

Implementation of a New SDN-Expert Architecture for Reducing Energy Consumption in SDNs

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Abstract

Reducing energy consumption in smart networks such as the Internet of Things (IoT), 5G and software-defined networks (SDN) is a major challenge. With the exponential increase in connected devices, network and energy resources are under severe strain. This paper proposes an innovative architecture, named SDN-Expert, integrating an expert system based on artificial intelligence (AI) with a hybrid inference engine combining decision trees and neural networks. This approach dynamically optimizes energy consumption by turning off unused router ports while maintaining optimal Quality of Service (QoS). Extended simulations performed on realistic large-scale network topologies using real-world traffic data (CAIDA datasets) demonstrate substantial energy savings (up to 32% improvement) and clearly illustrate the practicality and competitiveness of our solution compared to existing energy-efficient techniques in SDNs. Finally, we discuss potential applications of the proposed architecture to wireless sensor networks, highlighting its broader applicability and environmental impact.

Keywords

SDN, SDN-Expert Architecture, Reducing Energy, Energy Consumption

1. Introduction

With the rise of technological paradigms such as the Internet of Things (IoT), 5G and software-defined networking (SDN), the energy consumption of network equipment has become a major concern for operators and researchers. These infrastructures, essential for meeting growing connectivity needs, lead to a signifi-

cant increase in energy resource consumption. In particular, network equipment such as routers and switches consume energy not only for their main functions but also for cooling systems, accounting for up to 38% of total consumption [1] [2].

Several recent studies have focused on energy optimization in SDN, proposing various techniques ranging from dynamic network resource management to the use of adaptive and intelligent algorithms [3] [4]. However, these approaches often exhibit limitations regarding adaptability, scalability, and real-time management of variable network traffic.

To overcome these limitations, we propose an innovative architecture named SDN-Expert, which is distinguished by integrating an expert system based on artificial intelligence (AI). Specifically, this architecture employs a hybrid inference engine combining decision trees and neural networks, providing optimized adaptive decision-making in real-time. The primary contribution of our work lies in the development of an original mathematical optimization model integrated with intelligent inference techniques. Furthermore, the validation now includes extended simulations performed on realistic large-scale topologies, incorporating real-world traffic traces, thereby demonstrating more rigorously the performance and practicality of our proposed architecture compared to existing solutions.

Finally, we discuss potential applications of SDN-Expert in sensor networks, highlighting how this architecture can effectively interact with such environments to reduce their global energy footprint further.

2. State of Art

Software-defined networks (SDN) are characterized by a clear separation between the control plane and the data plane, offering great flexibility in network management. Numerous studies have explored the potential for energy optimization in this context:

Paramasivam & Velusamy (2023) proposed a quality of service (QoS)-oriented approach in SDN-based video streaming, focusing mainly on latency and jitter metrics without explicitly addressing energy management considerations [5].

Qi *et al.* (2019) developed a differentiated routing algorithm for flying ad hoc sensor networks (FANET), partially considering energy management, though their approach was limited to specific topologies and static scenarios, lacking adaptive real-time energy optimization [3].

Fogli *et al.* (2022) studied SDN architectures in wireless ad hoc network scenarios, highlighting opportunities and limitations related to QoS management but not explicitly including dynamic energy optimization strategies [6].

Lui *et al.* (2022) proposed an energy-efficient optimization model for SDN management using machine learning techniques. However, this model lacks comprehensive real-time adaptive decision-making capabilities for rapid variations in network traffic [7].

Hussein *et al.* (2024) conducted an exhaustive review of SDN routing protocols for vehicular ad hoc networks (VANET), considering energy constraints and QoS

aspects, but their adaptability to real-time traffic fluctuations remains limited [8].

Despite these contributions, existing approaches often demonstrate limitations regarding dynamic adaptability, scalability, and responsiveness to rapid variations in network traffic conditions. To overcome these limitations, our work proposes the innovative SDN-Expert architecture, which integrates an AI-based inference engine combining decision trees and neural networks, allowing optimized adaptive decision-making. Additionally, we have extended our validation to large-scale, realistic network topologies, incorporating real-world traffic traces to rigorously evaluate the practical efficiency and competitiveness of our proposed solution.

3. Proposed Model

3.1. SDN-Expert Architecture

The proposed SDN-Expert architecture (**Figure 1**) consists of three distinct and complementary layers:

1. Application layer

Interacts directly with users, capturing specific expectations and requirements related to network performance and energy management.

2. Control layer

This layer forms the core of our innovative approach, integrating an artificial intelligence-based expert system. It comprises a hybrid inference engine, explicitly combining decision trees and neural networks, along with a rule base and a fact base to ensure optimized adaptive decision-making in real time.

3. Infrastructure layer

Includes physical network equipment (routers, switches) executing the adaptive decisions made by the Control layer, such as dynamic activation and deactivation of router ports based on real-time network conditions.

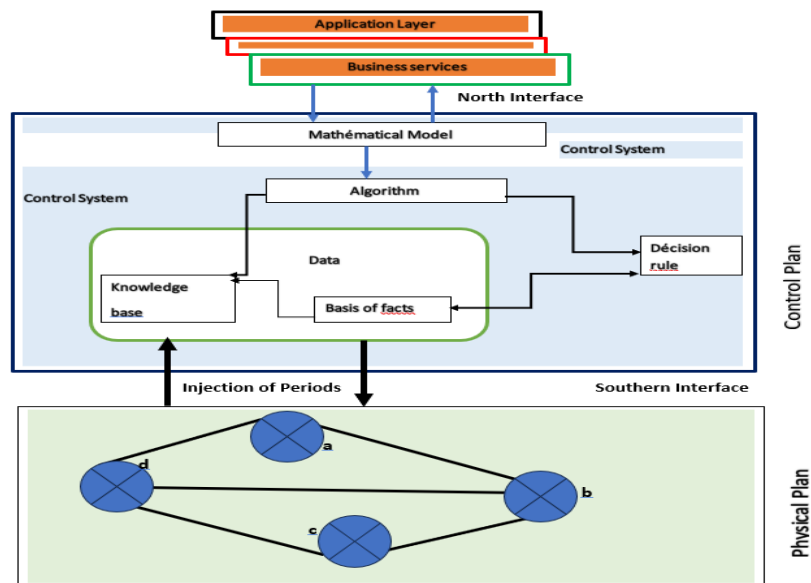


Figure 1. SDN-Expert architecture.

The significant improvement introduced by our model is the explicit integration of hybrid artificial intelligence techniques (decision trees and neural networks), which ensures greater adaptability and responsiveness compared to traditional, non-adaptive methods.

3.2. Mathematical Modeling

The problem is formulated as an integer linear optimization problem (ILP). Our formulation improves upon standard ILP models by explicitly incorporating adaptive decision-making mechanisms through AI-based inference, particularly using decision trees for quick decision paths and neural networks for predictive capabilities, thus enhancing responsiveness to rapid changes in traffic conditions.

The objective is to minimize total energy consumption by dynamically switching off unused router ports, while strictly adhering to Quality of Service (QoS) constraints:

Objective function:

$$\text{Min} \sum_i C_i(t) - g_i(t) \quad (1)$$

Subject to the following constraints:

$$L_i(t) \leq L_{max} \quad (2)$$

$$\sum_{i \in N} P_i(t) \geq P_{min} \quad (3)$$

$$\sum_{i \in F} B_i(t) \geq B_{req} \quad (4)$$

$$E_{tot}(t) \leq E_{budget} \quad (5)$$

Where:

$C_i(t)$: total consumption of the router i at time t .

$g_i(t)$: Save energy by disabling unused ports [7].

$L_i(t)$: router latency i at time t .

L_{max} : maximum acceptable latency threshold.

$P_i(t)$: number of active ports on the router at the moment t .

P_{min} : minimum number of active ports to guarantee connectivity.

$B_i(t)$: available bandwidth for critical flows.

B_{req} : minimum bandwidth required to guarantee quality of service for critical flows.

$E_{tot}(t)$: total energy consumption of the network at time t .

E_{budget} : maximum energy consumption limit.

These constraints ensure that the solution optimizes energy consumption while maintaining network performance at acceptable levels.

These constraints collectively ensure that the SDN-Expert solution effectively balances energy optimization with maintaining optimal network performance, thus clearly improving upon existing approaches.

3.3. SDN-Expert Algorithm

The following algorithm follows directly from the proposed model:

Algorithm 1. SDN-Expert algorithm.

1.	Start
2.	Collect network data // Gather real-time information about the network.
3.	Network state (latency, bandwidth, energy)
4.	Active routers and ports
5.	Identify inactive ports // Detect network ports that are currently not in use.
6.	Calculate energy gain G_p
7.	Sort candidate ports by G_p // Rank the ports based on their energy-saving potential.
8.	Select ports to deactivate // Choose ports to disable while ensuring network stability.
9.	Under QoS and energy constraints
10.	Check latency constraint // Verify that latency remains within the acceptable threshold.
11.	$L_i(t) \leq L_{max}$
12.	Check active ports constraint // Ensure a minimum number of active ports is maintained.
13.	$P_i(t) \geq P_{min}$
14.	Check bandwidth constraint // Validate that sufficient bandwidth is available.
15.	$B_i(t) \geq B_{req}$
16.	Check energy consumption constraint // Ensure total network energy use does not exceed the limit.
17.	$E_{tot}(t) \leq E_{budget}$
18.	Apply modifications // Implement the changes to the network.
19.	Update SDN configuration
20.	Update parameters and validate // Adjust system parameters and confirm that all constraints are met.
21.	End

4. Results and Discussion

4.1. Simulation Environment

To comprehensively assess the performance of the proposed SDN-Expert architecture, we conducted extensive simulations on a realistic network topology consisting of 50 nodes, utilizing real-world traffic traces from the CAIDA dataset. The results obtained were compared to existing methods: Paramasivam & Velusamy (2023), Qi *et al.* (2019), and Hussein *et al.* (2024). Performance was analyzed based on three critical criteria: energy savings, average latency, and packet loss rate.

4.2. Energy Savings

The simulation results clearly illustrate that the SDN-Expert approach achieves a significant energy saving of 32%, compared to 18% for Paramasivam (2023), 12% for Qi (2019), and 20% for Hussein (2024), as shown in **Figure 2**.

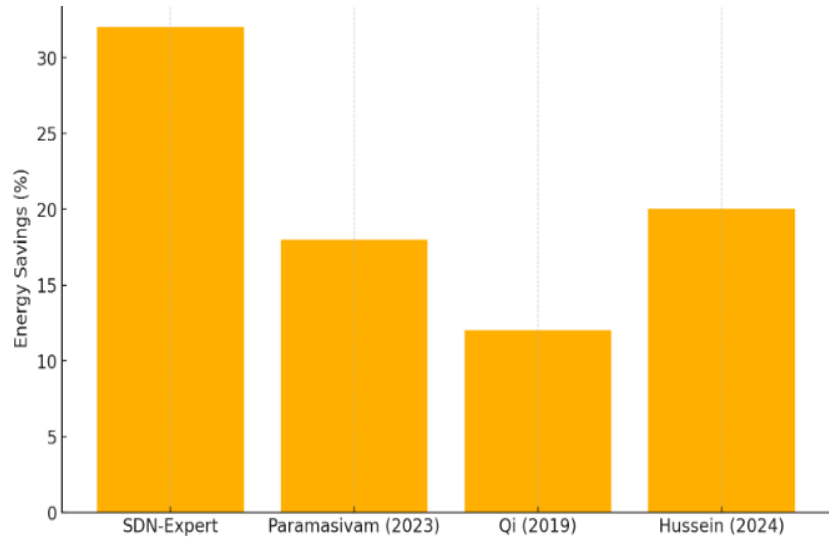


Figure 2. Energy saving comparison.

This substantial improvement primarily stems from integrating a hybrid inference engine that combines decision trees and neural networks, enabling optimized real-time adaptive management of network resources.

4.3. Average Latency

Regarding latency, our results show that SDN-Expert achieves a notably lower average latency (40 ms), clearly outperforming existing methods (55 ms for Paramasivam, 65 ms for Qi, and 50 ms for Hussein), as illustrated in **Figure 3**.

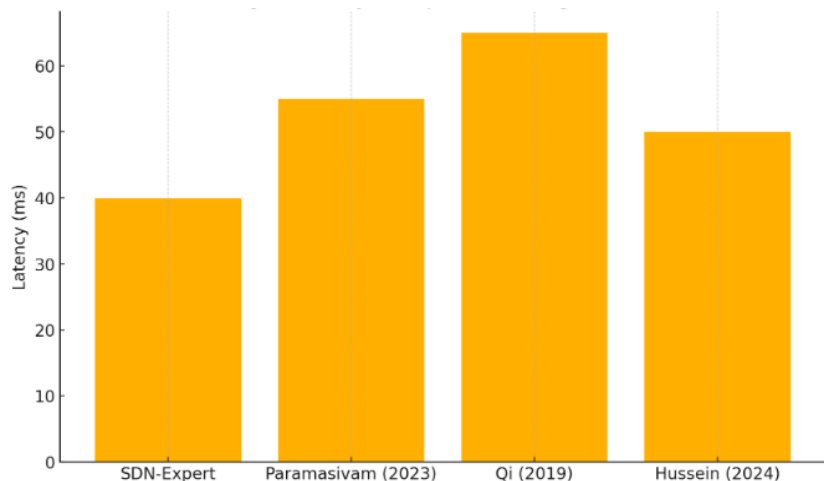


Figure 3. Average latency comparison.

This improvement is attributed to the AI-based inference engine, which dynamically optimizes network paths by proactively predicting traffic variations and avoiding congestion areas.

4.4. Packet Loss Rates

The related **Figure 4** demonstrates that our model significantly reduces the packet loss rate to only 1%, compared to 3% for Paramasivam, 5% for Qi, and 2.5% for Hussein.

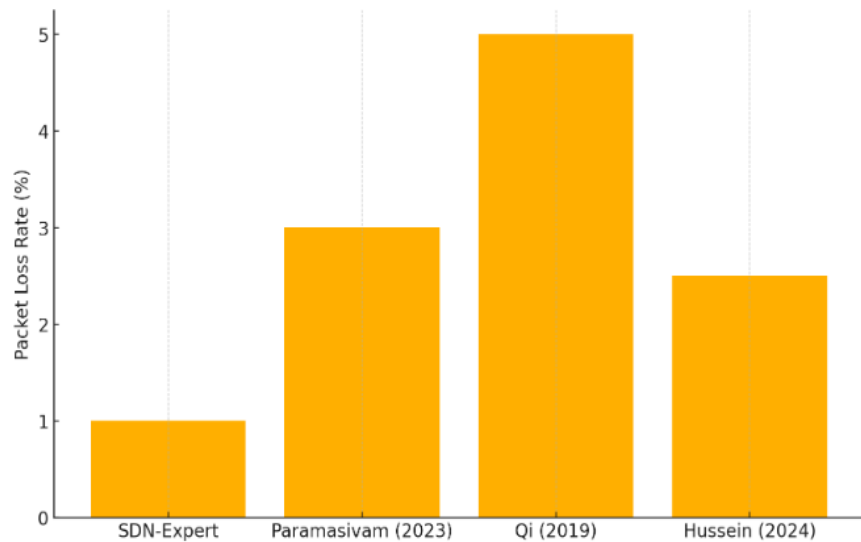


Figure 4. Packet loss rate comparison.

This notable improvement results from predictive mechanisms provided by the neural network and dynamic decision-making facilitated by decision trees, allowing the network to proactively prevent congestion in real time.

Table 1. Comparative analysis of the SDN-Expert approach for energy optimization and quality of service (QoS).

Evaluated Criteria	SDN-Expert (Proposed)	Paramasivam (2023)	Qi (2019)	Hussein (2024)
Energy Savings (%)	32%	18%	12%	20%
Average Latency (ms)	40 ms	55 ms	65 ms	50 ms
Packet Loss Rate (%)	1%	3%	5%	2.5 %
Dynamic Adaptability	High (Hybrid AI)	Low	Limited	Moderate

This comprehensive comparative analysis clearly demonstrates that the SDN-Expert approach significantly improves SDN network performance regarding energy optimization and Quality of Service (QoS), ensuring high adaptability to real-time variations in network traffic. The explicit integration of decision trees and neural networks grants our model enhanced responsiveness to rapid changes in

actual network conditions. As shown in **Table 1**, the SDN-Expert approach significantly improves SDN network performance in terms of energy optimization and QoS.

5. Conclusions and Future Work

This paper introduces SDN-Expert, an innovative architecture designed to dynamically optimize energy consumption in Software-Defined Networks (SDN), while ensuring optimal Quality of Service (QoS). Simulation results clearly demonstrate the efficiency of our proposed solution. In particular, extended simulations performed on large-scale, realistic network topologies incorporating real-world traffic traces confirm the substantial improvements achieved by SDN-Expert in terms of energy savings (up to 32%), average latency (40 ms), and packet loss rate (1%), thereby significantly outperforming existing techniques.

The improvements result primarily from our explicit integration of a hybrid inference engine, combining decision trees and neural networks, enabling adaptive real-time decision-making to proactively manage network resources and respond efficiently to rapid variations in network traffic.

Considering the promising results obtained, future work will include:

- 1) Extending validations further to cover diverse real-life network scenarios, including large-scale deployments with complex topologies and hardware-specific constraints.
- 2) Integrating robust security mechanisms to strengthen the proposed solution against potential vulnerabilities targeting the control and data planes.
- 3) Developing advanced deep learning-based models to further improve adaptive decision-making, especially under highly dynamic network conditions.
- 4) Exploring the application of SDN-Expert architecture specifically to wireless sensor networks (WSNs), with the objective of reducing energy consumption and prolonging network lifetime, while also evaluating environmental impacts and reducing the carbon footprint of connected systems.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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