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RESEARCH ARTICLE

Improving Energy Consumption in Software Defined Network by Predicting Optimized Flow Routing Using Deep Learning Method

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Abstract – Currently Software Defined Network (SDN) plays a major role in Data Centers (DCs) and widely used. These networks programmable has influenced the better features which admit innovation in deploying the enormous recent applications in faster and secured manner. This advancement exhibit with cost of high processing power as well as energy consumption. Several researchers have undertaken these problems by existing routing techniques in dynamic adjusting of forwarding plane network for saving energy. In accomplishing fine grained network performance through optimizations for flow routing using different routing packets traffic flow with distinct network paths. Implementation of centralized network optimizations can be controlled through SDN centralized controller by optimized flow routing. The flow routing implementation is adjustable by altering traffic loads for complex models. However, the study goal is in pursuing a model associated with Reinforcement Learning (RL) for rerouting the flow of SDN. Therefore, this paper introduced RL based Convolution Neural network (CNN) with hyperparameter modelling for better performance of energy efficiency of the network by improving the already proposed route selection. The proposed RL-CNN with hyperparameter model has provided a suitable Quality of Service (QoS) over hybrid IP or SDNs which assist in coordinating both IP and SDN paradigm. Traffic balancing using minimum network power consumption and link utilisation over hybrid IP or SDNs with assist of proposed RL-CNN with hyperparameter. The proposed RL-CNN is assessed over topologies of various sizes utilizing various techniques to determine which nodes need to be converted from IP to SDN.

Index Terms – Software Defined Networking, Convolution Neural network (CNN), Energy Consumption, Reinforced Learning (RL), Hyperparameter. Markov Decision Process, Network Topology, Energy Efficient Routing.

1. INTRODUCTION

Global Data Center (DC) traffic has been detonated with rapid advancement of an Internet services. Nevertheless, DC networks has carrying out various enormous services and its traffic demand which is distributed unevenly and high dynamic changes. Hence, the obtained outcome in the DC networks have faced an enormous energy consumption issue [1]. In the current decade, existing researchers discusses that energy consumption of DC network has accounted 8% of global electricity consumption. Energy consumption for network infrastructure has accounted 20% of DC energy consumption [2]. Basic issues in flow routing is communication network of packet switched in which each packet of a given flow such as a flow of Transmission Control Protocol (TCP) need to pursue the similar path of routing by the packet switching nodes network. There are various flows among the similar source and destination switch pairs may follows distinct routing path for optimizing the performance of the network. Thus, flow routing differs significantly from traditional path routing that simply considers the destination host or the source-destination switch combination. In order to execute congestion control and improve a variety of network performance indicators, routing flow has offered a huge range of adjustments in optimisation of the loads in the network communications. SDN controller has ability to configure the packet-switching nodes dynamically make decisions from a central location. The centralised controller is cognizant of the current status of the entire network, including all switching nodes and the links that connect it, as well as network monitoring metrics. Therefore, it seems that SDN is appropriate to facilitate the flow routing optimization [3-5].

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In this present decade, flow routing methods are comparatively complex and significant progress has been created but the flow routing remain complex in routing method. Routing method needs detailed patterns about network communication and network traffic [6] [7]. Based on the increase of recent technology like Artificial Intelligence (AI), researchers have enforced comprehensive researches on optimizing network performance by introducing various intelligent outing algorithm to optimize the network performance [8]. However, intelligent flow control method with respect to the Deep Learning (DL) is proposed. Therefore, the selection of best optimum strategy of routing with respect to the link congestion through specific state input using CNN [9]. When, comparing with traditional routing algorithm, less packet loss and average delay has been generated but these methods basically required for accomplishing large amount of exactly labelled datasets in the network and even require participation physically. Thus, the algorithm of intelligent routing is associated with supervised learning that implemented subjected to some limitations. Intelligent routing algorithm with respect to deep RL has proposed and SDN has assist for dynamic collection of information in network traffic, sequence of routing strategies is scheduled and understanding end-to-end delay optimization with distinct throughputs [10]. In this case, intelligent routing approach associated with deep RL in the DC networking is proposed by considering adaptive routing optimization from various network states by various recognition methods of network resources [11].

Figure 1 illustrates the process by which a decision-making agent first assesses the environment, selects its state, and then executes the appropriate action. One of the traditional methods in solving decision making problems through Markov process.

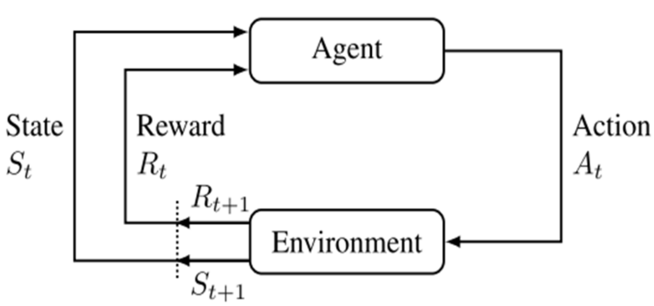

Figure 1 RL Working Interaction Among Environment and Agent

Markov Decision Process (MDP) contain of state set(S) in which the action set for the state is represented as A which is state dependent and the transition probabilities of the state reward is expressed in equation (1).

$$P(s_0, r|s, a) = \Pr(S_{t+1} = s_0, R_{t+1} = r|S_t = s, A_t = a) \quad (1)$$

Where,

Defined probability in reaching a succeeded state S_{t+1} = s and 0 from the previous state S_t = s while performing action A_t = a. Reward received as R_{t+1} = r there hasn't been much research done on how a RL agent might represent the routing flow of SDN challenge with effective decision making. It is particularly important to look into how states and actions should indeed be created in order for a RL agent to describe the flow routing problem successfully [12].

Optimization algorithm for energy saving topology in performing optimization of control plane has been proposed [13]. Accommodation of this method with control plane load as well as energy consumption of data plane by traffic design awareness and device sleeping technology. Thus, the accomplished energy saving topology has improved the control plane performance to some extent but cause some delay consumption. If the frequency of switches has modified among sleep and device activation which summarize the intelligent routing algorithms with respect to DL shown better performance merits over DC networks.

Moreover, the rerouting algorithms generally provides optimization in network performance or rather in optimising traditional energy saving network and doesn't establishing the goal of joint optimization in network performance as well as energy saving. Current scenario discusses about network scaling that expand constantly and demand in network traffic is constantly complex. This frequently resulted with less energy efficiency in routing algorithms, as well as performance measurements like energy consumption, delay, throughput and packet loss that still need an improvement. Such an intelligent routing algorithms challenge to establish unique optimization in energy efficient traffic goals using DL method.

1.1. Contribution of the Proposed Work

The proposed method takes into account the following objectives:

1. This research focuses on the energy saving of SDN that can be implemented through rerouting of flow routing using CNN based hyperparameter
2. The RL assist to obtain the best reward in rerouting the network topology which focuses on the preservation of flow with multipath routing by RL-CNN based hyperparameter of SDN.
3. SDN can be achieved significantly with less flow latency than earlier routing methods which define only a single route from source to destination.
4. Energy efficiency of the network is increased as well as lifetime of the network is also increased by using RL-CNN method.

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1.2. Organization of Paper

The organization of the paper is follows: Section 2 discusses the literature survey of this paper, section 3 presents the proposed research methodology to energy efficient in SDN, section 4 discusses the simulation results and section 5 concludes the paper.

2. LITERATURE REVIEW

This literature review has discussed about the selection of multi-path routing approaches by various algorithm and advantage of accomplishing energy efficiency by DL method.

Z.Rao, Y.Xu and S.Pan has enforced an intelligent routing technique associated with deep RL that resolves constraint issues by Lagrangian multiplier approach. This routing services may require comprehend user requirement in network performance. The proposed methodology stated in this high-quality routing between source to destination which was often occurred on SDN network devices and main drawback of this approach was its high computational complexity [14]. Algorithm for multi-path routing related to real-time link as well as traffic features is proposed from D.Peng, Y.Liu and X.Lai. Elephant and mice flows are routed by this method and evaluated through network performance optimizer and link weight proportion measures like throughput and average link utilization [15].Y.Huet al., proposed an architecture of intelligent driven network with respect to SDN has considered throughput and network delay over data plane as an optimization goal. This algorithm efficiently advances the load balancing of network while comparing with conventional routing algorithms like ECMP and OSPF. The main limitation of this work is that it does not support large number of switches in SDN [16].C.Yu et al., proposed deep RL in Traffic Engineering (TE) has endorsed tuples of throughput-latency vector in all current flow as state space. When the study of DROM (Dynamically Read Only Memory) is considered the source to destination flow as a state space of traffic matrix. The experimental findings demonstrate that DROM offers superior routing configurations to enhance network performance over current alternatives and has good convergence and effectiveness. This work primary drawback is its lack of support for end-to-end transport that is efficient, dependable, and QoS-aware.[17]. P.Sun et al., has discussed about TIDE for network status matrix with time series that consist of link utilisation levels. They presented TIDE, a deep reinforcement learning-based intelligent network control architecture that can dynamically optimize SDN network routing methods without the need for human intervention. This work primary drawback is its lack of complexity [18]. Indirect routing action specifications has been discussed in the earlier studies. However, the space actions over TIDE and DROM have been linked the weight setting when the space of action over deep RL-TE to set a probabilistic split ratio in every ongoing flow. Hence, the split ratio of probabilistic has specified the probability for the available packets that send to a specific path. Thus, the point out study during deep RL-TE probabilistic split method made a significant first contribution in understanding the routing of SDN with deep RF and the flow of probabilistic has breach strategy which is not appropriate to the network with high speed. This work primary drawback is its lack of performance [19].

T.F.Oliveira, S.Xavier-de-Souza, L.F.Silveira, has focused controlling plane of network technique to improve energy efficiency which has capacity in parallel processing that split multiple task in controlling by multicore processor. The control-plane of the network is the subject of this paper innovative approach to energy efficiency, which complements the several data-plane techniques now in use. It divides the several functions of the controller across the cores by utilizing the parallel processing capabilities of contemporary off-the-shelf multicore processors. One can reduce the frequency of operations and overall energy usage while maintaining the same level of service quality by distributing the duties among homogeneous cores [20]. Even though these tasks division between similar cores, the frequency get reduced has assist in minimising the energy consumption by not maintaining the similar QoS levels. It has utilised the multicore processor for saving the consumed energy with no compromising QoS level. The SDN proposed method evaluate energy efficiency, throughput and latency metrics for DC metrics like Communication Network Energy Efficiency (CNEE). The controller pane is defined through the less power nodes has discussed from Mohsin et al. whereas the shortest path selection in Wireless Sensor Networks (WSN) is analysed using the meta-heuristic SDN technique. This work primary drawback is more complexity[21]. The proposed method has improved Dolphin Echolocation Algorithm (DEA) is developed to address the issues with exploration and exploitation. This algorithm may assist in determining the nodes path with highly effective. In this study, the shortest path is chosen using selections of nodes residuals. In their research, Madhukrishna et al. emphasised the necessity for an energy-efficient method. For the huge and diverse SDN applications, they have concentrated on the active and sleep modes. This work's primary drawback is more complexity [22]. This energy consumption-based routing technique aids in energy savings for real-time applications and introduces a paradigm for SDN energy efficiency. Long Short-Term Memory (LSTM) and CNN are combined in creation of a hybrid DL model by Khan et al. that had a 95.17% overall accuracy. This work primary drawback is more high computational time[23]. Malik et al., has suggested a recent deep SDN technique to quick and accurate identification of various traffic applications. This suggested approach uses a novel deep learning model for software-defined networks that can quickly and reliably forecast a variety of traffic applications. Better results have been reported in terms of

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accuracy, precision, recall, and FScore when the suggested model performance was compared to state-of-the-art methods [24].The proposed model accomplished high accuracy while comparing against the traditional theatre models. Depending on classified priority flow by intelligent AMPS controller in which the Pasca et al., has ensures a high reliability and earlier flows in loaded network. This work primary drawback is more complex [25]. Awareness in application of the SDN environment is carried out by authors using a CNN-based DL method. This work provides a deep learning mechanism based on Convolutional Neural Networks (CNNs) to achieve application-awareness. It consists of three stages: traffic collecting, data pre-processing, and application-awareness [26]. There are three major metrics such as F-Score, recall and precision stability are surpassed by the suggested technique. Jun Xu et al. has discussed the benefit of DL in SDN, installed in classifying the traffic in Virtualized Network Functions (VNF) for addressing the issues with the computation resources of input or output from the controller of SDN. The network QoS is significantly enhanced by the suggested DL model [27].

To achieve low per-packet latency, CALVIN bypasses the batch processing of packets and the handling of metadata structures typical in the traditional Linux networking stack. In this comprehensive test using commercially available networking and computing hardware demonstrate that CALVIN can achieve round-trip times of approximately 0.32 ms from a MEC ingress point to a MEC egress point, utilizing two basic forwarding VNFs—one in kernel space and one in user space—along with a MEC server [28].

This study provides an overview of haptic interactions, communication, and tactile internet services. It details how 5G New Radio (NR) and the developed Long-Term Evolution (LTE) radio interface can ensure low-latency wireless transmission. Additionally, it explores how 5G's capabilities enable ultra-reliable and low-latency services. The study also examines the costs associated with delivering dependable and low-latency wireless transmission in terms of reduced spectral efficiency and coverage [29].

NF-SSOA algorithm emphasized to elect energy efficient CH by using Neuro Fuzzy algorithm and detect best route path by using Sparrow search optimization algorithm in Wireless Sensor Network (WSN). This algorithm improves the energy efficient and increase the lifetime of the sensor node in the network. The limitation is network overhead is high [30].

An intelligent, energy-efficient multi-objective routing protocol based on the Reinforcement Learning (RL) algorithm with Dynamic Objective Selection (DOS-RL) was presented in this methodology. Since wireless IoT devices have limited energy reserves and must be able to adapt to sudden changes in the network, the main objective of implementing the suggested DOS-RL routing scheme is to optimize energy consumption in IoT networks. This will help to minimize disruptions and improve overall network performance. [31].

This innovative method creates a clever, energy-efficient routing system by combining the adaptive powers of reinforcement machine learning with the AODV routing protocol. Reducing energy consumption and operational overhead while maintaining excellent packet delivery is the main problem in MANETs. RML-EEAODV addresses this by enhancing the AODV protocol's routing decisions. Nodes can use and maintain a dynamic database of state information for intermediary nodes along possible paths thanks to machine learning [32].

The importance of sustainability and dependability is emphasized by the suggested organized framework and the integrated system architecture that combines LTE-M technology with an application server for effective communication. Significant progress was made using a variety of optimization techniques, according to the data. Adaptive Power Control led with a 25% reduction, closely followed by Network Topology Optimization at 22%. Significant reductions of 15% to 20% were also attained by Duty Cycling, Data Aggregation, and Protocol Optimization [33]

By maximizing energy utilization through effective routing, this research proposes a method that uses a neural network trained via Deep Reinforcement Learning (DRL) to increase the lifespan of WSNs. When 2DCNN and 3DCNN neural networks are compared, 3DCNN performs better and has an 18% longer network lifetime. In order to ensure the network's longevity, the study also highlights how important it is to prevent resource depletion in high-traffic nodes by taki.ng other routing methods into account [34]

Table1 refers to the Analysis of the various existing research work methodology, advantages and disadvantages of the survey.

Table 1 Analysis of Different Methods Used in Energy Consumption

S.No	Author	Methodology	Advantages	Disadvantages
1.	Z.Rao et al[14]	Lagrangian multiplier Approach	High Quality Routing	High Computational Complexity

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2.	D.Deng et al [15]	Multi-path Routing algorithm	Large Stream Throughput	High Cost
3.	Y.Hu et al[16]	Novel Self Adaptive Routing Method	Reduce Packet Delivery-Delay	Does not support Large Number of Switches in SDN
4.	C.Yu et al [17]	Deep Reinforcement Learning	High Convergence	Lack of End to End Delivery
5.	P.Sun et al [18]	Time-Relevant Deep Reinforcement Learning	Dynamically Optimize SDN routing	Lack of Complexity
6.	Z.Xu et al [19]	Novel Experience Driven	Dynamic Routing Method	Low Performance
7.	T.F.Oliveria et al [20]	RYC Controller	Parallel Processing	Homogeneous method
8.	Moshin et al [21]	Meta Heuristics	Multi-Processing	More Complex
9.	Madhu Krishan et al [22]	Dolphin Echolocation Algorithm (DEA)	More Effectiveness	More Complex
10.	Khan et al [23]	Hybrid Deep Learning Method	Quality of Services	High Computational Time
11.	Malic et al [24]	Deep Software Defined Networking	High Accuracy and High Speed	More complex
12.	Pasca et. al. [25]	Yen-K- Shortest Path Algorithm	High Reliability	More Complex
13.	N. Hu et. al. [26]	CNN- based Deep learning	High Quality of Services	High Computational complexity
14.	Jun Xu et. al. [27]	Novel hybrid deep neural network	The massive network traffic is collected and processed	More complex
15	J. Sachs et.al [28]	Ultra-reliable and low-latency communication.	High Quality of Service	High Cost
16	Z.Xiang et.al [29]	Chain based low latency VNF implementation	High Speed	Low Bandwidth
17.	K.Dinesh et. al. [30]	NF-SSOA algorithm	High Energy Efficiency, security and Prolong lifetime of the network	Computational Overhead.

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18.	Daniel et. al. [31]	DOS-RL routing method	High Performance routing method	Limited energy resources
19.	Biradar et. al [32]	RL with AODV routing protocol	Reducing energy consumption	More complex
20.	Zanyao et. al. [33]	LTE-M method	High Energy efficiency	High Computational overhead.
21.	Sarah Mohammed et. al. [34]	2D-CNN	Efficient routing method	Network lifetime less.

2.1. Problem Statement

In the existing approach addresses the energy efficiency problems with SDN caused by higher latency and lower throughput. One factor contributing to the aforementioned problems with SDN design is the separation of the control plane from the data plane, particularly with regard to the control plane scalability. The energy efficiency is ascertained through throughput comparison research using the current Q-Learning, FEAR and 2D CNN network architecture.

3. RESEARCH METHODOLOGY

The proposed CNN model focuses in hidden layer modification that assist to reroute the routing flow while the network traffic is created and it is done through selection of best optimizer (random search CV). The optimizer purpose is to set up better learning rate using training dataset. When the fixed learning rate is not able to manage by an optimal hyperparameters tuning, then the value of learning rate has been reduced for improving the training model accuracy. SDN controller act as an environment to the RL module in which the network topology is send through path computing and passed through CNN with hyperparameter in which the features of the routing flow are identified and finally reached state phase (St) and reward (Rt).

Figure 2 illustrate the overall architecture of RL-CNN with hyperparameter for SDN controller which assist for better rerouting the network that can improve the performance of network topology of SDN as well as consume less energy due to avoidance of network traffic. In order to reduce energy usage in software-defined networking, we employed the Reinforced Learning (RL) technique. As a way to compare the energy performance of software-defined networking with the Q-Learning, TEAR models and 2D CNN, the following parameters were used: throughput, end-to-end delay, Network lifetime, Packet delivery ratio (PDR) and traffic density.

3.1. RL Module Working

State and action phases design are efficiently representing the issues of flow routing to process through a RL agent is experimented. Let G (V, E) network in which E as an edge set that connected to vertices sets as V. This research work focuses on the flow of unicast communication in which the flow has capability in transmitting data from an available sender to a single receiver. Application provided or context of transport layer for data transmission is done through TCP flow from source host (s_f) to a destination host (d_f) is considered as a flow f. Setup for any flows is denoted by F and assume a flow f that transmitted a represented traffic rate (R_f)from the sf available over network. A path (Psf),df has vertices sequence in which P = (v_1, v_2. . . , vn) from the all available path set as P ∈Psf ,df = {Psf ,df ,1, Psf ,df ,2, . . .} in which sf is connected to df that the set of Psf, df is determined through an algorithm of graph search namely Depth-First Search (DFS). The RL agent has operated at the SDN controller that can be observed in the environment, as network through measurement of the preferred key performance measurements like bandwidth or latency during time steps with discrete t = 0, 1, 2, ... Hence, this investigation environment's state (St) that from the state sets S = {S_1 , S_2 , . . .} as well as a reward R_t∈ R ⊂ R. Thus, the St involves in a table that consists of the recently designated path P to every flow f. The flows serve as the keys in the state space, and the present path serves as the value to every key. It points out the dictionary but considered for all potential way for building the state space.

Based on the St along with its respective Rt, the action At ∈ A has been selected in which set of probable action A is basically depend upon the state St. The action set A = {At,1, At,2, . . .At, n} can be determined through set of possible paths which includes recent path and A = Psf, df for flow f . However, the potential paths have the capability in selecting the current path by either keeping it or replace the current

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path. Hence, the action has significantly changed the value which is the key current path and the key value dictionary for the current path has represented the state space shown in equation (2).

$$A_t = \{f_{s1,d1} : P_{s1,d1,t} \Longrightarrow P_{s1,d1,t+1}\} \quad (2)$$

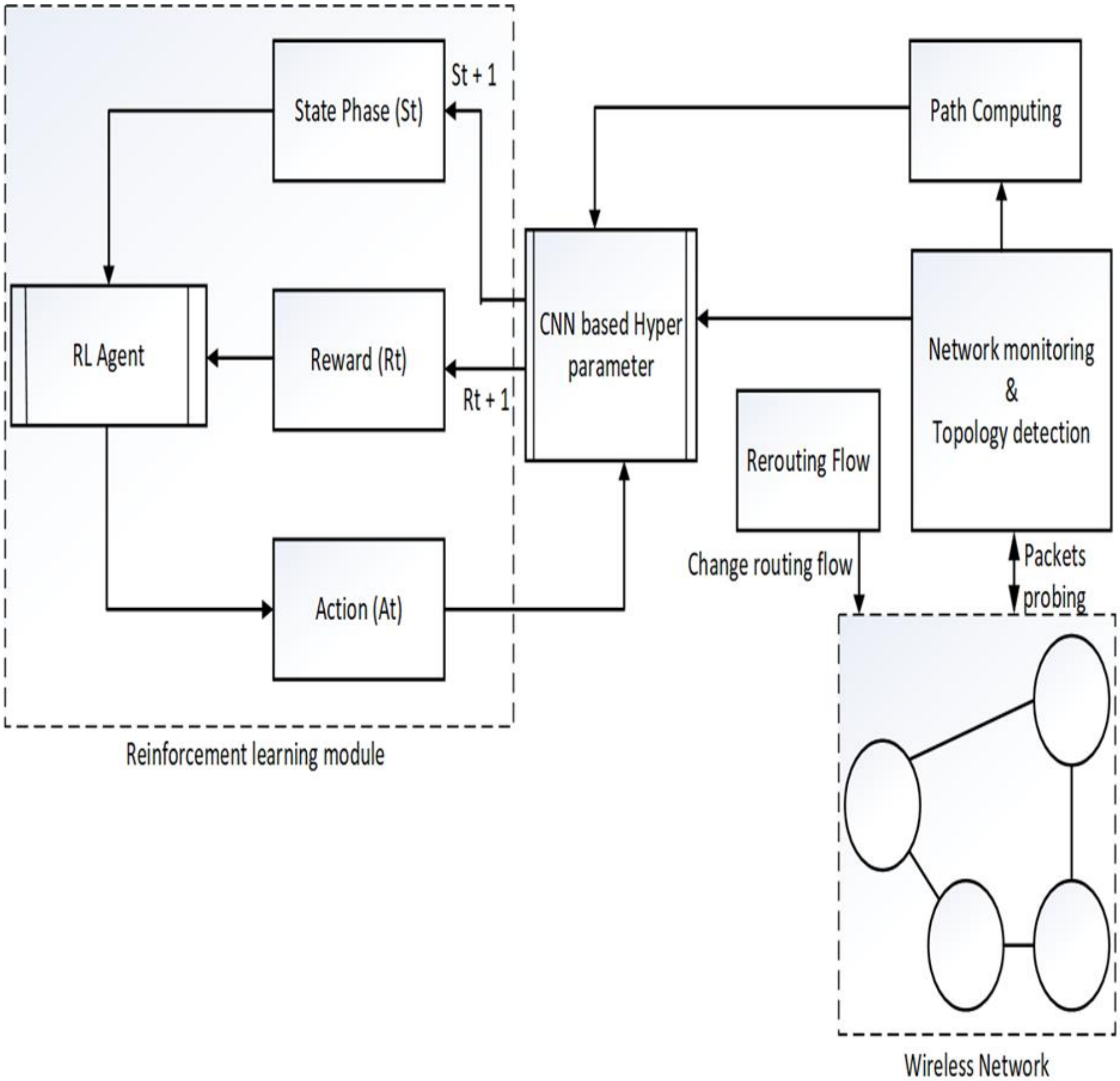

Figure 2 RL-CNN with Hyperparameter for SDN Controller Architecture

In a single action, there will be one or more flows may be considered. The change of a single flow at a time step which can be conducted in one action. Change ofa single flow during time step can deportment and One Flow modification as specified in equation (3). Instead, it can modify any flows at a time step while action is considered.

$$A_t = \begin{cases} \{f_{s1,d1} : P_{s1,d1,t} \Longrightarrow P_{s1,d1,t+1}\}, \\ \vdots \\ \{f_{sidi} : P_{si,di,t} \Longrightarrow P_{si,di,t+1}\} \end{cases} \quad (3)$$

Based on the principle of Markov decision process (MDP) state, the changes are seemed to be non-deterministic. This SDN environment has the routing paths may changes by selecting a current routing paths through performance of an action At. Hence, this states evolution conclusively and the current state St+1 is not to be recognized. Thus, the accomplished reward R_{t+1} with the action is required to be addressed. Reward R_{t+1} usage is measured well by an action during flow routing issues gets resolved. This has been focused through recent interest in the low-latency networking, the latency for the reward is evaluated in this study [28] [29].

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Moreover, the congestion is typically not observing bitrates of transmission instead it increases the latency.

Q-Learning principle has been reviewed and described the structure of q-table to QR-SDN. The Q-value with $Q(S_t, A_t) \in (-\infty, 0)$ has a principle with an estimated quality measure to action and executed in S_t at time t. Q-Learning has associated with iterative updated rules is shown in equation (4).

$$Q(S_t, A_t) \leftarrow (1-\alpha)\, Q(S_t, A_t) + \alpha \left(R_{t+1} + \gamma + \max_{a\in A} Q\left(S_{t+1,a}\right)\right) \quad (4)$$

Where,

α = Learning rate

γ = Discount factor

$Q(S_t, A_t)$ = Old Q-value

R_{t+1} = Observed rewards for Q-value

Adoption of recently learned Q-value can be determined through the learning rate and considering the discount rate to obtain the future expected rewards. The representation of $\max_{a\in A} Q\left(S_{t+1,a}\right)$ has considered when the highest action a value is accounted.

Each pair of S_t and A_t and its respective Q-value are saved in the data structure. Implementation of Q-table is generated in the SDN flow routing issues by nested dictionaries in which various states S have been considered as keys. The value considered in the dictionaries with an action represented in equation (1) and the respective key and the actual Q-value is mentioned in equation (2) is considered as shown in equation (5).

$$Q - Table = \begin{cases} S^1 : \begin{cases} A^1 : Q(S^1, A^1) \\ \vdots \\ A^n : Q(S^1, A^n) \end{cases} \\ \vdots \\ S^m : \begin{cases} A^1 : Q(S^m, A^1) \\ \vdots \\ A^n : Q(S^m, A^n) \end{cases} \end{cases} \quad (5)$$

Essential concept in practical operation is the Q-table initialization and the recent implementation has initialized the table in the Q-value of (-∞). It utilizes basically a random routing actions and initially Q-value for (-∞) has set due to general selection of action with respect to the highest Q-Value. In addition, the initial iteration is treated as Q-value for (-∞) is 0 and as per equation 3, the old Q-value is set as 0. Hence, the newly learned value is allowed to considered and improvised initialization is depend on the shortest routing path that assist in generating fast and optimal routing configuration.

3.2. CNN with Hyperparameter

Q-Learned model is trained through CNN technique and setting the shape of an input layer as 18 in which the shape of hidden layer is considered to be double as 36. Activation model utilized is “relu” and fits with 32 as batch size as well as considering adam optimizer for 100 epochs. This Model has compiled through setup the learning rate to 0.001 that is selected by an observation of the learning curve using objective function as a function of time for plotting. According to this class issues, binary classification and the loss can be estimated through cross entropy and the batch size is set to 32 as well as an epoch till 100.

The process of reducing the network error through optimization is optimizer that is significant for improving an accuracy of the model. Several optimizer variants include with automated hyperparameter tuning namely adam, FTRL, RMSprop, adaGrad, adadelta, adaMax and nadam. Based on the maintenance of saddle point, the optimizers utilized are adam, adaGrad and adadelta has been considered mainly. The major disadvantage of adaGrad optimizer has minimizes the capacity of the model for learning through learning rate with infinitesimally small. Independently created two optimizers such as adaDelta and RMSProp to address the issues faced by adaGrad. Nevertheless, the RMSProp and adaDelta optimizer functions are equivalent the only difference is adaDelta is not fit to continuous learning rate. Adam is one that combines the useful concept of adaDelta and RMSProp in which each optimizer learning rate parameter is considered to be best optimum optimizer. It performs in RMSProp and adaDelta but RMSProp illustrates better output than adam that has chosen as a top most optimizer in this experimental CNN model.

Learning rate is an essential role in fine tuning the model that update through network weight for reducing the error present in the model. Subsequently, the performance of model get minimized when the learning rate is set to be very low or very high that the learning rate has resulted with upgrades in optimal network weight as well as train with slow down. In the case of high learning rate, it has resulted in differing the error behaviour. In the real-time training of model, a high learning rate has utilized earlier due to random weight at the beginning are ahead than ideal. Learning rate is now fine-tuned the weight of the network through minimizing their value at training. Initially, the process of learning rate with large value namely 0.1 and minimized to smaller value namely 0.01, 0.001, etc. Number of epochs have indicated the iteration of training dataset that traversed and each epoch has mentioned the consideration of the training dataset number. Each epoch illustrates the capability of training sample in updating the internal parameter of the model. One or more batches to be presented are potential to be zero or infinitely in epochs. In several cases, epochs with hundreds or thousands are selected that assist the network for an adequate lowering of errors. Moreover, the error and accuracy learning curves are utilized in selecting the best epoch values. Therefore, the curve is utilized in identification of the model that learned very high or very low or an adequately prepared to train.

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In this research, the CNN technique is associated with Q-learning is applied with various optimizer for better epoch and the evaluated by corresponding ERR as well as accuracy in this paper. Algorithm of optimizer implementation in CNN technique is illustrated below:

3.3. Algorithm of Optimizer with CNN Technique

- Step 1: Once the RL module action is sent to the CNN technique with of hidden layer sequential classification has been initialized.
- Step 2: Dense type with process of convolution layer and pooling by relu activation function has been applied.
- Step 3: Conversion of non-linear vector to continuous linear vector through flatter process application.
- Step 4: Model has built with input layer and an output layer. Sequence of input layer by twice the input process layers.
- Step 5: Accumulating the loss function using "Root Mean Square" and adapt with variant optimizer in the CNN model.
- Step 6: Final values have fit the CNN in which generates train dataset and test datasets.
- Step 7: Finally, CNN model gets executed with 100 epochs and batch size 32.

The CNN can effectively extract complicated characteristics from the necessary RL module variables, and optimizer selection is crucial for enhancing model prediction. It effectively aggregates learning rate training to boost the CNN model's accuracy in forecasting better rerouting flow by changing the routing flow from SDN controller well with network topology.

4. RESULT AND DISCUSSION

This research work has evaluated the proposed method using network emulator Mininet and python library that assist in nearest resembling of operation over network in distributed hardware. In this emulation, experimental executes in real-time and acquire an actual process delay in real hardware and the emulation by hatching several Virtual Machines (VMs) have considered in these experiments. The specification of this experiment utilized available workstation with 128 GB DDR4 memory and Intel Xeon W-2155 CPU as well as used hypervisor as KVM with Ubuntu 18.04 as host Operating System (OS) with Debian 10 as OS to the guest machines. The software switch used is Open vSwitch. The evaluated metric considered for determining the efficiency of SDN performance through throughput value, delay and energy saving in percentage with respect to the intensity percentage of network traffic. The proposed RL-CNN method performance is evaluated and compared with existing methods are Time Efficient Energy Aware Routing (TEAR), Deep Q-Networkbased Energy-Efficient Routing (DQN-EER) and 2D Convolutional Neural Networks (2DCNN)

4.1. Performance Evaluation of SDN Models

4.1.1. Throughput

Figure 3 shows the traffic intensity with throughput values, intensity of traffic increases, throughput of the models also increased. Throughput comparison of the proposed RL-CNN model has high throughput while compared with existing TEAR, DQN-EER [13] and 2D CNN [34]. Throughput at 20% of traffic intensity is 32Mbps which is higher than other existing SDN model. Similarly, the maximum traffic intensity as 100% consists of better throughput with 71Mbps that is higher than other three existing SDN model. Thus, the efficiency of model can be determined through better and high throughput.

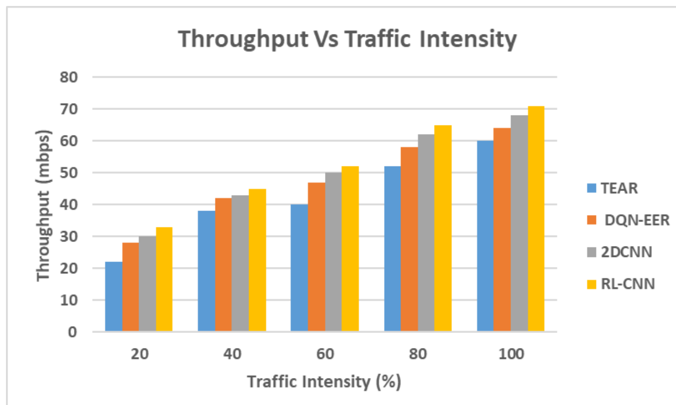

Figure 3 Comparison of Throughput Under Different Traffic Intensities

4.1.2. End to end Delay

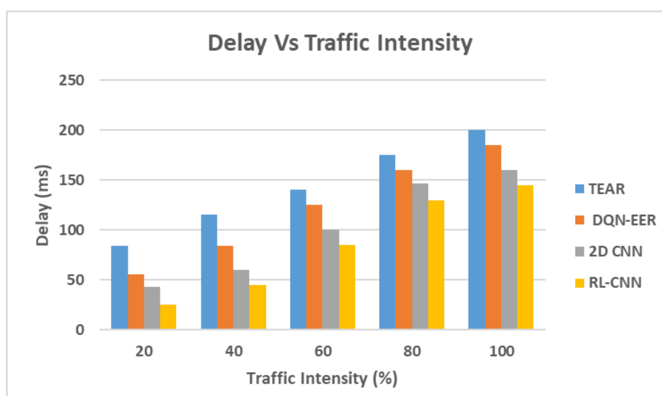

Figure 4 Comparison of Delay Under Different Traffic Intensities

Figure 4 demonstrates the delay value based on the traffic intensity. The intensity of traffic increases, the end to end

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delay of the proposed models is also decreased compared with other existing method TEAR, DQN-EER and 2D CNN. Delay time at 20% of traffic intensity is 25ms which is lesser than other existing SDN model. Similarly, the maximum traffic intensity as 100% consists of better delay with 140ms that is lower than other three existing SDN model. Thus, the efficiency of model can be determined through better and least delay time.

4.1.3. Network Lifetime

Figure 5 depicts the lifetime of the network for traffic intensity and network lifetime. Network lifetime comparison of the proposed RL-CNN model has high while compared with existing TEAR, DQN-EER and 2D CNN. Network lifetime at 20% of traffic intensity is 2200 rounds which is higher than other existing SDN model. Similarly, the maximum traffic intensity as 100% consists of better Network lifetime with 15000 rounds that is higher than other three existing SDN model. Thus, the efficiency of model can be determined through better and high Network life time.

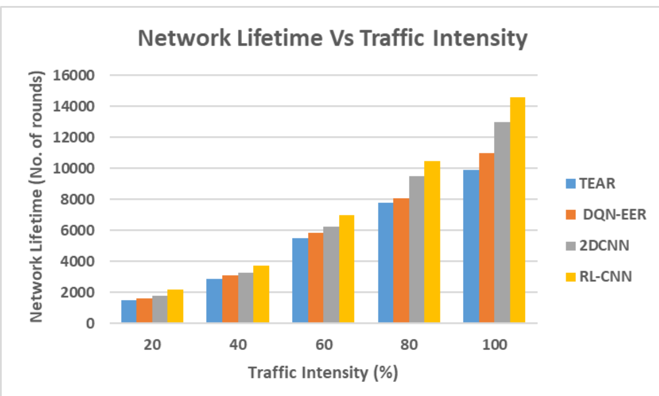

Figure 5 Comparison of Network Lifetime Under Different Traffic Intensities

4.1.4. Packet Delivery Ratio

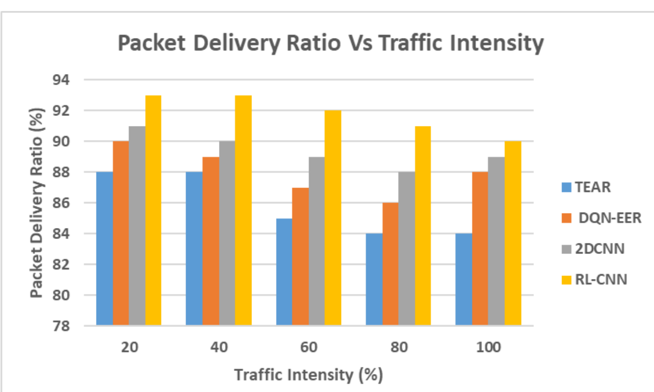

Figure 6 Comparison of Packet Delivery Ratio Under Different Traffic Intensities

Figure 6 depicts the Packet delivery ratio for traffic intensity Vs Packet delivery ratio. The proposed RL-CNN model has high while compared with existing TEAR, DQN-EER and 2D CNN. Packet delivery ratio at 20% of traffic intensity is 90% which is higher than other existing SDN model. Similarly, the maximum traffic intensity as 100% consists of better Packet delivery ratio with 92% that is higher than other three existing SDN model. Thus, the efficiency of model can be determined through better and high packet delivery ratio.

4.2. Energy Efficient Evaluation of SDN Models

Performance of the energy consumption saving effect can be verified by RL-CNN model in real network scenarios. The experiment setup in network load environments with various traffic intensities are considered. Highlighting the essential of energy saving using the parameter weight by reward function, energy consumption function, and setting the traffic intensity for 30%, 60%, and 80%. However, the proposed RL-CNN has been compared with existing TEAR, DQN-EER and 2D CNN methods. Hence, the experimental results are related with increases in traffic intensity and the RL-CNN method has energy saving performance and better than other existing routing algorithms. Thus, the energy consumption is evidently weakened with the condition of increase in traffic intensity. In the case of complicated network environment, DQN-EER is highly suitable than TEAR but it takes more epoch to attain the level. When the intensity of traffic is more, the training progress adopted in RL-CNN by optimization policy direction with random than DQN-EER. This resulted with an energy saving convergence with efficiency and effect of energy saving that need to be improved.

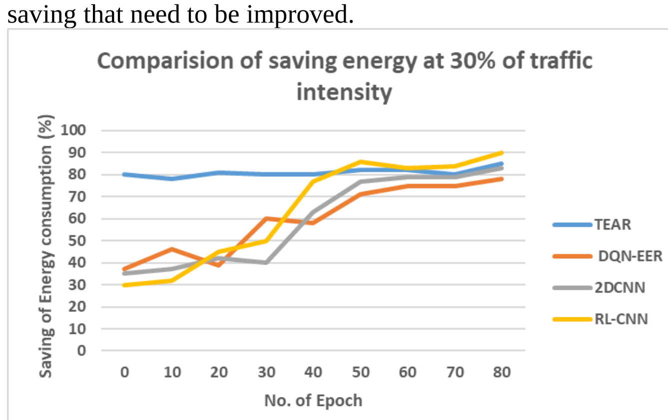

Figure 7 Comparison of Energy Saving at 30% of Traffic Intensity

The comparison of the SDN model energy-saving performance at 30% traffic intensity is shown in Figure 7. The TEAR model energy-saving percentage falls between 80 and 85 for the era up to 80. The energy-saving percentage for DQN-EER varies from 37 to 78 during the period up to 80. The 2D CNN energy-saving performance percentage falls between 35 and 83 within the time frame until 80. For the era

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up to 80, RL-CNN energy-saving % ranges from 30 to 88. According to this 30% traffic intensity, the energy saving percentage of TEAR has better energy efficiency than RL-CNN, DQN-EER and 2D CNN.

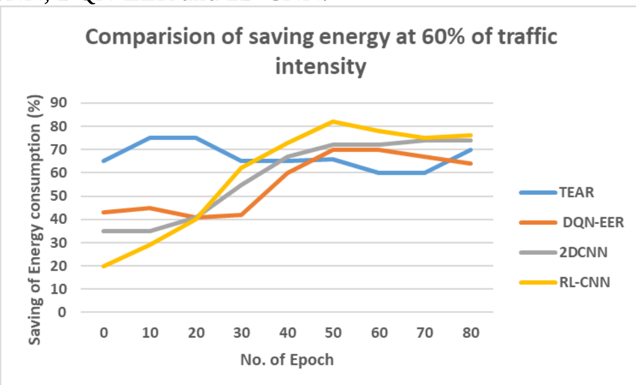

Figure 8 Comparison of Energy Saving at 60% of Traffic Intensity

The comparison of the SDN model energy-saving efficiency at 60% traffic intensity is shown in Figure 8. The energy-saving percentage calculated by the TEAR model ranges from 60 to 70 for the era up to 80. For the era up to 80, the energy saving percentage for DQN-EER ranges from 41 to 70. For the era up to 80, 2D CNN energy-saving % ranges from 35 to 74. Furthermore, the energy-saving performance percentage of RL- CNN varies from 20 to 76 during the time till 80. The energy saving percentage of RL-CNN is superior to that of TEAR, DQN-EER, and 2D CNN based on this 60% traffic intensity.

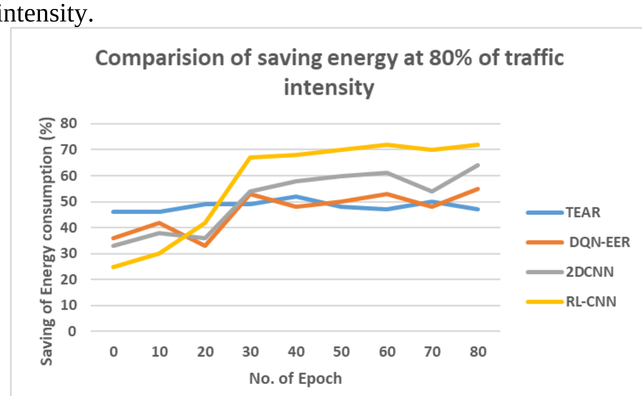

Figure 9 Comparison of Energy Saving at 80% of Traffic Intensity

The comparison of the SDN model energy-saving performance at 80% traffic intensity is shown in Figure 9. The energy-saving percentage calculated by the TEAR model ranges from 46 to 52 for the era up to 80. For the era up to 80, the energy saving percentage for DQN-EER ranges from 36 to 55. The energy-saving percentage of the 2D CNN model ranges from 33 to 64. Additionally, for the era up to 80, RL-CNN energy-saving % ranges from 25 to 72. Based on this 80% traffic intensity, RL-CNN energy saving percentage is more energy efficient than TEAR, DQN-EER, and 2D CNN, indicating that energy saving is increasing gradually as the epoch increases to 80.

5. CONCLUSIONS

This research has developed with a tabular RL with Q-Learning strategy to the flow of routing in SDN. RL-CNN model has referred to as RL-SDN that represents the flow routes directly in the Q-Learning state and action spaces which assist to empower flow preserving with multi-path routing. In this paper, the proposed RL-CNN an energy saving routing algorithm has rerouted the flow with respect to deep RL that utilized RL-CNN with hyperparameter model to dynamic perceive complex and modified network environments. This can accomplish the convergence and stability of rerouting, as well as rerouting with high energy saving path and network performance advanced at different traffic intensities. However, the evaluations proposed model from RL-CNN is done through various parameters like throughput, end to end delay, Network lifetime, Packet delivery ratio and Energy consumption saving. Hence, these experimental results determined that throughput at maximum traffic intensity (80%) with 71 Mbps and better, least end to end delay as 115ms, traffic intensity as 100% consists of better Network lifetime with 15000 rounds and the maximum traffic intensity as 100% consists of better Packet delivery ratio with 92%. Similarly, the energy consumption saving at 60% and 80% has better efficiency till 80% and 72% of energy saving in RL-CNN than other existing SDN model. Thus, the energy consumption saving performance is high in RL-CNN with hyperparameter which assist with better secure and quality of model.

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