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Innovative Deep Learning-based Energy-Efficient Joint User and Power Allocation System for Futuristic 5G Millimeter Wave Networks

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***Abstract*— The fifth generation (5G) of mobile networks is enhanced with millimetre Wave (mmWave) bands and the networks are rapidly developed in a vast range with the updated features that are accommodated with the end user. Further, this 5G network enhances obstacles in effective administration in Base Station (BS) and user association which pose high power consumption in the network. To overcome such limitations, energy-efficient joint-user and power allocation are enhanced. Moreover, lowering the power consumption in 5G mmWave is a vital process because of the density of the BS. Hence, the 5G mmWave network is developed with the standard framework to reduce the power consumption in Quality of Service (QoS). Further, this mechanism implements an on/off switching protocol with the BS model and the Dollmaker Optimization Algorithm (DOA) is implemented in the initial stage to enhance optimal data formation. It is contrasted with the existing mechanism, to achieve an effective power allocation, and to allow this framework with various applications in the system. Subsequently, various applications are utilized in the power allocation with the user mechanism in the Temporal Convolutional Network (TCN). Further, to achieve the best optimal solution, multi-objective functions are enhanced with throughput, energy efficiency and power consumption, which are analyzed to implement the developed model that achieves a standard outcome with the traditional methods.**

Keywords—Energy-Efficiency; Joint User and PowerAllocation; 5G Millimeter Wave Network; Dollmaker Optimization Algorithm; Temporal Convolutional Network

I. INTRODUCTION

In the advent environment, there is an expeditious growth in utilizing the network that is enhanced with the number of users and linked devices in the technology with communication and services[1]. Artificial Intelligence (AI) is implemented to achieve maximum performance in communication and system capability with an immense Multiple Input Multiple Output (MIMO) to develop the technology in the 5G wireless network, which contains device-to-device communication and Millimeter Waves (mmWaves) to achieve a better computing performance [2]. In wireless communication, the probability of device efficacy, protection, minimum network latency and valid communications are expanded in the developed technology[3]. Further, the extensive data traffic and capability demand in the wireless network have prevailing authorizations with the bandwidth and digital services applications[4]. Moreover, advanced architectural design methodologies are enhanced with the 5G system to utilize the dynamic spectral resource to obtain the capability of the network extension and network offloading that are streamlined with essential methodology[5]. Thus, the 5G network is intended to track the improved data rate, and reduced latency and integrate with a multitude of linked devices that are accommodated with "Enhance Mobile Broadband (eMBB), Massive Machine Type Communication (mMTC) and Ultra-Reliable Low-Latency Communication (URRLC) [6]."

The transmission power optimizes heterogeneous transmission that is enhanced with convergence, developed indoor connectivity and deployment adaptability that helps to reduce the radius in the network[7] [8]. Further, the hardware analysis, network resources, energy harvesting and unconventional network architecture are analyzed with different frameworks to optimize the issues in energy consumption, whereas the occurrence of Macro Base Stations (MBSs) and Small Cell BSs (SBSs) address some of the limitations like resource management and allocation, privacy, QoS, interference, scalability and energy efficacy[9] .Moreover, the effective resource distribution and management are less expensive but the upgrades in the hardware and network architecture are much expensive in energy consumption, hence to overcome such issues an effective resource allocation mechanism is implemented with flexibility and versatility to variate the network conditions [10]. Moreover, a vast range of applications faces vital challenges while optimizing the QoS in the network. In the 5G network, the data ranges are increased with a minimal cost because of the deployment solution in the spectral efficacy [11].Hence, the network coverage and data range contain the source and destination that is accommodated with the malfunction to deliver the 5G network with a maximum dense area. Further, analyzing the wireless network is a typical process and contains capability, coverage and energy efficacy optimized with the mobile network.

To analyze the resource allocation and challenges in the developed energy constraints, the Deep Learning mechanism is enhanced to analyze the energy efficacy in the network With the help of a deep learning mechanism, the optimal resource allocation strategies are enhanced with the power allocation and QoS to optimize the resource management in the network [12]. Moreover, it has achieved an effective optimization with the decentralized network, but it is provincially analyzed from the information in the power allocation mechanism [13]. Further, it handles the dynamic and intricate settings to enhance the communication network performance and address the issues in the heterogeneous network. Even though, deep learning can analyze the uneven level of resource allocation by enhancing with insufficient energy and data rate in the optimization mechanism to reduce the issues in the energy consumption. It can prevent traffic prediction with more accurate and effective solutions to validate the throughput with a dynamic and complex approach with capacity constraints in the power allocation

The contributions for the 5G wave networks are listed below.

- To introduce an efficient 5G network with mmWave that is enhanced with a vast bandwidth for better resource allocation. It helps to manage a massive growth in data traffic that can increase the capacity of the network and reduce the traffic flow because of the interlinked devices in the network. The deep learning mechanism is implemented to analyze resource management and increase network performance.
- To utilize the TCN with channel estimation and signal processing that can manage data effectively for long-term dependencies. It is used to optimize the power allocation with various users within the system. It can analyze the energy consumption with optimized power distribution, which helps to analyze the network to allocate the power consumption and reduces the overloading issues. Further, TCN is utilized to reduce the traffic in the network, detect anomalies and channel estimation, which helps to handle the large amount of data. It becomes stable in analyzing the network and helps to reduce the vanishing gradient issues.
- To suggest DOA to optimize the solution for allocating the power through the TCN model. This algorithm is majorly used for finding the target attribute to allocate the power over the system appropriately, thus it enhances the efficacy. It is a human-inspired meta-heuristic algorithm that helps to handle different patterns to provide an exact result with the implemented pattern. This algorithm helps to increase the efficacy in the network to reduce the latency and helps to manage the growing demand for 5G networks. Further, the network slicing is enhanced to analyze the overall network performance and helps to reduce the latency for better performance.

The Introduction section of this paper is elaborated in Section I. The literature review related to the 5G network is described in Section II. The power allocation in a milli-wave network with an optimization approach is explained in Section III. The developed Temporal Convolutional Network and fitness function are estimated in Section IV. The experimental result of the developed model is described in Section V. Further, the conclusion and future work are described in Section VI.

II. EXISTING WORKS

A. Related Works

In 2024, Gacanin *et al.* [14] have developed a coordinated multi-agent DRL by eradicating the centralized execution approach at the time of execution. The power restrictions are optimized with the multi-carrier system to analyze the exploration mechanism while transmitting the power with different parameters in the complex network environment.

In 2025, Yanan *et al.* [15] have proposed the Crayfish Optimization Algorithm (COA) to analyze resource allocation with UAV supported network that helps to decrease energy consumption and enhance accurate optimization technique. In the energy consumption, the transmission range is increased to attain maximum data transmission range in the wireless network.

In 2023, Zhao [16] have investigated resource allocation with edge computing that helps to reduce the cost of the network and accommodate a path between the base station and transmission power to reduce the energy variable in the decision variable. Further, the QoS was implemented with high-speed network accommodation with energy-saving resource allocation.

In 2023, Mughees *et al.* [17] have developed Multi-Agent Parameterized Deep Reinforcement Learning (MA-PDRL) to analyze the power accommodation with Machine Learning (ML) mechanisms that are enhanced to provide a better outcome optimized with QoS and energy efficiency with DRL techniques.

In 2025, Ahmad *et al.* [18] have proposed Deep Reinforcement Learning (DRL) to analyze the energy efficiency and throughput maximization. Further, the 5G network conserves energy with dynamic DRL to achieve maximum accuracy and throughput value.

B. Research Gaps and Challenges

Power allocation with a 5G network enhances various networks for transmission and interference management for network sustainability. Further, the deep learning mechanisms are implemented in this research that are listed in Table 1 and some of the research challenges are addressed below.

- In optimizing the 5G systems, a primary obstacle is the effective allocation of channels and power across a network environment that is characterized by its dynamism and diversity. This model can adapt an effective allocation with different network loads that help to reduce power consumption.
- While enhancing the deep learning mechanism, a wireless environment is enhanced for its adaptability with the optimal solution that has a massive number of users and devices to handle the scalability effectively. Further, the power allocations are enhanced with the different data to accommodate diverse network conditions.

Thus, a novel classification mechanism is introduced in analyzing the 5G network enhanced with a deep learning mechanism. Table I provides the challenges and features of the conventional classification.

TABLE I. FEATURES AND CHALLENGES OF 5G WAVE NETWORK INSPIRED BY DEEP LEARNING MECHANISM

Author [citation]	**Methodology**	**Features**	**Challenges**
Gacanin, *et al.* [14]	Deep Reinforcement Learning (DRL)	• It can easily analyze the optimal solutions in a complex environment. • It can handle high dimensional input and complex decision making.	• It can't handle a specific task and lacks different tasks in the environment. • It faces complexity issues and tackles the limitations with an effective multi-agent mechanism.
Yanan *et al.* [15]	Crayfish Optimization Algorithm (COA)	• It can solve multi-dimensional issues and enhance the high robustness of the data. • It can easily shift between the behaviour model even in a cooler environment.	• In analyzing the local optima it faces the issues in the convergence rate. • Imbalance between the exploration and exploitation phases while analyzing the accuracy.
Zhao. [16]	Hierarchical Aggregation Clustering Algorithm (HAC)	• It can easily handle different data structures to analyze the cluster range. • It can handle a large dataset to increase scalability.	• While analyzing the cluster mechanism, it can achieve maximum time and struggles with space complexity. • It is very sensitive to noise and enhances maximum dimensional data.
Mughees *et al.* [17]	Deep learning	• It can easily handle the interconnected nodes. It can achieve state-of-art mechanisms for achieving high accuracy.	• It can cause overfitting issues and limited hardware in analyzing the data.
Ahmad *et al.* [18]	Energy Efficient Resource Allocation	• It can reduce the energy consumption and reduce the processing time.	• It can't vary with the workload because of resource allocation • It can't balance the energy because of limited resources

III. Proposed Model of Power Allocation in 5G Millimeter Wave Networks and Optimization Approach

A. Elucidation of Proposed Scheme

The 5G network focuses on the energy-efficient to analyze different techniques to analyze the power consumption with energy-saving features. But, analyzing and improving the energy efficiency in the 5G network is vital. When there is a rise in network traffic, the interlinked devices with energy consumption are increased to sustain the network. Further, energy efficiency is classified with joint power and resource allocation that helps to reduce the network conditions. Moreover, the power is transmitted with energy efficiency reducing the transmission power in the base station. Various classification approaches like architectural approach, resource management mechanism and radio technologies are classified to reduce the power consumption in the network. Thus, the deep learning mechanism is deployed with complex patterns to analyze the network performance. Further, techniques like traditional patterns and resource allocation are optimised to reduce power consumption while developing the QoS. While 5G is developed with energy consumption, it can address some limitations like high data traffic, dense network with more base stations and cost efficacy. To prevent such limitations, a new model is introduced in this technique. The architectural view of the developed network is enhanced in Fig. 1.

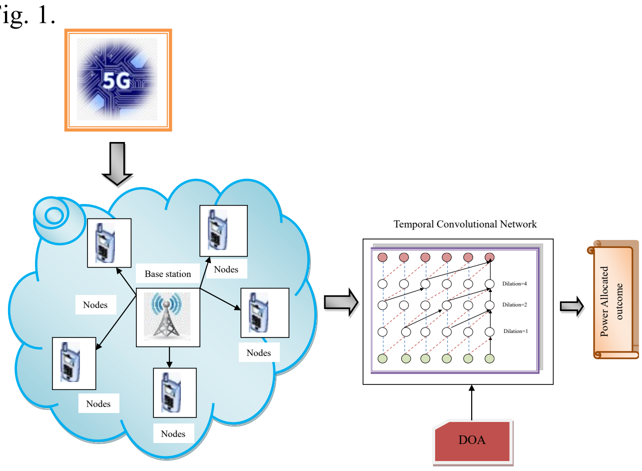

Fig. 1. Architecture diagram of designed deep learning-based 5G network.

The 5G network is developed with mobility, energy integration and clustering which helps to analyze the energy efficacy in the network. Further, the base station is accommodated to analyze the resource allocations that are mitigated to reduce the data packet and improve the quality of the transmission power. From the developed model, the images are collected from different datasets. The collected images are fed forward with the classification mechanism. Thus, a new model termed TCN-DOA is implemented. From the developed model, the TCN helps to reduce the traffic in the network and detect the anomaly accurately with a power allocation mechanism. Further, it helps to analyze the temporal patterns with a vast range of applications. It can easily manipulate long sequential data effectively which helps to reduce the vanishing gradient issues. But, it addresses some of the issues like computational cost, lack of encryption, maximized attack surface etc. To conquer such limitations, the optimization algorithm termed DOA is utilized. This algorithm helps to solve the optimization issues and balance the exploration and exploitation phase to provide a better outcome. Thus, the developed model can provide an effective result in analyzing the 5G wave network over the conventional mechanism.

B. Dollmaker Optimization Algorithm

The proposed DOA is developed to solve the optimization issues from the human skill of doll making to provide a better optimization result. Moreover, the developed DOA can tune the parameters like power allocation and user allocation which helps to maximize the data generation. The doll is considered an important toy sequence for children that is fabricated in various sizes and with unique materials. It helps to update the position with decision variables. In the sewing phase, the fabrication of a doll is a kind of art but is also considered a hobby and a skill for doing business. Initially, a formation is analyzed to make a contrast pattern of a doll and appropriate materials are selected to make the doll exactly. After gathering the materials and analyzing the formation it is encapsulated with cotton, wool and other contrasting substances that provide a complete outlook of the doll and embellish with some stuffed materials. It helps to increase the exploration phase with the selected patterns. Further in the beautifying or exploitation phase, the doll maker puts an effort to provide unique patterns through facial presence, materials, hair and shoes. Moreover, the process of making a doll is a cognitive feature because of gives the output the same as the designed pattern. Thus, DOA enhances a special skill to develop a unique pattern and provide a better outcome. Further, the position of the doll is updated using Eq. (1) and Eq.(2).

$$p_{a,b}^{v1} = p_{a,b} + r.(v_b - L \cdot p_{a,b}) \tag{1}$$

$$P_a = \begin{cases} P_a^{v1}, & F_a^{v1} \le F_a \\ P_a, & else \end{cases} \tag{2}$$

Term v is the selected doll-making pattern, v_b then b^{th} $\dim ension$, P_a^{v1} is the new position of the a^{th} phase based on DOA and $p_{a,b}^{v1}$ represents the objective function value. The pseudocode of the developed algorithm is represented in Algorithm 1.

Algorithm 1: DOA
Input: Initialized Data **Output:** Optimal solution for power allocation

Initialize the population
Do while
    Formulate the arbitrary variable r using Eq. (1)
    Upgrade the position of the processes.
    Update the final position.
  Save the optimum value
End while
Obtains the solution

IV. Temporal Convolution Network and its Fitness Formulation for Allocating the Power in Networks

A. Temporal Convolution Network

TCN is a type of Convolutional Neural Network (CNN) that can manage the time sequence with two major techniques the input series should have the same length when contrasted with the output series in the network and they prevent extravasations of information with causal convolutions. Further, the causal convolution varies with specific convolution to achieve the output at the time t. To analyze the kernel size e different values are optimized with the output value U_t. Without achieving the pooling mechanism, the amenable field is maximized with the convolutional network, without loss of resolution. Further, to achieve maximum range patterns, TCNs are employed with one-dimensional dilated convolutions. The skipping value r enhances the input of the dilation mechanism with the dilated convolution. With the sequential layer, the dilated causal convolutions are described in Eq. (3).

$$s_m^t = c\left(\sum_{e=0}^{E-1} a_m^e s_{(m-1)}^{(e\times x)} + h_t\right) \tag{3}$$

Here, the term s_m^e describes the output function of the neuron, E which is the width of the convolutional kernel. d Is the convolution for dilated factor, h_t is the bias function, a_m^e is the weight of the position and g indicates the ReLU function. Further, Rectified Linear Unit (ReLU) enhanced with the activation layer are described in Eq. (4).

$$c(s) = \max(0, s) \tag{4}$$

Further, the network amenable is maximized with TCN to achieve high parameters with the convolutional mechanism. Further, the residual connection is integrated with the TCN to achieve high performance in the dilated mechanism that is represented in Eq. (5).

$$u = c(s + F(s)) \tag{5}$$

Further, the TCN is accommodated with the deep learning mechanism to analyze the time sequence issues. The residual network can easily handle the input with a one-dimensional causal convolution kernel that can achieve maximum memory efficiency when contrasted with the convolutional network. Further, the residual network can handle the vast sequence in parallel to analyze the computation time. Moreover, the gradient issues are terminated with the backpropagation mechanism. The implemented network is represented in Fig.2.

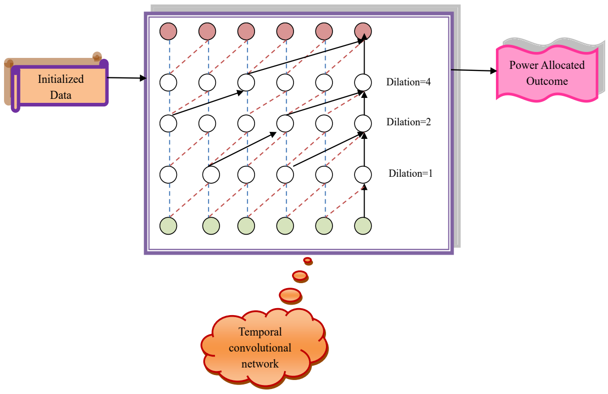

Fig. 2. Structure of TCN for 5G wave network with power allocation mechanism

B. Fitness Formulation

The Integer Linear Program (ILP) is optimized in the fitness formulation with the heuristic approach, which helps to reduce the power consumption in the 5G mm-wave network while upholding user QoS. Moreover, the decision variable is enhanced with the user and base station to analyze the binary variable. It is enhanced to reduce the power consumption in the network. Further, the fitness functions are accommodated with energy consumption in the base station that can effectively transmit the power among the connected users with the DOA mechanism. The Eq. (6) to Eq. (14) describes the objection function of ILP.

$$\underset{\{Pa^{TCN}, Ua^{TCN}\}}{Minimize} \sum_{l\in L} \left(g_l \cdot D_v + (1-g_l)\cdot D_k\right) \tag{6}$$

$$\sum_{l\in L} m_{an} = 1, \ \forall a \in A \tag{7}$$

$$g_l \geq m_{an}, \ \forall a \in A, \ n \in N \tag{8}$$

$$\sum_{l\in L} m_{an} \geq g_l, \ \forall n \in N \tag{9}$$

$$\sum_{n\in N} m_{an} \leq A_{\max}, \ \forall n \in N \tag{10}$$

$$\sum_{a\in A} m_{an} \cdot D_{tm}^{na} \leq D_{\max} \tag{11}$$

$$H_{an} \geq Ts_{\min} \cdot m_{an}, \ \forall a \in A, \ n \in N \tag{12}$$

$$m_{an} \cdot p_{an} \leq p_{\max}, \ \forall a \in A, \ n \in N \tag{13}$$

$$m_{an}, g_l \in \{0,1\} \ \forall a \in A, \ n \in N \tag{14}$$

Here, the term Pa^{TCN} indicates optimized power allocation, the term Ua^{TCN} indicates user allocation, the term D_v indicates the power consumed with the base station when it is activated, D_k represents power consumed with the base station when it is not activated, a represents several users, n represents the number of the base station, $D_{\max}$ indicates the maximum distance between the user and base station, $p_{\max}$ indicates the maximum transmitted power, $Ts_{\min}$ indicates the minimum threshold throughput, $A_{\max}$ represents the maximum number of users and H_{an} indicates data rate allocated with the base station.

V. Result And Discussion

A. Experimental setup

The developed 5G wave network was executed with the Python platform. Further, optimization algorithms like Red-billed Blue Magpie Optimizer (RBMO) [19], Golf Optimization Algorithm (GOA) [20], Namib Beetle Optimization Algorithm (NBOA) [21], Pelican Optimization Algorithm (POA) [22] and Dollmaker Optimization Algorithm (DOA) [23] were analyzed. Moreover, the networks like Deep Neural Network (DNN) [24], Support Vector Machine (SVM) [25], Long Short-Term Memory (LSTM) [26], Gated Recurrent Unit (GRU) [27] and TCN [28] were exploited in this experiment. During this process, some of the data attributes like area size, number of users, number of BSs, radius of BS, bandwidth, frequency, transmission and receiver length, mutation rate and power are considered for performing the power allocation. Amongst, the power is designated as target that is optimally find out using our proposed concept. After that, the TCN is applied for allocating the power with its optimized value.

B. Convergence Analysis

It is essential to select the efficient algorithm to analyze the better optimization processes. It helps to analyze the optimal solution in the final classification stage. Hence, the DOA is implemented to provide a better optimal result in the convergence without being stuck in the local optima. The developed DOA is variated with the existing algorithm by varying the iteration in Fig. 3. From the analysis, the cost function is analyzed with 8.7%, 14.5%, 8.9% and 7.4% for RBMO-TCN, GOA-TCN, NBOA-TCN and DOA-TCN respectively. Based on the analysis it is noted that the optimal solution provided by DOA is optimized with the 5G network in power allocation.

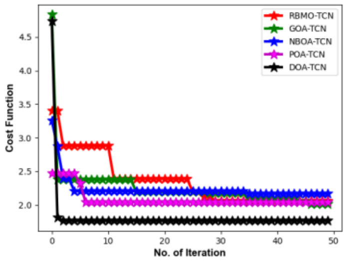

Fig. 3. Convergence estimation of the presented DOA algorithm compared with the previous algorithm

C. Performance Analysis

The developed TCN-DOA for the 5G wave network are classified in Fig. 4 and the performance investigation is analyzed in Fig. 5 with a standard algorithm. Thus, the developed TCN-DOA is more effective in classifying the 5G wave network with energy efficient joint-user and power allocation. Further, the accuracy is maximized to analyze the quality of the data in the classification mechanism.

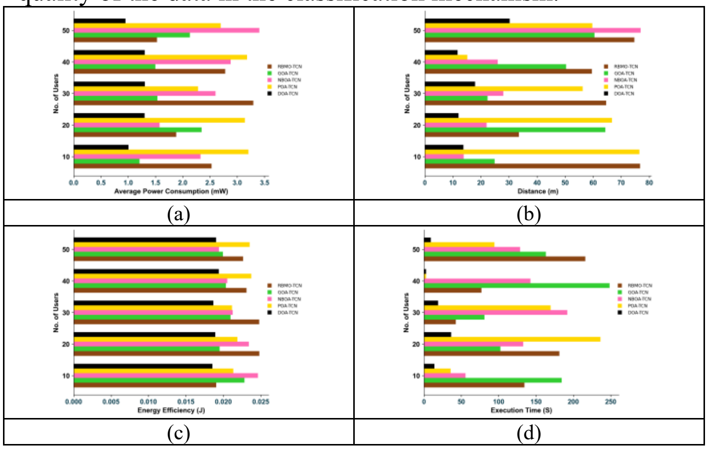

Fig. 4. Performance evaluation of the proposed power allocation system compared with another optimization algorithm in terms of “(a) Average Power consumption (b) Distance (c)Energy Efficiency and (d) Execution Time”

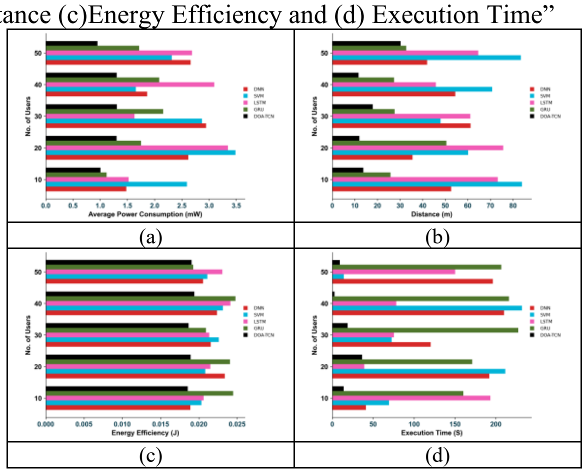

Fig. 5. Comparative evaluation of developed power allocation system compared with another deep learning model in terms

of "(a) Average Power consumption (b) Distance (c)Energy Efficiency and (d) Execution Time"

D. Statistical Analysis

The developed DOA algorithm is analyzed with statistical measures. The experiment is shown in Table II for analyzing the performance of DOA. From the analysis of DOA, 17% of RBMO-TCN, 20.1% of GOA-TCN, 21% of NBOA-TCN and 20.4% of POA-TCN are analyzed individually. This analysis elaborates on how the developed DAO can select the suitable parameter contrasted with the traditional algorithm.

TABLE II.
STATISTICAL INVESTIGATION OF THE PROPOSED ENERGY-EFFICIENT JOINT USER AND POWER ALLOCATION SYSTEM WITH OTHER ALGORITHMS

Terms	RBMO-TCN [19]	GOA-TCN [20]	NBOA-TCN [21]	POA-TCN [22]	DOA-TCN
BEST	2.058300001	2.017552744	2.165594159	2.043935307	1.763662688
WORST	3.398459123	4.833201747	3.252310403	2.467692219	4.734462636
MEAN	2.361035204	2.259387704	2.23724665	2.091850361	1.824043102
MEDIAN	2.292914617	2.194207243	2.208636094	2.043935307	1.763662688
STD	0.365596318	0.387092116	0.177965166	0.131131104	0.415829

E. Overall Comparative Analysis

Table III explains the overall comparative analysis of the developed DAO-TCN with a distinct approach. From the analysis, 58%, 52%, 47% and 44% of DNN, SVM, LSTM and GRU are optimized. Further, these outcomes were enhanced with the developed DOA-TCN to provide a better solution.

TABLE III. COMPARATIVE ANALYSIS OF THE PROPOSED POWER ALLOCATION SYSTEM IN A 5G MILLIMETRE WAVE NETWORK CONTRASTS WITH OTHER NETWORKS.

Optimizer	DNN [24]	SVM [25]	LSTM [26]	GRU [27]	DOA-TCN
Accuracy					
Adam	96.07257672	96.78824446	97.25210818	97.69469432	98.22317586
SGD	96.56826749	96.83046851	97.22094313	97.90797397	98.31061863
RMSprop	96.79520574	97.234569	97.68160208	98.14595935	98.42834751
Adamax	96.61993873	97.51287305	97.86245785	98.33312292	98.9245802
AdaGrad	96.90283547	97.41853199	97.83503261	98.40429036	98.7084867
MEP					
Adam	3.766687858	3.226319135	2.940241577	2.336300064	1.923076923
SGD	3.496503497	3.051493961	2.654164018	2.177368086	1.732358551
RMSprop	3.273998729	2.749523204	2.368086459	1.907183725	1.446280992
Adamax	3.130959949	2.606484425	2.145581691	1.748251748	1.255562619
AdaGrad	2.98792117	2.542911634	2.129688493	1.589319771	1.191989828
SMAPE					
Adam	0.043047861	0.036872219	0.033602761	0.026700572	0.021978022
SGD	0.03996004	0.034874217	0.030333303	0.024884207	0.019798383
RMSprop	0.037417128	0.031423122	0.027063845	0.021796385	0.016528926
Adamax	0.035782399	0.029788393	0.024520934	0.01998002	0.014349287
AdaGrad	0.034147671	0.029061847	0.024339297	0.018163655	0.013622741
MASE					
Adam	98.4087338	79.80764325	67.19903393	56.62952453	43.53881638
SGD	85.16474928	78.31097812	68.78985652	51.27466239	41.29398717
RMSprop	78.95520478	68.05045018	56.69323042	45.46138823	38.39172398
Adamax	83.75827578	60.61321667	52.42581364	40.69579481	26.06377446
AdaGrad	76.88901493	63.45312529	52.93808412	39.10765919	31.58727096
MAE					
Adam	0.019939858	0.016306353	0.013951278	0.011704231	0.009021086
SGD	0.017423195	0.016091978	0.014109506	0.010621392	0.008577131
RMSprop	0.01627101	0.014040326	0.011770701	0.00941312	0.007979412
Adamax	0.017160856	0.012627353	0.010852481	0.008462875	0.005459997
AdaGrad	0.015724565	0.01310633	0.010991722	0.008101552	0.006557122

VI. CONCLUSION AND FUTURE WORK

The 5G of the mobile network with millimetre Wave was analyzed as the developing network with end-user demand. In some cases, it can maximize the power allocation to reduce the energy usage in the network. The data are enhanced with power allocation with QoS to manage the power consumption. Further, TCNs are enhanced with user systems to enhance various applications and achieve effective power allocation mechanisms. Hence, DOA was enhanced with this mechanism to provide appropriate patterns in the designing phase, that help to provide a better outcome. To analyze the classification mechanism, the developed mechanism was varied with the existing approach and the performance validation of the developed DOA-TCN was 96.72% DNN, 96.86% SVM, 97.15% LSTM and 97.88% GRU respectively. Thus, the developed model provides an appropriate outcome for the developed 5G wave network. The 5G wave network could provide an appropriate outcome with the power allocation mechanism, but it addresses some of the issues like reduced range of the network because of different wave frequencies, signal degradation etc. Also, incorporating and integrating these complex DL-based models into existing and future networks could be a major difficulty. To overcome such limitations, the 5G network will improve energy efficiency with a power allocation mechanism. Further, it could help to reduce the traffic demand and provide effective energy over the network.

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