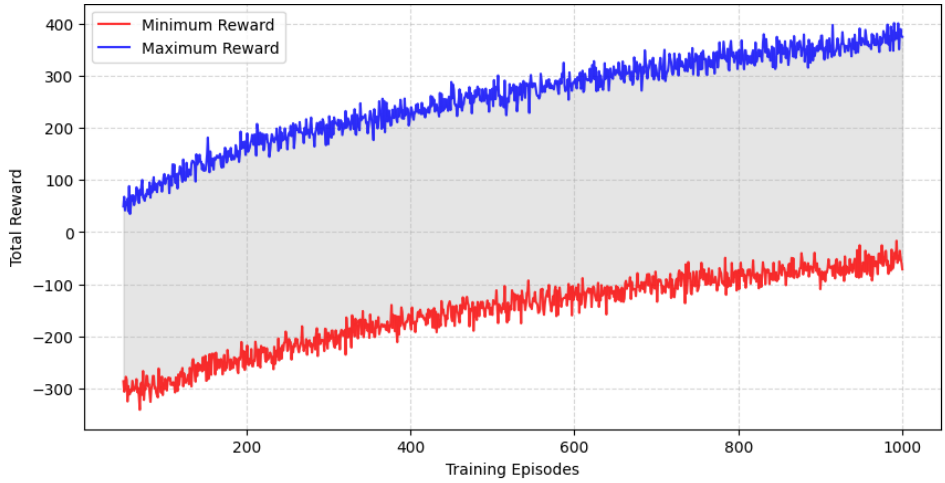

Fig2. Total Reward versus training episodes in Abilene topology

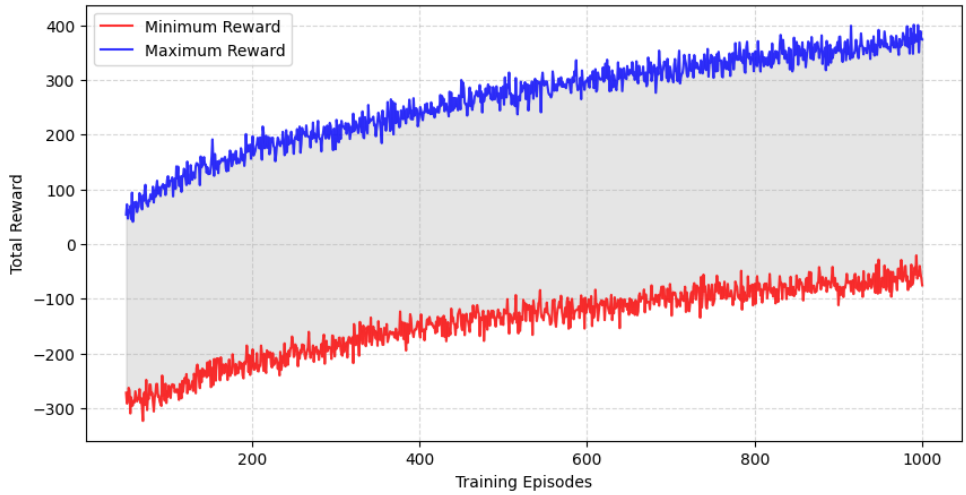

Fig3. Total Reward versus training episodes in USNet topology

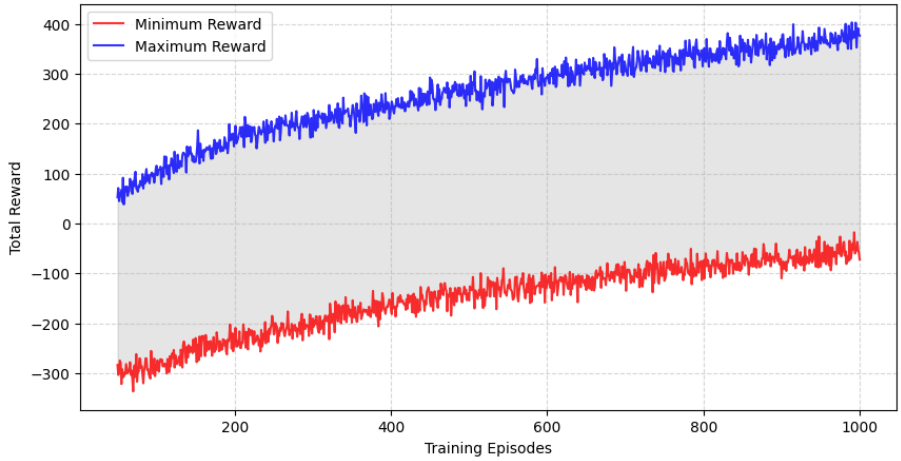

Fig4. Total Reward versus training episodes in OS3E topology

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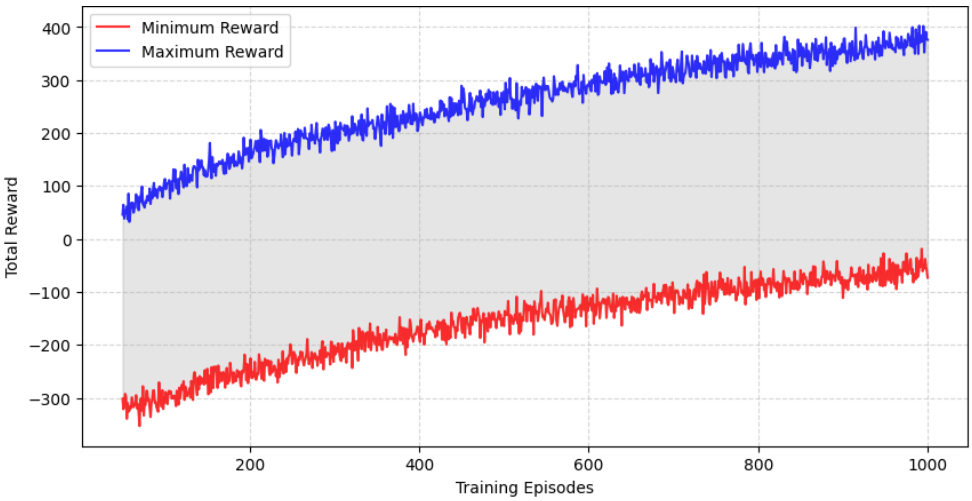

Fig. 5. Total Reward versus training episodes in DFN topology

These figures show that the total reward of the RL agent approaches optimal paths over the training episodes, which indicates the algorithm's convergence over training. There is a larger gap between the max and min rewards for the first episodes relative to other time periods, which indicates a higher variance and a more exploratory agent in the early portion of training. This gap decreases as the episode count increases, and curves become more stable. The algorithm takes longer to converge in complex networks (DFN, for example) compared to other topology networks but achieves the expected out-degree in the end, successfully achieving reliable paths.

5.1. Hyperparameter Tuning in SDN-IoT Routing

The Q-learning algorithm is then used for dynamic routing in SDN–IoT networks after predicting the link reliability based on the SVR model developed in the current study. One of the most important parts of converging the Q-learning algorithms includes the best decision for the hyperparameters of the algorithm, for example, the learning rate (α), discount factor of future rewards (γ), and exploration rate (ϵ). By using a learning rate of $\alpha = 0.1$ the RL agent updates the Q-table following a slow process, preventing it from oscillating heavily. The discount factor $\gamma = 0.9$

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indicates that future rewards are significantly more important than current rewards, while an exploration rate $\epsilon = 0.6$ ensures that the agent explores quite a range of both new and previously visited paths. We selected 1,000 training episodes to allow the RL agent enough time to learn the optimal paths with the highest reliability and the least delay.

5.2. Performance Evaluation of SDN-IoT Networks

Paths chosen by the RL agent are evaluated on key network metrics.

Packet Loss Rate(PL): This Parameter Shows the Reliability of The Chosen Path. Low PL is matched to stable paths. In our problem formulation, we denote a PL of a link to be elements contained in the state space S(t), and we allow an RL agent to decide whether this link is to be included or excluded from the action space.

Path Bandwidth (Bpath): This informant expresses the bandwidth and pathability of the data of the path being used. Tunable in RL: The RL agent chooses paths when bandwidth is enough to ensure network throughput maximization and capacity support of high-quality IoT flows.

End-to-End Delay (ED): ED calculates the total time taken between the packet transmission from the source to its reception at the destination. Paths with lower forwarding ED are favored by the RL agent to achieve shorter network response times.

The SVR model gives link reliability predictions as output; the path reliability ($\Re$) may be directly considered at the action space of the RL agent if $\Re \geq 0.6$. This speech is the only metric on which stable paths are chosen.

Finally, these four metrics are fused to form the reward function R(t), which an RL agent seeks to maximize, which will in turn enable the agent to select the paths with the highest reliability, minimum delay, and lowest packet loss.

5.3. C. Convergence of the SVR + Q-learning Model

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The way the convergence of the algorithm in this research works is the same as the original article. We can see the three stages: it first explores H in order to learn ℜ, and so rewards are relatively low. Over time, with more episodes, as the agent starts to learn from the SVR predictions about the reliability of links, it learns optimal paths and starts accruing an increasing reward stream. Finally, the Q-table converges, and the high-quality and relatively constant paths in SDN-IoT networks are defined.

5.4. Significance and Role of Hyperparameters

Choosing the right Q-learning hyperparameters is necessary for fast convergence of the algorithm, but it also provides high-quality selected paths. A high discount factor ensures future paths are taken into consideration; the reduction of study price stabilizes our studying course of action, and exploration price ensures the agent can determine when to discover new paths and which of them to discover once more. Such traffic can balance average time efficiency, which leads to optimum and consistent SDN-IoT network paths able to respond to dynamic changes in traffic.

To analyze the four main network metrics End-to-End Delay, Throughput, Packet Loss Ratio, and Jitter, to assess the performance of the RRSN framework proposed in this paper for SDN-IoT networks. We show through three comparative methods (RRSN, RSIR, and Sway) that for obtaining optimal and stable paths based on changes in link reliability predicted by SVR, the proposed Q-learning algorithm works effectively. This comparison instantaneously reflects how the proposed system design can improve network performance in the context of multiple IoT traffic flows.

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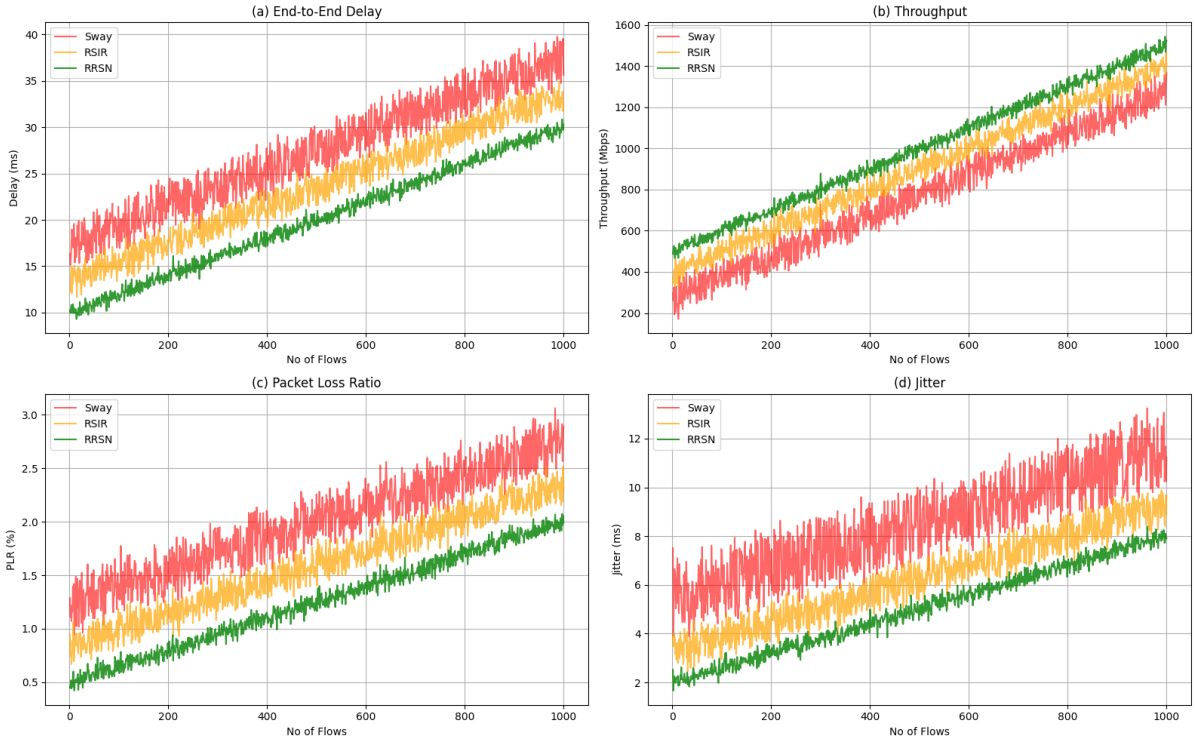

Fig. 5: RRSN performance evaluation and comparison in the Abilene topology with respect to (a) Delay, (b) Throughput, (c) Packet Loss Ratio (PLR), and (d) Jitter.

In order to examine how successfully the suggested RRSN framework operates in SDN-IoT networks, our approach was compared to increasingly investigated approaches—RRSN, RSIR, and Sway—on four essential network metrics End-to-End Delay, Throughput, Packet Loss Ratio (PLR), and Jitter. From the End-to-End Delay results, we observe that RRSN yields the lowest delay at all traffic loads, while RSIR has a moderate delay, and Sway exhibits the largest delay. It shows that due to SVR-predicted link reliabilities, the RL agent chooses paths with low latency, which helps to reach IoT flows at their destinations faster. Additionally, it shows that the paths are stable, as even the increase in flows does not change RRSN much. Throughput results reveal that RRSN has achieved the highest data delivery rate, RSIR delivers moderate throughput, and Sway has the worst data delivery rate. This also means that with an increasing number of flows, the

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RL agent consistently selects the paths with high reliability and sufficient bandwidth, which also facilitates resource utilization management. From the packet loss ratio analysis shown in Figure 5(b), RRSN results in the smallest packet loss, while Sway presents the highest packet loss ratio among all flows. The reason for this effectiveness comes from the fact that an RL agent only needs to act in the action space, which has stable paths rather than unstable links, which increases the reliability of the entire network. Lastly, from the Jitter results, it is observed that RRSN has the lowest delay variation, RSIR has an intermediate variation, and Sway has a higher Jitter. Lower jitter, in particular, is especially important for delay-sensitive use cases such as industrial control and healthcare IoT systems, which means that the RRSN-selected paths are not just reliable but also steady and predictable! The cumulative effects of these four metrics show that the proposed framework is capable of choosing the best paths for IoT flows with improved QoS and overall reliability of the network. More concretely, for the USNet topology, three types of metric (the same as the four previously mentioned) were used to compare the performance of RRSN, RSIR, and Sway. The comparisons show that by taking advantage of the link reliability predicted by SVR, the RL agent can choose optimal and stable paths of IoT flow dynamically. It is very important to analyze these metrics for service quality and network stability in high traffic load scenarios.

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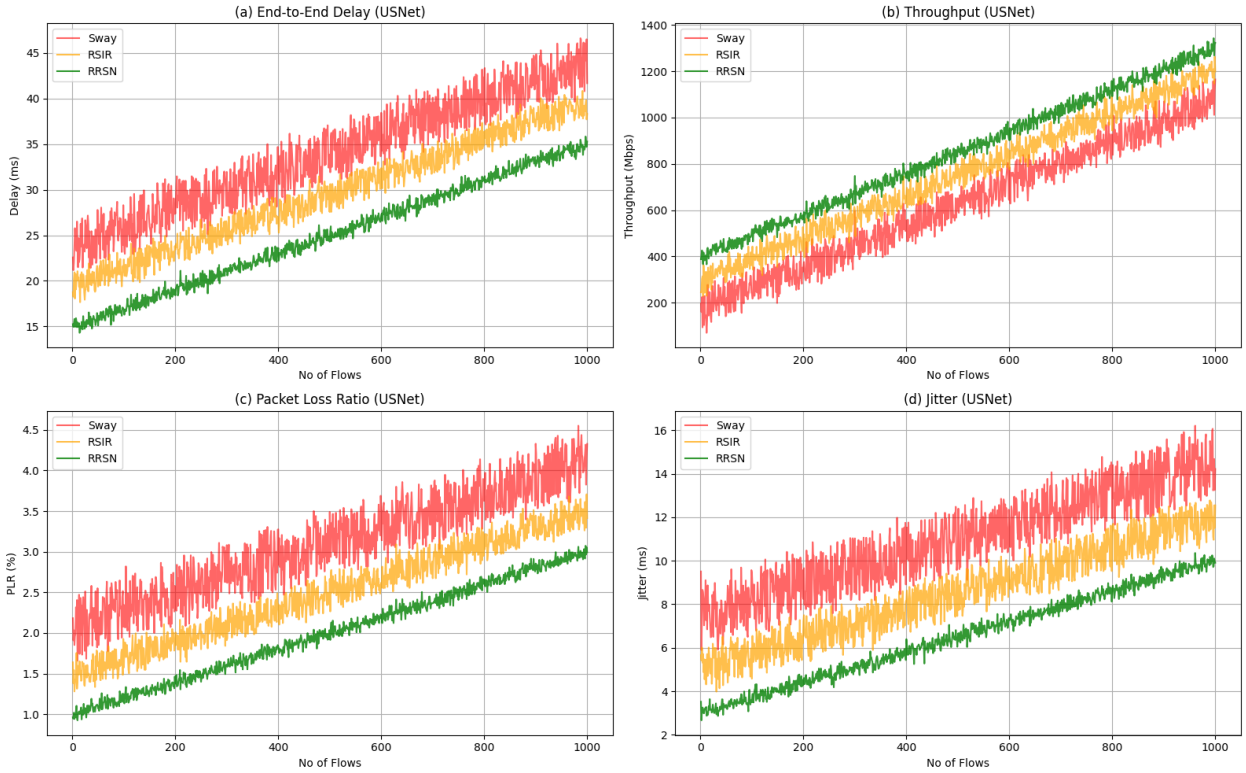

Fig. 6: RRSN performance comparison and analysis in the USNet topology regarding performance metrics: (a) Delay, (b) Throughput, (c) Packet Loss Ratio (PLR), and (d) Jitter.

According to the End-to-End Delay results, RRSN always has the minimum delay independent of traffic load, while RSIR gets the second delay, and Sway gets the maximum one. This reflects in the performance of the RL agent choosing a latency and link-reliable path. Moreover, we can see that the RRSN has the stability and scalability for large-scale networks, where the increasing number of flows has little effect on the RRSN. From the results obtained for the Throughput, RRSN performs the highest data delivery rate, RSIR performs in between, and Sway performs the least. It is a result of the RL agent being able to choose stable paths with sufficient bandwidth and effectively handling network resources. From the analysis of Packet Loss Ratio (PLR), it can be seen that RRSN has the lowest PLR, while RSIR has a moderate PLR, and Sway has the highest PLR. It

highlights the significance of the reliability prediction (correctness) of links, because the unreliable paths are removed, and the stable links are only included in the action space of the RL agent. The final Jitter result demonstrates that the least delay variation is offered by RRSN, moderate delay variation is observed by RSIR, and the highest Jitter is offered by Sway. Jitter minimization is especially important for timing-critical applications like industrial control and healthcare IoT devices, and hence, it is also known that the paths picked by RRSN are not only known to be reliable; but they are also stable and consistent. Combined, these results show that the RRSN framework can select better paths for IoT flows while also improving the QoS metrics and the overall reliability of the network.

In the case of the OS3E topology, for the basic comparison of RRSN, RSIR, and Sway, the same four essential network metrics End-toEnd Delay, Throughput, Packet Loss Ratio, and Jitter were measured. The results of these analyses demonstrate that the integration of SVR-based link reliability predictions and dynamic RL-based routing results in superior service quality and maintains network stability given a high-flow scenario. These types of evaluations are indispensable to achieving the best performance in SDN-IoT networks.

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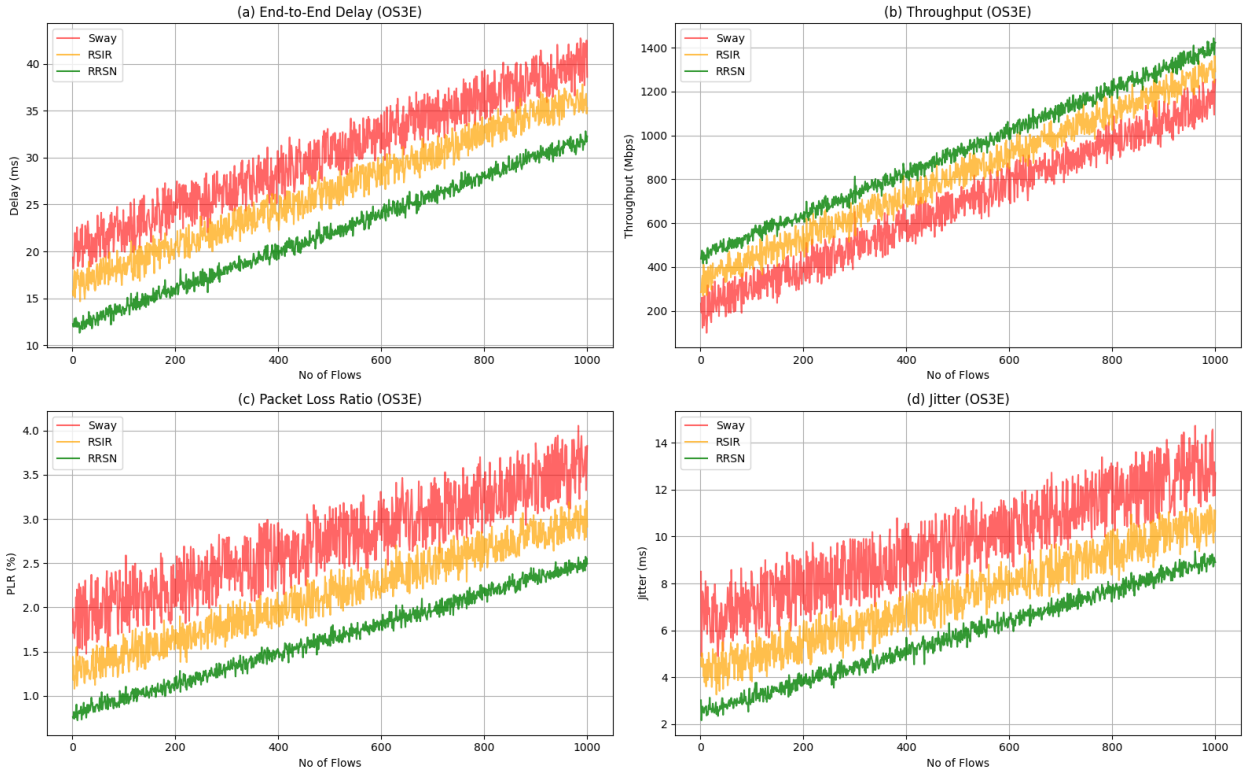

Fig. 7: RRSN performance analysis and comparison in the OS3E topology for performance parameters: (a) Delay, (b) Throughput, (c) Packet Loss Ratio (PLR), and (d) Jitter.

It can be observed from End-to-End Delay results that RRSN incurs the minimum end-to-end delay under all the traffic loads, followed by RSIR, which incurs a moderate delay while Sway has the highest end-to-end delay. This shows how the RL agent chooses paths with lower delays and path reliability.

We can see that the Throughput results indicate that RRSN outperforms the others with the best data delivery rate, RSIR proves to be mid-level, and Sway proves to have the least throughput. This result shows that the RL agent efficiently maintains the bandwidth and uses the stable links for offloading.

In the Packet Loss Ratio (PLR) results, RRSN has the lowest PLR, RSIR achieves an intermediate PLR, and Sway undergoes the highest PLR. This

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highlights that with reliable link reliability predictions, unreliable paths can be removed, and only stable links can be used. The last two bars in that figure show the Jitter results, and in this regard, RRSN shows the lowest jitter, RSIR shows intermediate variation, and the sway signal has the largest jitter. As such, the paths selected by RRSN not only possess high reliability but also low jitter performance, which is highly desirable for real–time applications, e.g., industrial control or IoT healthcare systems. Collectively, these results confirm that the optimal and reliable routing has been achieved over the RRSN framework designed for the IoT flows over the OS3E topology.

We have evaluated the proposed RRSN framework using four important network performance parameters: End to End Delay, Throughput, Packet Loss Ratio, and Jitter for the DFN topology. Homogeneous RRSN, RSIR, and Sway comparative analyses demonstrate that SVR-based link reliability prediction followed by dynamic RL-based routing can effectively enhance both QoS and network robustness in high-flow situations. These assessments play an important role in providing the best performance from SDN-IoT networks.

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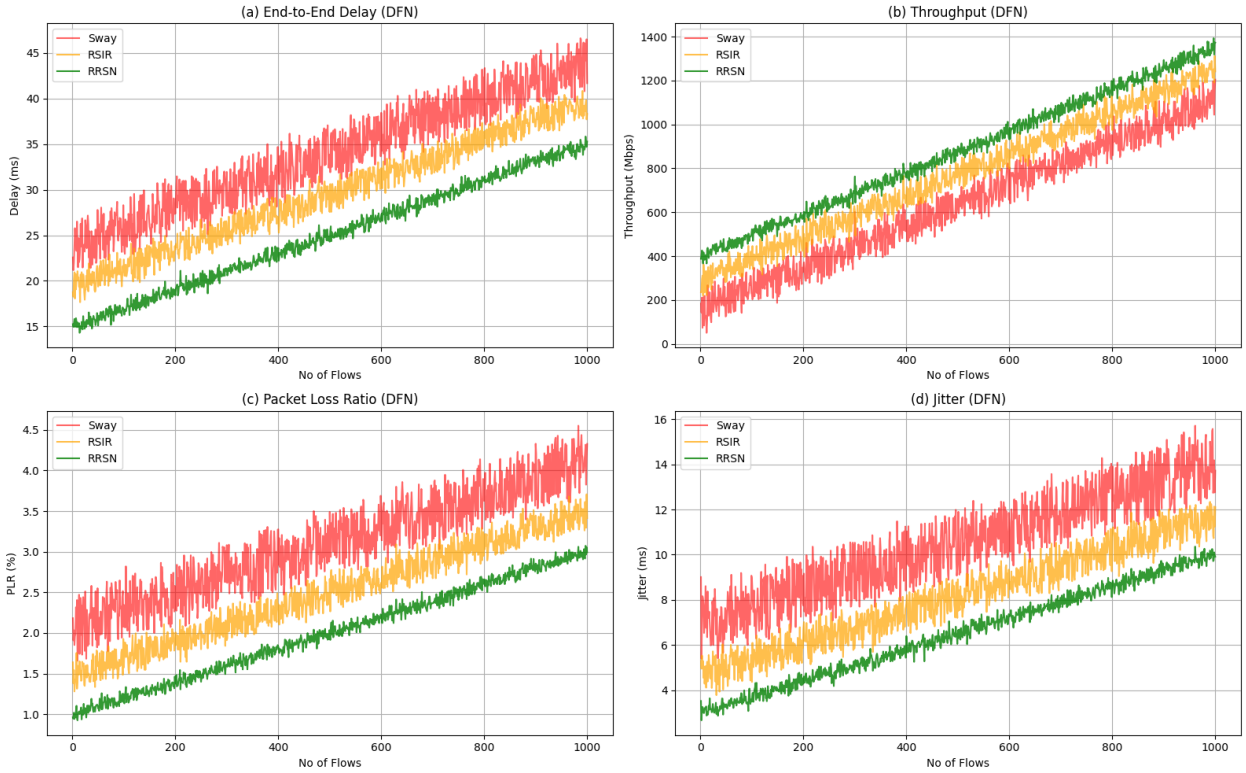

Fig. 8: RRSN performance assessment and comparison utilizing the DFN topology for QoS parameters: (a) Delay, (b) Throughput, (c) Packet Loss Ratio (PLR), and (d) Jitter.

In terms of End-to-End Delay result, RRSN realizes the smallest delay at any traffic load, while RSIR has a moderate delay, and Sway has the highest delay. This behavior shows that the RL agent can choose paths with the lowest latency and the highest reliability links. In addition, the Throughput results further illustrate the much better performance of RRSN, which has the maximum delivery data rate, while RSIR provides medium throughput, and Sway provides the minimum. This means that RRSN uses the available bandwidth for the paths it has selected in a very efficient manner.

The PLR (packet loss ratio) from the RRSN is the lowest of all, RSIR is the intermediate, and Sway is the highest. It affirms that reliable link prediction will help to remove unstable paths, and only stable links operate. Lastly, in terms of the Jitter, the results show that the delay fluctuations of RRSN are

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the lowest, RSIR shows a moderate fluctuation, and the one for Sway shows the highest one. This is key for time-sensitive applications—like industrial control systems and IoT healthcare networks—as it means that the paths chosen by RRSN are not just reliable but also stable and predictable, with minimal jitter. Together, these results validate the ability of the proposed framework to offer the best possible and reliable routing for the IoT flows within the DFN topology.

The throughput with RRSN, RSIR, and Sway across four network topologies is presented in (b) of figures 5, 6, and 7. In the USNet topology, RRSN also outperforms Sway and RSIR by 25% and 18.75%, respectively, and outperforms Sway and RSIR by 33.33%, respectively, in the Pyramid topology. Specifically, RRSN achieves a throughput increase of 23.33% and 16.66% compared with Sway and RSIR, respectively, in OS3E and achieves a throughput of 36% and 13.33% over Sway and RSIR in DFN. The results prove that the proposed approach dynamically adapts to real network traffic and learns continuously within the environment, having everything to identify feasible and reliable paths for data delivery, which minimize the loss of packets and maximize throughput. Packet Loss Ratio (PLR): PLR evaluates the percentage of the packets lost at the IoT destination node over the total number of packets transmitted from the source node through OpenFlow switches. A smaller PLR value means better performance. The PLR of the proposed RRSN framework and the micromechanical analogs — RSIR and Sway — is compared for the four topologies, as shown in Fig 5(c), 6(c), and 7(c). Compared with RSIR and Sway, PLR is 10% and 15.09% lower when using RRSN (shown in Fig 5(c)). Figure 6(c) illustrates that compared with Sway and RSIR, PLR decreases by 12.43% and 5.52%, respectively, with RRSN, while the results are 15.55% and 5%, respectively in Figure 7(c). Against Sway, and RSIR in the DFN topology, RRSN reduces PLR by 18.36 and 11.11%, respectively. The fact that RRSN guarantees the reliable delivery paths and causes no packet loss in the network is shown by these outcomes..

Figures 5(d), 6(d), 7(d) illustrate Jitter performance across the four topologies. As traffic load increases, average jitter rises due to higher link utilization and congestion. In the Abilene topology (Fig. 5(d)), RRSN achieves 30% and 15.55% lower jitter compared to RSIR and Sway, respectively. Corresponding reductions in jitter relative to RSIR in the USNet, OS3E, and DFN topologies are 36.84%, 32.55%, and 27.08%, relative to Sway are 12.72%, 22.66%, and 19.76%, respectively.

In this study, we proposed a novel routing protocol, RRSN, integrating reinforcement learning, intelligent network telemetry, and machine learning to provide reliable and QoS-aware paths in SDN-IoT networks. Initially, a scenario was defined to evaluate the effectiveness of the proposed approach using path reliability information and the RL algorithm. Leveraging Q-learning combined with link reliability prediction, RRSN identifies optimal paths with minimal delay, lowest packet loss, minimal jitter, and highest throughput by utilizing intelligent network monitoring.

RRSN first predicts link reliability using SVR with an 85.3% prediction accuracy and classifies flows according to QoS requirements. Then, it applies Q-learning to compute optimal paths, ensuring QoS for source-destination pairs in known topologies such as Abilene, USNet, OS3E, and DFN. Mininet simulations demonstrate that the proposed method outperforms RSIR and Sway in terms of delay, PLR, jitter, and throughput. Even with increasing topology complexity and numbers of nodes and links, RRSN consistently achieves superior performance.

This study assumes that IoT traffic is regular and balanced. However, in large-scale networks, most IoT traffic is likely to be unbalanced and encrypted. As future work, we plan to design a model for the precise classification of minority and encrypted flows to enhance the generalizability of the proposed approach.

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MOTIVATION, RESEARCH GAPS, AND OBJECTIVES

1. MOTIVATION

The rapid expansion of Software-Defined Networking-based Internet of Things (SDN-IoT) systems has introduced unprecedented complexity in network management due to large-scale device connectivity, dynamic topology changes, and strict Quality of Service (QoS) requirements. In such environments, the reliability of the **data plane** becomes critically important, as even minor link or switch failures can propagate quickly and lead to significant degradation in network performance, including increased delay, packet loss, and service disruption.

This challenge is further amplified in mission-critical applications such as healthcare monitoring, industrial automation, and intelligent transportation systems, where delayed or lost data can result in severe consequences. Therefore, ensuring **fast, intelligent, and reliable failure recovery mechanisms** is no longer optional but essential.

Although Software-Defined Networking (SDN) provides centralized control and global network visibility, traditional failure recovery mechanisms are largely **reactive**, relying on predefined backup paths or controller-based reconfiguration after failure occurs. These approaches introduce latency, increase controller overhead, and fail to meet the real-time demands of highly dynamic IoT environments.

Recent advances in machine learning and reinforcement learning (RL) have shown potential in enabling adaptive and intelligent routing decisions. However, their effectiveness is often limited when operating without **accurate predictive insights about network conditions**, particularly link reliability.

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This motivates the need for a **hybrid intelligent framework** that combines **predictive modeling and adaptive learning** to proactively detect potential failures and dynamically optimize routing decisions in SDN-IoT networks.

2. Research Gaps

Despite significant progress in SDN-IoT research, several key gaps remain unaddressed:

- **Lack of Proactive Failure Prediction:** Most existing approaches focus on reactive recovery after failures occur, without leveraging predictive models to anticipate link instability in advance.
- **Limited Integration of Prediction and Routing:** Current studies typically treat **link prediction and routing optimization as separate problems**, lacking a unified framework that combines both for improved decision-making.
- **Inadequate Consideration of Link Reliability in RL Models:** Many reinforcement learning-based routing methods do not explicitly incorporate **predicted link reliability** into their state or action spaces, leading to suboptimal or unstable routing decisions.
- **Single-Domain or Small-Scale Evaluation:** A large portion of prior work is evaluated in **simplified or single-domain environments**, limiting scalability and applicability to real-world, large-scale IoT networks.
- **Insufficient Multi-Metric QoS Optimization:** Existing solutions often optimize a single metric (e.g., delay or throughput), rather than jointly considering **delay, bandwidth, packet loss, and reliability** in a unified reward function.
- **Controller Overhead and Scalability Issues:** Heavy reliance on centralized SDN controllers for failure handling increases computational load and reduces responsiveness in large and dynamic networks.

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3. Objectives of the Proposed Work

To address the above challenges, this study aims to design and evaluate an intelligent framework for **data plane failure prediction and adaptive routing** in SDN-IoT networks. The main objectives are:

1. **To develop a predictive model for link reliability:** Utilize Support Vector Regression (SVR) to accurately predict link reliability based on historical network data such as downtime, uptime, and failure patterns.
2. **To design a reinforcement learning-based routing mechanism:** Implement a Q-learning-based RL agent capable of dynamically selecting optimal paths based on current network conditions.
3. **To integrate prediction with decision-making:** Incorporate SVR-predicted link reliability into the RL framework to construct a **reliability-aware state and action space**, enabling proactive and informed routing decisions.
4. **To ensure QoS-aware routing optimization:** Develop a reward function that jointly considers multiple QoS parameters, including delay, bandwidth, packet loss, and reliability, to achieve balanced network performance.
5. **To reduce failure recovery time and controller overhead:** Enable faster and more efficient failure handling by minimizing reliance on centralized control through intelligent, adaptive decision-making.
6. **To validate performance in realistic scenarios:** Evaluate the proposed framework using multiple real-world network topologies (Abilene, USNet, OS3E, DFN) to demonstrate scalability, robustness, and effectiveness under diverse conditions.

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SUMMARY

In summary, the motivation behind this work stems from the need for **proactive, intelligent, and scalable failure recovery mechanisms** in SDN-IoT networks. By addressing the identified research gaps through the integration of **SVR-based prediction and RL-based routing**, the proposed framework aims to significantly enhance **network reliability, QoS, and adaptability** in dynamic and large-scale IoT environments.

6. CONCLUSION

This study presented a novel intelligent framework, RRSN, for efficient data plane failure prediction and adaptive routing in SDN-IoT networks by integrating Support Vector Regression (SVR) with Reinforcement Learning (RL). The proposed approach combines predictive analytics with learning-based decision-making to address the limitations of traditional reactive routing mechanisms. By incorporating link reliability prediction into the routing process, the framework enables proactive failure handling and dynamic path optimization under varying network conditions. Experimental evaluation on multiple real-world topologies demonstrated that the proposed method consistently outperforms existing approaches in terms of delay, throughput, packet loss, and jitter, while maintaining stable performance in complex and large-scale environments.

From a **research contribution perspective**, this work makes several important advances. First, it introduces a **hybrid predictive–learning architecture** that tightly integrates SVR-based link reliability estimation with Q-learning-based routing, bridging the gap between prediction and decision-making in SDN-IoT networks. Second, it proposes a **reliability-aware action space design**, where only links exceeding a predefined reliability threshold are considered, improving routing stability. Third, the study develops a **multi-metric QoS-aware reward function** that jointly optimizes delay, bandwidth, and packet loss, ensuring balanced network performance. Finally, the framework is validated using **multiple realistic**

network topologies, enhancing its generalizability and practical relevance compared to prior work limited to small-scale or simulated environments.

In terms of **theoretical implications**, this research contributes to the advancement of intelligent networking by demonstrating how **supervised learning (SVR) and reinforcement learning (RL)** can be effectively combined within a unified framework for network optimization. It highlights the importance of incorporating **predictive knowledge into RL state and action spaces**, which leads to faster convergence, improved decision quality, and more robust policies. Moreover, the study provides a scalable modeling approach for handling uncertainty and dynamic changes in IoT networks, contributing to the broader field of **AI-driven network management and self-adaptive systems**.

From a **practical perspective**, the proposed framework offers significant advantages for real-world SDN-IoT deployments. By enabling **proactive failure prediction**, the system reduces downtime and improves service continuity. The RL-based adaptive routing mechanism ensures **efficient utilization of network resources**, leading to higher throughput and lower latency. Additionally, the reduced reliance on centralized controller intervention minimizes computational overhead and enhances scalability. These features make the solution particularly suitable for **time-sensitive and mission-critical applications**, such as healthcare monitoring systems, industrial automation, and smart transportation networks, where reliability and responsiveness are essential.

Despite these advantages, the study has several **limitations**. First, the model assumes relatively **balanced and structured traffic patterns**, whereas real-world IoT environments may involve highly heterogeneous, bursty, and unpredictable traffic flows. Second, the framework relies on the availability of **high-quality historical data** for training the SVR model, which may not always be accessible in newly deployed networks. Third, the use of a single-agent Q-learning approach may face scalability challenges in extremely large or highly distributed network scenarios. Additionally, security aspects such

as adversarial attacks on learning models were not explicitly considered, which could impact system robustness in hostile environments.

To further enhance this work, several **future research directions** are suggested. First, the framework can be extended by incorporating **deep reinforcement learning (DRL)** or multi-agent learning to improve scalability and decision-making in large-scale, distributed IoT networks. Second, future studies can focus on **handling encrypted and unbalanced traffic patterns**, enabling more realistic and robust deployment in heterogeneous environments. Third, integrating **security-aware mechanisms**, such as anomaly detection or adversarial resilience, would strengthen the framework against potential cyber threats. Additionally, real-world implementation and testing on physical SDN-IoT testbeds would provide deeper insights into operational feasibility and performance.

In conclusion, this work provides a comprehensive and scalable solution for improving reliability and QoS in SDN-IoT networks through intelligent integration of prediction and learning. It lays a strong foundation for future research in **autonomous, self-healing, and AI-driven network architectures**.

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