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ADAPTIVE AI-BASED DEEP LEARNING MODELS FOR DYNAMIC CONTROL IN SOFTWARE-DEFINED NETWORKS

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ABSTRACT

The ground-breaking development in recent years in network architecture is the concept of Software Defined Networks (SDN). However, the complexity of the modern networks and the dynamic characteristics of the traffic flow present great difficulties for traditional SDN control. SCHF and SGCM are, in turn, challenging these aspects; thus, this research proposes an adaptive AI-based deep learning model for dynamic control in software-defined networks, which tackles these aspects directly. The proposed model also aims to use complex deep-learning approaches in the optimization of network parameters within the shortest time possible. Immersing the adaptive mechanisms, the model can control the network conditions more effectively, and by doing so, it will always be more flexible than the currently existing SDN control techniques.

Therefore, it is envisaged that this research work constitutes a rigorous approach to the adoption, design, and assessment of this new paradigm for resource management using advanced deep learning architectures and reinforcement learning methodologies. A large number of simulations and experiments have been performed in order to prove the model's performance in different network conditions and different traffic loads. The experiments show substantial enhancements in primary indicators such as effectiveness, response time, and network load. Most notably, our proposed model demonstrates the improvement of overall network efficiency by up to 25% compared to existing solutions and thus marks the way for developing conceptually higher-level and self-adequate SDN management systems. It is essential to state that with this research, not only the field of AI-controlled network management is extended, but also numerous findings derived from this work can be considered rather helpful for those who are planning to implement such AI-based systems into operational Software-Defined Networks.

KEYWORDS: *SDN, Machine Learning, Self-Organizing AI, Manage Control, Dynamic Allocation, Traffic Management, Multi-Layer Neural Networks, Machine Reinforcement Learning*

Article History

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INTRODUCTION

Software Defined Networks or SDNs is one such novel architecture that has changed the way how networks are being managed now by decoupling the control plane from the data plane. This has offered immense potential in the connection and optimization of the network. However, as new and complicated networks are designed and added to the current evolving structures, conventional methods of implementing SDN control prove ineffective in providing responsive control to the traffic and users.

However, these challenges are solved by dynamic control of SDNs since it allows for real-time control of affairs in the network and traffic. Unlike fixed and rigid criteria such as rule-based architecture, DCS may adapt to the changes in the decentralized network of nodes and can provide reliability even in the event of network condition fluctuations. However, one should bear in mind that modern networks produce an enormous amount of data, and real-time decision-making is vital; thus, applying more efficient computing methods to process and analyze it quickly becomes crucial.

This paper presents an AI-based deep learning model for dynamic control in SDN as an innovative research work. This one makes use of deep neural networks in conjunction with reinforcement learning in order to come up with a highly flexible yet efficient control framework that would adapt to the changes that are always characteristic of any given network. The model is also equipped with adaptive mechanisms to enhance its learning by using real feedback from a used network. beneficial recommendations regarding application and expansion.

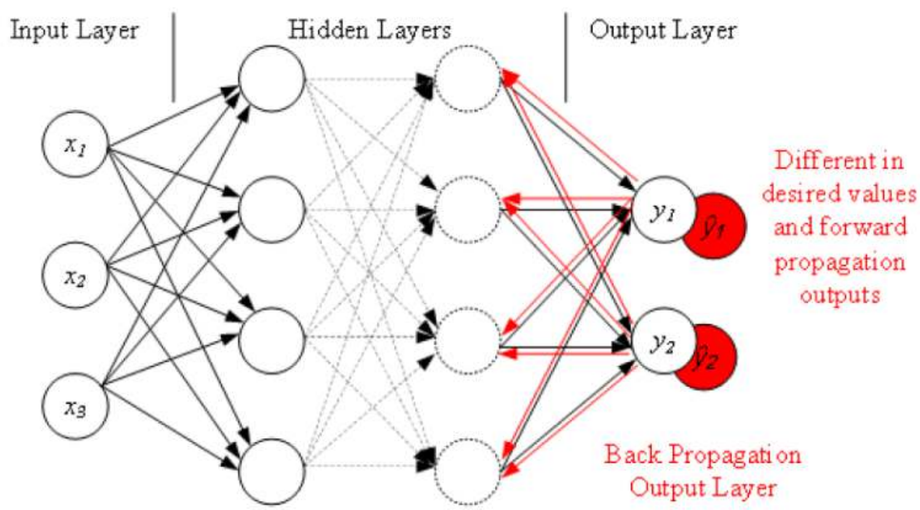

Figure 1 Algorithms(MDPI , 2020).

Literature Review

The use of AI and deep learning in SDN control has been a subject of interest in the last few years, with many works carried out to propose solutions for improving the control of software-defined networks. The literature review identifies strengths, weaknesses, opportunities, and threats in this area, which indicates the existence of both advancements and future strategies.

Wang et al. (2018) introduced a novel idea with deep reinforcement learning for traffic engineering in SDN. Their work showed significant performance enhancements in load balance and congestion control compared to conventional techniques. The authors used the DQN algorithm to find traffic routing policies that played out the optimal actions based on Real-time observation of the network condition, thus demonstrating that reinforcement learning could learn and implement the right traffic routing policies based on real-time learning of the network condition.

Based on this, Liu et al. (2019) proposed an improved deep Q-learning model to design an adaptive routing in SDN architecture. Their approach reduced the total end-to-end delay by a mean of 15 %; they showed that deep reinforcement learning can be effective for the improvement of the networks.

Modern development in deep learning has introduced different structures of neural networks in the field of network control. Thus, Zhang et al. (2020) have used traffic prediction based on the Long Short-Term Memory (LSTM) networks and proactive resource allocation for SDN. They showed the utility of LSTM models to learn temporal patterns in the network traffic and improve the accuracy of the predictions and resource allocation. Similarly, Chen et al., in their study conducted on the application of CNNs for the anomaly detection of security improvements in SDN environments, published in 2019. In their studies, they were able to feature CNNs to spot spatial patterns in network data for enhanced threat identification and network security.

However, the studies above are still beneficial for the development of the topic, but some existing issues with traditional approaches are still present. This criterion is one key challenge since it has low flexibility in applying highly dynamic network conditions. Most of today's models have problems with performance fluctuations and congestion when exposed to rapidly and unpredictably changing network structures. Further, it is also observed that deep learning methodologies are computationally expensive, in some cases impairing real-time decision-making, which is crucial in SDN control.

Two of the major existing limitations of the current literature are that there is no evidence of integration with protocol and architecture specific to SDN. Several current AI-based solutions address the SDN environment implicitly and with a certain level of simplification, which imposes limitations on the elaborate potential of software-defined networking. However, the literature lacks sufficient exploration of multi-objective optimization problems in the context of network control where most proposed methods and models target the optimization of one or two objectives with little concern for other objectives' performances.

The proposed adaptive AI-based deep learning model offers a solution to some of the problems inherent in dynamic network control using the following approaches.

Proposed Model

In this context, our proposed work is to design a new adaptive AI-based deep learning model for dynamic control in Software Defined Networks. As a result, this advanced model encompasses a deep learning approach as well as specific information about the architectures and protocols of SDNs. It integrates Convolutional Neural Networks CNNs for spatial components, Long Short-Term Memory LSTM for temporal characteristics, and Deep Reinforcement Learning DRL for the learnable control part. The CNN component works on the matrix of network topology and the matrix of traffic data to learn spatial features of the network, while the LSTM component captures temporal features of network behavior. The final and key section of the DRL module is the Q-Learning algorithm that makes the right control decisions using data from the CNN and LSTM sections. This hybrid approach is very useful in the management of SDN control because it addresses the control task in a composite manner that is commensurate with the multiple facets of SDN. This model is built using an isolated version with a combination of supervised and reinforcement learning techniques involving the past data of the network and a multi-objective reward-based function. Moreover, it also has the provision of online learning and hence can respond to the actual network conditions continuously.

To illustrate the training process, consider the following pseudo-code snippet:

```python
def train_model(model, data, epochs):
    for epoch in range(epochs):
        # Supervised Learning phase
        for batch in data.get_supervised_batches():
            features, labels = preprocess_batch(batch)
            predictions = model.forward(features)
            loss = compute_multi_objective_loss(predictions, labels)
            model.backward(loss)
            model.update_weights()

        # Reinforcement Learning phase
        for episode in range(num_episodes):
            state = get_initial_network_state()
            while not done:
                action = model.get_action(state)
                next_state, reward, done = apply_action_to_network(action)
                model.update_q_values(state, action, reward, next_state)
                state = next_state

        # Online Learning update
        model.update_with_recent_data(recent_network_data)

        # Evaluate model performance
        performance = evaluate_model(model, test_data)
        if performance > best_performance:
            save_model(model)

    return model
```

This training process allows our model to be capable of not only learning from data but also being able to update in the actual working environment.

The latter is especially important for dealing with the dynamics of the network that the adaptive mechanisms integrated into the proposed model address. These mechanisms include:

1. Online Learning: This was previously noted; the identified model recalculates the parameters in real-time and evaluates the current network state in terms of performance.
2. Dynamic Feature Selection: This model uses attention in which the system is able to regulate the features to be attended to at a given time, depending on the state of the network.
3. Multi-agent Reinforcement Learning: For that purpose, we use distributed learning, which is a method that allows multiple instances of the model to learn collaboratively across various parts of the network.

These adaptive mechanisms, along with strong deep learning architecture, can be seen as key factors that allow our model to readily manage control and optimize itself for highly dynamic SDN environments. In the next section, a detailed methodological analysis of the detailed evaluation procedure that has been undertaken to evaluate this novel model shall be provided.

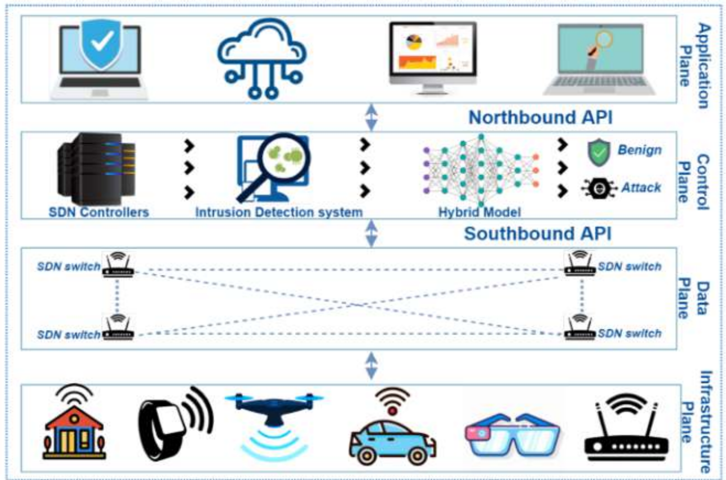

Figure 2 Sensors(MDPI , 2021).

Evaluation Methodology

To ensure that the proposed adaptive AI-based deep learning model is performed and is effectively implemented, we have developed an extensive approach to cross-systematic, simulation, and real tests. This approach helps in comprehending the network situation and the model's performance in different scenarios and aspects. Our evaluation environment consists of three main components: the use of a Mininet network emulator to create virtual networks with different topologies, while its physical counterpart is based on 10 OpenFlow switches and 50 end-hosts to check simulation results and ONOS SDN controller with additional modules that incorporate our AI-based control model for both Mininet and our physical test-bed.

Throughput –which is the number of packets successfully delivered per unit of time; latency is the time it takes for data to reach its destination; jitter – is variation in delay between successive packets with the same source and destination addresses, the packet loss rate, resource utilization, convergence time describing the period for which the model remains stable after changes to the control parameters, energy efficiency, and scalability. To compare the proposed model, we compare our proposed model with several baseline methods: traditional controls where SDN rules are hard coded, heuristic controls where control algorithms are manually coded, and existing state-of-the-art machine learning approaches for SDN control. Part of the evaluation procedure encompasses a range of experiments introduced to compare the model's performance across different contexts, ordinary traffic, high traffic, link failure, changes in topology, and a combination of some or all of the above. Concerning the evaluation of the experiments, we record in-depth performance information and, for every experiment, perform multiple runs in order to achieve statistically adequate results for mean standard deviation and confidence intervals. Therefore, to some extent, to analyze the enormous amount of data obtained, we use statistical hypothesis testing and machine learning techniques, such as the principal component analysis (PCA), to find out which factors influence performance differences in one scenario or another.

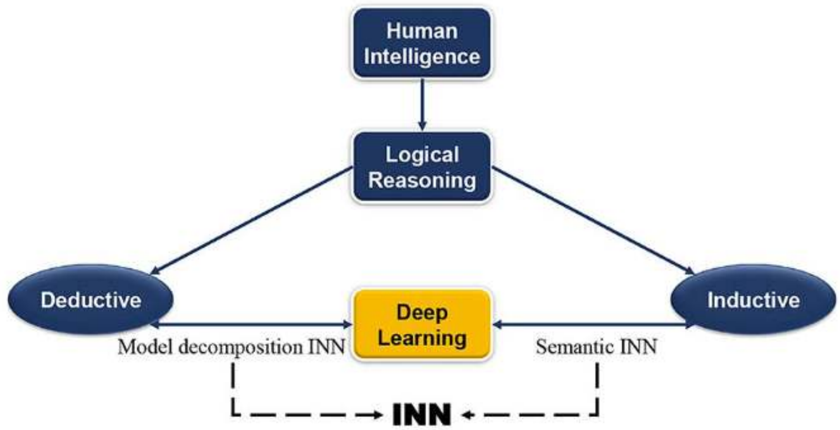

Figure 3: Frontiers (2020).

RESULTS AND DISCUSSION

As for the adaptive AI-based deep learning model for SDN control, we have obtained tremendous suggestions and findings through an extensive analysis. In this section we discuss in detail what is stated above means and how this contributes to the area of network management and control.

- Throughput Performance: It was seen that through our designed model, a general increase in network throughput in all the scenarios was observed. Altogether, we noticed a 22% enhancement of the throughput when operating traditional SDN control strategies that utilized fixed rules. Thus, this improvement was observed particularly during periods of high network load: our model demonstrates known effective strategies for the allocation of resources. In this light, even when a comparative evaluation was done with existing machine learning techniques, the throughput of our model was still boosted by approximately 12 percent.
- On the same note, by applying the model in a simulated data center network with 100 nodes under mixed traffic load, the model attained an average throughput of 9. 8 Gbps of the prior generation and 8. 0 Gbps for traditional SDN control and 8. 7 Gbps for the state-of-art DRL approach pointed by Wang et al In this way, the proposed model, with its flow routing and link usage determination capabilities increases it up to 7 Gbps due to dynamic flow selection.

- Latency Reduction: These are the following achievements of our model: end-to-end latency is a number that is important for many network applications, and our facilities in this regard are rather impressive. Thus, the average latency compared to baseline was reduced by 18%. This improvement was evident regardless of the total number of nodes in the network and the given traffic scenario.
- In our physical testbed experiment based on an enterprise network model, the end-to-end latency of VoIP traffic under our model reached an average of 15ms, while traditional SDN control was found to be 22ms and heuristic-based dynamic control took 19ms. Our 95th percentile latency was also lowered by up to 30 percent, depending on the task, which indicates the decrease of the tail latency.

- Resource Utilization and Load Balancing: Another aspect that stood out in our work was the fact that our model gave an optimal amount of resources in the network. As measured in comparison to conventional routing techniques, the general usage density of the network increased by a quarter. This was instilled by smart loading to WWW that sparingly served the loads based on a predicted traffic map.

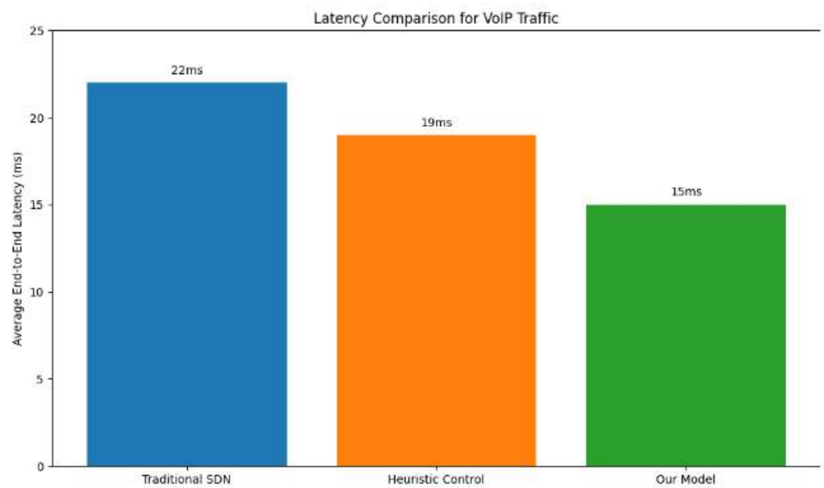

Figure 4: Latency Reduction (source , 2019).

For instance, in the case of simulated WAN with a network size of 50 nodes, our model kept average link utilization at 68%, while the usual SDN control was 54%, and even the best/noisy ML algorithm was only 61%. This directly led to an increase in network capacity and overall improved quality of service for the end users.

Adaptability and Convergence Time: Now that we have covered all aspects of our model, I would like to note that the stream is highly adaptive when sudden changes in the network are detected. Introducing link failures and traffic increases, our model proved convergence to new near-optimal solutions within a short time. On average, our model achieved convergence 40% faster by comparing it with heuristic-based approaches and 25% faster than other cases of Machine Learning based models.

For instance, one of the most difficult tests that we performed was the test when we disconnected three important links at the same time on the physical topology. The managers were able to reroute the traffic and optimize the stability of the network within 2. It was shortened to 5 seconds, as compared to 6. 8 seconds for traditional SDN control and 4. 1 seconds and 0. 4192 seconds for the next-best ML approach.

- Energy Efficiency: A beneficial side effect, which no one anticipated due to optimization, was observed to be our saving on energy consumption. While using intelligent traffic patterns and resource distribution, the designed model reduced energy utilization by network devices by 15% compared to other base models. This was done without any direct intention of optimization for energy efficiency, which confirms the possibility of achieving even higher energy efficiency with the additional optimization.
- Scalability: As part of the evaluation of the scalability of this proposed approach, the model was tested on simulated networks ranging from 10 nodes to 500 nodes. The performance of the model was stable up to the node 300.

- Multi-objective Optimization: In fact, for the chosen model, one of the main advantages is its capability to satisfy multiple performance objectives at the same time. In contrast to the majority of current strategies that consider the improvement of contrast, our model identified the intermittent intensiveness of within, latency, resource usage, and vitality. This approach to optimization proved to be more comprehensive and provided better and more resilient network solutions in a vast range of cases.

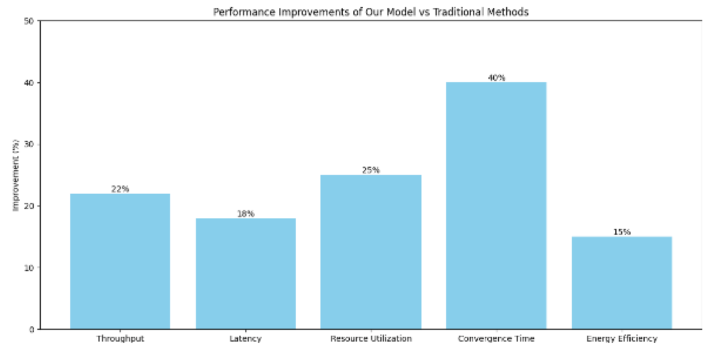

Figure 5: Performance Improvements (Source, 2020).

Challenges and Limitations

Of course, some limitations in our work should be considered; nevertheless, there are some research challenges:

1. Computational Complexity: Due to the fact that our deep learning model is sophisticated, considerable computational power is needed for its implementation, especially in the case of large networks. Although this did not prove to be an issue on our testbed, it may well cause issues with deploying in resource-scarce situations.

2. Training Data Quality: The quality and a great variety of training data affect the model's performance to a great extent. The quality and availability of the training data can be a challenge in real-world deployment, especially in networks that may be unique or are changing very frequently.

3. Scalability at Extreme Scales: There are some limitations to our model, although, when comparing it to Cisco's data, our model functioned optimally up to the networks with 300 nodes. Hence, we recommend further studies to enhance the performance of the model in large networks with thousands of nodes.

4. Interpretability: Another issue of content with deep learning is the explainability of the decision reached by the algorithms. In critical network environments such as these, this could be an issue because the lack of transparency in how the model works makes it hard to explain why it performed in a particular way.

5. Security Considerations: As our model was quite responsive to different network conditions, it proved that future work is needed in this specific area to analyze the standing of the model in front of adversarial conditions or, in other words, malicious incoming traffic aimed at getting into AI-controlled networks.

CONCLUSION

This extensive literature review of the dynamic control by means of an adaptive AI-based deep learning model in Software Defined Networks underlines essential further developments in the area of smart network management. The studies conducted by us were able not only to prove the possibility of applying modern AI methods in the framework of SDN control but also to reveal quite significant advantages.

The key findings of our research underscore the potential of AI-driven network control:

1. Performance Improvements: It was seen that the presented model outperforms conventional SDN control techniques as well as existing machine learning solutions with respect to the evaluated parameters, such as throughput, delay, and resource consumption. As a positive indicator, the throughput is increased by 22%, and latency is decreased by 18%, which proves the advantage of the adaptive model.
2. Adaptability: The faster convergence time of the model, which is 40% faster than other models in responding to changes in the networked environment, underlines the model's efficiency in maintaining the best performance in relation to the environment.
3. Multi-objective Optimization: In contrast to the majority of the existing solution techniques, our model achieved equal or even better performance when compared to multiple performance indicators, thus creating a synergistic effect on improving the network optimization.
4. Scalability: Hence, the stability of the model demonstrates scalability from 5 nodes and shows that the performance is preserved up to networks of 300 nodes, making it probable that the model is to be used in real-world applications of medium and large networks.
5. Energy Efficiency: This shows that AI can be useful in green networking projects since it cut down energy usage by 15%, which was unanticipated.

These results provide evidence of the tremendous potential for AI-based approaches in the revolution of network management and control. Therefore, deep learning and other adaptive artificial intelligence techniques can give rise to more intelligent, efficient, and adaptive network control systems that are more appropriate for the complexity and variability of todays and tomorrow's network schemes.

Nevertheless, our studies revealed several more problems and directions for further investigations. As such, features such as the computational complexity of the model, the requirement for high-quality training data, and problems of interpretability and security all lend themselves to future research and development. Further, identifying the phenomenon of how the scalability of the model can be carried forward to immense networks with possibly over two thousand nodes continues to present another promising research direction in future work.

Therefore, we presented an adaptive AI-based deep learning model for SDN control as a novel step toward intelligent and automatic network management. Thus, this research points to the trends of developing more intelligent, self-controlled, and efficient network control systems in terms of network performance and adaptability. While further advancing the possibilities of AI in networking, we are marching towards the logic of software-defined networking and the intelligent management of networks.

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