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Research Article

Double Deep Q- energy aware Service allocation based on Dynamic fractional frequency reusable technique for lifetime maximization in HetNet-LTE network

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Abstract:

The development of mobile communication in heterogeneous networks is incredible in providing various services through wireless cellular communication through advanced long-term evaluation networks. Increasing multi-concern services and frequencies in spectrum channels are highly layered to select the bandwidth to provide the fastest network without interference. Selecting the channel through macro cell selection is essential to improve network communication and provide the quickest service. Most frequency reuse techniques use service optimality and route selection-based protocols to enrich the packet flow. Still, the improper spectrum delights create more delay tolerance due to short-range service optimality due to energy loss by selecting the short spectrum signal to reuse, which doesn't support the lifetime improvement of the LTE network. To resolve these problems, we propose a Double Deep Q- energy-aware Service allocation based on a Dynamic fractional frequency reusable technique for lifetime maximization in the HetNet-LTE network. Initially, the heterogenous communication environment and node deplanement were carried out to construct the LTE network under the WCC. The communication logs are Route Table (RT), and its services are taken by all node LTE Communication Impact Rate (LTE-CIR). Then, the Backhaul Traffic Algorithm (BTA) is applied to predict the interference on traffic rate from the channel frequency margin. Select the balanced node using the Channel Interference Macro Cell Selection (CIMCS) technique. Considering frequency limits with the Double Deep Q- Network (DDQN) approach, energy-aware selects the optimal route to reuse the frequency level using Frequency Domain Packet Scheduling (FDPS) to improve communication. The proposed system improves the overall throughput by up to 97.8 % with adopted channel selection from the macro unit to improve the latency performance. Also, the interference frequency limits are dynamically reused at an energy optimal level with low-level delay tolerance to improve the link stability by up to 98.4 % with higher lifetime maximation in the LTE network.

1. Introduction

Mobile devices increasingly use Long-Term Evolution (LTE) technology to facilitate effective wireless broadband communication. LTE ensures user Quality of Service (QoS) by coordinating resource allocation to enhance system performance. It solves a significant problem by utilizing various scheduling techniques and downlink algorithms in LTE implementations. Wireless networks are evolving rapidly as this technology continues to impact the future significantly. The LTE downlink algorithm determines the user's transmission order during the resource allocation phase by utilizing the QoS specifications and channel status reports [1].

An example of this approach is the development of today's LTE technology based on IP network architecture [2,3]. LTE technology calculates the required capabilities of each User Equipment (UE) by assigning network resources based on factors such as packet scheduling delay, channel quality, the number of active UEs, throughput, and QoS requirements. In LTE systems, numerous radio stations are strategically deployed and configured. As the demand for communication increases and the user base expands, LTE networks evolve to support a more extensive clientele. Consequently, multiple LTE nodes are configured within the same network to manage the growing traffic load effectively. Introducing smaller cells with limited coverage within more giant cells, such as microcells or picocells within microcells, helps improve spectrum utilization and network coverage in heterogeneous networks [4]. Specifically, they enhance the performance of micro and pico base stations and allow them to share spectrum with macro base stations.

However, due to severe co-channel interference, the limited radio resources can only efficiently support a few base stations transmitting data simultaneously [5]. Consequently, optimizing the system's data capacity is essential, and it can be achieved through performance measures like efficient resource allocation and effective interrupt management in developing different strategies. Moreover, assessing all potential combinations of resource allocation to reach optimal outcomes poses several challenges. The contribution of the research begins by establishing a comprehensive understanding of the heterogeneous communication environment within the LTE network. It accurately examines the node deployment strategies under the Wireless Communication Channel (WCC) framework, ensuring a solid foundation for subsequent analyses. The communication logs, specifically the RT and the LTE-CIR are analysed to provide insights into service utilization and traffic patterns. This foundational work is crucial as it informs the application of the BTA, which predicts interference based on traffic rates and channel frequency margins.

A significant contribution of this research is the introduction of the CIMCS technique, which enables the selection of balanced nodes to mitigate interference effectively. By considering frequency limits and employing the DDQN approach, the research focuses on optimal route selection and emphasizes frequency reuse through FDPS. This dual focus on route optimization and frequency management is vital for improving communication efficiency and network throughput.

The empirical results of the proposed system demonstrate a remarkable improvement in performance metrics, with an increase in overall throughput by up to 97.8%. This enhancement is achieved by strategically adopting channel selection from macro units, significantly reducing latency. Furthermore, the dynamic management of interference frequency limits contributes to achieving an impressive link stability of 98.4%, showcasing the effectiveness of the energy-aware approach in maintaining low delay tolerance.

2. Literature Survey

Based on carrier aggregation, they suggested a novel approach to resource block allocation in LTE-Advanced (LTE-A) networks to minimize overall energy usage and determine the energy balance between downlink and uplink [6]. They offer low cost based on Energy Efficiency Smart Allocating (EESA) algorithms that assign requests to the best servers [7]. To tackle the challenges above, Binary Search-Based Recursion (BSR) techniques will be employed to jointly solve sub-problems, including energy efficiency calculations and communication resource allocation [8]. The accuracy data obtained from the simulation evaluations are used to assess the proposed resource allocation scheme's performance. Using unsupervised learning, they evaluate using the Femtocell Base Station (FBS) algorithm for optimal clustering [9].

However, severe interference makes achieving optimal resource allocation between densely and randomly deployed FBSs impossible. These strategies should also enhance learning accuracy by utilizing delays and bounded averaging, all while ensuring controlled energy consumption [10]. An Energy-Efficient Resource Allocation Model (EERAM) has been proposed to efficiently allocate communication power among network devices, reducing energy consumption and extending the service life of communication between devices. [11]. They proposed an efficient federated learning scheme that relies on slope measurement and resource allocation [12] in a dynamic user selection system. A previously conducted analysis proposed a classification method to explain the operational and implementation specifics and summarize significant discoveries [13]. They implement the Gaussian Mixture Model (GMM) algorithm, built from two different ML clustering algorithms, and distribute the clustering model in the antenna system [14]. Similarly, users employ scheduling and energy allocation to analyze a solution unsuitable for real-time applications [15]. Moreover, they designed an Augmented Deep Convolutional Neural Network (ADCNN) to calculate real-time power allocation [15]. Furthermore, it proposed a Federated Edge Learning (FEEL) framework in wireless networks to enable energy-efficient implementation by designing collaborative computing and communication resource management [16].

They are determining the distributed communication problem for delay reduction in multi-user wireless networks by training Machine Learning (ML) models. In addition, Non-Orthogonal Multiple Access (NOMA) local models are introduced to prevent them from achieving low latency for the radio station and transmitting the performance parameters to the base station [17]. Additionally, they deploy virtual machines based on a Deep Q-Network (DQN) model and provide resource scheduling across physical servers [18]. However, solving large-scale networks using optimization models based on mathematical programming is challenging due to their high computational complexity [19]. Therefore, in the proposed heuristic, each flow in the fixed flow demand matrix is selected sequentially based on Q-learning using an Auxiliary Graph (AG)-based greedy method. Table 1 describes the methods acquired in the previous section for enhancing energy-efficient resource allocation in LTE networks and conducting performance evaluations, limitations, and accuracy analyses.

Table 1. *Energy Efficient Resource Allocation in LTE Netw*

Author	Year	Technique Used	Performance Evaluation	Achieved Accuracy	Limitation
M. G. Brahmam [20]	2024	Bidirectional Long Short-Term Memory (Bi-LSTM)	Deadline Hit Ratio (DHR)	86.6%	Assessing the complexity of virtual machine migration reduces energy consumption.
H. Yang [21]	2022	Multi-Agent Dueling Deep-Q Network (MADQN) algorithm	Learning efficiency, network data rate	85.4%	Distributing sensitive energy without a central controller that monitors strategies locally is difficult.
R. Yin [22]	2024	Two-Layer Iterative algorithm	Communication cost	89%	Collecting data from all devices takes time and effort.
Z. Wang [23]	2021	Deep Neural Network (DNN)	Complexity-reducing and time-saving.	92.67%	Conventional resource allocation methods that rely on optimization technologies tend to be more complicated and exhibit subpar real-time performance.
S. Zhou [24]	2022	Multi-Agent Twin Delayed Deep Deterministic (MATD3)	lower computational complexity	82%	Ensuring the network is fast, low-cost, and energy-efficient is essential.
A. Shahid [25]	2021	Carrier Sense Adaptive Transmission (CSAT)	Spectrum Efficient Schemes	79.8%	Achieving the QoS requirements of existing cellular networks has become a significant challenge.
H. Nashaat [26]	2020	Dragonfly-based Joint Delay/Energy (DJDE)	energy consumption, Energy efficiency, Throughput	88%	The energy consumption of the presented method is not considered optimal.
S. Kumar [27]	2020	LTE-Advanced Heterogeneous Networks (LTE-HetNets)	Throughput variation, Power, and resource block usage variation	93%	If network congestion occurs, packet loss may occur.
P. B. Pankajavalli [28]	2023	Flower Pollination Optimization Algorithm (FPA).	Spectrum Efficiency, Throughput, Transmission Delay	86%	Influencing the scheduling process does not improve overall QoS as perceived by the client.

In addition, the author [29] presented an algorithm for scheduling and resource allocation links based on LTE-Advanced (LTE-A) systems to reduce packet loss and increase energy efficiency. Furthermore, the presented method analyzes the mathematical model to define the NP-hard problem. They represent the optimization problem and propose a Device-to-Device Resource Allocation and Power Control (DRAPC) framework to optimize network connectivity [30]. The hybrid memory-based Differential Evolution Dragonfly Algorithm (DADE) delivers simulation results regarding the network's integration properties. The different service classes optimize network utilization by fine-tuning the associated parameter settings [31]. Once the optimal value is reached, the overall system spectral performance is automatically optimized using the Support Vector Machine (SVM) technique [32]. They improve the estimation of simulation parameters to 92.5% by providing better reliability, energy efficiency, and computational efficiency than existing technologies.

Heterogeneous networks consist of multiple types of cells, including macro cells, micro cells, and small cells, each serving different user densities and service requirements. The complexity of these networks necessitates sophisticated methods for managing resources, particularly in spectrum allocation and channel selection. The current methodologies often rely on frequency reuse techniques that prioritize service optimality and route selection to improve packet flow. However, these approaches frequently encounter issues such as increased delay tolerance and energy loss due to suboptimal spectrum selection, particularly when short-range signals are reused without adequate consideration for network lifetime and stability.

2.1 Problem Statement

The primary challenges in the current mobile communication landscape within HetNets can be summarized as follows:

- **Interference Management**: The coexistence of multiple cells leads to interference, adversely affecting the QoS and overall network performance.
- **Spectrum Allocation**: The improper selection of frequency bands can result in delays and reduced throughput, limiting the network's ability to meet user demands.
- **Energy Efficiency**: Short-range spectrum signals often lead to energy losses, impacting the sustainability and lifetime of LTE networks.
- **Latency Issues**: Delays introduced by inefficient routing and spectrum allocation strategies can degrade the user experience.

To address these challenges, we propose implementing a double-deep Q-energy-aware Service allocation system based on a Dynamic Fractional Frequency Reusable technique to maximize the lifetime of HetNet-LTE networks.

3. Materials and Methods

The proposed system, Double Deep Q-Energy Aware Service Allocation (DDQN-EAS), optimizes resource allocation in HetNet-LTE networks. The architecture consists of several key components: The initial step involves establishing a communication environment that incorporates various node types within the LTE network. The communication logs are maintained in an RT, which tracks the services utilized by each node. LTE-CIR is calculated to assess the performance of the LTE network based on the service demands of connected devices. The BTA predicts interference levels based on traffic rates and channel frequency margins. This predictive capability is crucial for identifying potential bottlenecks and optimizing resource allocation. The CIMCS technique is implemented to select balanced nodes while considering the interference levels associated with different channels. Figure 1 shows the architecture diagram of FDFS –CIMCS. By minimizing interference, the system can enhance the overall communication quality. A DDQN framework is utilized to select optimal routes for frequency reuse. FDPS mechanism is integrated into the system to facilitate the efficient scheduling of packets across

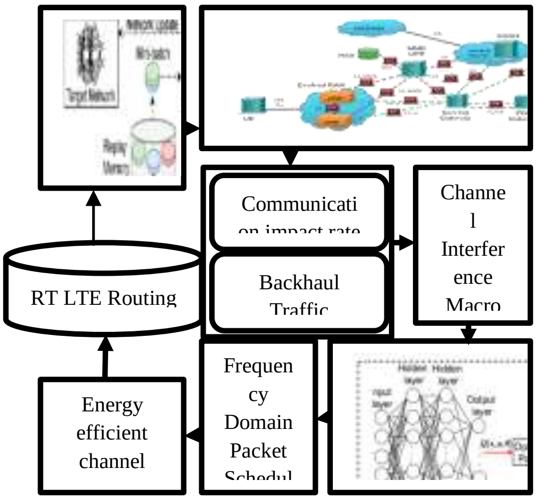

Figure 1: *Architecture diagram CIMCS- FDFS*

frequency channels. This scheduling ensures that resources are allocated dynamically based on demand, enhancing communication efficiency.

3.1 Communication Impact Rate (CIR)

This section employs the communication impact rate based on the nodes process in HetNet to accurately predict noisy sensor data influenced by uncertainty and random external factors. The derivative value is derived from the Taylor series of positions and the observed covariance matrix. Furthermore, the signal-to-interference-plus-noise ratio can be estimated using channel-level predictions from the observed gradient model. The Kalman filter technique also analyzes the covariance matrix of measurement errors and identifies the channel gain matrix as the identity matrix. Additionally, it can ascertain the structure of the covariance matrix for prediction errors within the state matrix. Equation 1 demonstrates that the Taylor series can be used to find expressions for states and observations. Evaluate the channel condition prediction in Equation 2 to calculate the state and observation system. Let's assume A-initial value, w-time,

$A(w)$ −state matrix, $\dot{A}(0), \ddot{A}(0)$ − first and second derivate, $O(w)$ −observed matrix, r-user, s-scheduling interval, d_r −gradient, b_{rs} −, T-transpose.

$$A(w) = A(0) + \dot{A}(0)t + \frac{1}{2}\ddot{A}(0)w^2 \tag{1}$$

$$A(w)=(b_{rs},d_r,y_r)^w$$
$$O(w)=(b'_{rs},d'_r,y'_r)^w \tag{2}$$

The observation matrix is directly derived from the state matrix. The transfer matrix shown in Equations 3 and 4 is then calculated to determine the identity of the channel gain matrix.

$$\Phi = \begin{vmatrix} 1 & w & w^2/2 \\ 0 & 1 & w \\ 0 & 0 & 1 \end{vmatrix} \quad (3)$$

$$F = \begin{vmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{vmatrix} \quad (4)$$

Calculate the error measurement covariance after the position matrix is determined as described in Equation 5. Let's assume R-measurement error, $\left(A_{g,A}(w), A_{g,b}(w), A_{g,o}(w)\right)^w$ −random variable measurement error.

$$I = \begin{cases} E\left[\left(A_{g,A}(w), A_{g,b}(w), A_{g,o}(w)\right)^w, \left(A_{g,A}(w), A_{g,b}(w), A_{g,o}(w)\right)\right] \\ \begin{vmatrix} \sigma_{g,A}^2 & 0 & 0 \\ 0 & \sigma_{g,b}^2 & 0 \\ 0 & 0 & \sigma_{g,o}^2 \end{vmatrix} \end{cases} \quad (5)$$

Estimate the covariance matrix of the state group errors as shown in equation 6.

$$M_0 = \begin{vmatrix} b_{rs}^2 & 0 & 0 \\ 0 & d_r^2 & 0 \\ 0 & 0 & y_r^2 \end{vmatrix} \quad (6)$$

The average mean rate consequences are taken 'M_0' to reduce the errors on more consecutively frequency nodes carried from the channels in the nodes response in the routing.

3.2 Backhaul Traffic Algorithm (BTA)

The total traffic duration taken from each node 'M_0' for each user's enhanced node B in the cellular network depends on the backhaul traffic algorithm for each user's equipment. Additionally, the BTA technique can estimate the parameters used to connect devices based on combined traffic rather than individual devices per user. Furthermore, the proposed method can determine the parameters associated with each user's device and model downlink traffic requirements. Backhaul the traffic pattern for each user's device and evaluate the enhanced node B following the Poisson process. Moreover, traffic arrivals are determined to be independent by evenly distributing each user's equipment within the coverage area. Equation 1 illustrates that the average data rate is determined by expressing the average service time needed to meet the traffic demand at the user equipment location. Additionally, the user device has a traffic load. Let's assume r-location, $v_{\bar{e}}$ −average service time, $\lambda(w)$ −Distribution traffic load, $d(w)$ −average traffic load, W-traffic.

$$X(w) = \frac{d(w)}{v_{\bar{e}}} \quad (7)$$

$$W_r(w) = \frac{\lambda(w)\zeta_{\bar{e}}(w)d(w)}{b_{\bar{g}}} \quad (8)$$

As Node B is enhanced for a portion of the average traffic load time, we calculate the average service time as shown in Equation 3. Let's assume $\Psi_{\bar{e}}$ −fraction time, $L(w)$ −average service time, $\bar{e}$ −enhanced node, $W_{\bar{e}}(w)$ −total traffic load, $T_{\bar{e}}(w)$ −average waiting time, and $\Phi_{\bar{e}}(w)$ −latency ratio at measure user time.

$$\Psi_{\bar{e}} = \int_{w \in O} \zeta_{\bar{e}}(w) b_a$$
$$L(w) = \frac{d(w)}{b_{\bar{e}}(w)}$$
$$W_{\bar{e}}(w) = \frac{d(w)}{b_{\bar{e}}(w)(1-\Psi_{\bar{e}})}$$
$$w_{\bar{G}}(t) = X_{\bar{e}}(w) - L(w)$$
$$\Phi_{\bar{e}}(w) = \frac{T_{\bar{e}}(w)}{X(w)} \quad (9)$$

Calculate the average traffic load of the user equipment with the latency ratio, as shown in Equation 4.

$$\Phi_e(\Psi_{\bar{e}}) = \frac{\Psi_{\bar{e}}}{1-\Psi_{\bar{e}}} \quad (10)$$

From the traffic density $\Phi_e(\Psi_{\bar{e}}) \leftarrow M_0$ based on the frequency retained by the energy on each node.

3.3. Double Deep Q-Network (DDQN) Approach

This section analyses the energy efficiency of resource allocation using the dual deep Q network method. The DDQN model enables the selection and evaluation of a function using the mathematical maximum value. Modifications in the technique the learning user chooses or assesses actions may lead to more favourable action values. In addition, the DDQN method can improve the Q-value function based on the optimistic biased estimator of the maximum mathematical evaluator. Therefore, the DDQN method will improve the overestimated action values.

Algorithm 1: DDQN
Input: Random weights and dependent values for experiential memory Output: Update the target deep network **w** Start 1. Compute the empirical memory set ← $\mathbf{j}(\mathbf{w}\ \boldsymbol{\Phi}_{\mathbf{e}}(\boldsymbol{\Psi}_{\bar{\mathbf{e}}}) \leftarrow \mathbf{M0}) = \mathbf{1}$ 2. Compute the target network as a copy of the weights and biases of the primary network← $\boldsymbol{\theta}'$ For each $\mathbf{g}_{\mathbf{mr}}$, do Calculate the status of the agent's total user data rate requirements over a given time← $\mathbf{j}(\mathbf{w})$ $\mathbf{j}(\mathbf{w}) =$ $[\mathbf{v_1}(\mathbf{w}), \mathbf{v_2}(\mathbf{w}), \dots, \mathbf{v_c}(\mathbf{w}), \mathbf{D_1}(\mathbf{W}), \mathbf{D_2}(\mathbf{w}), \dots, \mathbf{D_I}(\mathbf{w}), \mathbf{e_{1,1}}($

(1)

If $\mathbf{j_{lot}}$ do

Select the actions based on the greedy strategy ← $\boldsymbol{\varepsilon}$

Attain rewards directly and compute the next state$\mathbf{E}(\mathbf{w}) \leftarrow \mathbf{j}'$

Evaluate best beamforming solutions

For each store experience, $(\mathbf{j_w}, \mathbf{x_w}, \mathbf{E}(\mathbf{w}), \mathbf{j}'_\mathbf{w}) \leftarrow \mathbf{Q_v}$

A random sample of mini-batches $(\mathbf{j_w}, \mathbf{x_w}, \mathbf{E}(\mathbf{w}), \mathbf{j}'_\mathbf{w})$ $\mathbf{from Q_v}$

End for each

3. Compute the target j value in the target deep network.

For each set target, $\mathbf{V_{RL}} = \mathbf{V_{nq}}$

$$\mathbf{b}(\mathbf{w}) = \mathbf{e}(\mathbf{w}) + \boldsymbol{\mu}\mathbf{max}\,\mathbf{n}(\mathbf{j}', \mathbf{x}', ; \mathbf{n}'_\mathbf{w})$$

For set target value $\mathbf{V_{RL}} = \mathbf{V_{nq}}$

$$\mathbf{b}(\mathbf{w}) = \mathbf{e}(\mathbf{w}) + \boldsymbol{\mu}\mathbf{n}\mathbf{j}', \underset{\mathbf{x}'}{\mathbf{arg\,max}}\ \mathbf{n}\big(\mathbf{j_w}, \mathbf{x_w}; \boldsymbol{\theta}(\mathbf{w}); \boldsymbol{\theta}'(\mathbf{w})\big)$$

Calculate the main network to minimize the loss function← $\mathbf{K}(\boldsymbol{\theta})$

$$\mathbf{K}(\boldsymbol{\theta}) = \mathbb{G}\left[\big(\mathbf{b}(\mathbf{w}) - \mathbf{n}(\mathbf{j_w}, \mathbf{x_w}; \boldsymbol{\theta})\big)^2\right]$$

Calculation according to the gradient descent

$$\big(\mathbf{b}(\mathbf{w}) - \mathbf{n}\ (\mathbf{j_w}, \mathbf{x_w}; \boldsymbol{\theta})(\mathbf{w})\big)$$

Update the target deep network

$$\mathbf{n}'(\mathbf{w}) = \boldsymbol{\tau}\boldsymbol{\theta}(\mathbf{w}) + (\mathbf{1} - \boldsymbol{\tau})\mathbf{n}'(\mathbf{w})$$

$$\mathbf{w} = \mathbf{w} + \mathbf{1}$$

End for each

End for each

Return ← $\mathbf{w}$

End if

End for each

End

Let's assume t-time slot, $V_c(w)$ −user data rate demand, $e_{I,c}(w)$ −transmission rate between remote radio heads, $j(w)$ −state space, q_v −experience memory, τ −soft update, θ' −primary network weight, and bias, V_{RL}− deep reinforcement learning, V_{nq} −deep Q network, $k(\theta)$ −loss function, ε −greedy policy, j' −success state, x' −action state, $j_w, x_w, e(w),$ −trained adjusting weight, $n(j', x', ; n'_w)$ −target Q network.

3.4 Frequency Domain Packet Scheduling (FDPS)

This section proposes a frequency-domain packet scheduling algorithm that manages the subgroup formation hierarchy by optimizing QoS parameters. Furthermore, the proposed FDPS scheduler selects user equipment distribution and the optimal subassembly configuration. Additionally, user satisfaction can be assessed by collecting feedback during multicast sessions. The maximum data rate supported by user equipment is optimized based on the data rate assigned by the packet scheduler. A packet consists of potential subsystems linked to creating a computational load set. Estimate user satisfaction using the User Dissatisfaction Index (UDI), as demonstrated in Equation 1. Let's assume y_r–maximum data rate, v_r −packet scheduler, and t_r −User Dissatisfaction Index (UDI).

$$T_r = W(\Phi_e(\Psi_{\bar{e}}) \leftarrow M0)\begin{cases} y_r - v_r & y_r \geq v_r \\ \infty & y_r < v_r | v_r = 0 \end{cases} \quad (11)$$

Equation 2 shows that the UDI value is calculated by assigning a group dissatisfaction index. Let's assume the t_u −UDI user, C_u −user channel link value, and L-total number of multicast user equipment.

$$\Omega = \frac{1}{L}\sum_{u=1}^{U} t_u C_u \quad (12)$$

As shown in Equation 3, estimate the proportion of common data assigned to the subgroups. Let's assume U-subgroup, genetic data, I-rate, m-packet, i_m −resource packet, bounded packet, and v_u^I −bounded resource channel data.

$$v_u^I = \{P(y_m, i_m), m = 1, \ldots, u\} \quad (13)$$

Equations 4 and 5 show that the user distribution vector of the group dissatisfaction index experienced by subgroups is estimated. Let's assume C-user, f^I −vector of dissatisfaction index, y_u −minimum data rate vector

$$\Omega = \frac{1}{L}\sum_{u=1}^{U} t_u C_u = \frac{1}{L}\sum_{u=1}^{U}[y_u - v_u^I]\, C_u \quad (14)$$

$$\Omega = \frac{1}{L}\sum_{u=1}^{U} t_u C_u = \frac{1}{L} f^I . C \quad (15)$$

Equation 6 calculates the user allocation cost function for deciding the optimization problem based on the FDPS algorithm. Let's assume I-subgroup set.

$$Fr \rightarrow X \text{ at each} \begin{cases} \prod \underset{I \in I}{\arg\min} \left\{\frac{1}{L} f^I . C\right\} \\ \sum_{u=1}^{U} C_u = Q \end{cases} \quad (16)$$

The Fr returns the maximum frequency of node reuse at the tolerance on each route to schedule according to the domain tolerance rate.

3.5 Energy efficient channel aware routing (EECAR)

Finally, the channels remain the frequency reuse energy depending on route scheduling with energy-efficient scheduling algorithms to maximize energy use while retaining acceptable performance, especially in systems where energy consumption is reusable. The algorithm constraints are to reduce energy consumption by balancing workload allocation, lowering idle time, and minimizing inefficient computations. In equation 1, we compute the total energy consumption G_t.

$$G_t = Fr \rightarrow X\,(Q_d . u_a + Q_s . u_i) \quad (17)$$

Here, $Q_d -$ dynamic power consumption during active operation, $u_a -$active mode that spends (time), $Q_s -$static power consumption in idle mode, and $u_i -$ system time spent in idle mode. This equation evaluates energy consumption as the sum of dynamic energy required while processing and static energy spent when the system is idle. In equation 2, we calculate Dynamic Voltage and Frequency Scaling (DVFS). One of the most extensively used strategies in energy-efficient scheduling is DVFS, which adjusts a processor's supply voltage and frequency to match workload requirements.

$$Q_d \propto V^2 O \quad (18)$$

here, $V -$ voltage supply, and $O -$ operating frequency. DVFS reduces energy usage by lowering V and $O -$periods of low workload, resulting in lower dynamic power consumption. Then we compute energy-delay product P through equation 18,

$$P = G_t . L \quad (19)$$

Here, L is known for the delay in the task's time. The P metric integrates energy and performance, emphasizing that energy reductions should not significantly increase delay. In multi-core or multi-tasking systems, the efficiency of power-aware scheduling η_e can be expressed as below equation 20,

$$\eta_e = \frac{W_r}{G_t} \quad (20)$$

Here, $W_r -$ processed workload. In this equation, the efficiency metric represents how effectively energy is used for the workload processed by the system. Equation 5 calculates sleep secluding for energy efficiency; nodes or processors enter a low-power state when no jobs are given.

$$G_h = Q_h \times u_h \quad (21)$$

Here, G_h is known for energy consumption during sleep mode, Q_h is represented by power consumption during sleep mode, and u_h is the sleep period time. After computing the G_h then, we assign the task to the processor; it is computing through equation 22,

$$G_x = min(G_y) \forall y \quad (22)$$

here, G_x is the energy consumed by the task (x), and G_y is the energy consumed by the processor (y). In this equation, when numerous processors or nodes are available, an energy-aware scheduling algorithm sends work to the processor with the lowest energy consumption. The goal is to allocate each x to the y with the lowest energy consumption. In real-time scheduling for energy efficiency, the utilization factor for a y can be described by equation 23.

$$Z = \sum_{x=1}^{n} \frac{C_x}{U_x} \quad (23)$$

Here, Z is known for the utilization factor, x is known for the task, C_x is the computation time in x, and U_x is the x period. The Z parameter specifies how much of the y capacity is used by real-time workloads. Lower utilization factors can save energy by allowing the y to enter low-power modes more frequently. Techniques such as DVFS, energy-delay trade-offs, and utilization-based scheduling help to reduce energy use. These equations can dramatically minimize power consumption, particularly in systems limited by energy resources.

4. Result and Discussion

In this section, we analyze the LTE network model based on simulation parameters to evaluate the performance of the proposed technology. Additionally, the proposed technique compares the performance of traditional fixed frequency under different network conditions with other Dragonfly-Based Joint Delay/Energy LTE Downlink Scheduling Algorithm (DJDESA), Adaptive Energy-Aware - Quality of Service Reliability (AEA-QoS), and Cooperative Energy Path Aware Cluster-based Algorithm (CoEPACA) methods with proposed Backhaul Link Stability Frequency Switch Over Algorithm (BLSFSOA) and CIMCS-FDFS methods. The LTE downlink implementation of the proposed approach is performed using an LTE link condition simulator. Furthermore, the proposed method allows performance evaluation using metrics such as packet delivery rate, delay performance, power consumption, packet loss, routing overhead, throughput, etc. The simulator can understand all transmission characteristics between the base station and the terminal.

Table 2. *Simulation Parameter*

Parameter	Variable
Tool	NS2 HetNet simpack
Noise Power	-103dBm
Bandwidth	15.MHz
Active Power	6.9W
Transmit Power	1W
Small scale fading	C N (0,1)
Shadowing coefficient	8DB
Amplifier energy efficiency	25.5%
Inter-site distance	1735
Resource block size	13 subcarrier per resource block
Maximum antenna	12.5DB

gain	
Group size	101
Scheduling Interval	1MS
Simulation Frequency	2sec
Simulation Duration	4 hours

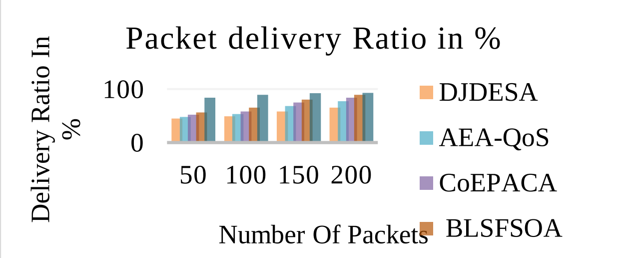

Figure 2: *Performance of Packet Delivery Ratio (PDR)*

Table 2 demonstrates that the proposed method's accuracy can be enhanced by incorporating simulation parameters such as frequency, duration, and various variable parameters to evaluate the total number of packets received in the LTE network.
As shown in Figure 2, network nodes can use the packet delivery ratio of resource block allocation in LTE networks to see improvement in energy efficiency. The proposed method compares significantly with other DJDESA, AEA-QoS, and CoEPACA methods with proposed BLSFSOA and CIMCS-FDFS methods methods for PDR performance evaluation. The proposed method achieved a PDR estimate of 87.9% on 250 nodes by minimizing the data transmission rate.

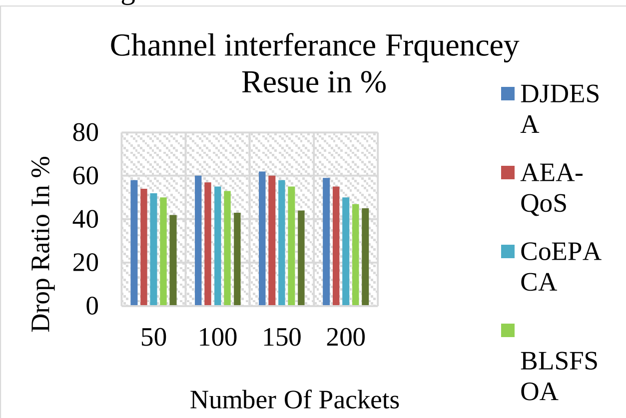

Figure 3: *Performance of channel interference frequency reuse*

PDR evaluates the percentage of data packets transmitted by the receiver and improves the performance of the LTE network. Figure 3 shows that the PDR performance of the three protocols decreases as the transmission rate increases. Furthermore, the PDR estimate achieved 88.9% by comparing the proposed and previous DJDESA, AEA-QoS, and CoEPACA methods with the proposed BLSFSOA and CIMCS-FDFS methods. Figure 4 illustrates that the latency performance evaluation assesses the efficiency of the proposed

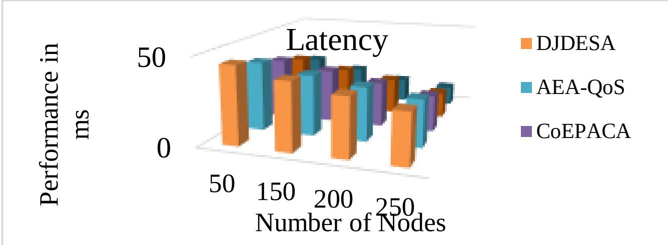

Figure 4: *Performance of Latency*

method. The average latency of the proposed algorithm is comparable to that of DJDESA, AEA-QoS, and CoEPACA methods with proposed BLSFSOA, CIMCS-FDFS methods, measured at 29 ms, 27 ms, 21 ms, and 15 ms across different nodes. Furthermore, compared to conventional technology, the proposed algorithm achieved an average delay of 11.5 ms while analyzing 250 nodes

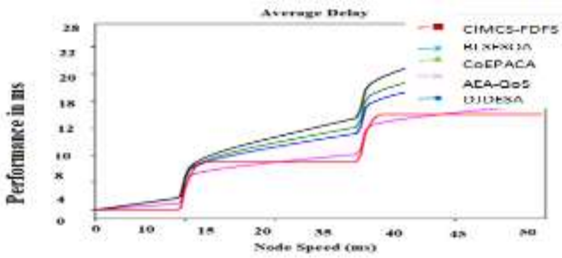

Figure 5: *Performance of Node Speed Vs Delay*

Figure 5 illustrates the movement speed of different underwater sensor nodes, plotting delay against node speed. The proposed protocol enables optimal routing in less time than current algorithms; however, its performance diminishes as node speed rises. It also exhibits lower latency than the DJDESA, AEA-QoS, and CoEPACA methods with proposed BLSFSOA and CIMCS-FDFS methods protocols.

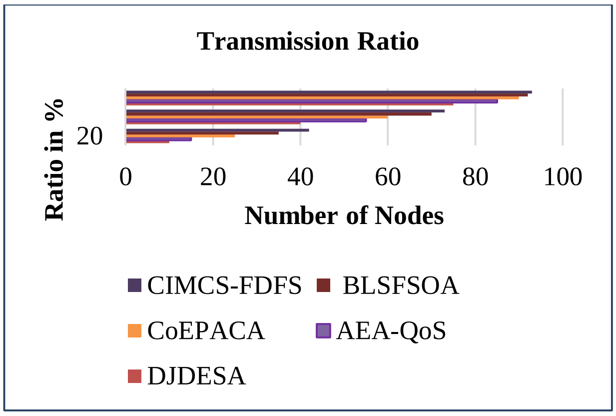

Figure 6: *Performance of Energy Consumption in transmission ratio*

Figure 6 compares the energy consumption of the DJDESA, AEA-QoS, and CoEPACA methods with the proposed BLSFSOA and CIMCS-FDFS methods protocols, including the proposed protocol's energy consumption and node variance. Performance evaluations using the proposed method show a power consumption of 7.28 Joules for 250 nodes. The proposed BLSFSOA and other methods have efficiency ratings of 28.9 Joules, 24.16 Joules, 16.9 Joules, and 11.8 Joules, respectively.

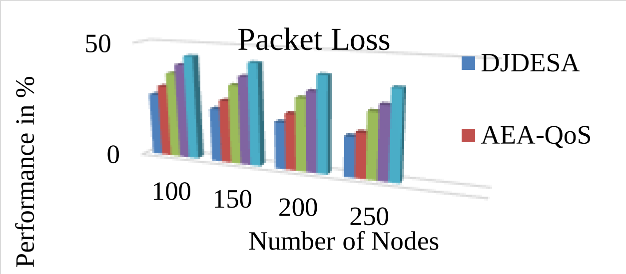

Figure 7: *Result for packet loss*

Packet loss occurs when transmitted packets do not reach their destination. Figure 7 compares the DJDESA, AEA-QoS, and CoEPACA methods with the proposed BLSFSOA and CIMCS-FDFS methods algorithms and the proposed algorithm's performance against these methods, resulting in packet losses of 17 %, 19%, 27%, and 31%. In contrast, the proposed method experienced a loss of 38% for 250 nodes.

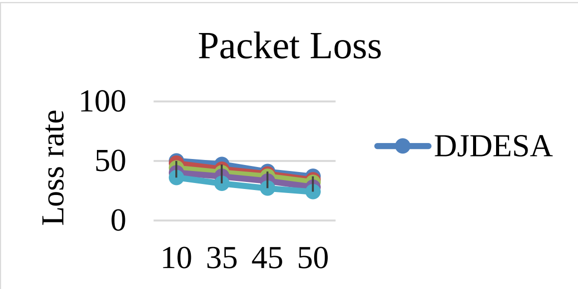

Figure 8: *Performance of Packet Loss Vs Node Speed*

Figure 8 illustrates packet loss in various systems, including wireless sensor networks, by analyzing variations in node speed and packet loss rate. The proposed technique shows a reduction in packet loss compared to existing methods [33-37]. Comparison of packet loss performance. Among the technologies used in algorithm discovery are DJDESA, AEA-QoS, and CoEPACA methods with proposed BLSFSOA and CIMCS-FDFS methods. As shown in Figure 9, there is a clear correlation between node speed and routing overhead.

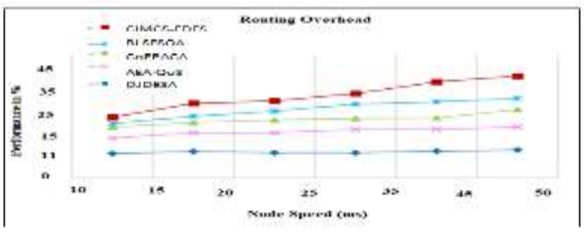

Figure 9: *Analysis of Routing Overhead Vs Node Speed*

To evaluate the routing overhead, the performance of the proposed method can be compared to existing algorithms such as DJDESA, AEA-QoS, and CoEPACA methods with proposed BLSFSOA and CIMCS-FDFS methods across various node counts. In tests involving 250 nodes, the proposed method exhibited a routing overhead performance of 16.05%, whereas the existing algorithms consecutively achieved routing overheads of 53.18%, 46.38%, 37.9%, and 25.4%, respectively.

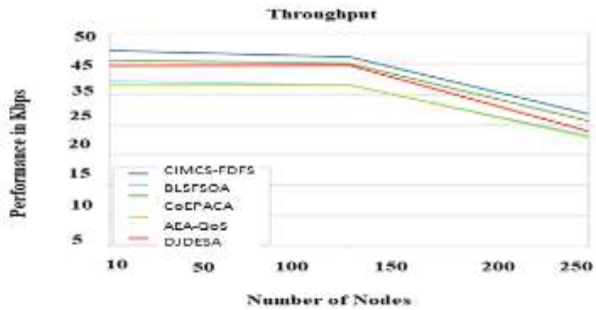

Figure 10: *Performance of Throughput*

In Figure 10, network performance decreases as the number of nodes increases. State-of-the-art models such as DJDESA, AEA-QoS, and CoEPACA methods with proposed BLSFSOA and CIMCS-FDFS methods outperform existing algorithms. Specifically, for 250 nodes, the proposed method achieved a performance efficiency of 33.02 kbps while consecutively achieving 21.06 kbps, 25.04 kbps, and 13.08 kbps, respectively.

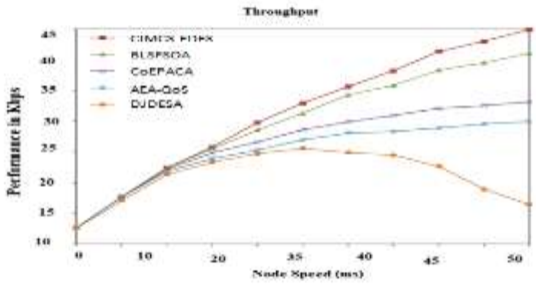

Figure 11: *Result for Throughput Vs Node speed*

Figure 11 illustrates the predicted performance versus tip velocity, highlighting the impact of different underwater sensor tip motions on overall performance. Analyzing relative changes in performance metrics, such as the speed of the sensor tip changes, can provide valuable insights and improve underwater monitoring systems.

5. Conclusion

The proposed DDQN-EAS system represents a significant advancement in managing heterogeneous LTE networks. By addressing the challenges of interference, resource allocation, and energy efficiency, this system lays the groundwork for a more robust and sustainable communication infrastructure. As mobile communication continues to evolve, integrating intelligent algorithms and dynamic resource management strategies will be essential in meeting the demands of an increasingly connected world. The DDQN-EAS system not only enhances the performance of HetNet-LTE networks but also paves the way for future innovations in wireless communication technology. The proposed BLSFSOA and CIMCS-FDFS systems achieve high performance in throughput, up to 97.8 % in balanced latency at 91.5 %, to reuse the frequency level and reduce the delay tolerance, as well as the other system.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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