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Golden Tortoise Beetle Optimized Deep Learning Framework for Resource Allocation in 6G Networks

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Abstract: 6G(Sixth-generation) technology is the next generation of mobile wireless communication networks, designed to deliver more inclusive and long-lasting wireless connectivity. Great security, secrecy, and privacy should be the fundamental qualities of 6G. However, 6G faces challenges in overcoming limitations like congested networks that lead to poor Quality of experience (QoE) and high energy consumption for continuous operation. In this work, a novel 6G Resource Allocation Detection USing Deep Learning (6G-RADIUS) technique has been proposed to allocate resources and enhance QoE efficiency and energy efficiency in a 6G network. Data from the user's equipment is sent to the base station to begin the procedure. The Golden Tortoise Beetle Optimizer (GTBO) assigns subbands, potentially choosing those with the most important information or strongest signals. The resource allocation method is carried out using a Multi-Head Attention-based Bidirectional Gated Recurrent Unit (MHA-BiGRU) model. The output of the MHA-BiGRU model is supplied into the BaseBand Unit (BBU) pool, which regulates and distributes resources among many BBU. The proposed techniques' performance is assessed using QoE, resource utilization, energy efficiency, Mean Square Error (MSE), Cumulative Distribution Function (CDF), and spectral efficiency. The proposed method has a higher resource utilization factor of 8.16%, 6.12%, and 3.06% compared to existing QJEEO, EKF and SDWN techniques, respectively.

Keywords: Resource allocation, Quality of experience, Energy efficiency, Golden tortoise beetle optimizer.

1. Introduction

Sixth-generation mobile communication systems will serve as the cornerstone for digitization in society going forward, and it will significantly impact how services are created, provided, and used. [1, 2]. 6G will offer a wide range of services with exceptional performance: near-zero latency, seemingly endless capacity, and 100% dependability as well as accessibility will render the communication infrastructure completely transparent to applications [3, 4].

With portable devices, 6G networks hope to enable smart automation systems by delivering excellent energy efficiency and QoE during multimedia communication [5, 6]. To improve the user experience, QoE is vital to achieve overall satisfaction with the DT service on 6G networks. [7, 8]. There are various metrics and scales available for measuring QoE. Both qualitative and quantitative measurements are possible [11, 12]. For instance, an ordered scale with ratings between 1 to 5 is employed for computing the QoE metric "user satisfaction." [13, 14] On this scale, 1 implies poor quality while 5 represents exceptional attributes [15-17].

Energy efficiency refers to minimizing the overall consumption of energy by reducing the volume of data entering the data centre [18, 19]. 6G introduces a new service class called Massive Ultra-Reliable Low-Latency Communications, which allows for quantitative design and evaluation of QoS

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performance [20, 21]. The explosive growth of novel technologies that involve virtual reality, artificial intelligence, three-dimensional media, and the Internet of Everything has resulted in a tremendous load.

This paper proposes a 6G Resource Allocation Detection Using the Deep Learning technique to allocate resources and enhance QoE efficiency and energy efficiency in 6G. The major contributions of the proposed 6G-RADIUS technique are as follows.

- The process begins with user equipment (UE) data being transmitted to the base station.
- In the subband allocation process the GTBO assigns subbands, potentially picking those with the most important information or strongest signals.
- The allocated Subband is sent into the Multi-Head Attention-based BiGRU model to allocate resources.
- The output of the BiGRU model is fed into the BBU pool, which is most likely used to regulate and allocate resources across several baseband units.

The remaining components of the suggested approach are described below. Section 2 summarizes the literature review in full. Section 3 explains the recommended technique [9, 10]. Part 4 explores the results as well as the discussion. Section 5 explains the conclusion.

2. Literature survey

Several research have used various approaches to improve QoE efficiency and energy efficiency in recent years. The next part highlights a few of the current evaluation methodologies and their shortcomings, which are as follows:

In 2020, Sodhro, A.H., et al [22] suggested A QoS-based joint energy and entropy optimisation (QJEEO) approach. Experimental findings illustrate that QoE is modelled & estimated with acquisition time and coupled with quality-of-service characteristics such as packet loss ratio and average transfer latency throughout energy-efficient multimedia transmission in 6G-based systems to enhance client endorsement. Heterogeneity, scalability, integration, interoperability, capacity of networks, congestion in networks, and battery lifetime are some of the challenges that 6G massive IoT will face.

In 2020, Mao, B., et al. [23], suggested an AI-driven adaptive security approach for 6G IoT networks, accommodating devices linked via Terahertz (THz) and millimeter wave (mmWave) bands. Our method integrates anticipated energy harvesting features of 6G IoT devices, leveraging Extended Kalman Filtering (EKF) for future harvesting power prediction. The result demonstrates that this concept not only offers effective security protection across various functions but also adjusts security measures to mitigate energy fatigue, resulting in significant enhancements in throughput and operational efficiency.

In 2023, Purba Daru Kusuma and Ashri Dinimaharawati [24] suggested a new metaheuristic called the extended stochastic coati optimizer (ESCO), which is an enhancement of the existing coati optimization algorithm (COA). ESCO expands on COA by increasing the number of searches and references used, incorporating a stochastic process for selecting search strategies, and implementing three sequential phases in each iteration with multiple options for selection. The results highlight ESCO's superiority over the GPA, POA, GSO, ASBO, and COA in solving 13, 21, 23, 16, and 13 functions, respectively. This suggests that utilizing a multiple search approach is more effective than a single search approach.

In 2024, P. D. Kusuma and A. Dinimaharawati [25] introduces the swarm bipolar algorithm (SBA), a novel metaheuristic based on the non-free-lunch (NFL) doctrine. SBA divides the swarm into two sub-swarms to enhance search diversity and intensification, aiming to overcome the limitations of universal optimizers by balancing exploration and exploitation effectively. The result presents the superiority of SBA among its contenders by being better than NGO, LEO, COA, FISA, and TIA in 21, 16, 16, 21, and 18 functions. The single search assessment is performed to evaluate each strategy involved in SBA. The result shows that the search toward the middle between the two finest sub-swarm members is the best among the four searches in SBA.

In 2024, Purba Daru Kusuma and Meta Kallista [26] introduces the Migration-Crossover Algorithm (MCA), a novel swarm-based metaheuristic incorporating crossover techniques and unbalanced local search space. MCA outperforms TIA, OOA, MA, COA, and WaOA in 20, 19, 17, 20, and 17 functions, respectively.

In 2021, Nabeel, M., et al [27] suggested a new cellular architecture called SpiderNet: Data-Aided Demand Driven Elastic Architecture for 6G Wireless Networks that is both spectrally and energy efficient. The results show that SpiderNet can significantly improve both SE and Energy Efficiency while maintaining QoE when compared to the present BS-centric cellular design. The main issues that must be resolved to implement the SpiderNet design in practice, as well as possible fixes.

In 2023, Priya, B., et al [28] suggested an intelligent QoE-aware RAT selection architecture based on SDWN and edge computing towards 5G-enabled healthcare networks. The analytical measurement confirms that the suggested strategy beats other current schemes to improve customized user experience while maximizing resource use. Context-aware RAT selection is challenging when utilizing 5G HetNets efficiently because RATs have a wide range of radio bands, protocols, and physical and media access control layers with several access mechanisms.

In 2024, P. D. Kusuma and M. Kallista [29] introduces the Swarm Space Hopping Algorithm (SSHA), a novel metaheuristic that improves swarm-based methods by incorporating directed searches towards high-quality solutions, adaptive adjustments based on agent performance, and arithmetic crossover with randomized solutions. SSHA demonstrates superior performance compared to NGO, ZOA, CLO, OOA, and TIA in various functions, with the second search proving most effective and the third search showing significant contribution in select cases.

Using Golden Tortoise Beetle Optimization (GTBO) for subband allocation offers several advantages. GTBO efficiently prioritizes crucial data or strong signals, optimizing resource utilization and enhancing system performance. Its adaptive nature enables continuous optimization in dynamic network conditions, ensuring reliable subband allocations. GTBO's strategy allows the effective selection of critical data while being robust against noise and interference. It scales well for large-scale network scenarios and can optimize based on multiple objectives, improving overall system efficiency. GTBO is not only used for the application, we have also explored the GTBO for subband allocation in a 6g network. Overall, GTBO is a promising solution for enhancing wireless communication systems through optimized subband allocation. Comparison of existing methods with merits and demerits is shown in Table 1.

Table 1. Comparison of existing methods with merits and demerits

S/No	Author	Proposed	Advantages	Disadvantages
1	Sodhro, A.H., et al [22]	QJEEO	Focus on Energy Efficiency, Integration of IoT and Automation, Academic Rigor	Limited Practical Validation, Scope Limitations, Dependency on Technological Assumptions
2	Mao, B., et al [23]	EKF	Integration of AI for Optimization, Addressing Emerging Challenges, Innovative Approach	Complex Implementation, Security-Performance Trade-offs, Empirical Validation, Resource Intensiveness
3	Purba Daru Kusuma and Ashri Dinimaharawati [24]	ESCO	Potential Performance Benefits, Novel Approach	Limited Scope or Applicability, Lack of Comparative Analysis, Complexity or Practical Implementation Challenges
4	P. D. Kusuma and A. Dinimaharawati [25]	SBA	Innovative Metaheuristic, Potential Performance Improvements	Limited Evaluation or Validation, Complexity and Practical Implementation, Scope and Generalizability
5	Purba Daru Kusuma and Meta Kallista [26]	MCA	Innovative Metaheuristic, Enhanced Optimization Performance, Experimental Validation	Applicability and Generalizability, Limited Evaluation Scope, Complexity of Implementation
6	Nabeel, M., et al [27]	SpiderNet	Innovative Architecture, Spectral Efficiency, Energy Efficiency, Demand-Driven Elasticity	Complexity of Architecture, Empirical Validation, Adoption and Standardization
7	Priya, B., et al [28]	SDWN	QoE Optimization, Intelligent RAT Selection,	Complexity of Framework, Integration Challenges, Scalability and Adaptability
8	P. D. Kusuma and M. Kallista [29]	SSHA	Innovative Algorithm, Potential Performance Gains	Scope and Applicability, Complexity and Implementation Challenges, Limited Evaluation

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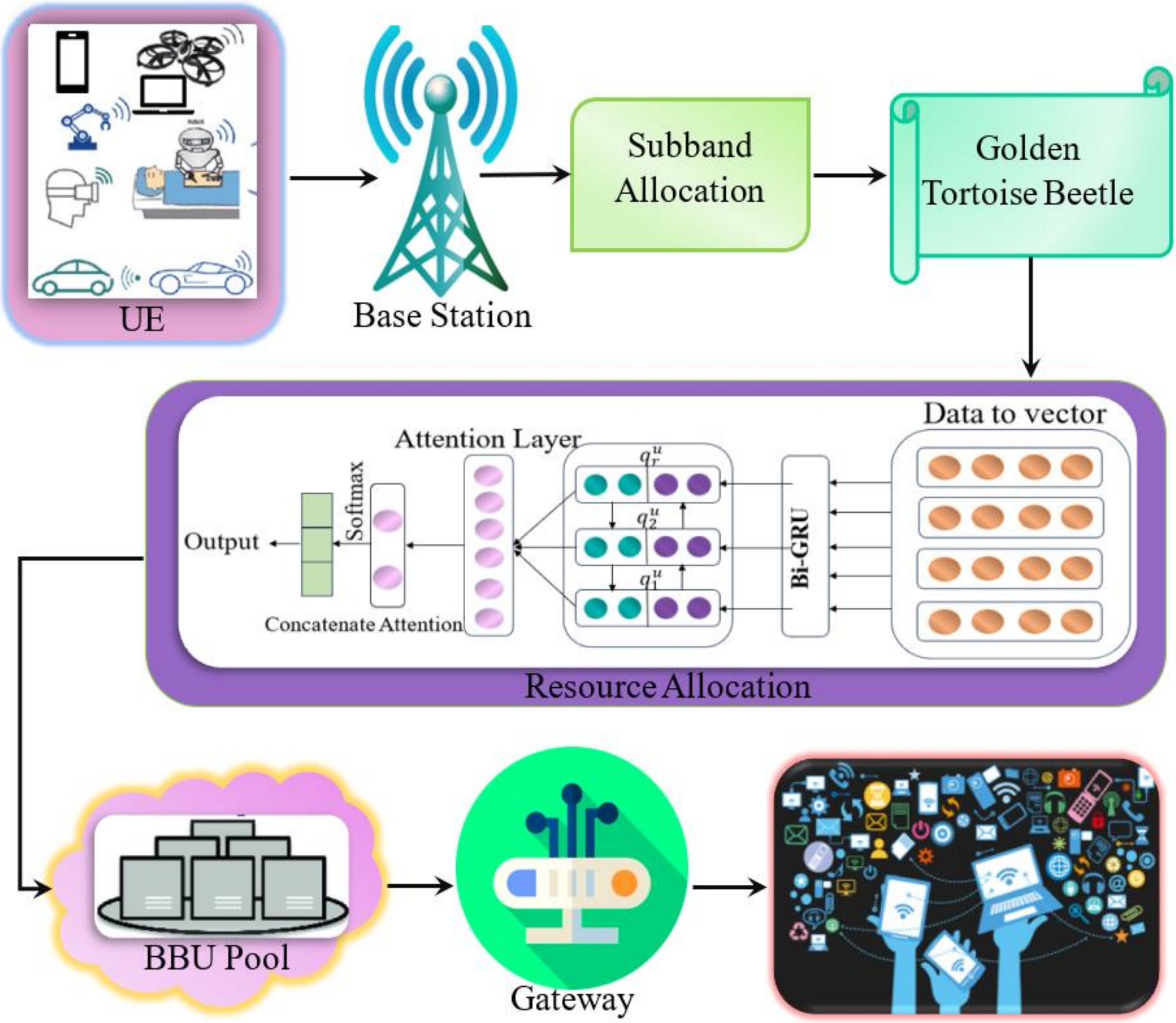

Figure. 1 6G-RADIUS Framework

3. Proposed method

This section presented a 6G-RADIUS strategy for allocating resources. The process begins with user equipment data flowing to the base station. The GTBO allocates subbands, possibly selecting those with the most vital information or strongest signals. Following the Subband allocation procedure, an MHA-BiGRU model receives the assigned subbands as input and decides how to allocate resources. The MHA-BiGRU model's output is fed into the BBU pool, which most likely controls and distributes resources across various BBUs. Figure 1 shows the 6G-RADIUS.

3.1 Subband allocation

In the subband allocation process, a Golden Tortoise Beetle Optimizer is used to select the most vital data or strongest signals.

3.2 Golden tortoise beetle

We developed an optimization method based on golden tortoise beetles' colour-switching behaviour for pairing and reproduction, as well as their survival strategy against hunters. In the present research, every beetle symbolizes either a solution or a person. This GTBO employs the reproduction idea for developing Results and ensuring mechanisms for survival to choose which ones carry forward to a subsequent generation. The remaining parts will provide the two primary operators, followed by the algorithm for optimization.

Inspired Operators: The Color-Switching Operators reflects the behaviour of golden tortoise beetles, which change colour during mating and disturbance. The shifting colour process is based on the reflecting index and wavelength in thin-layer interference. Assume u and v are stackable elements.

Table 2. Symbols and notations

Notation	Abbreviation
d_u and d_v	Layer thicknesses
m_u and m_v	Reflecting indexes
ω	Wavelength
$\overline{\varphi}$	Reflective index
β	Layers thickness
a × b	Position matrix
T_{beetle}	Fitness value
t	Objective value
Randn ()	Normal randomized function
σ	Sigmoid function
p_r	Input vector
Z_b, Z_d, and Z_q	Current input weights
S_b, S_d, and S_q.	Cyclic input weights

The optical dimension of every layer is 1/4 wavelength. In other terms, $d_u.m_u = d_v.m_v$, where d_u and d_v are layer thicknesses and m_u and m_v are reflecting indexes. Equation 1 indicates the considered reflected colour.

$$l.\omega = (d_u.m_u.\cos(\theta_u) + d_v.m_v.\cos(\theta_v)) \quad (1)$$

Where l represents the constant number

ω indicates the wavelength of light that is reflected

$\theta_u$and θ_v were normal angles.

$$\omega = \frac{2\beta\sqrt{\overline{\varphi}^2 - \sin^2(\theta_q)}}{d} \quad (2)$$

Where, ω represents wavelength

$\overline{\varphi}$ denotes the mean reflective index

β represents layers thickness

d constant number

θ_q indicates normal angle

Generating Initial Solutions: The ability of a beetle to attract another gender and protect its larvae against hunters significantly affects the following generations reproductive. To answer an optimization issue, the variables must be expressed in a matrix, known as a "position" in GTBO. As a female beetle attracts a golden male beetle, each approach eventually converges toward an optimal value through evolution. In an n-dimensional optimization issue, the factors could be expressed as an a × b position matrix, as shown below:

$$G_{beetle} = \begin{pmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,b} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,b} \\ \vdots & \vdots & \ddots & \vdots \\ s_{a,1} & s_{a,2} & \cdots & s_{a,b} \end{pmatrix} \quad (3)$$

In this equation, $s_{i,j}$ represents the j^{th} variable of the i^{th} beetle, where a denotes the total amount of insects and b indicates the count of elements. The specified matrices contain floating values. The measure of fitness for every GTBO is established by assessing its economic functionality. The profitable function for the recommended approach is stated below:

$$T_{beetle} = \begin{pmatrix} t([s_{1,1} & s_{1,2} & \cdots & s_{1,b}]) \\ t([s_{2,1} & s_{2,2} & \cdots & s_{2,b}]) \\ \vdots & \vdots & \ddots & \vdots \\ t([s_{a,1} & s_{a,2} & \cdots & s_{a,b}]) \end{pmatrix} \quad (4)$$

T_{beetle} represents the fitness value of an individual beetle, t represents the objective value. The function of profit can be specified as either minimizing or maximizing.

The program uses the randomized function to create the initial beetle. Randomly establish real-valued quantities within the lower and higher boundaries of dimensions $[Y_{mini}, Y_{maxi}]$, where $Y_{mini} = Y^1{}_{mini}, \cdots, Y^R{}_{mini}$ and $Y_{maxi} = Y^1{}_{maxi}, \cdots, Y^R{}_{maxi}$ function.

Equation (5) determines the initial value for the d^{th} component in the e^{th} beetle during production P = l for an R-dimensional problems.

$$x^d_{e,1} = x^d_{mini} + ran(0,1).\left(x^d_{maxi} - x^c_{mini}\right), \quad d = 1,2, \ldots, R. \quad (5)$$

Switching Color Operator: To calculate the number of mature beetles, use the following equations: (4) … (8).

$$F^P_e = Y^P_e + G_{color}.(Y^P_{w1} - Y^P_{best}) \quad (6)$$

In generation P, the present female beetle (Y^P_e) travels towards the golden male beetle (Y^P_{w1}), whose color is determined by the color switching operator (G_{color}). Specifically, w1 represents a randomly generated integer in [1, N P], omitting e, where N P the amount of beetle populations, and Y^P_{best} denotes a response having the highest fitness at production. P.

The female beetle switches posture to pair up with the golden beetle, which has a beautiful golden colour and reproduces to the next generation.

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The best result from every generation is retained by subtracting it from other generated solutions. Equations 7 and 8 mathematically model the value of G_{color}.

$$G_{color} = (d_u.m_u.\cos(\theta_u) + d_v.m_v.\cos(\theta_v))+(l.\omega) \quad (7)$$

$$\text{were, } \begin{cases} d_u.m_u = \text{Randn}() \\ d_v.m_v = \text{Randn}().\alpha \\ \overline{\varphi} = \text{Cauch}(\mu, \sigma) \\ \theta_u, \theta_v = \alpha \\ \beta, d, l = \text{rand}(\,) \\ \theta_q = 2.\pi.\text{rand}() \end{cases} \quad (8)$$

Randn () represents normal randomized function that yields values in the range of [l, b], α is an even randomized function that generates numbers between [0.1, 0.9], whereas rand( ) creates random values from 0 to l, and Cauchy represents the standard Cauchy distributions with starting values of 0.5 and 0.2 for location and scaling parameters. The algorithm initializes Cauchy distribution values to 0.5 when they fall beyond the lower and upper bounds of zero and one, respectively. Equations 1 and 2 specify the variables $l, \omega, \overline{\varphi}, \alpha, d$, and θ_q.

Survival Operator: Tortoise beetle eggs may survive due to effective predator-deterrent measures, as described above. The survival function is represented by equation 9 and 10.

$$\begin{cases} \text{Beet}_1 = \beta.y_{w1} + (1-\beta).(y_{w2} - \sigma_1) \\ \text{Beet}_2 = \beta.y_{w2} + (1-\beta).(y_{w1} - \sigma_2) \end{cases} \quad (9)$$

where y_{w1} and y_{w2} represents two randomly generated values within the range of [l, N P]. N P is the sum of populations, and β denotes a uniform random value within [0, 1]. Equation 10 defines the variables σ1 and σ2.

$$\begin{cases} \sigma_1 = (1-h).(y_{best} - y_{w1}) \\ \sigma_2 = (1-h).(y_{best} - y_{w2}) \\ k = \frac{\beta-\mu}{|g|^{\alpha}} \end{cases} \quad (10)$$

where y_{best} represents th most appropriate response so far, μ and g are regular integers connected to the dimension of outcome y_{w1}, α represents a continuous uniform random integer formed within [0.1, 0.5], and k is an element that determines the values of α, β, μ, and g.

3.3 Resource allocation

In the resource allocation process, the MHA-BiGRU model is used for allocating resources. The allocated Subband are given to the input of MHA-BiGRU model for resource allocation. Then the output of the BiGRU model is given to the BBU pool

3.4 Multi head attention based BiGRU

BiGRU Layer: GRU neural systems are a subset of the recurrent neural network (RNNs). To address the issue that typical RNNs rewrite their memory in unit steps and suffer from gradient dispersion, based on RNN. GRU represents a simple LSTM neural network that may be determined much easier while retaining the effectiveness of LSTM neural networks. LSTM neural systems require input, forget, and output gates.

In Figure 2, p_r indicates the input vector, q_{r-1}represents the concealed state at time r−1, and q_r supplies the present GRU's output vector. At time r, p_r and q_{r-1} are inputs into GRU networks, yielding output q_r. Formulas 11, 12, 13, 14 express q_r as follows:

$$b_r = \sigma(Z_b p_r + S_b q_{r-1} + f_b) \quad (11)$$

$$d_r = \sigma(Z_d p_r + S_d q_{r-1} + f_d) \quad (12)$$

$$\tilde{q}_r = \tanh\,(Z_q p_r + S_q(q_{r-1} \otimes b_r) + f_r) \quad (13)$$

$$q_r = (1 - d_r) \otimes q_{r-1} + d_r \otimes \tilde{q}_r \quad (14)$$

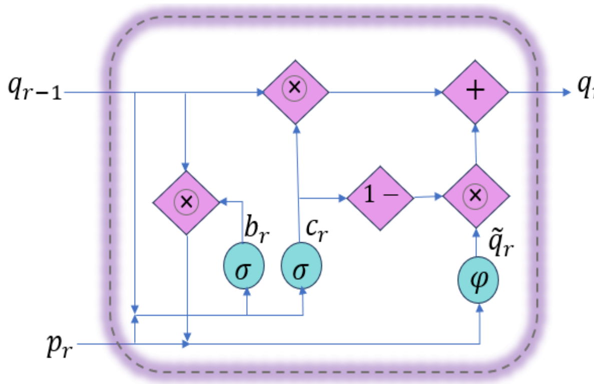

Figure. 2 GRU Structure

The symbol σ represents the Sigmoid function, used to help GRU neural networks store or forget information. The elementwise production is ⊗, and the update and reset gates are d_r and b_r, respectively. Additionally, $\tilde{q}_r$ represents the candidate's assumed state at time r. The current input weights are Z_b, Z_d, and Z_q, whereas the cyclic input weights are S_b, S_d, and S_q. Furthermore, f_b, f_d, and f_r represent the offset vectors for Z_b, Z_d, Z_q, S_b, S_d, S_q.

The BiGRU structure consists of two hidden layers: one forward and one backward. Each data pattern is fed into both the forward and reverse GRU network, this produces two symmetric hidden layer state vectors. After symmetrically merging Using both of those state vectors, we may obtain an overall coded representation of the input text, as seen below:

$$Q_r = [\overrightarrow{Q_r} \oplus \overleftarrow{Q_r}] \tag{15}$$

Multi Head Attention Layer: Initially, the mechanism of attention was employed in eyesight and processing images. Google Mind also applied it to picture classification using a recurrent neural network model. The attention function maps a query (U) to a set of key & value pairs. The evaluation for the attention mechanism is broken down into three stages. First, a similarity function $c(U, L_i)$ is created to determine the similarity between U and each L. As demonstrated in equation (12), dot, general, and concat have several functions of similarity that obtain a comparable attention score c:

$$c(U, L_i) = \begin{cases} U^D L_i & \text{Dot} \\ U^D V L_i & \text{General} \\ V[U; L_i] & \text{Concat} \end{cases} \tag{16}$$

After that, use a softmax function to obtain the weighed vector, β. At last, the weighted sum of β and E yields the context vector r:

$$\beta_i = \mathrm{softm}(c_i) \tag{17}$$

$$r = \sum_{d=1}^{m} \beta_i W_i \tag{18}$$

The dimensions of queries (U) and keys (L) are x_l, whereas the dimension of value (E) is x_e. The scaled dot-product attention method calculates attention scores utilizing the equation:

$$\mathrm{Atten}(U, L, E) = \mathrm{Softm}\left(\frac{UL^D}{\sqrt{x_l}}\right)E \tag{19}$$

Multi-head attention is made up of multiple attention layers that work in tandem, allowing the structure to simultaneously attend to information from distinct appearance subspaces across various locations. The multi-head attention system translates queries, keys, and value vectors with various linear projections before calculating their significance using scaled dot-product attention. After q repetitions, each such operation is referred to as a "head," and the vectors generated by parallel heads are concatenated to form a single vector.

$$\mathrm{hea}_i = \mathrm{Atten}(UV_i^U, LV_i^L, EV_i^E) \tag{20}$$

$$\mathrm{MultiHea}(U, L, E) = \mathrm{Conca}(\mathrm{hea}_1, \cdots, \mathrm{hea}_q)V \tag{21}$$

3.5 BBU pool

The output of the MHA-BiGRU model is fed into the BBU pool, which is most likely used to regulate and allocate resources across several baseband units. The resource allocation procedure takes place at a specialized controller that is interconnected with the BBU pool. The BBU pool performs all baseband processing functionalities.

4. Result and discussion

The 6G Resource Allocation DetectIon USing Deep Learning method’s experimental results are analyzed in this section. Performance is discussed in terms of various metrics. The 6G-RADIUS approach utilizes the Discrete-Event Simulation and Modelling in Java package (DESMO-J). The suggested model's efficacy is contrasted with that of the QJEEO [22], EKF [23] and SDWN [28] regarding energy efficiency, spectral efficiency, QoE, resource utilization, CDF and MSE. Simulation Parameter is shown in Table 3.

Figure 3 displays a comparison of the CDF with the proposed and existing methods. The CDF is used to calculate the probability of allocating average

Table 3. Simulation Parameter

Parameter	Value
Bandwidth	2GHz
Path Loss	8dB
Simulation Duration	100s
Mobility Support	Up to 100 km/h
Spectral Efficiency	100 bps/Hz
Time Step	1000
SNR	20dB
Modulation	64QAM
MIMO	3 sector, 4 lambda spacing

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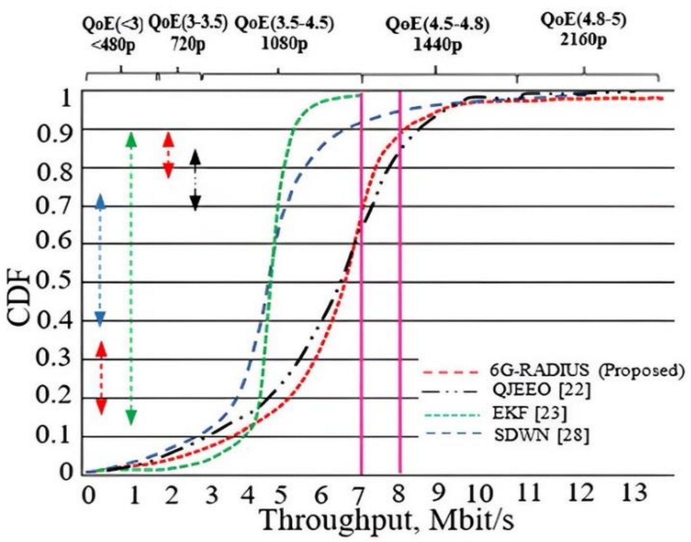

Figure. 3 Comparison of CDF of user Throughput

throughput for users. The proposed strategy outperforms the existing QJEEO [22], EKF [23] and SDWN [28] methods in terms of resource flexibility and ensuring ordered QoE.

Figure 4, contrasts the QoE of the suggested 6G-RADIUS with existing techniques such as QJEEO 22], EKF [23] and SDWN [28]. The proposed 6G-RADIUS approach has a greater QoE performance than the other existing methods.

Figure 5, illustrates about resource utilisation, the suggested technique outperforms the existing QJEEO [22], EKF [23] and SDWN [28] techniques. In terms of resource utilisation, the suggested scheme achieves more precise estimations of value than the SDWN [28]-based method, ensuring an efficient and personalized user experience through improved network resource management.

Figure 6, compares the error of the suggested 6G-RADIUS approach with the existing techniques. The proposed approach error is 0.002% which is lesser than the existing QJEEO [22], EKF [23] and SDWN [28] techniques which are 0.013%, 0.008% and 0.004% respectively.

Figure 7 shows that the suggested 6G-RADIUS technique achieves faster convergence and has a higher spectral efficiency than existing QJEEO [22], EKF [23] and SDWN [28] schemes.

Figure 8, demonstrates that the proposed 6G-RADIUS approach achieves superior performance in energy efficiency compared to existing techniques such as QJEEO [22], EKF [23], and SDWN [28], reaching convergence within 300 rounds. This comparison highlights the effectiveness of the 6G-RADIUS approach in optimizing energy consumption while maintaining performance, showcasing its potential for enhancing sustainability and resource utilization in 6G networks.

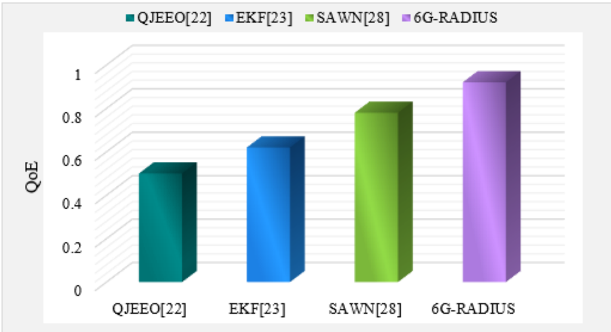

Figure. 4 QoE-based Performance Comparison

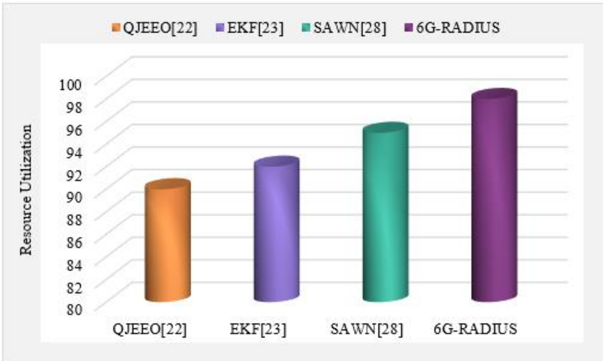

Figure. 5 Comparison of Resource Utilisation

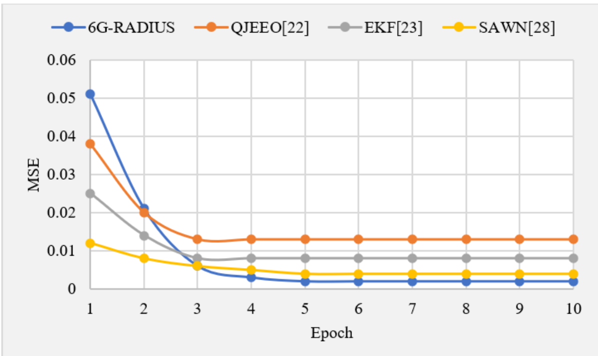

Figure. 6 Error Comparison

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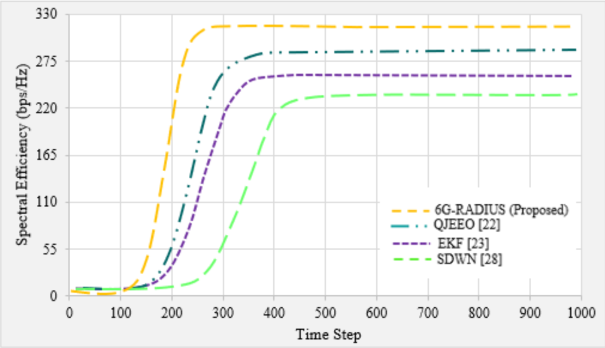

Figure. 7 Spectral efficiency convergence

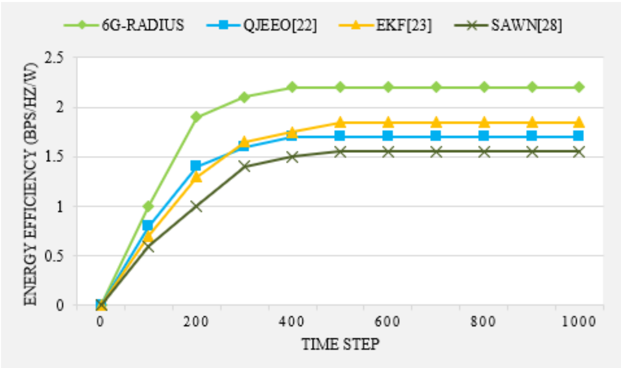

Figure. 8 Energy Efficiency Convergence

5. Conclusion

This paper proposed a 6G-RADIUS technique to allocate resources and enhance QoE efficiency and energy efficiency in 6G. The procedure begins with user equipment data being transmitted to the base station. Following that the subbands are allocated using a GTBO. An MHA-BiGRU model accepts the assigned subbands as input and determines how to allocate resources. The output of the MHA-BiGRU model is fed into the BBU pool, which is most likely used to regulate and allocate resources across several BBUs. The 6G-RADIUS technique allocates resources efficiently and improves the QoE and energy efficiency performance. The 6G-RADIUS approach utilizes the Discrete-Event Simulation and Modelling in Java (DESMO-J) package. The suggested technique's performance is evaluated using QoE, resource utilisation, energy efficiency, MSE, CDF and spectral efficiency. The proposed method has a higher resource utilization factor of 8.16%, 6.12%, and 3.06% compared to existing QJEEO, EKF and SDWN techniques, respectively. In future research, to enhance the suggested technique with AI technology to increase QoE and reduce energy usage in 6G networks.

Conflicts 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.

Author Contributions

The following statements should be used as follows: "Conceptualization, Maria Jesi. P and Venkatesh. R; methodology, Raju Dandu. V. S. R. K; software, Satheesh. P. G; validation, Maria Jesi. P, Venkatesh. R, and Raju Dandu. V. S. R. K; formal analysis, Satheesh. P. G; investigation, Maria Jesi. P; resources, Venkatesh. R; data curation, Raju Dandu. V. S. R. K; writing—original draft preparation, Satheesh. P. G; writing—review and editing, Maria Jesi. P; visualization, Venkatesh. R; supervision, Raju Dandu. V. S. R. K; project administration, Satheesh. P. G; funding acquisition, Maria Jesi. P", etc.

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