Energy-Efficient Bandwidth Orchestration for Industrial IoT in Softwarized 6G Networks

Lalita Agrawal, *Graduate Student Member, IEEE,* and Ayan Mondal, *Senior Member, IEEE*

***Abstract*—The advent of the sixth-generation (6G) wireless networks promises to revolutionize the telecommunications landscape by offering significantly high data rates, low latency, and enhanced reliability compared to the predecessors, i.e., 5G and 4G. In the existing literature, the problem of heterogeneous bandwidth management using Software-Defined Networking (SDN) is not explored to leverage the 6G technology in the Industrial Internet of Things (IIoT). In this work, we propose a novel framework, FALCON, to dynamically manage bandwidth in softwarized 6G networks while focusing on the sustainability of IIoT applications. We simulate the effectiveness of FALCON framework using the Mininet simulator. In FALCON, the Ryu SDN controller orchestrates bandwidth dynamically across SDN-capable Open vSwitches. The proposed dynamic FALCON scheme improves the average packet drop by 26.32% over data, VoIP, and video traffic than the existing schemes. Through extensive simulation, we observe that FALCON reduces packet loss, enhances throughput, and reduces energy consumption at edge nodes for heterogeneous data traffic in comparison to the existing schemes on the IIoT ecosystem.**

***Index Terms*—6G Network, SDN, IIoT, Meter Table, Bandwidth Allocation, Mininet Emulator.**

I. Introduction

The rapidly evolving telecommunications landscape has witnessed significant advancements with the introduction of fifth-generation (5G) networks [1]–[3]. However, as the demand for higher data rates, ultra-low latency, and improved network reliability continues to grow, researchers are making an effort toward the development of sixth-generation (6G) wireless networks. 6G promises to offer unprecedented capabilities, while surpassing its predecessors [4], [5]. We envision that the advancement of 6G networks will also have a high impact on the Industrial Internet of Things (IIoT). The presence of IIoT in Industry 5.0 highlights the need for energy-efficient solutions, where intelligent resource allocation aligns energy consumption with operational demands [6], [7]. It also emerges as a pivotal aspect of future network design, aligning with global sustainability goals and addressing climate change concerns. Though several schemes are proposed for IIoT applications in the existing literature, there is a need to address the challenges posed by heterogeneous bandwidth management and the integration of emerging Industry 5.0 technologies, such as network bandwidth optimization, Software-Defined Networking (SDN), and energy-efficient mechanisms, to achieve sustainable and high-performance 6G networks [8]–[11].

For heterogeneous traffic in dynamic IIoT environments, the existing work often results in either underutilized link capacity or congestion, leading to increased retransmission energy. This necessitates a dynamic SDN-enabled orchestration framework that adapts bandwidth provisioning in real time while minimizing energy consumption in softwarized 6G networks. [12]–[14]. To address these challenges, this work introduces a novel architecture, *named FALCON*, that aims to manage bandwidth efficiently while addressing energy efficiency and sustainability concerns of IIoT. By leveraging the advantages of SDN and bandwidth slicing, FALCON ensures an adaptive, resilient, and user-centric wireless network infrastructure. A key feature of FALCON is that it dynamically allocates available bandwidth in real time while significantly reducing packet loss, enhancing throughput, and optimizing energy consumption. We design the practical feasibility of this architecture through simulation using mininet and the Ryu SDN controller. We use the iPerf tool to generate UDP traffic and measure the throughput improvements achieved by dynamic bandwidth allocation. Figure 1 depicts the integration of edge nodes and bandwidth slicing for ensuring optimal Quality of Service (QoS). It highlights three network slices, where each meter table is used for managing different traffic types — video, Voice over Internet Protocol (VoIP), and data originating from IIoT devices. The Ryu SDN Controller at the edge oversees the traffic distribution, ensuring optimal resource utilization across the slices.

Motivation Scenario: An industrial smart factory deploying IIoT devices connected through a softwarized 6G network. The factory generates diverse types of traffic, including real-time video surveillance, VoIP communications, and periodic data from sensors. In such a heterogeneous environment, static bandwidth allocation often results in wasted capacity and traffic bottlenecks for critical real-time services. To ensure reliability and energy efficiency, bandwidth must be dynamically allocated based on traffic priority. Leveraging SDN with programmable meter tables allows high-priority traffic to receive preferential bandwidth while limiting low-priority flows. This scenario highlights the practical need for a dynamic and energy-aware bandwidth management framework.

In this work, we use a meter table to enforce rate-limiting policies. The SDN controller defines distinct flow categories by setting up different meter table rules and applying specific actions to ensure optimal resource utilization. For instance, high-priority flows associated with real-time IIoT services, such as VoIP and video streaming, are assigned a high band-

Lalita Agrawal and Ayan Mondal are with the Department of Computer Science and Engineering, Indian Institute of Technology Indore, India. (Email:{phd2101201003, ayanm}@iiti.ac.in)

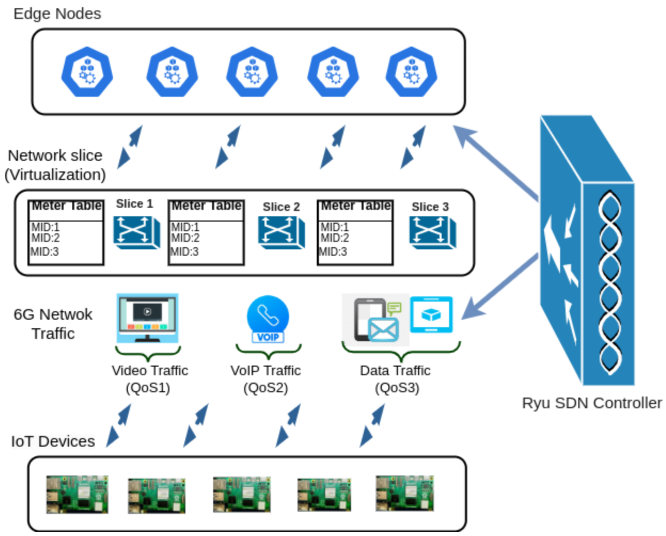


Fig. 1: Schematic Architecture for Traffic Management in IIoT-Enabled Softwarized 6G Networks

width to ensure smooth service delivery. Moreover, the meter tables restrict low-priority traffic to avoid resource starvation and ensure fairness across the IIoT network. The proposed framework, FALCON, improves the network performance metrics, such as increased network throughput, improved energy efficiency, and reduced packet loss. The summarized contributions of this work are as follows:

1) We introduce a novel architecture, *named FALCON*, that integrates SDN, network slicing, and a heuristic-based bandwidth allocation strategy to address the unique demands of IIoT in softwarized 6G networks.
2) We use meter tables for the dynamic bandwidth distribution at runtime. FALCON aims to reduce packet loss and improve overall network throughput for IIoT applications. Additionally, the framework enhances energy efficiency by minimizing packet retransmissions to ensure sustainable IIoT operations.
3) The FALCON framework employs network bandwidth slicing to manage different traffic types, such as video, VoIP, and IIoT data, within distinct slices. Each slice is governed by a meter table that applies rate-limiting policies to ensure optimal resource allocation for different traffic flows.
4) We evaluate the practical feasibility of FALCON by implementing it using the mininet simulator, Open vSwitches, and the Ryu SDN controller. The performance of FALCON is benchmarked against the existing schemes for diverse IIoT traffic scenarios.

II. Related Work

In the existing literature, a few researchers have studied the challenges of efficient bandwidth management and resource allocation in next-generation wireless networks. For instance, Jhaveri *et al.* [15] proposed an SDN-based framework called SDN-RMbw for fault resilience and dynamic bandwidth management in Industrial Cyber-Physical Systems (ICPS). The proposed approach relied on bandwidth contracts to manage network resources and handled runtime changes or link failures through a resilience manager. In another work, Son and Buyya [16] presented a virtual machine (VM) allocation algorithm (PAVA) and a bandwidth allocation (BWA) technique ensure that high-priority applications receive sufficient computing and network resources in cloud environments. The system improved resource utilization in multi-tenant SDN-enabled cloud data centers. In the context of 5G edge networks, Bera and Mehta [17] addressed the challenges of managing network slices in 5G edge networks. The authors proposed a heuristic approach, RESET, to optimize the allocation of resources, including bandwidth, computing, and storage, while maximizing operator rewards and minimizing the costly redistribution of active slices. Beyond 5G networks, Cao *et al.* [13] formulated energy-cost models for vehicle-assisted B5G networks to support both NFV and network slicing. The authors aimed to minimize total energy cost while maintaining high slice acceptance by prioritizing active nodes and jointly allocating both wireless and wired resources. Sasan *et al.* [14] introduced a joint optimization framework for slicing, routing, and in-network computing to improve energy efficiency in 6G networks. Another work by Zhang and Zhu [18] proposed a scalable SDN-based framework integrating network function virtualization (NFV) with WiFi and device-to-device (D2D) offloading. This architecture enhances statistical QoS provisioning for heterogeneous multimedia services in 5G networks. For the Software-Defined Edge Networks (SDENs), Agrawal *et al.* [19] used an evolutionary game-theoretic approach to optimize resource allocation across multiple tiers, aiming to enhance system throughput while managing the heterogeneous data flow of Internet of Everything (IoE) devices. Building upon their earlier work, D-RESIN [20] enhanced the SDEN framework by dynamically reducing processing delays at the access and edge tiers, leading to a significant performance improvements for delay-sensitive IoT applications. To address the challenges of Mobile Edge Computing (MEC) environments, Sami *et al.* [21] proposed IScaler, a deep reinforcement learning-based solution, for intelligent resource scaling and service placement in 6G networks. In another work, Li *et al.* [22] proposed a framework to efficiently manage resources across multiple scenarios in 6G networks using a Time-Expanded Graph (TEG). Energy efficiency has been a key focus in IIoT. For that purpose, Manogaran *et al.* [23] presented a deep learning-based concurrent resource allocation method for 6G Network-in-Box (NIB) architecture. The authors leveraged attuned slicing and deep neural networks to optimize resource allocation and improve service response for UAV-assisted communications. In another work, Lyu *et al.* [24] proposed a 5G-enabled framework for energy-efficient transmission and state estimation in IIoT systems. The framework used a hierarchical approach that integrates adaptive resource allocation and state estimation strategies to enhance transmission reliability and accuracy under constrained energy and communication resources.

Synthesis: The evolution of wireless communication technologies towards 6G networks highlights the critical need for advanced resource management techniques that meet stringent

TABLE I: Comparison of Existing Resource Orchestration Schemes along with the Proposed Schemes, S-FALCON and D-FALCON, for IIoT in 5G/6G Networks.

Existing Work for Resource Orchestration Scheme	SDN-Enabled 5G/6G Networks Features			
	Dynamic Configuration	Heterogeneous Traffic	Edge Computing (Energy Efficient)	Beyond 5G and 6G network
Jhaveri *et al.* [15]	✓	✗	✗	✗
Bera and Mehta [17]	✓	✗	✗	✓
Agrawal *et al.* [19], [20]	✓	✗	✓	✗
Sami *et al.* [21]	✓	✗	✓	✓
Manogaran *et al.* [23]	✓	✗	✗	✓
S-FALCON	✗	✓	✗	✓
D-FALCON	✓	✓	✓	✓

requirements for energy efficiency, ultra-low latency, and high reliability. Existing works in this field have made notable contributions, including SDN-enabled dynamic bandwidth management, priority-based resource allocation, and network slicing techniques. Frameworks such as SDN-RMbw [15], RESET [17], and D-RESIN [20] demonstrated progress in fault tolerance, contract-driven bandwidth allocation, and delay-aware orchestration. However, these approaches primarily relied on static traffic patterns, neglected real-time feedback control, and lacked support for fine-grained bandwidth control mechanisms. Similarly, recent AI-based orchestration frameworks, viz., [21], [23] required high computational overhead and lack real-time reallocation logic suitable for IIoT environments. Overall, these limitations hinder the holistic integration of real-time bandwidth adaptation and energy efficiency, particularly in softwarized and heterogeneous 6G infrastructures. Table I presents a comparative overview of the existing resource orchestration schemes and the proposed schemes, S-FALCON and D- FALCON in SDN-enabled 5G/6G networks. Hence, in this work, we aim to propose a novel architecture that will enable advancing the state of the art by combining SDN and network slicing to achieve dynamic, real-time resource allocation tailored for IIoT applications.

III. System Model

We consider that $\mathcal{N}$, $\mathcal{S}$, and $\mathcal{E}$ represent a set of IIoT devices, SDN switches, and edge nodes, respectively. Each IIoT device $n \in \mathcal{N}$ generates D_n data traffic. The bandwidth associated with each switch $s \in \mathcal{S}$ is represented as B_s. Each switch has a meter table consisting of meter entries as a rate limiter to enable OpenFlow to implement various simple QoS operations. The meter table is represented with meter ID and associated bandwidth for each switch $s \in \mathcal{S}$. Let b_i represents the bandwidth requirement for traffic t_i, where $i \in (\mathbb{Z}^+ \cap [0, D_n])$ associated with meter m_j having a bandwidth b_j of Meter Table M_{xm} for the switch $s \in \mathcal{S}$. Thus, b_j represents a fraction of the total switch bandwidth B_s, such that $\sum_j b_j \leqslant B_s$. This indicates that b_j is a local bandwidth allocation under the global bandwidth constraint B_s. If incoming traffic t_i exceeds the bandwidth b_j of the meter, the overflow traffic is considered *dropped traffic*. Hence, the traffic throughput T_i is measured as:

$$T_i = \begin{cases} b_i, & \text{if } b_i \leqslant b_j \\ b_j, & \text{otherwise} \end{cases} \tag{1}$$

Each switch $s \in \mathcal{S}$ has a ternary content addressable memory (TCAM) with capacity of maximum flow rules R_s^{max}. We consider that F_s represents the number of flow rules associated with each switch $s \in \mathcal{S}$ and needs to satisfy the constraint —

$$F_s \leqslant R_s^{max} \tag{2}$$

The energy consumption at an edge node depends on the amount of data processed, the bandwidth allocation, and any overheads associated with maintaining QoS (e.g., packet drops, throughput optimization). Based on the work by Heinzelman *et al.* [25], the energy required to transmit a $k-$bit packet over a distance d depends on energy consumed per bit by the transmitter and energy consumed by the transmitter's amplifier for distance-based signal propagation. We do not consider amplifier energy, as the edge nodes and IIoT devices are within a single hop range of SDN switches. Hence, energy consumption E^e_{use} of each edge node $e \in \mathcal{E}$ is as follows:

$$E^e_{use} = E_{\text{Tx}} \sum_{n \in \mathcal{N}} \sum_{i \in [0, D_n]} x_{t_i,n,e} T_i \tag{3}$$

where an edge node $e \in \mathcal{E}$ processes T_i data transmitted from the IIoT devices; and E_{Tx} denotes the energy cost to transmit one unit of data traffic. Here, the binary variable $x_{t_i,n,e}$ is defined as follows:

$$x_{t_i,n,e} = \begin{cases} 1, & \text{if traffic } t_i \text{ of IIoT devices } n \in \mathcal{N} \text{ is} \\ & \text{associated with an edge node } e \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

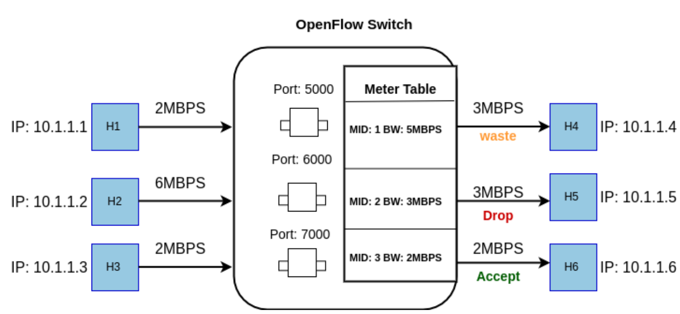


Fig. 2: Bandwidth Allocation in an OpenFlow Switch with Static Meter Table.

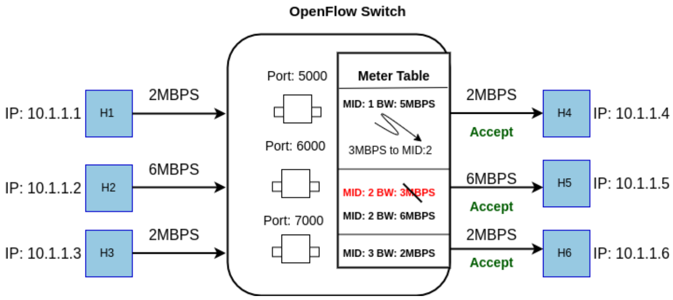


Fig. 3: Bandwidth Allocation in an OpenFlow Switch with Adaptive Meter Table.

Problem Scenario: Figure 2 illustrates how an OpenFlow switch employs a meter table for static bandwidth allocation among hosts (H1, H2, H3). It highlights bandwidth assignments and the resulting traffic classifications, i.e., accepted, dropped, or considered waste, for hosts (H4, H5, H6). Due to fixed meter assignments, excess traffic from some hosts is dropped even when unused bandwidth exists elsewhere, leading to poor utilization and degraded QoS for critical IIoT applications. In contrast, Figure 3, the meter table dynamically adjusts bandwidth among hosts (H1, H2, H3) based on real-time traffic demands. It shows how bandwidth is reassigned from MID 1 to MID 2, allowing all traffic to be accepted for hosts (H4, H5, H6), improving bandwidth utilization. Together, these figures underscore the transition from static to dynamic bandwidth management in OpenFlow switches, illustrating the critical improvements in performance and resource allocation efficiency achievable through the FALCON architecture.

IV. FALCON: The Proposed Energy Efficient Bandwidth Orchestration Framework

In this section, we propose a heuristic-based model for efficient bandwidth management in a softwarized 6G network, utilizing two algorithms — S-FALCON for static bandwidth allocation and D-FALCON for dynamic bandwidth allocation. The model employs a heuristic approach to address the complexities of bandwidth allocation in heterogeneous traffic environments by integrating SDN with network slicing and meter tables.

A. Justification for using Heuristic Approach

The problem of dynamic bandwidth allocation in softwarized 6G IIoT networks is inherently complex due to the combinatorial nature of flow-switch-edge mapping and multiple constraints on bandwidth and energy consumption. Hence, this problem can be modeled as a three-layered *bipartite graph* [26], where IIoT traffic flows, SDN switches, and edge nodes form distinct layers. The mapping of flows to switches and subsequently to edge nodes constitutes a *multistage assignment problem* [26], which is an NP-hard problem. Furthermore, modeling our problem as a three-layered *bipartite graph* inherently ensures the absence of odd-length cycles. This is because IIoT traffic flows, SDN switches, and edge nodes constitute distinct, non-overlapping vertex sets, as required by the definition of a *bipartite graph*. Traditional optimization and learning-based methods often result in high computational overhead and latency; hence, these solutions are impractical for real-time, resource-constrained IIoT environments. In contrast, heuristic approaches provide a lightweight and scalable solution, with minimal computational effort. The FALCON framework employs a heuristic strategy to dynamically reallocate bandwidth using programmable SDN meter tables, while ensuring a trade-off between performance and computational efficiency.

TABLE II: List of Symbols

Symbol	Description
$\mathcal{N}$	Set of IIoT devices
$\mathcal{S}$	Set of SDN switches
$\mathcal{E}$	Set of edge nodes
M_{xm}	Meter table of each SDN switch $s \in \mathcal{S}$
B_s	Bandwidth associated with each switch $s \in \mathcal{S}$
D_n	Data traffic generated by each IIoT device $n \in \mathcal{N}$
F_s	Number of flow rules associated with each switch s
R_s^{max}	Maximum number of flow rules in switch $s \in \mathcal{S}$
$P_{drop}(s)$	Packet drop at each switch $s \in \mathcal{S}$
E_{Tx}	Energy cost to transmit/retransmit data traffic unit
E_{use}^e	Energy consumption of each edge node $e \in \mathcal{E}$
E_{drop}	Retransmission energy required for dropped packet
E_{total}^e	Total energy consumption of each edge node $e \in \mathcal{E}$ including retransmission energy
α and β	Weights for throughput and packet drop in the objective function, respectively

B. S-FALCON: Static Bandwidth Allocation

S-FALCON is presented in Algorithm 1 and provides a novel integration of static bandwidth allocation with OpenFlow meter tables tailored for heterogeneous IIoT traffic in softwarized 6G networks. It offers analytical insight into the limitations of fixed provisioning that the existing works have not addressed, and also contributes by modeling energy consumption explicitly under static constraints. Moreover, S-FALCON serves as a necessary baseline to demonstrate the performance and energy-efficiency gains of the dynamic D-FALCON algorithm.

C. D-FALCON: Dynamic Bandwidth Allocation

We propose D-FALCON, i.e., Algorithm 2, to allocate bandwidth dynamically across IIoT devices, switches, and edge nodes. This approach ensures adaptive resource allocation and improved energy efficiency while minimizing packet loss. It also leverages real-time traffic monitoring to reallocate bandwidth resources based on traffic type and demand dynamically. It ensures that high-priority flows, such as VoIP and video traffic, receive sufficient bandwidth while maintaining network stability. Table II summarizes the symbols with their descriptions, which are frequently used throughout the paper. We aim to *maximize* the objective function $f(y_s)$ while ensuring that an optimal amount of the bandwidth is allocated by meter table M_{xm} of each switch $s \in \mathcal{S}$. Hence, we define $f(y_s)$ as follows:

$$f(y_s) = \alpha \sum_{s \in \mathcal{S}} \sum_{n \in \mathcal{N}} \sum_{i \in [0, D_n]} y_{t_i,n,s} T_i - \beta \sum_{s \in \mathcal{S}} P_{drop}(s) \quad (5)$$

where $P_{drop}(s)$ refers to the packet drop at each switch $s \in \mathcal{S}$. Here, the parameters α and β serve as weights in the objective function, balancing the trade-off between maximizing throughput and minimizing packet drops. The parameters α and β are positive real values in the range $(0, 1)$, where α emphasizes throughput maximization and β prioritizes packet drop minimization. These parameters depend heavily on the specific operational context, network requirements, and priority constraints of individual IIoT applications. Finally, the binary decision variable $y_{t_i,n,s}$ is defined as follows:

$$y_{t_i,n,s} = \begin{cases} 1, & \text{if traffic } t_i \text{ of IIoT devices } n \in \mathcal{N} \text{ is} \\ & \text{transmitted through switch } s \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

For packet drop consideration, there is additional retransmission energy E_{drop} represented in Equation (7), where E_{Tx} is the energy cost of retransmitting a dropped packet.

$$E_{drop} = E_{\text{Tx}} \sum_{s \in \mathcal{S}} P_{drop}(s) \tag{7}$$

The total energy consumption E^e_{total} at an edge node $e \in \mathcal{E}$ is expressed as:

$$E^e_{total} = E^e_{use} + E_{drop} \tag{8}$$

In FALCON, we aim to minimize the total energy consumption E^e_{total} of an edge node $e \in \mathcal{E}$ with respect to the binary decision variable $x_{t_i,n,e}$. This variable indicates that traffic t_i from IIoT device $n \in \mathcal{N}$ is associated with an edge node e. Mathematically,

$$\arg_{x_{t_i,n,e}} \min E^e_{total} \tag{9}$$

while satisfying the following constraints.

Bandwidth Allocation Constraint: The total allocated bandwidth for each switch s cannot exceed the available bandwidth B_s. Mathematically,

$$\sum_{t_i} y_{t_i,n,s} b_i \leqslant B_s, \quad \forall s \in \mathcal{S} \tag{10}$$

Meter Table Fairness Constraint: Each meter M_{xm} prioritizes high-traffic flows, such as video and VoIP, while ensuring fairness for low-priority flows. Hence, we get —

$$y_{t_i,n,s} M_{xm} \leqslant \frac{B_s}{F_s}, \quad \forall M_{xm} \in \mathcal{S} \tag{11}$$

Edge Node Energy Constraint: The total energy consumption at an edge node $e \in \mathcal{E}$ does not exceed its maximum energy capacity E^e to prevent energy exhaustion of edge nodes while optimizing network performance. Mathematically,

$$E^e_{total} \leqslant E^e, \quad \forall e \in \mathcal{E} \tag{12}$$

On the other hand, using FALCON, the packet drop $P_{drop}(s)$ for traffic flow t_i is minimized by dynamically reallocating unused bandwidth from underutilized meters, where

$$P_{drop}(s) = \frac{\sum_{\text{OM}} (b_i - B_s)}{T_i} \times 100 \tag{13}$$

Algorithm 1: S-FALCON: Static Bandwidth Allocation Algorithm

Input: $\mathcal{N}$: IIoT Devices, $\mathcal{S}$: SDN Switches, $\mathcal{E}$: Edge Nodes, M_{xm}: Meter Table
Output: T_i: Traffic Throughput, P_{drop}: Packet Drop, E^e_{total}: Total Energy Consumption
Parameters: b_i: Bandwidth requirement for traffic t_i, B_s: Bandwidth of switch s

```
Procedure:
  for Each switch s ∈ S and edge node e ∈ E do
    for Each meter m ∈ M_xm do
      if b_i ⩽ b_j then
        Calculate output traffic using Equation (1).
        Compute energy consumption E^e_use using Equation (3).
        Return T_i, E^e_use
      end if
      else
        Calculate output traffic using Equation (1) and drop the overflow traffic.
        Compute energy consumption E^e_use and energy for packet drop E_drop using Equation (3) and (7), respectively.
        Return T_i, P_drop, E_drop, E^e_use
      end if
    end for
    Compute total energy consumption E^e_total of an edge node using Equation (8)
  end for
  return T_i, P_drop, E^e_total
```

OM denotes the overloaded meters of meter table M_{xm}. Equation (13) defines the packet drop percentage at each switch $s \in \mathcal{S}$ based on the amount of traffic exceeding the bandwidth allocation by overloaded meters. Specifically, it calculates the overflow traffic $(b_i - B_s)$ at each overloaded meter and normalizes this by the total throughput, converting it into a percentage. Therefore, Equation (13) reflects the performance for bandwidth allocation using meter tables in SDN-based IIoT networks. Moreover, bandwidth reallocation is dynamically adjusted based on real-time traffic demands, as represented below.

$$y_s(t) = \arg\max_{y_s} \left(\frac{\text{Available bandwidth}}{\text{Traffic type demand}} \right) \tag{14}$$

D. Complexity Analysis

Let $|\mathcal{S}|$, $|\mathcal{E}|$, and $|\mathcal{M}|$ denote the number of SDN switches, the number of edge nodes, and the average number of meter entries per switch, respectively. These notations are uniformly used for the complexity analysis of both algorithms — S-FALCON and D-FALCON for consistency. The time complexity of Algorithm 1 (S-FALCON) is $\mathcal{O}(|\mathcal{S}||\mathcal{E}||\mathcal{M}|)$, which results from the nested iterations over switches, edge nodes, and their associated meter table entries during static bandwidth allocation. The time complexity of Algorithm 2 (D-FALCON) is $\mathcal{O}(|\mathcal{S}||\mathcal{M}| + |\mathcal{M}|^2 + |\mathcal{S}||\mathcal{E}|)$. This complexity arises because the algorithm first iterates over all switches and their respective meter entries to monitor bandwidth utilization, followed by bandwidth adjustments among overloaded and underutilized meters, which requires pairwise comparisons between meter

Algorithm 2: D-FALCON: Dynamic Bandwidth Allocation Algorithm

Input: $\mathcal{N}$: IIoT Devices, $\mathcal{S}$: SDN Switches, $\mathcal{E}$: Edge Nodes, M_{xm}: Meter Table
Output: T_i: Optimize Traffic Throughput, P_{drop}: Packet Drop, E^e_{total}: Total Energy Consumption
Parameters: b_i: Bandwidth requirement for traffic t_i, B_s: Bandwidth of switch s

```
Procedure: D-FALCON Dynamic Bandwidth Allocation
    cbw ← 0
    Initialize new_meters = [ ]
    for Each switch s ∈ S do
        for Each meter m ∈ M_xm do
            if (b_i > b_config) then
                new_meters ← m
            end if
            Calculate total consumed bandwidth as:
              cbw ← cbw + b_i
        end for
        Compute available_bw = B_s − cbw
    end for
    if new_meters is empty then
        Return 0
    end if
    for Each meter m in new_meters do
        Gather the list of meters with free bandwidth
        Adjust bandwidth allocations for meters with free
          capacity
    end for
    for Each switch s ∈ S and edge node e ∈ E do
        Reallocate bandwidth and adjust the meter table
          dynamically to optimize throughput and reduce
          packet drop.
        Calculate output traffic using Equation (1).
        Compute total energy consumption E^e_total using
          Equation (8).
        Return T_i, P_drop, E^e_total
    end for
    Return optimized traffic throughput, reduced packet
      drop, and total energy consumption based on the
      updated meter table.
    return T_i, P_drop, E^e_total
```

entries. The number of IIoT devices $|\mathcal{N}|$ influences the volume of incoming traffic processed by SDN switches and edge nodes. Although this impact is implicitly captured through traffic-related computations and has a limited effect on computational complexity compared to the structural parameters $|\mathcal{S}|$, $|\mathcal{E}|$, and $|\mathcal{M}|$, which drive bandwidth allocation and meter table adjustments. It is to be noted that increasing $|\mathcal{N}|$ affects runtime in practical deployments.

V. Performance Analysis

A. Experimental Setup

This section details the experimental setup to evaluate the FALCON architecture for efficient bandwidth management in a softwarized 6G network. The setup leverages Mininet[1] for network simulation, Ryu[2] as the SDN controller, and Open vSwitches[3] are served as the virtual switches to facilitate communication between hosts and manage flow entries, as mentioned in Table III. We evaluated the performance of FALCON architecture for topological configuration, including 50 IIoT devices, 5 Open vSwitches, and 10 edge nodes as depicted in Table IV. Each host is connected to every switch using TCLink, configured with a maximum link capacity of 10 Mbps to simulate realistic bandwidth constraints. Traffic generation is performed using the iPerf[4] tool to create UDP traffic, including data, VoIP, and video, simulating different traffic types and loads. Each test case runs for 120 seconds to observe how the system handles traffic flows under realistic network constraints. We define the QoS parameter as the allocated bandwidth for each meter-table entry. For simulation, we consider three-meter entries of the meter table — M1: 5 Mbps, M2: 2.5 Mbps, and M3: 2.5 Mbps as allocated bandwidth for each switch. Table V outlines the five test cases (T1-T5) with varying incoming traffic distributions assigned to each SDN switch's meter table at different bandwidth levels.

[1]https://mininet.org/
[2]https://ryu-sdn.org/
[3]https://www.openvswitch.org/

TABLE III: Experimental Setup

Hardware	Intel® Core™ i7-9700 CPU @3.00GHz × 8
Operating System	Ubuntu 20.04.6 LTS
RAM	24 GB DDR4
Disk Space	1.0 TB
Network Emulator	Mininet (Version 2.3.1b1)
SDN Controller	Ryu Controller (Version ryu 4.34)
SDN Switch	Open vSwitch (Version ovs-vsctl 2.13.8)
Network Traffic Generator	iPerf tool (Version 2.0.13)
Network Interface Standard	Ethernet
Programming Language	Python3 (Version 3.8.10)
Benchmarks	T-RESIN, S-FALCON

TABLE IV: Simulation Parameter

Parameter	Value
Number of IIoT Devices	50
Number of Open vSwitches	5
Number of Edge Nodes	10
Maximum Link Capacity	10 Mbps
Bandwidth for Meter-Table Entry	5 Mbps, 2.5 Mbps, 2.5 Mbps
Initial Energy of each Edge node	20 Joule [19]
Network Energy Consumption	50 nJ/bit [25]
Ethernet frame Size	1518 Byte [27]
Simulation Duration	120 Seconds

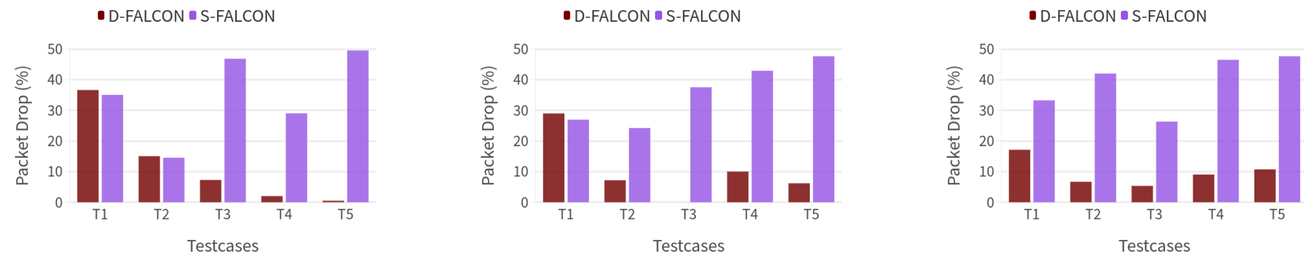
TABLE V: Test cases for Incoming Traffic Associated with SDN Switch's Meter Table

Testcases	Incoming Traffic (Mbps)		
	M1	M2	M3
T1	5	5	5
T2	5	1	4
T3	1	7	2
T4	8	1	1
T4	1	1	8

B. Benchmarks

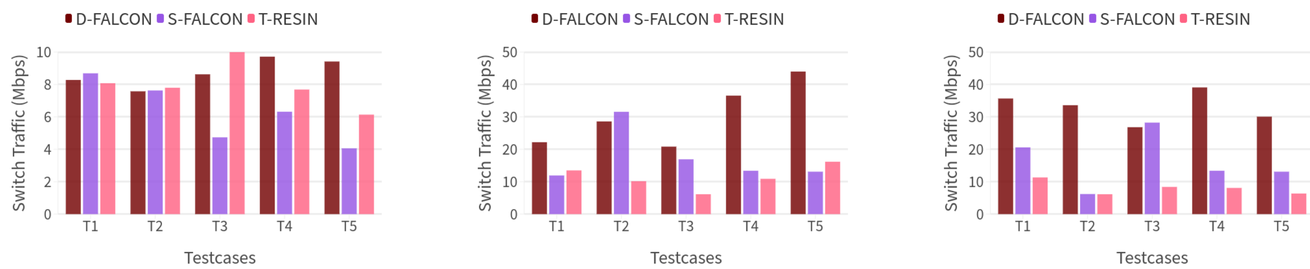
We assess the performance of D-FALCON, i.e., Algorithm 2, and S-FALCON, i.e., Algorithm 1, with the existing scheme — T-RESIN. For S-FALCON scheme, SDN switch's meter tables are static and preinstalled. Hence, S-FALCON employs

[4]https://software.es.net/iperf/



(a) Data Traffic (b) VoIP Traffic (c) Video Traffic

Fig. 4: Percentage of Packet Drop for Heterogeneous Network Traffic— Data, VoIP, Video.



(a) Data Traffic (b) VoIP Traffic (c) Video Traffic

Fig. 5: Analysis of Switch Traffic for Heterogeneous Network Traffic— Data, VoIP, Video.

a static bandwidth allocation model where resources are pre-allocated without real-time adaptation. On the other hand, we consider T-RESIN as a benchmark proposed by Agrawal *et al.* [19] in comparison with D-FALCON scheme. The authors have optimally allocated the resources to achieve high throughput and data flows, supporting a sustainable SDEN network. However, T-RESIN did not use the concept of a meter table for dynamic bandwidth allocation.

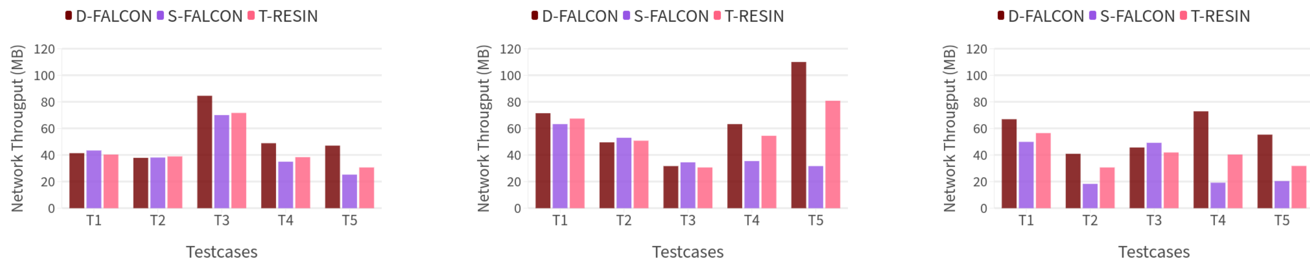
C. Performance Metrics

- *Packet Drop:* It calculates the percentage of packets that are dropped during transmission in the network. This metric helps to assess the reliability of the network and the effectiveness of bandwidth management under varying load conditions.
- *Switch Traffic:* It is calculated as the total amount of traffic handled by each Open vSwitch per unit of time. It provides insights into how traffic is distributed and processed within the SDN switch.
- *Network Throughput:* It examines the overall throughput of the network, focusing on how efficiently the network can handle heterogeneous traffic types. It helps evaluate network performance and resource allocation using dynamic bandwidth allocation.
- *Energy Consumption at Edge Node:* The total energy consumed at the edge node includes energy required for transmission and retransmission of data. It is evaluated based on the amount of data processed and allocated bandwidth. FALCON framework minimizes the retransmission energy by reducing packet loss and efficient bandwidth management to maintain network sustainability.

D. Result and Discussion

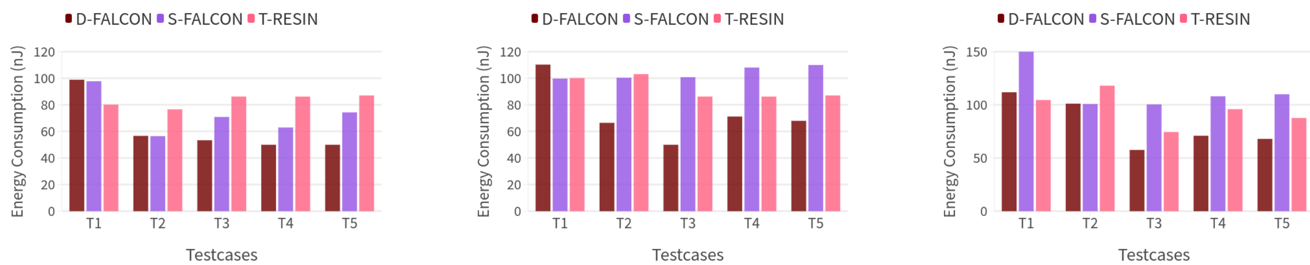
This section presents the performance evaluation of the proposed FALCON framework based on extensive simulation. We evaluate key network parameters such as packet drop rate, switch traffic, overall network throughput, and energy consumption at the edge nodes to demonstrate the effectiveness of dynamic bandwidth allocation. The proposed D-FALCON scheme is attributed to its real-time adaptive capability and dynamic bandwidth management. D-FALCON continuously monitors bandwidth usage through programmable SDN meter tables and dynamically reallocates resources from underutilized traffic flows to those experiencing congestion. This adaptive reallocation directly reduces packet drops, maximizes throughput, and minimizes retransmission-related energy consumption. Thus, the flexibility offered by real-time, heuristic-driven adjustments in D-FALCON inherently ensures better network performance and energy efficiency, particularly under fluctuating and heterogeneous IIoT traffic conditions.

Figure 4 depicts that S-FALCON experiences significant variability, with packet drop percentages fluctuating significantly across test cases. In contrast, D-FALCON demonstrates a more stable performance with lower packet drop rates. For data traffic, S-FALCON shows an average packet drop of 35.98%, while D-FALCON improves this with a substantially lower average of 11.78%, as shown in Figure 4(a). Similarly, for VoIP traffic, S-FALCON records an average packet drop of 35.84%, whereas D-FALCON outperforms with a reduction to 10.47%, as illustrated in Figure 4(b). Figure 4(c) depicts packet drop percentages for video traffic, where S-FALCON has a fluctuating average packet drop of 43.18% in contrast to D-FALCON with an average packet drop of 13.78%.



(a) Data Traffic (b) VoIP Traffic (c) Video Traffic

Fig. 6: Overall Network Throughput for Heterogeneous Network Traffic— Data, VoIP, Video.



(a) Data Traffic (b) VoIP Traffic (c) Video Traffic

Fig. 7: Energy Consumption at Edge Nodes for Heterogeneous Network Traffic— Data, VoIP, Video.

The results suggest that D-FALCON outperforms S-FALCON while reducing the overall packet drop by 26.32% over data, VoIP, and video traffic.

Switch traffic, as illustrated in Figure 5, demonstrates the efficiency of D-FALCON over S-FALCON and T-RESIN for all traffic scenarios. As depicted in Figures 5(a)–5(c), using D-FALCON, the associated switch traffic improves by 2.44%, 15.06%, and 13.73% compared to S-FALCON for different traffic — data, VoIP, and video, respectively. For data traffic, D-FALCON and T-RESIN handle almost the same switch traffic as shown in Figure 5(a). Figures 5(b) and 5(c) demonstrate that D-FALCON outperforms T-RESIN in handling switch traffic with 21.07%, and 25% for VoIP and video traffic scenarios, respectively. In summary, D-FALCON tends to handle switch traffic across all scenarios, particularly in resource-intensive cases like video and VoIP, while S-FALCON and T-RESIN maintain a low switch traffic.

Figure 6(a) analyzes the network throughput for D-FALCON, S-FALCON, and T-RESIN for data traffic. D-FALCON increases network throughput by 9.59% and 7.94% in comparison to S-FALCON and T-RESIN, respectively. Similarly, for VoIP traffic, D-FALCON improves network throughput by 21.61% and 8.36% in comparison to S-FALCON and T-RESIN, respectively, as depicted in Figure 6(b). Figure 6(c) also analyzes that D-FALCON achieves higher throughput in high resource-intensive test cases, and T-RESIN and S-FALCON perform similarly in most test cases. D-FALCON improves network throughput by 24.95% and 16.09% in comparison to S-FALCON and T-RESIN, respectively, for video traffic.

As illustrated in Figure 7, D-FALCON demonstrates a remarkable reduction in energy consumption at edge nodes across all test cases and traffic types. D-FALCON reduces energy consumption by 10.71% and 21.5% compared to S-FALCON and T-RESIN, respectively, for data traffic, as shown in Figure 7(a). The reduction is even more significant for VoIP traffic, with 30.62% and 19.37% reductions compared to S-FALCON and T-RESIN, respectively, as observed in Figure 7(b). Figure 7(c) depicts the energy consumption reduction of D-FALCON by 39.82% and 12.24% with respect to S-FALCON and T-RESIN, respectively.

These findings highlight D-FALCON's efficacy in dynamically managing network resources within IIoT environments, particularly in reducing packet drops, efficiently handling higher traffic loads, and significantly lowering energy consumption at edge nodes. This supports the sustainability goals of modern telecommunication networks, aligning with the advancements and high reliability required by next-generation 6G infrastructures.

VI. Conclusion

In this paper, we presented FALCON, a network architecture, that incorporates SDN and network slicing for enhanced bandwidth management in softwarized 6G networks, particularly tailored for IIoT applications. FALCON dynamically optimizes bandwidth allocation to efficiently handle diverse traffic types, including data, VoIP, and video, that are critical in IIoT environments. We observed that FALCON significantly reduces packet loss, increases throughput, and optimizes energy consumption effectively. Furthermore, the dynamic allocation strategies of D-FALCON outperform the static methods employed by S-FALCON. The adaptive FALCON, i.e., D-FALCON, enhances adaptability for fluctuating network conditions and sustainability objectives of advanced 6G developments in the IIoT ecosystems.

This work can be extended while focusing on bandwidth orchestration in IIoT-enabled 6G network environments in the presence of network link failures and faulty IIoT devices. The addressed problem can also be revisited by incorporating machine learning (ML) technologies to refine resource allocation dynamically based on the availability of the corresponding network configuration datasets.

References

[1] S. Wijethilaka and M. Liyanage, "Survey on Network Slicing for Internet of Things Realization in 5G Networks," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 957–994, 2021.

[2] R. Trivisonno, R. Guerzoni, I. Vaishnavi, and A. Frimpong, "Network Resource Management and QoS in SDN-enabled 5G Systems," in *Proc. of IEEE Global Communications Conference (GLOBECOM)*, San Diego, CA, USA, Dec. 2015, pp. 1–7.

[3] L. Agrawal and N. Tiwari, "A Review on IoT Security Architecture: Attacks, Protocols, Trust Management Issues, and Elliptic Curve Cryptography," in *Social Networking and Computational Intelligence*. Springer, Singapore, 2020, pp. 457–465.

[4] S. Ebrahimi, F. Bouali, and O. C. L. Haas, "Resource Management From Single-Domain 5G to End-to-End 6G Network Slicing: A Survey," *IEEE Communications Surveys & Tutorials*, April 2024.

[5] T. Kumar, J. Partala, T. Nguyen, L. Agrawal, A. Mondal, A. Kumar, I. Ahmad, E. Peltonen, S. Pirttikangas, and E. Harjula, "Secure Edge Intelligence in the 6G Era," in *Security and Privacy for 6G Massive IoT*. Wiley, 2024.

[6] W. Mao, Z. Zhao, Z. Chang, G. Min, and W. Gao, "Energy-Efficient Industrial Internet of Things: Overview and Open Issues," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 11, pp. 7225–7237, 2021.

[7] I. Behnke and H. Austad, "Real-Time Performance of Industrial IoT Communication Technologies: A Review," *IEEE Internet of Things Journal*, vol. 11, no. 5, pp. 7399–7410, 2024.

[8] I. Alam, K. Sharif, F. Li, Z. Latif, M. M. K. arim, S. Biswas, B. Nour, and Y. Wang, "A Survey of Network Virtualization Techniques for Internet of Things Using SDN and NFV," *ACM Computing Survey*, vol. 53, 2020.

[9] S. S. Jazaeri, S. Jabbehdari, P. Asghari, and H. H. S. Javadi, "Edge computing in SDN-IoT networks: a systematic review of issues, challenges and solutions," *Cluster Computing*, vol. 24, p. 3187–3228, 2021.

[10] A. Sahbafard, R. Schmidt, F. Kaltenberger, A. Springer, and H.-P. Bernhard, "On the Performance of an Indoor Open-Source 5G Standalone Deployment," in *Proc. of IEEE Wireless Communications and Networking Conference (WCNC)*, Glasgow, United Kingdom, March 2023, pp. 1–6.

[11] B. A. Salau, A. Rawal, and D. B. Rawat, "Recent Advances in Artificial Intelligence for Wireless Internet of Things and Cyber–Physical Systems: A Comprehensive Survey," *IEEE Internet of Things Journal*, vol. 9, no. 15, pp. 12 916–12 930, 2022.

[12] Y. Wu, H.-N. Dai, H. Wang, Z. Xiong, and S. Guo, "A Survey of Intelligent Network Slicing Management for Industrial IoT: Integrated Approaches for Smart Transportation, Smart Energy, and Smart Factory," *IEEE Communications Surveys Tutorials*, vol. 24, no. 2, pp. 1175–1211, 2022.

[13] H. Cao, H. Zhao, A. Jindal, G. S. Aujla, and L. Yang, "Energy-Efficient Virtual Resource Allocation of Slices in Vehicles-Assisted B5G Networks," *IEEE Transactions on Green Communications and Networking*, vol. 6, no. 3, pp. 1408–1417, 2022.

[14] Z. Sasan, M. Shokrnezhad, S. Khorsandi, and T. Taleb, "Joint Network Slicing, Routing, and In-Network Computing for Energy-Efficient 6G," in *Proc. of IEEE Wireless Communications and Networking Conference (WCNC)*, Dubai, UAE, April 2024.

[15] R. H. Jhaveri, S. V. Ramani, G. Srivastava, T. R. Gadekallu, and V. Aggarwal, "Fault-Resilience for Bandwidth Management in Industrial Software-Defined Networks," *IEEE Transactions on Network Science and Engineering*, vol. 8, no. 4, pp. 3129–3139, 2021.

[16] J. Son and R. Buyya, "Priority-Aware VM Allocation and Network Bandwidth Provisioning in Software-Defined Networking (SDN)-Enabled Clouds," *IEEE Transactions on Sustainable Computing*, vol. 4, no. 1, pp. 17–28, 2019.

[17] S. Bera and N. B. Mehta, "Network Slicing in 5G Edge Networks with Controlled Slice Redistributions," in *Proc. of the 17th International Conference on Network and Service Management (CNSM)*, Izmir, Turkey, Dec. 2021, pp. 118–124.

[18] X. Zhang and Q. Zhu, "Scalable Virtualization and Offloading-Based Software-Defined Architecture for Heterogeneous Statistical QoS Provisioning Over 5G Multimedia Mobile Wireless Networks," *IEEE Journal on Selected Areas in Communications*, vol. 36, no. 12, pp. 2787–28 048, 2018.

[19] L. Agrawal, A. Mondal, and M. S. Obaidat, "T-RESIN: Throughput-Aware Dynamic Resource Orchestration for IoE-Enabled Software-Defined Edge Networks," *International Journal of Communication Systems, Wiley*, vol. 37, no. 12, April 2024.

[20] L. Agrawal, A. Mondal, M. S. Obaidat, and E. Harjula, "Delay-Aware Dynamic Resource Orchestration for IoT-Enabled Software-Defined Edge Networks," *International Journal of Communication Systems, Wiley*, vol. 38, no. 7, March 2025.

[21] H. Sami, H. Otrok, J. Bentahar, and A. Mourad, "AI-Based Resource Provisioning of IoE Services in 6G: A Deep Reinforcement Learning Approach," *IEEE Transactions on Network and Service Management*, vol. 18, 2021.

[22] J. Li, C. Li, W. Yue, N. Cheng, Z. Sha, and M. Tian, "A Unified Framework for 6G Cross-Scenario Resource Representation and Scheduling," in *Proc. of IEEE Wireless Communications and Networking Conference (WCNC)*, Glasgow, United Kingdom, March 2023, pp. 1–6.

[23] G. Manogaran, J. Ngangmeni, J. Stewart, D. B. Rawat, and T. N. Nguyen, "Deep-Learning-Based Concurrent Resource Allocation Method for Improving the Service Response of 6G Network-in-Box Users in UAV," *IEEE Internet of Things Journal*, vol. 10, no. 4, pp. 3130–3137, 2023.

[24] L. Lyu, C. Chen, S. Zhu, and X. Guan, "5G Enabled Codesign of Energy-Efficient Transmission and Estimation for Industrial IoT Systems," *IEEE Trans. on Ind. Inf.*, vol. 14, no. 6, pp. 2690–2704, 2018.

[25] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-Efficient Communication Protocol for Wireless Microsensor Networks," in *Proc. of the 33rd Hawaii International Conference on System Sciences*, Hawaii, USA, 2000, pp. 1–10.

[26] H. P. Williams, *Logic and Integer Programming*, ser. International Series in Operations Research and Management Science. Boston, MA: Springer, US, March 2009.

[27] Z. Zhao, Z. Qiu, W. Pan, H. Li, L. Zheng, and Y. Gao, "Design and implementation of a frame preemption model without guard bands for time-sensitive networking," *Computer Networks*, vol. 243, 2024.

Lalita Agrawal (S'24) is currently pursuing her Ph.D. degree from the Department of Computer Science and Engineering at the Indian Institute of Technology (IIT) Indore, India. She was a Visiting Researcher at the Centre for Wireless Communications - Networks and Systems, University of Oulu, Finland, in August-September 2023. Prior to this, she was a Junior Research Fellow at IIT Guwahati, India. Her research interests include Software-Defined Networking, Edge computing, Beyond 5G and 6G Networks.

Ayan Mondal (S'13-M'21) is an Assistant Professor at IIT Indore. Prior to this, he was a Postdoctoral Researcher at Univ Rennes, Inria, CNRS, IRISA, Rennes, France. He completed his Ph.D. degree from the Department of Computer Science and Engineering, Indian Institute of Technology (IIT) Kharagpur, India in 2020. His current research interests include algorithm design for data center networks, software-defined networks, sensor-cloud, edge/fog networks, smart grid, and wireless sensor networks. He is also a professional member of ACM. For more details, please visit https://people.iiti.ac.in/~ayanm/