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Spatio-Temporal Hybrid Learning-Based Cross-Layer Resource Allocation for Energy-Efficient in 5G IoT Networks

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Abstract

Fifth-generation (5G) wireless networks have brought the Internet of Things (IoT) devices to unprecedented levels of difficulty due to the rapid growth and development of the devices in the wireless networks. Massive Machine-Type communications (mMTC) involves the use of thousands of low-power and battery-constrained devices that create heterogeneous and changing traffic. Despite the superior spectral performance, ultra-reliable low-latency communication (URLLC), and network slicing of 5G, the efficient utilization of the resources is a life-threatening problem because of the dynamic channel scenarios, the interference, and varied Quality of Service (QoS) demands. The classic optimization-based resource allocation techniques usually make use of precise mathematical models and make fixed assumptions, and are therefore computationally costly and less responsive to quickly evolving network conditions. In order to overcome these drawbacks, smart cross-layer optimization solutions have been considered as the potential solution. Cross-layer resource allocation is a common parameter that is considered jointly on the parameters of the physical, MAC, and network layers to obtain the global performance: transmit power, subcarrier assignment, scheduling, modulation schemes and queue states. Nevertheless, a majority of current methods lack the ability to represent both spatial correlations (e.g., pattern of interferences, topology) and temporal fluctuations (e.g., bursts in traffic, variations in channels). The paper suggests a spatio-temporal hybrid learning-based cross-layer framework of distributing resources in 5G IoT networks with energy-efficiency. The proposed approach will adaptively optimize resource allocation by combining spatial feature modeling with temporal learning processes and decision policies measured by reinforcement learning and reducing energy use and meeting QoS thresholds. The framework facilitates scalable, data-driven network control, which is much more energy efficient, latency performance and system reliable in dense IoT deployments.

Keywords: 5G IoT Networks, Cross-Layer Resource Allocation, Spatio-Temporal Learning, Energy Efficiency, Hybrid Reinforcement Learning.

1. Introduction

The fast growth of IoT has had a great change in the contemporary wireless communication, especially with the implementation of 5G networks, which can be used in various types or categories of services, such as mMTC and URLLC, which could be used to provide large-scale connectivity to smart cities, industrial automation, healthcare monitoring, and smart transportation systems [1]. The use of mMTC case, thousands of battery-powered IoT devices create intermittent or intermittent traffic, and URLLC applications require high reliability and latency guarantees. Despite the fact that 5G has a higher spectral efficiency and versatile radio access schemes, the co-location of heterogeneous services poses considerable challenges on efficient use of resources. One of the most important issues related to the 5G IoT networks is the energy limit of the devices. The vast majority of sensors and edge devices have small batteries and require installation in remote and inaccessible locations, thus battery replacement is not always viable [2]. This in turn makes us to consider energy efficient communication and smart radio resource management that would extend the network lifetime but still maintain QoS. The conventional static or layer-isolated resource allocation models are not sufficient to deal with the dynamic and dense characteristics of contemporary IoT ecosystem.

1.1 Research Motivation

Traditional optimization-based resource allocation methods are usually based on convex formulations, heuristic scheduling, or rule based methods. Although these methods have the benefit of analytical tractability, they usually make simplified channel models and stationary traffic assumptions. On realistic topology

dynamics, interference variations, and bursty traffic, such approaches are not scalable and fail on scalability and real-time adaptability.

In addition, the majority of solutions currently in use work at one protocol layer, without regard to the interdependence of the physical layer parameters (e.g. transmit power, modulation schemes), the MAC layer scheduling, or the queue dynamics in the network layer [3]. This does not lead to cross-layer coordination, and thus leads to suboptimal performance, especially on energy usage and latency. As such, there is an urgent requirement on adaptive, scalable, and learning-based solutions which can jointly optimize multiple layers and which can also capture both spatial and temporal correlations of network behavior.

1.2 Problem Statement

This study is connected to the issue of the energy-efficient allocation of resources in cross-layers of 5G IoT networks, which can occur in dynamic and heterogeneous conditions [4]. It is a network of tightly packed IoT devices that report to a 5G base station where both channel conditions, interference, and traffic requirements are time-varying. Also, the spatial distribution of devices leads to complicated relationships of interference that have to be taken into account in the process of the scheduling of resources.

The aim is to come up with a framework that is able to optimize transmit power, resource block allocation, scheduling policies and queue management strategies at the same time. The optimization problem is multi objective in nature because the focus of the optimization is to maximize energy performance and minimize transmission delay and throughput requirement [5]. The necessity to assure fairness and meet the QoS requirements in these dynamic conditions only aggravates the problem further.

1.3 Research Contribution

The main contributions of this paper are summarized as follows:

- **Cross-layer formulation:** We come up with common cross-layer optimization model, which takes physical, MAC, and network layer parameters into account to achieve energy-efficient functioning in 5G IoT networks.
- **Spatio-temporal hybrid learning model:** Our hypothesis is to develop an architecture that can be used to adaptively allocate resources by combining spatial feature learning and temporal dependency learning with reinforcement learning.
- **Reward design that is energy conscious:** This is a multi-objective reward scheme, which balances energy efficiency, delay performance and throughput under the QoS restriction.
- **Scalability and convergence study:** The given approach is examined concerning the computation complexity and the convergence characteristics of dense IoT deployments.
- **Complete performance validation:** Large-scale simulations with different densities and traffic patterns of the IoT show that energy-saving, latency, and system reliability are greatly improved over traditional and unlayered learning solutions.

The rest of this paper is structured in the following way: Section 2 provides a literature review of similar research in the area of cross-layer optimization and AI-assisted resource allocation of 5G IoT networks. Section 3 shows the system model and the formulation of optimization problem. In section 4 the proposed spatio-temporal hybrid learning framework is presented in detail. Section 5 gives performance analysis and comparative analysis. The section 6 deals with issues of complexity and practical implementation. Lastly, Section 7 provides a conclusion to the paper and outlines the future research directions.

2. Related Study

He et al., in [6] presents a four-layer Mobile Edge Computing system (MEC) network relating user devices to the core network via the Radio Access Network (RAN) to enhance communication efficiency. This system also includes blockchain-based authorization to guarantee the safe storage of data and managed access rights, which deals with security issues of the traditional cloud computing systems. The architecture will minimize high latency and enhance flexibility in data communication. In addition, the paper presents a MEC server positioning algorithm to optimize the communication distance and a resource allocation algorithm based on the Q-learning algorithm to achieve efficient resource allocation and task selection. Our experiment results demonstrate that the proposed approach has been able to save a substantial amount of energy and increase the performance level in contrast to the current baseline algorithm.

Zhao et al., in [7] explores the energy efficiency of resource allocation in Mine Internet of Things (MIoT) systems with Non-Orthogonal Multiple Access (NOMA) technology where several smart devices are using the same subchannel to enhance the use of the spectrum and connectivity between the devices. It is aimed at optimizing the energy efficiency of small networks of cells using joint power allocation and subchannel assignment when imperfect channel state information (CSI) is available. This has been reduced to an optimization problem which is a mixed-integer nonlinear fractional programming problem taking into account cross-layer interference, power constraints and QoS requirements. The channel model to solve the CSI uncertainty is modeled by

elliptical uncertainty set and the Dinkelbach method is used to transform the problem into the convex form. A rough solution is then derived by Lagrangian dual method. Numbers prove that the proposed algorithm can make the energy use much more effective and be far more relevant to the current baseline solutions.

Liu et al., in [8] studies the resource allocation and 3D location of multiple UAV-mounted base stations (UAV-BSSs) in an uplink IoT network with a goal of minimizing the total transmission power of IoT devices, and meeting the SINR requirements. The practical issues that are put into consideration in the study include balanced workload sharing among UAV-BSSs, the limited channel resources, and signal interference. To evenly allocate devices, a better K-means clustering algorithm will be suggested to cluster the IoT devices in a way that each UAV is in-charge of a similar number of devices. To effectively allocate subchannels and avoiding interference, a modified version of Hungarian-based dynamic many-to-many matching (HD4M) algorithm, which is grounded on the matching theory, is proposed. Moreover, the transmission power of IoT devices and the heights of UAVs are optimised together by the alternating iterative optimization method. The results of simulation show that the proposed algorithms can significantly decrease the sum of transmission power in contrast to the base approaches.

Mukherjee et al., in [9] discusses the model of energy consumption problem based on the massive IoT system with dynamic network architecture or cluster with a multiagent system (MAS) in industrial applications in 6G. Distributed artificial intelligence (DAI) is applied in its work to cluster the sensor nodes in the system to locate the main node and predict its location. The work firstly applies the backpropagation neural network (BPNN) and convolutional neural network (CNN), which are, respectively, presented to be optimized. Also, the work examines the connection between mutual clusters so that the resources can be allocated to the individual nodes within a cluster effectively. The outcomes of the simulation demonstrate that the suggested approach will minimize the wasting of resources due to the repetitive data, enhance the energy conservation of the entire network, as well as information preservation.

Boamah, Sharon A et al., in [10] carry out a survey of the use of blockchain technology in edge network resource management, and note that the technology could enhance the efficiency, security and reliability of network infrastructures. The paper is dedicated to blockchain adoption in three main aspects, including cloud and edge computing, Radio Access Networks (RAN) in future wireless networks, and smart resource management based on reinforcement learning and federated learning. It offers a thorough discussion of new research initiatives and presents the summaries of the most important findings regarding blockchain-facilitated network management. Also, the survey names open research opportunities and constraints of integrating blockchain and edge network resource management and outlines future research expectations to create a more secure and efficient network system.

To address the shortcomings of the battery and processing performance of a single UAV, Yu et al., in [11] explores a multi-UAV-aided mobile-edge computing (MEC) system to support an application in the Industrial Internet of Things (IIoT). Under the suggested system, various UAVs are controlled by a ground base station (BS) to facilitate computing and communication services to IIoT devices. The research presents a long-term system energy optimization problem, which consists of the joint optimization of UAV-trajectories, task offloading decisions and resource allocation, with respect to task deadline constraints. The network is dynamic and complex, which is why the problem is formulated as a Markov Decision Process (MDP) and addressed with the help of a Multi-Agents Twin Delayed Deep Deterministic Policy Gradient (MATD3) algorithm. The outcomes of the simulation prove that the presented approach offers more rewards and converges quicker than other existing techniques, including MADDPG and Proximal Policy Optimization (PPO).

Abuajwa et al., in [12] discusses various important findings: methods of power allocation have the potential to increase the energy efficiency by up to 30 percent in particular cases; relay-aided and hybrid NOMA schemes can be used in order to increase the data rate by 20-25 percent; energy harvesting has the potential to be used in an attempt to increase the energy efficiency, reducing the power consumption up to 15 percent in some instances. These difficulties are system complexity which may lead to the computational overhead 40 percent to optimise resource allocation, user fairness where power allocation trade-offs may cause the edge user data rate reduction to 10 percent in some cases and the total energy efficiency depends.

Liu X et al., in [13] present the Non-Orthogonal Multiple Access (NOMA) green multi-UAV assisted IoT system that will enhance user capacity and power consumption of UAVs. The paper develops a reasonable energy efficient resource optimization model that takes into account the limits on transmit power of UAVs, the minimum user communication rate and UAV mobility. To address it, the authors coordinate the communication scheduling, transmit power distribution, and UAV path with the help of the Dinkelbach method and Successive Convex Approximation (SCA). The simulation findings reveal that the proposed solution has a fair energy efficiency between UAVs and has a higher level of energy efficiency than conventional OMA-based UAV-assisted IoT systems.

3. Proposed Model

This section introduces the proposed Spatio-Temporal Hybrid Learning-Based Cross-layer Resource Allocation Framework of energy-efficient 5G IoT networks. The presented approach is aimed at the drawbacks of traditional optimization techniques in the IoT setting that is highly dynamic, where the channel conditions, traffic arrivals, queue state, and interference patterns constantly change over time [14]. The framework is a combination of spatial learning, temporal learning and hybrid decision-making to derive near-optimal policies in resource allocation considering realistic QoS as well as energy restrictions.

The suggested framework could be implemented on the centralized controller of the 5G gNB or at an edge-based intelligent controller that is coupled with the MEC server. The controller monitors the network surroundings continuously, derives the spatio-temporal characteristics, chooses resource assignment measures, and modifies the learning policy based on the accepted reward received. There are three key stages involved in the whole process of decision:

- **State observation-** The controller collects and past data on the network, such as channel conditions and interference, queue, device position, and traffic arrivals.
- **Action selection-** The agent chooses the best cross-layer actions of the learned policy taking into account the extracted features, which include transmit power, resource block allocation, scheduling priority, and modulation/coding levels.
- **Reward assessment and policy revision-** Since the environment responds back with energy efficiency, delay, packet loss and throughput performance indicators after the implementation of the chosen actions. These measures are transformed into a scalar reward which directs policy learning.

The interaction may be described as Markov Decision Process (MDP):

$$M = (S, A, P, R, \gamma) \quad (1)$$

where S is the state space, A is the action space, P is the probability of state transition, R is the reward function and $\gamma \in (0,1)$ or the discount factor.

3.1 Network Model

In the suggested Spatio-Temporal Hybrid Learning-Based Cross-layer Resource Allocation, the network model is a real-life situation of 5G Internet of Things (IoT) communication scenario in which many IoT devices are connected to a 5G Next Generation NodeB (gNB) [14]. The model represents the spatial distribution of equipment, dynamics of wireless channels and network topology which are critical in determining effective resource allocation plans.

1. 5G Base Station (gNB)

The network model in the suggested Spatio-Temporal Hybrid Learning-Based Cross-layer Resource Allocation framework poses a realistic 5G Internet of Things (IoT) communication scenario in which a great number of IoT devices are interacting with a 5G Next Generation NodeB (gNB). The model represents the spatial distribution of devices, wireless channel dynamics, and network topology dynamics, all of which are needed in the design of efficient resource allocation policies [15].

Where $u = \{1,2,3, \dots, N\}$ is the set of IoT devices and $k = \{1,2,3, \dots, K\}$ is the set of available Resource Blocks (RBs). The devices send data packets to the gNB via one or multiple RBs of the uplink channel. The gNB is in charge of constant monitoring of the network state and resources allocation.

The average uplink rate of device i achieved is

$$R_i = \sum_{k=1}^K s_{i,k} B_k \log_2(1 + SINR_{i,k}) \quad (2)$$

Where,

$s_{i,k}$ -RB assignment indicator B_k bandwidth of RB k , $SINR_{i,k}$ signal-interference plus noise.

As the IoT number of devices may be extremely large (hundreds or thousands), the system matches massively scaling Machine Type Communication (mMTC) scenarios described in 5G specifications [16]. The gNB serves as the master controller which gathers the state information and implements the hybrid learning-based resource-allocation algorithm.

2. Channel Mode (Fading, Interference, Path Loss)

The IoT has several physical phenomena that influence wireless communication between the gNB and the IoT devices, including distance attenuation, fading, and interference. The channel gain between device i and the gNB on RB k at time t may be represented as:

$$h_{i,k}(t) = g_{i,k}(t) \cdot PL_i$$

(3)

Where,

$g_{i,k}(t)$ is small-scale fading and PL_i is large-scale path loss.

3. Network Topology

Spatially, the IoT devices are spread in the coverage of the gNB. Topology of network defines the extent to which devices interfere with one another and how this impacts on scheduling decisions.

i. Static Nodes

There are a number of IoT which are stationary i.e. environmental sensors, smart meters and industrial monitoring sensors. Their positions are not changing and this makes the system acquire stable spatial interference patterns.

Assume the location of device i to be.

$$L_i = (x_i, y_i) \quad (4)$$

These states constitute a spatial topology graph that the Graph Neural Network utilizes in the proposed structure.

ii. Dynamic Nodes

Mobility can be observed with some IoT devices, e.g. wearable health sensors, vehicle-mounted sensors and mobile robots. Location in these devices varies with time:

$$L_i(t) = (x_i(t), y_i(t)) \quad (5)$$

This presents time changing channel conditions and interference patterns.

4. Interference Graph Representation

The network is modeled in the form of a graph to record the spatial relations of the devices.

$$G = (V, E) \quad (6)$$

Where,

V is the collection of IoT devices and E is interference connections among devices. The adjacency matrix A is set to be defined as

$$A_{ij} = \begin{cases} 1, & \text{if device } i \text{ and } j \text{ interfere} \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

3.2 Traffic Model

The traffic model in the proposed work is the data generation behavior of the IoT devices in a 5G network. IoT traffic is very heterogeneous and dynamic unlike the traditional mobile broadband traffic. Devices can be periodic in nature regarding the generation of monitoring data or can be event-driven in nature in regards to burst traffic. Moreover, most IoT applications have high demands in terms of QoS including low latency and high reliability. In order to be realistic in capturing these characteristics, the traffic model in the proposed work accommodates periodic sensing traffic, event based burst traffic and QoS requirements.

Qos Requirements - Latency and Reliability

QoS of numerous IoT services is essential. Resource allocation algorithm has to provide guarantees that packets are transmitted in the latency and reliability specifications of the required bounds.

Latency Requirement

Latency describes the delay that is created between transfer of a packet between a device and the base station.

The mean delay of the device i can be defined as:

$$D_i = \frac{Q_i(t)}{R_i(t)} \quad (8)$$

Where,

$Q_i(t)$ = length of queue, $R_i(t)$ = rate of transmission.

The delay has to be D_i to meet application requirements $D_i \leq D_i^{max}$.

Where D_i^{max} is the maximum allowable delay.

Reliability Requirement

Reliability is defined as a likelihood of a packet being delivered. The reliability of packets may be stated as:

$$\rho_i = 1 - P_{loss,i} \quad (9)$$

Where,

$P_{loss,i}$ is the probability of packet loss.

The constraint of reliability is $\rho_i = 0.15$.

3.3 Energy Consumption Model

One of the most urgent design goals of 5G IoT networks, therefore, is energy efficiency, as the majority of the IoT devices are battery operated and frequently have to be deployed in locations where renewing batteries is not very simple or costs a lot. The proposed Resource Allocation framework, therefore, expressly considers the energy consumption on IoT devices to model resource allocation decision, in addition to increasing network lifetime. Each IoT device has three significant energy components and they are: Transmission energy, Circuit Energy and Idle or sleep energy.

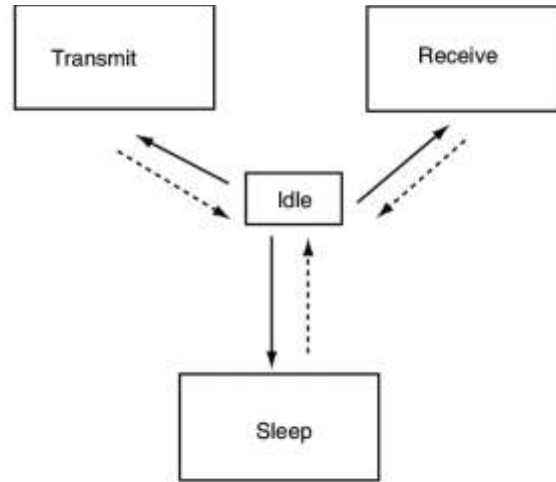


Figure 1: Power State

i. Transmission Energy

Transmission energy is the energy that is used when an IoT device sends data packets to the 5G base station (gNB). This energy largely relies on the level of transmit power, channel conditions and length of transmission. Assuming that device i sends a power of $P_{i,k}(t)$ in resource block k in time interval T , the energy spent in the transmission can be given by

(10)

$$E_i^{tx}(t) = \sum_{k=1}^K P_{i,k}(t) \cdot T$$

Where,

$P_{i,k}(t)$ means transmit power of device i on RB k , T is the time that the transmission takes and K is the total number of resource blocks.

Transmission energy is typically the greatest portion of energy in wireless communication as more transmit power is needed when:

- the device is distant to the base station,
- channel conditions are poor,
- level of interference is high.

The maximum transmission rate is connected to SINR as

$$R_{i,k}(t) = B_k \log_2(1 + SINR_{i,k}(t)) \quad (11)$$

Where, B_k is the bandwidth of resource block k .

The reinforcement learning agent in the proposed framework is used to dynamically control the transmit power to trade energy usage and throughput.

ii. Circuit Energy

In the suggested model, the reinforcement learning agent uses dynamic power adjustments to regulate energy usage and rate. The circuit energy consumption is modeled as:

The circuit energy consumption is modeled as:

$$E_i^{circuit}(t) = P_i^c \cdot T_i^{active} \quad (12)$$

Where,

P_i^c is the power consumption of a circuit and T_i^{active} is the time period of the active state of the device.

The common circuit power is tens to hundreds of milliwatts based on the hardware of a device. Energy in the circuit is important, as during transmission and reception, the device will still have to maintain its internal circuitry in operation even when transmit power is reduced to a minimum. Circuit energy reduction in dense networks of IoT can be realized by minimizing the active communication time by scheduling efficiently.

iii. Idle/ Sleep Energy

The IoT devices spend a significant percentage of their time in idle or sleep mode to save battery power. In this state, the device will not send any data but can still have some little functions like hearing or feeling the control signal. The energy consumption which is idle can be represented as follows:

$$E_i^{idle}(t) = P_i^{idle} \cdot T_i^{idle} \quad (13)$$

Where,

$$P_i^{sleep} < P_i^{idle} \quad (14)$$

In the suggested model, devices are capable of staying in the sleep mode longer, as a result of efficient scheduling and predicting the traffic, thus saving a lot of energy.

3.4 Total Energy Consumption Model

The energy consumption of device i at time t is the sum of the three components.

$$E_i(t) = E_i^{tx}(t) + E_i^{circuit}(t) + E_i^{idle}(t) \quad (15)$$

Or equivalently,

$$E_i(t) = \sum_{k=1}^K P_{i,k}(t)T + p_i^c T_i^{active} \quad (16)$$

The total energy consumption is system-wide,

$$E_{total} = \sum_{i=1}^N E_i(t) \quad (17)$$

where N being the number of IoT devices.

3.5 Energy Efficiency

The ratio of the total data rate to the total energy consumption is referred to as the energy efficiency.

$$EE = \frac{\sum_{i=1}^N R_i}{\sum_{i=1}^N E_i} \quad (18)$$

This is a measure of the efficiency of the network in the use of energy to pass information in bits/ Joule. This metric is one of the main goals of the proposed resource allocation framework to maximize.

3.6 Cross Layer in Proposed work

The classical way of wireless communication system is that, each protocol layer (Physical, MAC, Network, etc.) has a limited amount of information exchange with the other one. Nevertheless, the inefficiency of using resources at the layers in 5G IoT networks can result from the fact that many performance indicators, including energy consumption, delay, and throughput, can be closely interdependent in a few layers.

The proposed Spatio-Temporal Hybrid Learning-Based Resource Allocation model will address these limitations by taking a cross-layer design methodology, which involves the joint utilization of information across many layers to make resource allocation decisions. This helps the system to optimize the whole performance as opposed to optimization of each layer. The cross-layer model incorporates the parameters of the Physical Layer, MAC Layer and Network Layer to attain energy-efficient communication and QoS-sensitive communication.

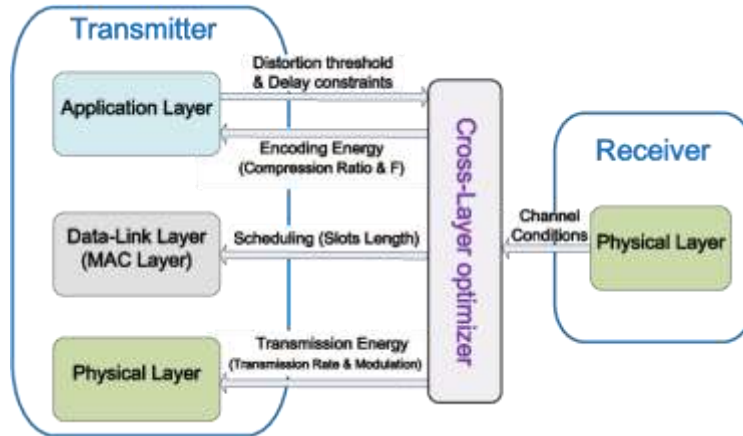


Figure 2: Architecture of Cross Layer Optimization in proposed work

i. Physical Layer Optimization

The wireless transmission and reception of the signal occurs on the physical layer (PHY). The physical layer in the proposed system provides a number of parameters which are significant in the cross-layer optimization.

Power allocation

Transmit power has a great impact in the energy and communication reliability. High power enhances the strength of the signal but consumes more power whereas low power minimizes the usage of power but can compromise the quality of the signal.

The accepted transmit power of device i on resource block k is denoted as:

$$P_{i,k} \in [0, P_i^{max}] \quad (19)$$

Where,

P_i^{max} is the peak power of device i .

The signal to interference plus noise ratio (SINR) is the resulting ratio.

$$SINR_{i,k} = \frac{P_{i,k}h_{i,k}}{P_{j,k}h_{j,k}+N_0} \quad (20)$$

This value is the direct determinant of the attainable data rate.

Modulation and Coding Scheme (MCS)

The modulation and coding scheme is also adjusted by the physical layer to channel conditions. With increased modulation levels, there is increased throughput but channel quality is required.

The data rate that can be achieved can be written as:

$$R_{i,k} = B_k \log_2(1 + SINR_{i,k}) \quad (21)$$

Where,

B_k refers to the bandwidth of resource block k .

ii. MAC Layer Optimization

The Medium Access Control (MAC) layer is the layer that controls the sharing of the wireless medium by a number of devices. The important part is efficient MAC-layer decisions to enhance the reduction of interference and spectrum efficiency.

Resource Block Assignment

Resource blocks (RBs) are used in 5G networks. Subsets of RBs are allocated to each device. RB assignment variable can be determined as:

$$\begin{cases} 1, & \text{if RB } k \text{ is assigned to device } i \\ 0, & \text{otherwise} \end{cases} \quad (22)$$

The following constraint is used to avoid excessive interference:

$$\sum_{i=1}^N s_{i,k} \leq 1 \quad (23)$$

iii. Network Layer Optimization

The network layer is involved with packet routing and queue management. Queue management is very vital in the IoT networks since the arrivals are usually bursty in nature.

Queue Management

Each device has a transmission queue in which the packets are awaited before being sent out. The queue dynamics are formulated as

$$\max(Q_i(t) - R_i(t), 0) + A_i(t) \quad (24)$$

Where,

$Q_i(t)$ queue length at time t , $R_i(t)$ transmission rate and $A_i(t)$ packet arrival.

Queue-based scheduling is used to avoid the loss of packets and guarantee latency.

Delay Management

The queue size is associated with the average delay of the gadget:

$$D_i = \frac{Q_i}{R_i} \quad (25)$$

The system ensures $D_i \leq D_i^{\max}$ to satisfy QoS requirements.

To guarantee QoS, the system ensures D_i is not more than $D_i^{\max}$.

iv. Integrated Cross-Layer Optimization

The suggested framework collaboratively maximizes PHY, MAC and Network layer parameters. The decision vector may be given as $A_t = \{P_{i,k}, s_{i,k}, \pi_i, MCS_i\}$.

Where,

$P_{i,k}$ transmit power, $s_{i,k}$ RB assignment, π_i scheduling priority and MCS_i modulation and coding scheme. The hybrid learning agent selects these parameters together as a result of the observed network state.

v. Cross-Layer Objective Function

Cross-layer optimization aims at maximizing energy use and QoS limitation.

The above equation can be used to define energy efficiency.

4. Proposed Spatio-Temporal Hybrid Learning Framework

This section describes the Proposed Spatio-Temporal Hybrid Learning Framework which is aimed at solving the energy-efficient cross-layer resources allocation problem in dense 5G IoT networks. The architecture combines spatial feature learning, temporal traffic modeling and decision making that is based on reinforcement learning to allocate network resources dynamically, and meet Quality of Service (QoS) constraints.

The wireless resource allocation problems are dynamic, far-dimensional, and non-convex which can be difficult to solve using traditional optimization methods. Thus, the proposed structure uses deep learning methods that are able to infer intricate spatial-temporal associations within the network setting. The Energy Efficient framework in 5G IoT network is shown in Figure 3 below:

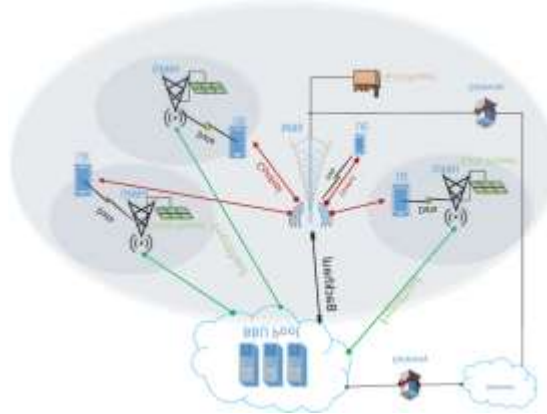


Figure 3: EE resource in 5G IoT network

The framework proposed is a smart controller that is based on the 5G base station (gNB) or edge computing server. It keeps on interacting with the network environment and carries out three primary operations:

- State Observation
- Action Selection
- Reward evaluation and policy update

The communication between the wireless network and the controller is described by a Markov Decision Process (MDP) which is described by:

$$M = (S, A, P, R, \gamma) \quad (26)$$

4.1 Spatial Learning using Graph Neural Network (GNN)

The communication between the wireless network and the controller is described by a Markov Decision Process (MDP) which is described by:

$$H^{(l+1)} = \sigma(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^{(l)}W^{(l)}) \quad (27)$$

Where,

A is adjacency matrix, D Degree Matrix and $W^{(l)}$ is trainable weights.

4.2 Temporal Learning using LSTM / GRU

Wireless networks are very dynamic in time because they have fluctuations in the traffic and channel. The networks of Gated Recurrent Unit (GRU) or Long Short-Term Memory (LSTM) are used in the framework to capture these time dependencies.

Hidden state update of LSTM is given as:

$$h_t = f(W_h h_{t-1} + W_x x_t) \quad (28)$$

Where,

h_t denotes hidden state and x_t is sequence of inputs.

The temporary learning system helps to anticipate the future traffic demand and the channel changes.

4.3 Hybrid Learning Decision Module

The framework involves a reinforcement learning agent to calculate optimal decisions related to cross-layer resource allocation decisions after the extraction of both spatial and temporal features. The decision matrix comprises,

$$A_t = \{P_{i,k}, s_{i,k}, \pi_i, MCS_i\} \quad (28)$$

Where,

$P_{i,k}$ power transmitted, $s_{i,k}$ RB assignment, π_i scheduling priority and MCS_i modulation and coding scheme.

4.4 Training and Learning Process

The reinforcement learning cycle under which the training is conducted is as follows:

1. Initialization of parameters of the neural network.
2. Monitor the existing network condition.
3. Elaborate spatio-temporal characteristics.
4. Choose an action with policy network.
5. Carry out the performance in the environment.
6. Record award and state to come.
7. Gradient descent model parameter estimation.

The parameter update rule is:

$$\theta = \theta + \eta \nabla_{\theta} J(\theta) \quad (29)$$

Where, η is the learning rate.

5. Result and Discussion

In this section, the performance of the proposed work as an energy-efficient 5G IoT network is evaluated. The proposed solution is contrasted with some of the base solutions to show energy efficiency, delay, throughput, packet loss, and convergence performance. The simulation experiments are carried out in the dense IoT deployment conditions in which several devices vie with scarce wireless resources.

5.1 Simulation setup

A simulated 5G IoT network setting with the following parameters is used to make performance evaluation. Table 1 shows the simulation parameter settings of proposed work.

Table 1: Parameter Setting

Parameter	Value
Network Type	Single-cell 5G
Base Station	1 gNB
Number of IoT devices	50-300
System Bandwidth	20 MHz
Number of Resource Blocks	50
Channel Mode	Rayleigh fading
Max Transmit Power	23 dBm
Learning Algorithm	GNN+LSTM+RL
Simulation time slots	10,000

i. Energy Efficiency model

Energy efficiency can be determined as the amount of bits sent per unit energy use. According to simulation outcomes, the proposed framework is much more efficient in energy use than baseline ones.

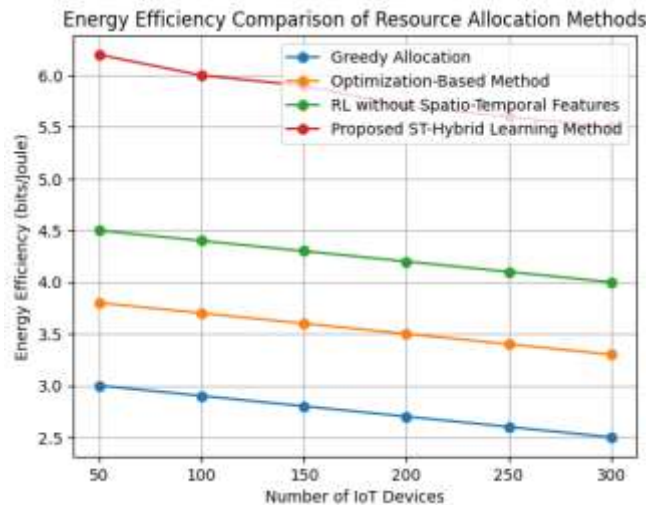


Figure 4: Energy efficiency analysis

The Figure 4 demonstrates that energy efficiency decreases with the quantity of IoT devices because the number of devices interferes with each other and competes with one another. Nevertheless, the suggested method is always more energy-efficient than the Greedy, Optimization-based and traditional RL methods. This is enhanced by learning relationships between spatial interference with GNN and depth temporal traffic with LSTM/GRU in order to make more intelligent cross-layer decisions on power control, resource allocation, and scheduling. Consequently, the suggested approach will minimize energy usage and enhance general network throughput in large 5G IoT systems.

ii. Delay Performance

Average packet delay is an important QoS metric defined as

$$D_i = \frac{Q_i}{R_i} \quad (30)$$

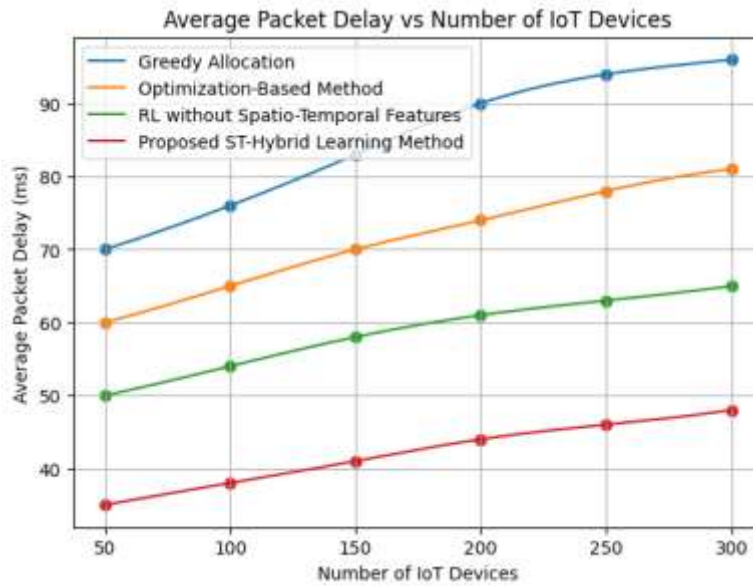


Figure 5: Analysis of Packet Delay

Figure 5 is a comparison of the average packet delay amid varying resource allocation techniques as the quantity of IoT devices also increases. Every approach increases the delay of packets as a result of increased traffic density and network interference. Nevertheless, the suggested Spatio-Temporal Hybrid Learning scheme has the lowest delay at all times, thus providing higher performance compared to Greedy, Optimization-based, and traditional RL schemes. It is done with the help of spatial interference by using Graph Neural Networks and the temporal traffic pattern with the help of LSTM/GRU, which allows to schedule the cross-layer and allocate the resources efficiently. Consequently, the suggested approach lowers the waiting time in queues and enhances latency performance and QoS in the 5G IoT large-scale networks.

iii. Throughput Performance

System throughput is determined by data rate of all the devices.

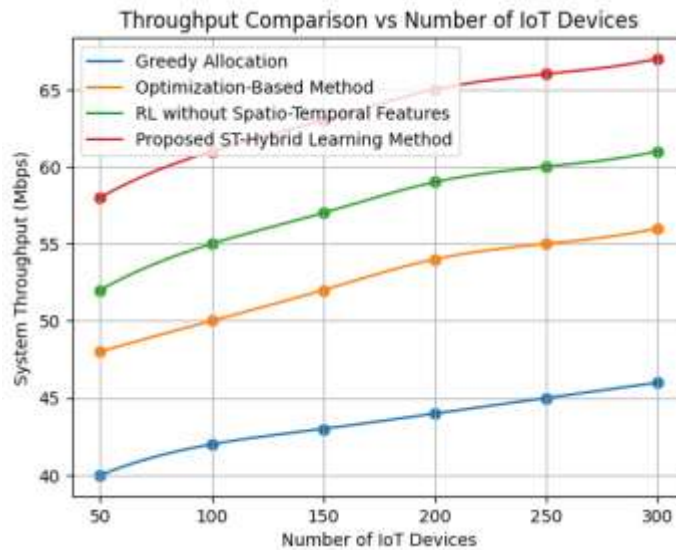


Figure 6: Analysis of Throughput

The Figure 6 shows the system throughput and the number of IoT devices of Greedy Allocation, Optimization-based approaches, Reinforcement Learning in the absence of spatio-temporal characteristics, and the suggested Spatio-Temporal Hybrid Learning system. The throughput slowly increases with the increase in the number of devices since the devices will be adding up to the total data transmission. Nevertheless, the proposed approach has the largest throughput at all network sizes. It can achieve this because it is capable of capturing

spatial interference relationship with Graph Neural Networks (GNN) and temporal traffic pattern with LSTM/GRU models, resulting in more efficient resource block allocation, power control and scheduling decisions. The proposed framework therefore uses the network resources more efficiently resulting in increased throughput in comparison to the traditional greedy, optimization based, and state-of-the-art reinforcement learning methods.

iv. Packet Loss

Packet loss will be experienced when packets are not able to be sent before a queue gets full or because of unfavorable channel conditions.

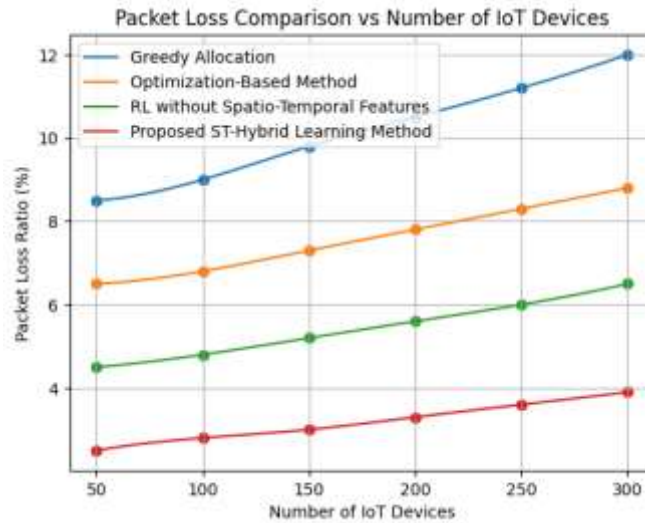


Figure 7: Analysis of Packet Loss

The Figure 7 represents the ratio of packet losses to the quantity of IoT devices of the various ways of resource allocation. With an increase in the number of devices, all the approaches experience an amplified packet loss percentage as the network becomes more congested, more interfered, and the wireless resources are exhausted. Nevertheless, the suggested Spatio-Temporal Hybrid Learning structure was always the lowest in the number of lost packets in comparison to Greedy allocation, Optimization-based, and Reinforcement Learning without the feature of spatio-temporality. It is improved by the fact that the proposed framework trains spatial interference relationships with Graph Neural Networks (GNN) and temporal traffic patterns with LSTM/GRU, which allows to organize the scheduling process and assign resources blocks more productively. Consequently, the network reliability and Quality of Service (QoS) under congested networks with a high density of 5G IoT devices is enhanced by eliminating packet collisions and queue overflow.

Table 2: Overall comparison of Performance

Method	EE (bits/Joule)	Delay (ms)	Throughput (Mbps)	Packet loss (%)
Greedy Allocation	2.8	85	42	8.5
Optimized Method	3.6	62	51	6.2
RL without Spatio-temporal features	4.2	48	56	4.3
Proposed	5.7	31	64	2.1

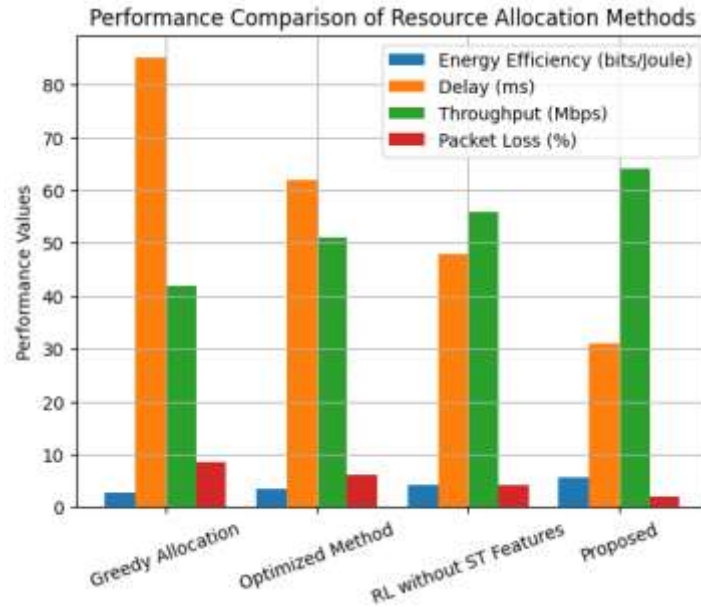


Figure 8: Overall analysis of proposed work

Figure 8 proves the superiority of the proposed Spatio-Temporal Hybrid Learning framework in terms of performance compared to the current methods such as Greedy Allocation, Optimized Method, and Reinforcement Learning without spatio-temporal features. The suggested approach has the best energy efficiency (5.7 bits/Joule) and throughput (64 Mbps), at the same time, it has the lowest delay (31 ms) and packet loss (2.1%). This is enhanced by the fact that the proposed framework combines spatial learning with Graph Neural Networks (GNN) and temporal traffic modeling with LSTM /GRU to intelligently allocate resources across the layers. The framework enables more efficient allocation of resources, less congestion, and enhanced network reliability by taking the channel conditions, the relationship between interferences, the queue states, and the traffic dynamics into account. These findings indicate that the proposed solution offers a high potential of improving energy efficiency, latency performance, throughput, and packet reliability, hence it is very appropriate in dense 5G IoT networks.

6. Conclusion

In this study, a Spatio-Temporal Hybrid Learning-Based Cross-layer Resource Allocation framework was described that can optimize the energy efficiency and Quality of Service in 5G IoT networks. The suggested solution combines the Graph Neural Networks (GNN) to learn the relationship between spatial interference of IoT devices and time-varying traffic patterns (LSTM/GRU) based on time-varying learning models. Integrating these spatio-temporal components with a reinforcement learning based decision-making process, the framework allows to optimize the important network components such as power distribution, resource block allocation, scheduling choices, and modulation choices intelligently. The simulation outcomes indicated that the suggested method is much better in comparison to traditional methods like Greedy allocation, the traditional optimization-based methods, and reinforcement learning without spatio-temporal information. To be more specific, the proposed framework obtained greater energy efficiency (5.7 bits/Joule) and system throughput (64 Mbps) along with lower average packet delay (31 ms) and packet loss ratio (2.1) at the scenario of massive IoT deployment. All these enhancements demonstrate how the proposed system can be effective in the control of interference, minimization of transmission delay and overall network reliability. Thus, the suggested spatio-temporal hybrid learning can offer a cross-sized and efficient resource management tool to deal with large-scale 5G IoT conditions, which is in line with the increased demands of the energy-efficient and latency-sensitive IoT application.

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