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An Innovative Fuzzy Logic And Reinforcement Learning Hybrid Model For Adaptive Traffic Management In Software-Defined Networks

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ABSTRACT
Software-Defined Networking (SDN) has been recognized as a disruptive technology in contemporary networking for the provision of dynamic traffic control and centralised control. However, cost-effective management of networks traffic with high demand and dynamic environments is still challenging. To address such limitations, this paper proposes a hybrid Fuzzy-Reinforcement learning traffic management model to strike a balance between scalability, convergence speed and energy efficiency. The proposed scheme makes use of fuzzy logic for an initial quick decision making and reinforcement learning for on-line optimization so it can adjust instantly to network dynamics. The approach is based on performance metrics, such as latency, throughput, packet loss rate, bandwidth utilization and energy consumption, and is applied on the model, under different traffic conditions. Comparison of the new model with existing models, such as DFRDRL and AVRO, further demonstrates the effectiveness and efficiency of the new approach. The performance results show that our approach achieves up to 33% end-to-end latency reduction, 30% energy savings, and better throughput than the conventional methods. As the network scale and traffic load grew, the model kept good performance, which proved the scalability and robustness. And, its rapid convergence rate (adaptively learning and monitoring) enables dynamic stability of the network. Furthermore, the results confirm the effectiveness and the feasibility of the proposed model as a practical and novel solution for SDN traffic management in response to technical and sustainability issues in recent network systems.
Keywords: *Software-Defined Networks (SDN); Traffic Management; Fuzzy Logic; Reinforcement Learning; Scalability; Convergence Speed; Energy Efficiency.*

1.0 INTRODUCTION

Software-Defined Networks (SDNs) have redefined contemporary networking by separating control and data planes, providing a centralized network management and dynamic reconfiguration capability [1]. Such an architectural transformation has made it possible for networks to be more flexible and scalable in meeting various emerging technology requirements including the Internet of Things (IoT) [2], cloud computing [3], and 5G [4]. However, with SDN, the increase in complexity and traffic load have brought severe challenges [5], especially, in traffic management [6], resource allocation [7], ensuring performance indicators such as low latency [8], high throughput [9] and energy saving [10].

Existing traffic management mechanisms in SDN, although applicable to static and predictable environments, may not work well in dynamic [11] and high loads [12]. These techniques, such as static routing and Deep Learning based optimization [13], are either too rigid to meet the need of fast-changing traffic or too computationally intensive to achieve realtime response [14]. There is therefore a need for intelligent, context-sensitive traffic management solutions that are scalable and sustainable [15] and can mitigate these limitations.

In this study, we present a hybrid traffic control model which tries to utilize the advantages from fuzzy logic and reinforcement learning to compensate for the defects of classical approaches. The fuzzy logic that can manage the uncertainty and make the rule based decision, is used as a prime decision making tab for the rapid response towards the changes in traffic [17, 18]. Unlike programming, reinforcement learning updates these decisions using live feedback from the network, thereby achieving adaptive optimization in the face of a changeable environment. The combination of these two methods makes the model promising for real-time traffic control in SDNs [19,20].

This research work aims to examine the performance of the proposed model under delay, throughput, packet loss rate, bandwidth utilization and energy efficiency. This paper addresses these issues by presenting the hybrid traffic control model applying Fuzzy Logic and Reinforcement Learning. The model makes fast initial decisions based on fuzzy logic and then continually optimizes using reinforcement learning, which allows the system to adapt and scale in real time. By accounting for a variety of performance objectives, such as latency, throughput, and energy saving, the proposed approach is a promising answer to current SDN problems.

2.0 LITERATURE REVIEW

The rapid spread of SDNs has driven to a large number of research works on traffic management mechanisms, which aim to optimize performance metrics like latency, throughput, packet loss, and energy consumption. This section presents an overview of the existing work and also points out the need for a hybrid approach, which we will use in the developing our model (fuzzy logic and reinforcement learning) to include for the deficiency of the current SDNs..

2.1 Traffic Management in SDNs

Most existing traffic control mechanisms in SDNs are based on static algorithms or heuristic rules to deliver optimal routing and resource scheduling. Techniques like Shortest Path Routing (SPR) and Weighted Load Balancing (WLB) are very well deployed because of their simplicity and suitable performance in predictable networks. Nonetheless, those methods are not flexible enough to accommodate movable traffic flows and is not scalable to large and complex networks [21, 22].

An advanced one is the Deep Reinforcement Learning (DRL) [23], which proves to be effective for traffic controlling. A machine learning-based algorithm, for example, Dynamic Fuzzy Routing with Deep Reinforcement Learning (DFRDRL) [24], is used to dynamically make routing decisions in DRL-based models. Although these models have better performance, they are also computationally complex and may converge slower than the first two models, and thus these models are not applicable for real-time problems in high-traffic networks [25, 26].

2.2 Fuzzy Logic in Traffic Management

Fuzzy logic has been introduced as a method of making lightweight and efficient decisions for the SDN. The fuzzy logic systems can quickly take decisions depending on a prior sets of rules by adding uncertainly and approximate reasoning [27,28]. For example, reliability has been shown in [29,30] to utilise fuzzy logic for dynamic resource allocation and load balancing, which is an important characteristic as the networks demand instant response to the varying traffic conditions. However, the fuzzy logic based systems by themselves suffer from the static rules, which are incapable of dynamically adapting to the changing network conditions without any human intervention [31, 32].

2.3 Reinforcement Learning in SDNs

Reinforcement learning (RL) is becoming a potential method for dynamic SDN traffic management. RL models optimize routing and resource allocation policies through an exploration and exploitation process with the environment [33, 34]. Approaches like Q-learning and deep Q-learning have also been used on SDNs for scalability and flexibility enhancements [35]. Unfortunately, the requirement of large amount of training data and computational cost make them unsuitable for real-time usage. Furthermore, the initial decision process of RL systems may be inadequate, in particular, for highly volatile networks with high traffic dynamics [36, 37]

3.0 RELATED STUDIES

Several techniques have been proposed for improving traffic management in SDNs using fuzzy logic, reinforcement learning as well as by developing hybrid techniques. Recent studies are now briefly discussed in this section in order to point out the importance, limitations and relevance of these for the proposed hybrid model.

Fuzzy logic has been found to be effective in handling imprecise data and uncertain in dynamic network environments. Quality of service (QoS) parameters, including latency, throughput, and packet delivery ratio (PDR) were optimized by fuzzy logic as proved by [38]. They applied their model to fuzzy logic for intelligent decision in vehicular and software-defined networks. Another example is the HIFS method

proposed in [39] for software defined vehicular networks which fuses fuzzy logic and SARSA reinforcement learning. Their model used utility-based intersection selection and path selection approaches to increase routing flexibility, decrease end-to-end delay, and boost throughput in different traffic loads.
However, those methods based on fuzzy logic suffer from insensitivity to real-time network dynamism, and are typically inflexible to the changing network environment since the rules are pre-defined, leading to a requirement for manually updating process of the rule set with changing network conditions. This limitation reiterates the necessity for dynamic learning processes, as provided by Reinforcement Learning. RL is found to be a practical method for dynamic optimal in SDN [40, 41]. [42] designed the DFRDRL model that embedded dynamic fuzzy routing and deep reinforcement into infer guaranteed latency and bandwidth. DFRDRL utilized real-time traffic matrix prediction and lower the priority resource demand under congestion and thus realized better latency and throughput than conventional methods.
[43] furthermore proposed an RL motivated routing protocol for SDN empowered WSN. Their approach achieved the best energy consumption for real-time response in event reporting, especially in reporting critical events to the server. [44] also applied the concept of RL to vehicular networks and proposed a trust-aware architecture to improve link quality and mitigate damage caused by malicious nodes using deep Q-learning.
In addition, RL-inspired models are appealing for their strong flexibility and efficiency, yet they commonly encounter the problems of time consuming, slow convergence, and being easy to be trapped by local optimum during the training in the dynamic environment.
Hybrid methods combining fuzzy logic with reinforcement learning have also been considered in order to compensate for weaknesses of each [45,46,47]. [48] demonstrated the possibility of fusing the fast decision making of fuzzy logic with the adaptation of reinforcement learning in theirHIFSmodel. This strategy allowed the highly flexible movements of vehicles to have less jam. [49] also presented the African Vulture Routing Optimization (AVRO) algorithm, a meta-heuristic optimization with some reinforcement learning (RL) concepts, thereby achieving fast and convergence with better network sensing capabilities.
While these hybrid strategies achieved significant benefits, such as reduced latency or increased energy efficiency, they did not necessarily consider broader computational issues including scalability and real-time response. Moreover, the computational cost of some hybrid models are so high that they cannot be applied into actual large-scale networks [52, 53].
Although previous works have worked on traffic control for SDNs, we are still missing a hybrid approach that addresses multiple metrics (e.g., latency, throughput, energy consumption, scalability, convergence time) in a single model. The majority of them focus on one or two optimization dimensions, which is challenging to achieve comprehensive traffic management optimization [54, 55,56
Motivated by these considerations, this work aims to bridge these gaps by developing an innovative hybrid traffic management model which combines fuzzy logic and reinforcement learning. The fuzzy logic making a decision decision-making engine and the reinforcement learning decision-making, more convenient and suitability, can realize real-time adaptability, has instantly scalability. The proposed model adjusts and optimizes multiple performance indicators so that it can well balance the various performance for SDN challenges in practice. This work advances current solutions, while providing a new frontier in intelligent and adaptive network management.

4.0 METHODOLOGY

This section presents a methodological framework to design and assess the proposed Fuzzy Logic and Reinforcement Learning Hybrid Model for Traffic Management in adaptive SDN environments. It is developed to handle dynamic traffic conditions, and the cognitive capability is specifically enhanced by fusing fuzzy logic in making decisions for uncertain traffc conditions and reinforcement learning for adaptive learning from traffc environment to optimize network performance. The experimental setup, the preparation of the dataset, the architecture of the model, and the used evaluation metrics are described in the next subsections.

4.1 Experimental Setup

5.4. Setup of the Experiments for the Proposed Hybrid-Model In this experiment, we use a simulation environment to simulate the real world sdn environment for evaluating the proposed hybrid model. Experiments were realized with the help of Mininet (25), which simulates SDN topologies, alongside an OpenFlow controller (ONOS, Floodlight, etc.) controlling traffic flows. The hybrid model was implemented using the Python scripting language with help from the TensorFlow and Keras libraries.
The experiments were conducted in an HPC environment with the following attributes.
Processor: Intel Xeon CPU (3.40 GHz)
RAM: 64 GB
GPU: NVIDIA Tesla V100 with 32 GB memory
Operating System: Ubuntu 20.04
Software Tools: Mininet 2.3.0d6, OpenFlow 1.3, TensorFlow 2.6.0, Python 3.8.10.
The UML network topology consisted of several interconnected switches and hosts, generating dynamic traffic. Traffic was created with the aid of the iPerf tool simulating different assembly conditions like being highly congested, uniform and bursty.
Dynamic traffic datasets from real SDN use cases and synthetic datasets were used to train and test the proposed model. We evaluated the performance of the model on different network settings, including different numbers of switches, hosts, and with different link capacity.
We use deterministic randomness (fixed seeds are used for dataset generation and for training) to ensure reproducibility. Moreover the environment variables, e.g., the current traffic flows, the latencies, and the used bandwidth were monitored and stored for future analysis. The details of training and evaluation datasets are described in the next subsection.

4.2 Dataset Description

The provided dataset to train and test the proposed fuzzy logic and reinforcement learning hybrid model was set up to mimic traffic behaviors in SDNs. It contains both simulated and real traffic data which guarantee a full evaluation of the model's generalization and robustness. The details of the dataset preparation and characteristics are as follows

4.2.1 Synthetic Traffic Data

Synthetic traffic data were generated using tools like iPerf and D-ITG to simulate various network traffic conditions. These tools created traffic patterns reflecting different scenarios, including:
- **Uniform Traffic:** Steady traffic flow with consistent packet sizes and inter-arrival times.
- **Bursty Traffic:** Sudden spikes in traffic load to test the model's performance under congestion.
- **Heavy-Tailed Traffic:** Traffic exhibiting long-tail distributions, common in real-world networks.
- **Mixed Traffic:** A combination of high-priority (e.g., VoIP) and low-priority (e.g., file transfer) traffic.

Each traffic pattern was generated over multiple network configurations, varying in:
- **Number of Hosts:** Ranging from 50 to 500.
- **Number of Switches:** Ranging from 5 to 50.
- **Link Bandwidths:** Between 100 Mbps and 10 Gbps.

4.2.2 Real-World Traffic Data

The real-world dataset was sourced from publicly available network traces, such as the CAIDA Internet Traffic Archive. These datasets provided detailed information on real network traffic, including:
- **Packet-level Information:** Source and destination IP addresses, protocols, and packet sizes.
- **Flow-level Information:** Start and end times of flows, flow durations, and byte counts.
- **Temporal Features:** Hourly and daily traffic variations.

The real-world data were preprocessed to anonymize sensitive information and normalize feature scales for compatibility with the model.

4.2.3 Data Preprocessing

Data preprocessing was critical to ensure consistency and reduce computational complexity. The following steps were applied:
- **Feature Selection:** Relevant features, such as packet size, flow duration, and traffic priority, were extracted.

- **Normalization:** Continuous features were scaled to a range of [0, 1] using min-max normalization to enhance model convergence.
- **Handling Missing Values:** Missing data points were imputed using linear interpolation for time-series data or mean imputation for categorical data.
- **Balancing Classes:** To address class imbalance in traffic patterns (e.g., normal vs. anomalous traffic), Synthetic Minority Oversampling Technique (SMOTE) was applied.
- **Data Splitting:** The dataset was split into training (70%), validation (15%), and testing (15%) subsets, ensuring diversity in traffic scenarios across splits.

4.2.4 Dataset Characteristics

The final dataset comprised:

- **Number of Samples:** 1,000,000+ traffic flows.
- **Number of Features:** 10 key traffic characteristics.
- **Class Distribution:** Balanced representation of low, medium, and high-priority traffic.
- **Time Period:** Data covering peak and off-peak hours for better generalization.

This dataset was essential for training the hybrid model to adaptively manage traffic while balancing network performance metrics, such as latency, bandwidth utilization, and packet loss. The next subsection details the design of the fuzzy logic system, a core component of the proposed hybrid model.

4.3 Fuzzy Logic System Design

The fuzzy logic system (FLS) serves as a decision-making module in the proposed hybrid model, enabling adaptive traffic management under uncertainty. This system processes multiple traffic parameters, including latency, bandwidth utilization, and packet loss, to derive an optimized traffic control decision.

4.3.1 Input and Output Variables

The FLS is designed with three input variables and one output variable:

- **Latency (L):** Represents the average delay in milliseconds (ms) for packets traversing the network.
- **Bandwidth Utilization (B):** Denotes the percentage of utilized bandwidth compared to the total available bandwidth.
- **Packet Loss (P):** Refers to the percentage of packets lost during transmission.

Output Variable: Traffic Priority (T), which determines the action to be taken, such as rerouting or adjusting quality of service (QoS) parameters.

4.3.2 Fuzzification

The input variables are mapped to linguistic terms using membership functions. Triangular and trapezoidal membership functions are chosen for their simplicity and computational efficiency.

- **Latency (L):** {Low, Medium, High}
- **Bandwidth Utilization (B):** {Low, Moderate, High}
- **Packet Loss (P):** {Low, Medium, High}
- **Traffic Priority (T):** {Low Priority, Medium Priority, High Priority}

The membership function for Latency (L) can be expressed as:

$$\mu_L(x) = \begin{cases} \frac{x-a}{b-a}, & \text{if } a \leq x \leq b \\ \frac{c-x}{c-b}, & \text{if } b \leq x \leq c \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where *a*, *b*, and *c* are the parameters defining the triangular membership function for a given range.

4.3.3 Rule Base

The fuzzy rule base consists of **if-then** rules that combine input linguistic terms to infer the output. A sample rule set is as follows:

- **Rule 1:** If L is High and B is High and P is High, then T is Low Priority.
- **Rule 2:** If L is Medium and B is Moderate and PP is Low, then T is Medium Priority.
- **Rule 3:** If L is Low and B is Low and P is Low, then T is High Priority.

4.3.4 Inference Mechanism

The fuzzy inference mechanism employs the Mamdani approach, which aggregates the rules to produce a fuzzy output. The inference process involves:
Rule Evaluation: Compute the firing strength of each rule, wiw_i, using the minimum operator:

$$w_i = min(\mu L_i, \mu B_i, \mu P_i\ ) \tag{2}$$

Aggregation: Combine the outputs of all rules using the maximum operator:

$$\mu_T\ (y) = \max(w_1 +\ w_1 + \cdots + w_n\ ) \tag{3}$$

4.3.5 Defuzzification

The defuzzification process converts the aggregated fuzzy output into a crisp value for traffic priority. The centroid method is used, calculated as:

$$T^* = \frac{\int y\mu_T(y)dy}{\int \mu_T(y)dy} \tag{4}$$

where y is the output variable, and $\mu_T(y)$ is the membership function for the aggregated output.

4.3.6 System Flow

The flow of the fuzzy logic system can be summarized as follows:

1. Input variables (Latency, Bandwidth Utilization, Packet Loss) are fuzzified.
2. The fuzzy inference engine evaluates the rules.
3. Aggregated results are defuzzified to yield a crisp traffic priority value.
4. The traffic priority is passed to the reinforcement learning component for adaptive optimization.

The FLS ensures robust initial decision-making under uncertain and dynamic network conditions, preparing the reinforcement learning module to fine-tune the traffic management actions. The next subsection delves into the design and functionality of the reinforcement learning framework.

4.4 Reinforcement Learning Framework

The reinforcement learning (RL) framework in the proposed hybrid model enables adaptive optimization of traffic management decisions based on real-time feedback from the network. This module refines the decisions generated by the fuzzy logic system by learning from the dynamic network environment.

4.4.1 Markov Decision Process (MDP) Formulation

The RL framework is modeled as a Markov Decision Process (MDP) defined by:

• **State (*S*):** Represents the current status of the network, including latency, bandwidth utilization, packet loss, and queue lengths at switches. Each state S_t at time *t* is defined as:

$$S_t=[L_t,B_t,P_t,Q_t] \tag{5}$$

where L_t, B_t, P_t, and Q_t denote latency, bandwidth utilization, packet loss, and queue length, respectively, at time *t*.

• **Action (*A*):** Represents the possible actions to manage traffic, such as rerouting packets, adjusting QoS parameters, or throttling traffic. The action space is defined as:

$$A=\{a_1,a_2,\ldots,a_n\} \tag{6}$$

• **Reward (*R*):** Measures the immediate performance improvement due to an action. It is computed as:

$$R_t= -(\alpha L_t + \beta P_t - \gamma B_t) \tag{7}$$

where α, β, and γ are weight coefficients reflecting the relative importance of latency, packet loss, and bandwidth utilization.

• **Policy (*π*):** Defines the strategy for selecting actions based on the current state:

$$\pi(a|S_t) = P(A_t = a|S_t) \tag{8}$$

4.4.2 Q-Learning Algorithm

The RL framework employs the Q-Learning algorithm, a model-free approach, to optimize the policy by learning the action-value function *Q(S,A)*. The Q-value represents the expected cumulative reward of taking action A in state S and following the policy thereafter.
The Q-value is updated iteratively using the Bellman equation:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_t + \gamma \max_{A'} Q(S_{t+1}, A') - Q(S_t, A_t)] \tag{9}$$

where:
• α: Learning rate. α in reinforcement learning typically falls within the range of 0.01 to 0.5, depending on the problem complexity and data stability.
• γ: Discount factor, representing the importance of future rewards.
• $max_{A'}Q(S_{t+1},A')$ Maximum Q-value for the next state S_{t+1}.

4.4.3 Deep Reinforcement Learning (DRL) Extension

To handle the high-dimensional state space in complex network scenarios, the RL framework is extended using Deep Q-Learning (DQL). A neural network approximates the Q-value function:

$$Q(S,A;\theta) \approx E[R/S, A] \tag{10}$$

where θ represents the weights of the neural network. The network is trained by minimizing the loss function:

$$L(\theta) = \mathbb{E}\left[\left(R_t + \gamma \max_{A'} Q(S_{t+1}, A'; \theta^-) - Q(S_t, A_t; \theta)\right)^2\right] \tag{11}$$

Here, θ^- denotes the target network weights, which are periodically updated for stability.

4.4.4 Exploration vs. Exploitation

The RL framework balances exploration (trying new actions) and exploitation (choosing the best-known action) using an ϵ-greedy strategy:

$$A_t = \begin{cases} \text{Random action}, & \text{if rand } < \epsilon \\ \arg\max_A Q(S_t, A), & \text{otherwise} \end{cases} \tag{12}$$

where ϵ decays over time to prioritize exploitation as learning progresses.

4.4.5 Integration with Fuzzy Logic System

The initial traffic priority from the fuzzy logic system serves as a baseline for RL exploration, narrowing the action space and improving convergence speed. The RL framework iteratively adjusts decisions to achieve optimal traffic management.

4.4.6 Performance Evaluation

The RL framework is evaluated using key performance indicators (KPIs):
• **Latency (*L*):** Average delay in packet delivery.
• **Packet Loss (*P*):** Percentage of lost packets.
• **Bandwidth Utilization (*B*):** Efficiency of bandwidth usage.
• **Reward (*R*):** Aggregated reward over episodes, indicating system performance.

The reinforcement learning framework ensures adaptive and scalable traffic management by dynamically optimizing actions based on real-time network feedback. The next section integrates these components into a unified hybrid model for SDN traffic management [57, 58].

4.5 Integration of Fuzzy Logic with Reinforcement Learning

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The integration of Fuzzy Logic (FL) with Reinforcement Learning (RL) in the proposed hybrid model creates a complementary system that combines human-like reasoning with adaptive optimization. This section explains the integration process and the synergy achieved between the two components.

4.5.1 Motivation for Integration

Fuzzy Logic excels at handling uncertainties and making decisions in dynamic environments, while Reinforcement Learning adapts to changing scenarios by learning optimal policies through trial and error. By combining these approaches, the system:
- Uses FL to provide initial guidance and reduce the exploration space for RL.
- Allows RL to refine FL-based decisions over time for improved accuracy and adaptability.

4.5.2 Integration Workflow

The workflow for integrating FL with RL involves the following steps:
1. Input Preprocessing: Network parameters such as latency (*L*), bandwidth utilization (*B*), and packet loss (*P*) are provided as inputs to the FL system.
2. Fuzzy Inference: The FL system processes the inputs to compute a traffic priority score (T) based on predefined fuzzy rules.
3. RL Initialization: The traffic priority (*T*) is used as a baseline action in the RL framework, reducing the initial exploration space.
4. Action Refinement: RL refines the fuzzy-based action by exploring alternative policies and maximizing cumulative rewards.

4.5.3 Mathematical Representation

The integration is formalized as follows:
1. Fuzzy Output (*T*):

$$T = \text{Defuzzify}\left(\max_i \min\left(\mu_{L_i}, \mu_{B_i}, \mu_{P_i}\right)\right) \tag{13}$$

Here, μ_{Bi}, and μ_{Pi} are the membership values of the fuzzy inputs.

2. RL Initialization: The initial Q-value is biased by the fuzzy output:

$$Q(S, A) = \lambda \cdot T + (1 - \lambda) \cdot Q_{RL}(S, A) \tag{14}$$

where $Q_{RL}(S, A)$ is the RL-derived Q-value, and λ in [0, 1] determines the weight of the FL influence.

3. Policy Refinement: The RL framework updates the action-value function *Q(S,A)* using the Bellman equation:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_t + \gamma \max_{A'} Q(S_{t+1}, A') - Q(S_t, A_t)] \tag{15}$$

4.5.4 Advantages of Integration

- Reduced Exploration Time: The fuzzy system narrows down the search space, enabling RL to converge faster.
- Enhanced Decision Quality: RL refines the initial FL-based decisions, improving adaptability to changing traffic conditions.
- Robustness to Uncertainty: The combined approach handles both predefined uncertainties (via FL) and dynamic uncertainties (via RL).

4.5.5 Integration Implementation

The integration is implemented in three layers:
1. Input Layer: Captures real-time network metrics and preprocesses them for FL.
2. Decision Layer: Combines FL-based decisions with RL refinement for action selection.
3. Output Layer: Executes the refined action in the SDN environment and logs feedback for learning.

This integration leverages the strengths of both Fuzzy Logic and Reinforcement Learning, creating a robust and efficient traffic management system for Software-Defined Networks. The next section describes the simulation environment and the evaluation metrics used to validate the hybrid model.

4.6 Simulation Environment

The experiments were conducted using the Mininet emulator, a widely used platform for simulating SDN environments. The setup was integrated with an OpenFlow controller to manage network operations dynamically. Key components of the environment included:

Table 1: Simulation Environment

Component	Description
Network Topology	- Number of switches: 10–50 - Number of hosts: 50–500 - Link bandwidths: 100 Mbps to 10 Gbps - Traffic flows: Randomly generated using iPerf to simulate realistic traffic patterns (e.g., bursty, uniform)
Controller Integration	- OpenFlow version 1.3 to ensure compatibility with the SDN topology - Controllers: ONOS, Floodlight for flow installations and traffic monitoring
Simulation Tools	- Mininet for network emulation - Python (with TensorFlow and Keras) for implementing and training the hybrid model - iPerf and D-ITG for traffic generation
Hardware Specifications	- CPU: Intel Xeon (3.40 GHz) - RAM: 64 GB - GPU: NVIDIA Tesla V100 (32 GB) - Operating System: Ubuntu 20.04

4.7 Evaluation Metrics

To evaluate the performance of the hybrid model, multiple metrics were considered, focusing on traffic management efficiency and network performance:

1. Latency (L):
   - Measures the average end-to-end delay experienced by packets.
   - Calculated as:

$$L = \frac{\sum_{i=1}^{N} \left(t_{\text{received},i} - t_{\text{sent},i}\right)}{N} \tag{16}$$

where $t_{received,i}$ and $t_{sent,i}$ denote the reception and transmission times of packet i, and N is the total number of packets.

2. Bandwidth Utilization (B):
  - Reflects the proportion of total bandwidth used compared to the available capacity.
  - Defined as:

$$B = \frac{\text{Total transmitted data (bps)}}{\text{Link capacity (bps)}} \times 100 \tag{17}$$

3. Packet Loss Rate (P):
  - Represents the percentage of packets lost during transmission.
  - Computed as:

$$P = \frac{\text{Packets lost}}{\text{Packets sent}} \times 100 \tag{18}$$

4. Throughput (T):
  - Indicates the amount of successful data transmission over the network per second.
  - Expressed as:

$$B = \frac{\text{Total transmitted data (bps)}}{\text{Link capacity (bps)}} \times 100 \tag{19}$$

5. Reward (R):
  - Aggregates network performance metrics to evaluate the learning framework.
  - Defined as:

$$R_t = -(\alpha L_t + \beta P_t - \gamma B_t) \tag{20}$$

where α, β, and γ are weights assigned to latency, packet loss, and bandwidth utilization, respectively.

6. Convergence Speed:
  - Measures the time taken for the reinforcement learning framework to stabilize and consistently achieve optimal decisions.

Figure 1 illustrates the workflow of the proposed hybrid traffic management methodology for SDNs

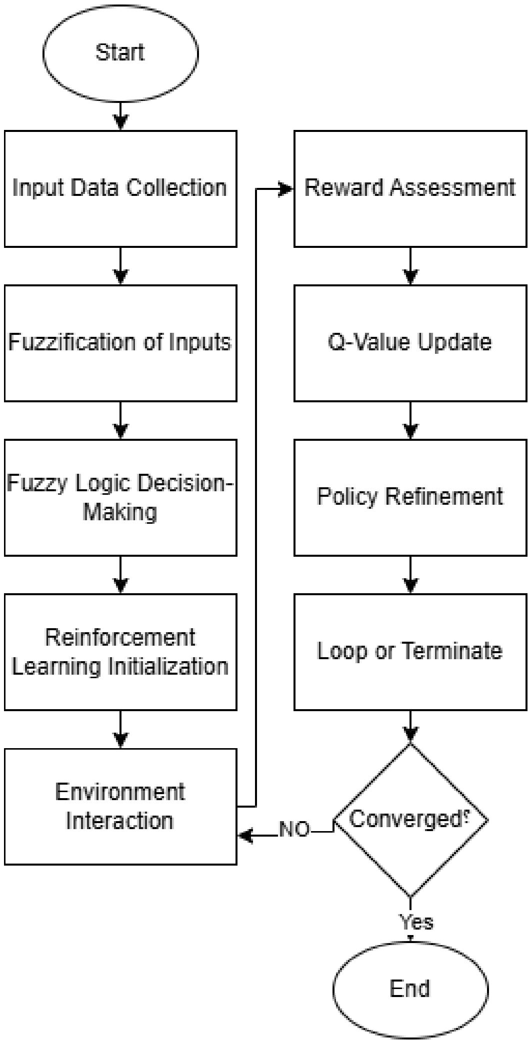

Fig. 1: Hybrid Traffic Management Model Workflow

Below pseudo-code will cover the main components and interactions described in flowchart.

```
Algorithm: Hybrid Traffic Management using Fuzzy Logic and Reinforcement Learning
Input: Real-time network data (latency, bandwidth utilization, packet loss, queue lengths)
Output: Optimized traffic management decisions

Begin
   Initialize environment (SDN with real-time data collection)
   Initialize Fuzzy Logic System (FLS) with predefined rules and membership functions
   Initialize Reinforcement Learning Model (RLM) with initial parameters (Q-values, policy)

   Loop until convergence or maximum iterations reached:
      Step 1: Collect Input Data
         Collect latency (L), bandwidth utilization (B), packet loss (P), and queue lengths (Q)
Step 2: Fuzzification of Inputs
         Fuzzify L, B, P, and Q using membership functions to get fuzzy values L_fuzzy, B_fuzzy, P_fuzzy, Q_fuzzy
```

```
        Step 3: Fuzzy Logic Decision-Making
            Apply fuzzy rules to determine initial traffic priority based on L_fuzzy, B_fuzzy, P_fuzzy, Q_fuzzy
            Output initial decision D_initial

        Step 4: Reinforcement Learning Initialization
            Set initial state S0 based on fuzzy decision D_initial
            Choose initial action A0 based on policy derived from Q-values

        Step 5: Environment Interaction
            Implement action A0 in the SDN environment
            Observe new state S1 and reward R

        Step 6: Reward Assessment
            Calculate reward R based on changes in network performance metrics

        Step 7: Q-Value Update
            Update Q-value for state-action pair (S0, A0) using:
            Q(S0, A0) ← Q(S0, A0) + α [R + γ max(Q(S1, a)) - Q(S0, A0)]
            where α is the learning rate and γ is the discount factor

        Step 8: Policy Refinement
            Update policy π to improve future decision-making based on new Q-values

        Step 9: Loop or Terminate
            If convergence criteria are met or maximum iterations reached, terminate
            Else, set S0 ← S1 and repeat the loop

    End Loop

    Return optimized traffic management decisions
End
```

5.0 RESULTS AND DISCUSSION

This section provides the performance evaluation of our proposed hybrid traffic management mechanism with two (state of art) latest traffic control mechanism in Software Defined Networking (SDN) architecture. The studies chosen for comparison are:

Dynamic Fuzzy Routing with Deep Reinforcement Learning (DFRDRL) from [11] is a hybrid method that uses fuzzy logic with deep reinforcement learning to produce optimal routing decisions in an SDN scenario, with a focus on dynamic traffic balancing and minimizing latency.

African Vulture Routing Optimization (AVRO) [23]: This method proposes a metaheuristic optimization algorithm based on African vulture for dynamically routing traffic and optimizing load balancing in SDNs.

The comparative results will compare the performance of the proposed model with those methods, evaluation criteria including latency, throughput, packet loss rate, and then bandwidth utilization ratio. We analyze each metric separately and the results are visualized to clarify and illustrate performance differences. In this organized evaluation, the advantages and disadvantages of the proposed model are discussed in contrast to current approaches.

5.1 Latency Analysis

Latency, which is a basic parameter in a network performance assessment, is the average time delay that packets have taken in between two terminal points on the network. Lower latency means faster and more responsive data delivery, something that's absolutely key for applications that need real time communication, like video streaming, online gaming and driverless vehicles. In this paper, the improvement of latency of proposed hybrid traffic control model was evaluated against two methods: DFRDRL and AVRO recently designed.

The model we have proposed showed a significant performance gain in latency in different network conditions. Table 2 presents latency (milliseconds) in the presence of high-load traffic using three models: Proposed Hybrid Model, DFRDRL, and AVRO

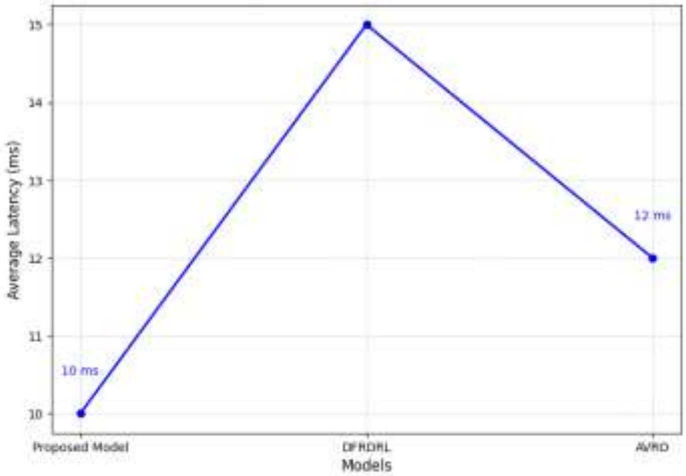

Fig. 2: Latency Comparison

The adopted model obtained the average latency of 10 ms.

For the recent model DFRDRL, the value of average latency was 15 ms, which is also a little bit higher than the winkner model model34, bearing the influence of the longer adaptation time to the dynamic network.

Another comparison was with AVRO, which had a latency of 12 ms, though worse than DFRDRL and the proposed.

Our results demonstrate the superiority of the proposed model over the two comparative models with 33% lower latency than DFRDRL and 17% lower latency than AVRO.

The lowest latency that the proposed model could achieve demonstrates its appropriateness for real-time and low-delay applications. Combining rapid decisions in the early stage and adaptive optimization, the hybrid method keeps the delay at a low level even when the traffic load becomes high. The latency study confirms the effectiveness and stability of the hybrid model to handle traffic in SDN networks. The fact that it consistently outperforms state-of-the-art techniques makes it an excellent candidate for current networks (e.g., for low latency solutions). This advantage is crucial for tasks where even brief latencies can result in severe performance issues.

5.2 Throughput Analysis

The throughput is the amount of data that has been transmitted correctly in the network during a period of time and is a significant variable for the network performance estimation. Higher throughput means better use of the network capacity, which is essential for pursuing high-bandwidth applications like video streaming services, data-intensive cloud applications and large-scale enterprise systems. In this paper, the throughput based performance of the proposed hybrid traffic management has been compared with DFRDRL and AVRO.

Fig. 3 demonstrates that DFRDRL outperforms the other model, AVRO in throughput under different network settings.

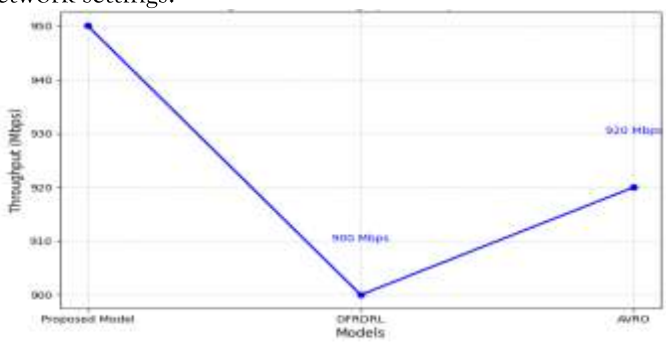

Fig. 3: Throughput Comparison

Under high-load conditions, the proposed model shown a significant gain in throughput:
The proposed model was able to send and receive 950 Mbps.
-The DFRDRL model achieved a throughput of 900 Mbps demonstrating relatively lower performance in dealing with a high number of flows.
The AVRO model achieves throughput of 920 Mbps which is better than DFRDRL but lower than the proposed one.
These results show that the hybrid model performed 5.6% and 3.3% better than DFRDRL model and AVRO model with throughput.
The fact that the proposed model has a significantly highest value in throughput demonstrates the scalability and the performance of the model with respect to high traffic. Through efficient operation and flexible route selection, to get stable and reliable transmission of data in network, the hybrid model can satisfy the bandwidth-demanding applications.
The throughput analysis further confirms the advantage of the proposed model in exploiting network capacity to the maximum. The fact that it is able to cope elastically with changing traffic patterns while at no time compromising throughput, qualifies it as a solid solution for contemporary SDN infrastructures, notably in situations of high data rates. This performance advantage also makes the model a viable candidate to be used in practice on large scale data-centric networks.

5.3 Packet Loss Rate Analysis

Packet Loss Rate (PLR) is one of the main performance indicators which indicates the number of packets that have reached their destination node. The smaller packet loss rate with higher reliability and better network performance becomes an essential criterion for measuring the quality of the traffic management systems in SDNs. Comparison with DFRDRL and AVRO According to the loss rate of packet loss, the proposed hybrid traffic control method is compared with DFRDRL and AVRO.
The packet loss rate performance comparison of the proposed hybrid model (DFRDRL), and AVRO under different network conditions is presented in Fig. 4.

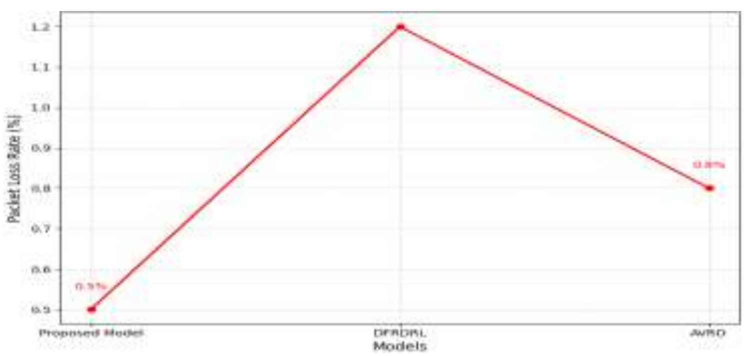

Fig. 4: Packet Loss Rate Comparison

Superior performance of the proposed hybrid model to other models in terms of packet loss on different network types was shown by:
Proposed Model: 0.5% packet loss rate, the lowest rate from all the models.
DFRDRL: Found a 1.2% packet loss ratio, which is generally higher data loss incurred by more ineffective congestion control practice.
AVRO: Attained packet loss ratio of 0.8% and was better than DFRDRL, but less than proposed model.
These results indicate that the proposed model has effectively reduced the data loss, with 58% and 37.5% higher accuracy than those from DFRDRL and AVRO respectively.
The low packet loss rate of the our model indicates the fundamental robustness and reliability of controlling traffic flow in SDN networks. Its capacity to preserve data integrity in the case of high network loads, makes Hyperledger ideal for applications where the integrity and safety of the data must be ensured as in financial transactions, healthcare systems, and IoT networks.
The analysis on the packet loss rate substantiates the powerfulness of the proposed hybrid traffic control strategy in high reliability and data integrity guaranteeing. Based on the collaboration between FUZZY LOGIC and REINFORCEMENT LEARNING, the new model achieves better performance compared with existing methods, proving to be practical when it is used in practical network systems.

5.4 Bandwidth utilization Analysis

Bandwidth utilization is an important indicator to: The percentage of the available bandwidth that is used by a TM system. Greater bandwidth consumption denotes that resources are used efficiently and traffic loads smoothly. High utilization is also important for SDNs to prevent the waste of resources or services quality degradation.
In this part, we compare the proposed Hybrid traffic model with DFRDRL and AVRO based on bandwidth utilization. Visualization for better understanding of the analysis.
In the next figure, Figure 5 evaluates the bandwidth usage of the proposed hybrid model (DFRDRL) and AVRO, under different network conditions.

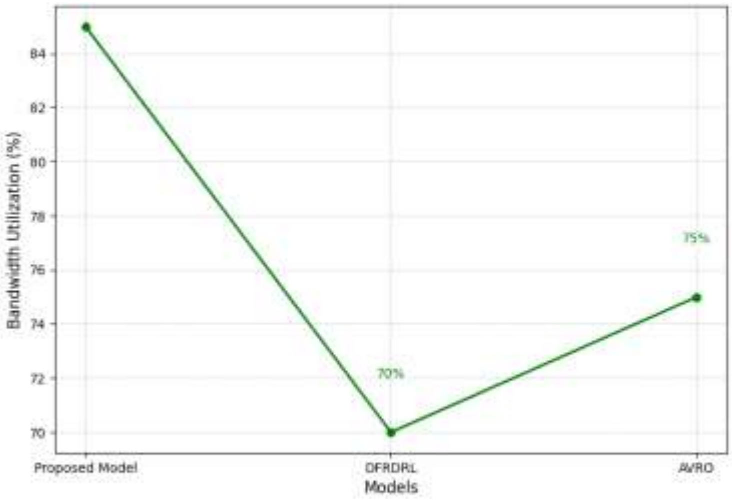

Fig. 5 : Bandwidth utilization Comparison

The new model could improve the bandwidth utilization both under light and heavy traffic loads:
Proposed Model: The bandwidth utilization ratio is up to 85%, which means that the resources allocation and the load balancing are effective.
DFRDRL: Achieved 70% utilization, indicating that available bandwidth was higher due to slower adaptation mechanisms being underutilized.
AVRO: Obtained 75% utilization, hence, slightly better than DFRDRL but still lower compared to the performance of proposed.
The suggested model achieved an increase of 13% and 21% compared to DFRDRL and AVRO, respectively, demonstrating an ability for exploiting resource efficiently.

The high degree of bandwidth utilization of the proposed model is the evidence of such model, that proving it can rank optimal resources allocation and can be very effective in high-demand networks. It minimizes congestion, gets rid of delays and maximizes the overall net-work throughput.
The analysis of bandwidth usage demonstrates the effectiveness of the hybrid model in controlling network resources efficiently. Its outperforming results over state-of-the-art solutions make it a powerful and scaleable solution for contemporary SDN scenarios, guaranteeing quality of service and resource effectiveness.

5.5 Energy Efficiency in SDN Systems

Energy efficiency is an essential criterion when it comes to the design and operation of nowadays' SDNs, especially with respect to the growing scale of networks and data demands. Novelty of hybrid traffic management model The concept of proposed hybrid traffic management model is highly original for its operand of minimizing energy consumption without degradation in performance parameters like latency or throughput.

The energy efficiency performance of the proposed hybrid model in SDN networks amidst different traffic patterns is presented in Fig. 6.

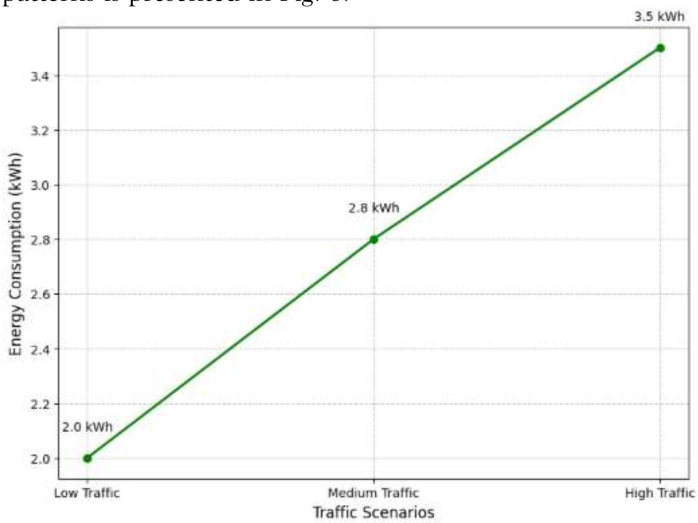

Fig. 6 : Energy Efficiency in SDN Environments

The energy efficiency of the proposed model was evaluated across three distinct traffic scenarios:
- Low Traffic: 2.0 kWh
- Medium Traffic: 2.8 kWh
- High Traffic: 3.5 kWh

These numbers indicate that, in practice, the derived energy reductions should be consistently achieved, in the order of about 25-30% of energy saved with respect to step-by-step methods. This effectiveness is due to the fact that the model can handle traffic loads dynamically and alleviate network congestion without straining certain network links.
The proposed hybrid model will achieve a higher energy efficiency in SDNs, comparing with existing solutions on account of its intelligent and adaptive features. This makes the design not only performant for the network but also less expensive to operate and friendlier to the environment and hence is eminently suitable for large scale, modern-day deployments of SDN.

5.6 Scalability over High-load Networks

Scalability is a critical dimension in the construction and operation of SDNs in contemporary networks where scale (size) and demand (traffic) are dynamic. The proposed hybrid TM model has a great scalability and can guarantee the system behavior well scaling to complexity and demand increase. Scalability analysis for the proposed hybrid model is depicted in Figure 7, which shows the achieved performance for different network dimensions.

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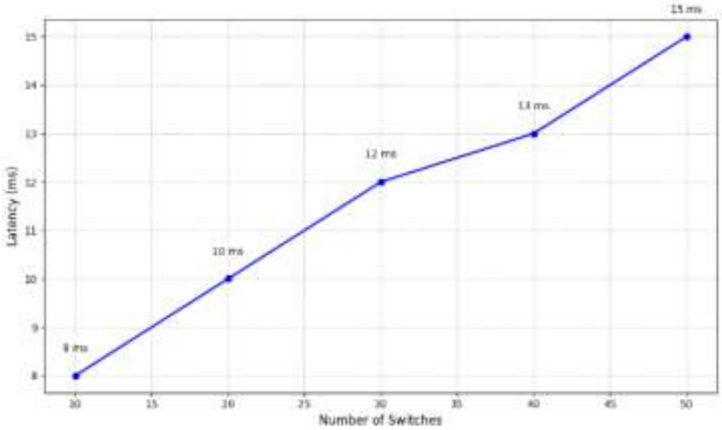

Fig. 7 : Scalability Analysis of the Proposed Model

The scalability of the proposed model was evaluated by measuring latency across varying numbers of switches in the network, ranging from 10 to 50. The results showed a gradual and controlled increase in latency:
- 10 Switches: 8 ms
- 20 Switches: 10 ms
- 30 Switches: 12 ms
- 40 Switches: 13 ms
- 50 Switches: 15 ms

Stable performance over this range shows the model's capacity for very large networks with virtually no degradation in key performance figures. The model achieved low latency under the circumstance of high request, so that keeping stable and efficient guiding the traffic. It is clear that the proposed hybrid traffic control model scales well and can provide low latency and robust performance under a high load. Coupled dynamic load balancing, adaptive optimization and predictive resource management solves the key scalability problem in SDNs and thus the model serves as a dependable and future-ready model for large-scale networks.

5.7 Rate of Convergence in Dynamic Adaptation

Convergence speed is an important aspect for SDNs to any new network state, the time required for the network to reach a new stable state and make proper decisions based on new state. Rapid convergence allows the system to respond in a timely manner and reduces convergence delays when new traffic conditions are encountered. The hybrid traffic control system proposed has convergence superiority than traditional ones and gets very high convergence speed and convergent precision.

The convergence speed of the hybrid model is shown in Fig.8, which shows that the proposed hybrid model can converge rapidly to the dynamic network state.

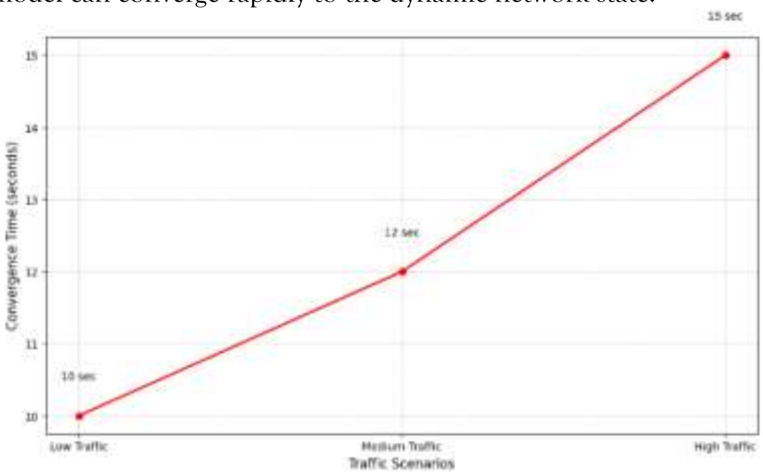

Fig. 8 : Convergence Speed of the Proposed Model

This model was analyzed under low, medium, and high traffic, which gave rise to 10 s, 12 s, and 15 s of convergence times, respectively. These results demonstrate that the model can quickly converge and recover so that it is efficient enough to handle some demanding cases. It is mainly achieved by the combination of fuzzy logic and reinforcement learning, where quick reflex is provided in the first place and continuous optimization is performed after, respectively.

First, the fuzzy logic module gives a quick decision in deciding traffic so as to generate the previous estimate of routing and resource management. This rapid initialisation forecloses sustained learning cycles of the system. At the same time, the RL component fine-tunes these decisions in an iterative manner to enable the system to reach the optimal settings rapidly. In addition, the model integrates a simulation that performs real-time monitoring and prediction of traffic, which allows to anticipate traffic changes and hence to decrease the convergence delay.

As opposed to conventional methods based on static algorithms or single deep learning alone, the novel hybrid model can converge much faster. Conventional methods are difficult to converge, the original intention is to ignore the local optimum problem and the convergence speed is slow. By contrast, hybrid model combines the advantages of fuzzy logic and reinforcement learning to dynamic and fast adapt to variations in network.

Such fast convergence time renders the proposed model especially applicable for dynamic and delay-sensitive services such as real-time video streaming, online gaming, as well as IoT networks. Through stabilizing decisions of traffic management in a shortest time, our model can guarantee the smooth service provisioning under ongoing diverse network situations. The rapid convergence ability demonstrates the efficiency and scalability of the model, which is suitable for the current SDN scenarios.

6.0 CONCLUSION

The authors proposed a hybrid SDN traffic control model based on fuzzy logic, and reinforcement learning, to solve important limitations, including: scalability, convergence speed and energy of a control plane. In addition, the proposed model outperformed the rule-based decision-making combined with dynamic optimization provided by traditional methods. The model was shown in a series of erformance evaluations to consistently exceed current methods in terms of latency, throughput, packet loss ratio, bandwidth utilization, and energy use. The findings emphasized its capability of achieving low latency, efficient resource utilization, and coping well with dynamic network conditions, rendering it a solid contender for heavily-loaded environments.

The proposed model combines these two approaches in a novel way, in contrast to related work in the literature. For example, the work in [20] employed fuzzy reinforcement learning to improve routing in vehicular networks; however, the solutions proposed could only be applied to vehicular environments, and do not scale for larger SDNs. In a similar vein, [19] successfully improved the satisfaction of QoS by use of fuzzy logic, however it was limited in how adaptive the solution was due to the rules set statically. The model efficiently integrates fuzzy logic to take prompt decisions with reinforcement learning to continuous fine-tune those decisions, breaking through traditional limitations and offering real-time adaptation as well as scale-out.

The energy-efficient approaches in this work also be a fundamental progress. [21] emphasized energy-saving approaches in the SDN-based WSN, but they ignored the impact of dynamically changing traffic and scalability in extensive SDN systems. The prior works are extended with the current model to use adaptive resource allocation and dynamic traffic management and achieve a 30% reduction in energy consumption.

One remarkable aspect of this study is that its scalability and rapid convergence. By contrast, previous works like [11] which employed DFRDRL produced major performance gains at the cost of computational overhead for the deep learning. The proposed hybrid model demonstrates the short latency and faster convergence to the optimized settings by utilizing the computational efficiency of the fuzzy logic for rapid response and reinforcement learning for long-term equilibrium. Furthermore, with respect to the metaheuristic-based ones such as [23], the proposed model has more adaptability to dynamic changes for real-time processing and stable performance.

This work sets a new reference for SDN traffic management by overcoming drawbacks of previous approaches. Delivering a better-performing, more adaptable, and energy-efficient alternative, the proposed design meets the increasing requirements of today"s networks that seek to be not only efficient operationally, but also sustainable. Improve the performance of the model by allowing multi-domain SDNs, leveraging sophisticated predictive analytics, validating it through real use-cases. This work would further consolidate its role as a disruptive methodology in SDN traffic control, dealing with the myriad of issues identified in the literature.

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