Received: 19 September 2023 | Revised: 27 December 2023 | Accepted: 13 January 2024

DOI: 10.1049/tje2.12353

The Journal of Engineering

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH

Joint delay and energy aware dragonfly optimization-based uplink resource allocation scheme for LTE-A networks in a cross-layer environment

Leeban Moses[1] | **Perarasi Sambantham**[1] | **Muhammad Faheem**[2] | **Shoukath Ali K**[3] | **Arfat Ahmad Khan**[4]

[1]Department of Electronics and Communication Engineering, Bannari Amman Institute of Technology, Sathyamangalam, Tamil Nadu, India

[2]Department of Computing Science, School of Technology and Innovations, University of Vaasa, Vaasa, Finland

[3]Department of Electronics and Communication Engineering, Presidency University, Bengaluru, Karnataka, India

[4]Department of Computer Science, College of Computing, Khon Kaen University, Khon Kaen, Thailand

Correspondence
Muhammad Faheem, School of Technology and Innovations, University of Vaasa, Vaasa 65200, Finland.
Email: muhammad.faheem@uwasa.fi

Abstract

The exponential growth in data traffic from smart devices has led to a need for highly capable wireless networks with faster data transmission rates and improved spectral efficiency. Allocating resources efficiently in a 5G communication system with a huge number of machine type communication (MTC) devices is essential to ensure optimal performance and meet the diverse requirements of different applications. The LTE-A network offers high-speed mobile data services and caters to MTC devices and has relatively low data service requirements compared to human-to-human (H2H) communications. LTE-A networks require advanced scheduling schemes to manage the limited spectrum and ensure efficient transmissions. This necessitates effective resource allocation schemes to minimize interference between cells in future networks. To address this issue, a joint delay and energy aware Levy flight Brownian movement-based dragonfly optimization (DELFBDO)-based uplink resource allocation scheme for LTE-A Networks is proposed in this work to optimize energy efficiency, maximize the throughput and reduce the latency. The DELFDO algorithm efficiently organizes packets in both time and frequency domains for H2H and MTC devices, resulting in improved quality of service while minimizing energy consumption. The Simulation results demonstrate that the proposed method increases the energy efficiency by producing the appropriate channel and power assignment for UEs and MTC devices.

1 | INTRODUCTION

Advancements in wireless communication networks have made it possible for network operators to meet the growing demand for services. In the next generation of networks, it is expected that each user device will be able to use multiple applications simultaneously, each with its own specific quality of service (QoS) requirements [1]. For instance, the applications like augmented or virtual reality require high data rates, low delay, and reliable connections. The rapid progress in wireless communication technologies has led to the development of 5G (fifth generation) networks. The 5G network needs to cater to diverse types of applications and devices that operate without wires. It must provide different levels of service for various scenarios [2]. These scenarios include faster internet access for mobile devices, connecting a large number of machines, and ensuring reliable and fast communication with minimal delays. In Internet of Things (IoT) networks based on cellular technology, numerous IoT devices initially connect to the cellular base station for network access directly or through IoT gateways. This is done through a random-access procedure [3]. However, when a large number of IoT devices simultaneously access and transmit small data packets or frequently send real-time status updates, collisions in the initial signals are unavoidable. Improving the access mechanism of current cellular systems to enhance the QoS and reduce the power consumption of IoT devices is a significant challenge for cellular-based IoT networks [4].

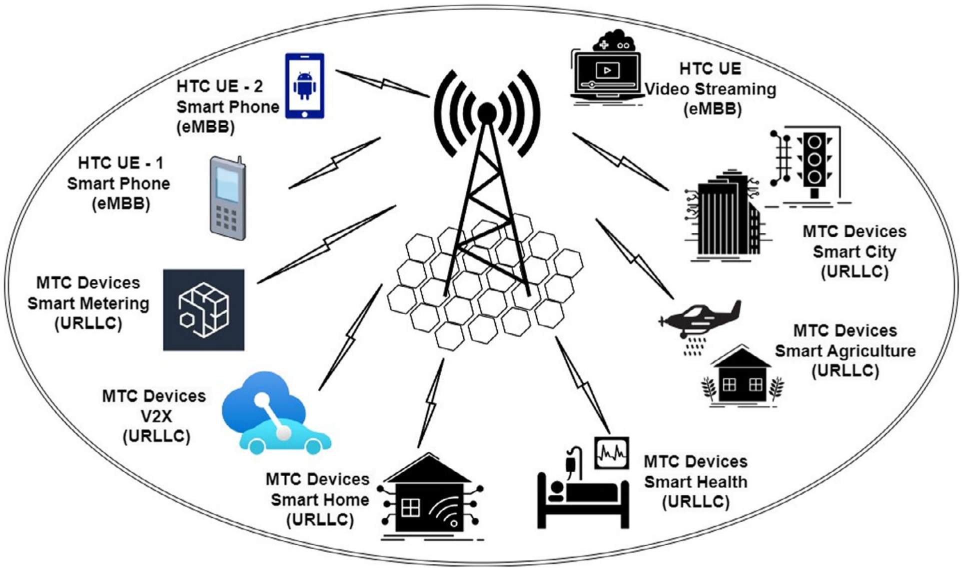

FIGURE 1 Single cell scenario with one Human Type Communication Device and N Machine Type Communication devices with k-sensor data types.

Different IoT services have varying QoS requirements based on traffic data and functionality. Providing access mechanisms with satisfactory network performance for a massive number of IoT devices and diverse network services is a key challenge. Heterogeneous networks (HetNets) are considered a useful method to improve the efficiency of wireless networks and expand their capacity [5]. This is achieved by transferring some of the workload from large base stations to smaller ones that cover smaller areas. By reducing the size of the cells and using different transmission power levels, HetNets offer benefits such as better coverage, improved connectivity indoors, balanced distribution of network traffic, and flexible deployment options [6]. However, the coexistence of large and small base stations in HetNets can present challenges in managing network resources, handling interference, ensuring security, maintaining QoS, scaling the network, and optimizing energy usage. M2M communication for Human Type Communication (HTC) interactions can lead to efficiency and congestion challenges due to the varying data rates between them [7]. As shown in Figure 1, an eNB serves both HTC devices for voice calls and multimedia communications and N MTC devices with K different types of sensor data, each with a unique data size and sampling period. The differences in signalling packet sizes at higher layers result in lower efficiency. In certain areas, there can be a large number of MTC devices that communicate with each other. These devices are often triggered by external events, and if deployed quickly in large numbers, they can cause network congestion. Unlike devices used for person-to-person communication, MTC devices send much more data from the device to the network (uplink) than they receive from the network [8]. This difference in data flow can impact the overall efficiency of the network. MTC devices also have specific needs, such as long battery life, short delays, and reliable connections. These needs aren't usually important for other types of devices, like smartphones, and the current cellular network technology isn't designed for them, so they do not work as well as they could. Additionally, MTC devices send data regularly from specific locations and do not move much, which is different from how people use their phones [9].

LTE-A is a cellular communication standard that provides high bandwidth, mobility, and flexibility to meet the different needs of UEs, but MTC involves low-bandwidth data bursts and has different QoS requirements compared to H2H communication. MTC data transmission primarily depends on the uplink direction and competes with uplink H2H traffic [10]. There are various critical applications of MTC communication that require prioritization over H2H communication, and managing this competition is a challenge for the uplink scheduler. Since M2M systems involve a large number of devices with diverse QoS requirements, designing scheduling schemes that support MTC over the LTE-A network is a difficult task. MTC devices often send infrequent data packets of varying sizes, and the LTE-A bandwidth has limited physical resources optimized for H2H communication. To ensure efficient MTC communication, it is important to develop a solution that optimizes the use of available resources while meeting the specific quality of QoS requirements of MTC communication. Several optimization algorithms used for resource allocation (RA) can also be performed and tested in the transmission path using antenna like falcate patch [11], leaky-wave microstrip patch [12], and isolation microstrip patch [13].

Interference management is a major challenge in MTC communication, as it can affect the quality of communication or even lead to complete loss of communication when multiple devices use the same resources [14]. Techniques like power control, frequency selection, and resource allocation can be used to address this challenge and minimize interference. Energy efficiency is another significant challenge in MTC communication, especially when there are a large number of devices in the network. It is important to minimize power consumption while ensuring effective communication. Techniques such as power control, duty cycling (turning devices on and off periodically) and implementing sleep modes can help enhance energy efficiency [15]. Additionally, optimal power allocation plays a significant role in enhancing network performance, mitigating interference, and improving energy efficiency. However, it is important to note that resource allocation schemes have a critical impact on both QoS and energy efficiency, and optimizing one parameter may have trade-offs with other parameters [16]. Therefore, joint optimization of user association and power allocation is essential to enhance energy efficiency.

To address these challenges, we propose a novel cross-layer joint delay and energy aware Levy flight dragonfly optimization algorithm for the LTE-A Network with MTC infrastructure. Our focus is on the coexistence of crowded MTC users and traditional cellular users within a network environment. In this scenario, the base station (BS) exercises centralized control over all users within a cell. It has the capability to collect channel state information from the system's links and allocate spectrum resources to individual users based on their specific requirements. In our proposed approach, we assume that all spectrum resources are shared among both traditional cellular users and newly introduced MTC users. By considering the transmission opportunities for traditional cellular users and analyzing the interference levels in the MTC communication mode, we assign communication modes to all users. This algorithm aims to allocate resources to users, ensuring better QoS and fairness index. The rest of the Paper is organized as follows: Section 2 illustrates the related work; Section 3 presents the resource allocation problem and establishes the system model. In Section 4, a novel resource allocation algorithm is introduced, considering the multi-objective function. Section 5 evaluates the performance parameters of the proposed algorithm.

2 | RELATED WORK

Resource allocation is the process of assigning frequency components to different types of services. It determines how much time and frequency is shared between the base station and mobile users. During each scheduling phase in the uplink (UL) channel, each HTC-UE/MTCD sends its buffer status information and buffer size to the eNB using a dedicated channel called the physical uplink control channel (PUCCH). Scheduling algorithms, which manage traffic flows at a base station while considering QoS, can be broadly categorized into two types: channel independent and channel dependent. In channel independent scheduling, resource allocation doesn't consider channel state information or buffer size. On the other hand, channel dependent scheduling allocates resources to UEs based on channel state information. These algorithms are beneficial for wireless cellular networks aiming to provide uninterrupted services to UEs. Channel dependent scheduling algorithms are specifically designed for applications with guaranteed bit rate (GBR) and those sensitive to delays [10]. The eNodeB's packet scheduler employs specific strategies to allocate the shared spectrum among users. To achieve maximum spectral efficiency, an optimal resource allocation technique is employed.

Heuristic algorithms are already in use to significantly reduce computational complexity. Multiobjective resource allocation schemes have been developed to achieve desired outcomes, such as minimizing interference, improving fairness, and enhancing resource utilization efficiency. The combination of firefly algorithm and particle swarm optimization (FFA-PSO) algorithm [17] are employed to obtain a Pareto-optimal solution. A two-sided matching RA algorithm for optimizing and allocating the resources between HTC-UEs is implemented in [18] to ensure stability and manage complexity. This approach uses multipoint transmission and reception, along with carrier aggregation, to send multiple components to users in different cell corners. The aim is to make efficient use of bandwidth, improve received signals, and reduce interference. The research article in [19] enumerate a mode selection algorithm to effectively allocate the resources available in a mixed traffic environment by considering the MTC and HTC traffic. In this approach, we determine the communication mode for users based on traditional cellular transmission opportunities and analyze interference from different MTC communication modes. Users are then categorized into three tiers based on their distances from the base station to address interference problems. Spectrum resource allocation mechanisms are developed for different communication modes using the Hungarian algorithm.

The chunk-based and heuristic-based RA algorithm (CBRA & HORA) developed in [20] solves the tradeoff that exists between the performance of QoS parameter and computational complexity of the algorithm. The HORA algorithm allocates resource blocks to users, taking into account their QoS requirements, while CRBA assigns RB chunks to user groups based on channel conditions. The HORA algorithm optimizes data rate through 3-tuplet constraints, while the CRBA algorithm groups users by signal to noise ratio (SNR) values, assembles RB chunks, and allocates them based on channel conditions and RB requirements. The cross-layer resource allocation formulated by [21] enhances the RA mechanism of HTC-UEs in a single cell by considering the HTC traffic. Statistical QoS assurance is applied to fulfil critical MTC demands in the cell, restricting the probability of delay-bound violation for each critical MTC device. This approach provides an accurate statistical guarantee for latency and packet losses due to queuing delays. The author in [22] has proposed an optimized bidirectional RA algorithm for HTC UEs based on QoS requirements. Users are prioritized based on a probability function, and scheduling occurs by selecting each user from the higher-ranked positions in the priority queue. These weights are transformed into a probability function during each transmission time interval, based on QoS requirements. In [23], the author tackled the complex joint problem of allocating resources and power. They used a mixed integer programming model to handle the stochastic optimization issue associated with the drift-plus-penalty (DPP) approach for Lyapunov opportunistic optimization.

The amended barnacles mating optimizer (ABMO)- [24] and modified whale optimizer-based [25] RA algorithms, aims to improve the performance of 5G networks by enhancing the number of connected users and reducing transmit power consumption. This algorithm increases its accuracy and effectiveness by optimizing the best locations for base stations, considering the principles of green communications. A three-step genetic algorithm (GA) for coexistence of MTC and HTC UE proposed in [26] includes new operations like initialization, crossover, mutation, and a QoS-aware fitness function. GA with a single block approach leads to slow convergence as the algorithm spends time evaluating solutions, even when users could delay their transmission without exceeding the delay budget. Sliding window-based RA algorithm for coexistence of MTC devices with HTC UEs is proposed in [27] takes advantage of frequency and time diversities by capturing channel coefficients that vary over time and frequency. To improve uplink throughput in network resource allocation and to enhance energy efficiency, particle swarm optimization (PSO) with fuzzy logic control (FLC) and Taguchi method is proposed in [28]. The proposed method utilizes priority weighted rate control to increase uplink throughput. PSO is employed to determine the optimal position for the cluster head, while FLC combined with the Taguchi method adjusts the PSO fitness parameter value.

The RSMA technique involves splitting a message into two parts for transmission. Two resource allocation modes are created to maximize throughput while adhering to interference constraints. The switch between modes is determined by deriving the coverage radius expression. The optimization of D2D transmit power and reduction of overall network computational complexity are achieved using Lagrange's dual-optimization method. The author in [3] has proposed a scalable type of priority-based RA scheme when MTC devices coexist with HTC UEs in a single cell. This allocation scheme considers both channel quality and application priority as metrics for distribution. This is beneficial to minimize the balance between making efficient use of the channel and ensuring satisfaction with QoS. In [2], the author uses a combination of the fixed variable method and the Lagrangian method to address the issues faced in resource allocation for a mixed environment. They suggest an enhanced particle swarm method for resolving the power allocation problem and introduce a bilateral stable matching algorithm to find a solution for energy cooperation. To enhance energy efficiency, the author puts forth a convergent iterative algorithm that integrates the three mentioned methods to jointly solve the original optimization problem.

Table 1 summarizes the objectives of the existing work. Here EE denotes energy efficiency of the HTC/MTC nodes, SE represents the spectrum efficiency of the resource allocation strategy, TE denotes the efficiency of throughput, QoS denotes the QoS parameters, IA denotes the signal to noise interference parameter, DA denotes the delay parameter, FI denotes the Fairness index parameter and CLO denotes whether the model represented represents cross layer scenarios by considering two objective function or not.

3 | SYSTEM MODEL AND PROBLEM FORMULATION

We consider the single-cell architecture illustrated in Figure 1. A cell consists of n UE terminals and m M2M devices to form sets $M = \{1, 2, 3, \ldots m\}$ and $N = \{1, 2, 3, \ldots n\}$ of UE terminals and M2M devices, respectively. The frequency division duplex scheme is adapted in M2M devices since the channel occupies half of the spectrum. One uplink and downlink orthogonal channels are allocated to UE to prevent interference between two UEs. To perform allocation and mitigate interference, we assume that the uplink and downlink channels can be reused once by the M2M spectrum, and each M2M device cannot reuse the channels. The channel gain between nth UE and the base station of a single cell can be denoted as:

$$G_{nUE} = \lambda \psi_{nUE}\, \rho_{nUE}\, \ell_{nUE}^{-\alpha} \tag{1}$$

where λ represents the path loss constant, ψ_{nUE} represents the fast-fading gain, ρ_{nUE} represents the slow fading gain. ℓ_{nUE} represents the length between the nth UE and BS, and α represents the path loss factor. To define the system capacity, the status parameter of the UE in the uplink channel can be denoted by a binary variable and is denoted as:

$$\Gamma_{mn}^{uplink} = \begin{cases} 1 & when\ M2M\ device\ reuses\ the\ uplinkchannel\ of\ n^{th}\ UE \\ 0 & otherwise \end{cases} \tag{2}$$

When the n^{th} UE is allocated in the uplink channel it can use its entire spectral width and its signal to interference and noise ratio for nth UE and base station shall be denoted as:

$$\Gamma_{n,UL}^{i} = \frac{E_n^k G_{nUE}}{\beta^2 + \sum_{m\in M} E_m^l \alpha_{mn}^u y_{mn}} \tag{3}$$

where E_n^k, E_m^l denotes the transmission energy of nth UE and m^{th} M2M device pair, G_{nUE} and α_{mn}^u represents uplink channel gain of UE and BS, M2M and BS respectively and β^2 denotes the Energy of the Noise Gaussian on both D2D Pair and UE channels. In uplink channel the UE causes interference with the M2M pairs and Signal to Interference Noise Ratio (SINR) of the m^{th} M2M pair under the channel of the n^{th} UE can be denoted as:

$$\Gamma_{m,UL}^{j} = \frac{E_m^l G_{m,M2M}}{\beta^2 + \sum_{n\in N} E_n^k \alpha_{mn}^u y_{mn}} \tag{4}$$

where $G_{m,M2M}$ is the channel gain for uplink of the M2M devices and BS, y_{mn} denotes gain of the interference channel link between n^{th} UE and m^{th} M2M devices. Considering of both SINR of M2M device pairs and UE with base station the overall system capacity can be written as:

$$C_{UE,\ M2M}^{Uplink} = B\log_2\left(1 + \Gamma_{n,UL}^{i}\right) + B\log_2\left(1 + \Gamma_{m,UL}^{j}\right) \tag{5}$$

An optimal resource allocation scheme is proposed here for uplink communication by considering both UE and M2M device pairs in a single cell structure. We consider the optimization problem as the maximization of capacity system and to assure the SINR requirements. Overall optimization related to

TABLE 1 Comparison of multi-objective hybrid optimization-based resource allocation models.

Reference	Model	EE	SE	TE	QoS	IA	DA	FI	CLO	Priority
[19]	Energy-aware mode selection for D2D resource allocation	✓	-	✓	✓	-	-	✓	Resource allocation based on MTC devices with single cell	Statistical QoS
[17]	FFA-PSO multiobjective cooperative swarm intelligence algorithm	-	-	✓	✓	-	-	✓	Resource allocation based on HTC devices with macro/femto cell	GBR & Max weight
[20]	HORA and CRBA algorithms	-	-	✓	✓	✓	-	✓	HTC devices with three eNBs and based on MCS	CQI
[21]	Two sided cross-layer matching-based scheduler	-	✓	✓	✓	-	✓	-	single eNB that serves a set of HTC users and critical MTCD	CQI, Delay
[22]	Bidirectional allocation of radio blocks using MUJCS algorithm based on weight factors	-	✓	✓	✓	-	-	✓	Both uplink and downlink, RA based on HTC devices with macro/femto cell	GBR & Max weight
[23]	Joint stochastic Lyapunov DPP optimization to solve MILP problem for the multiple resource allocation	✓	✓	✓	-	✓	-	-	Multi-tier and multi-cell heterogeneous Network for micro and small base station UEs	QCI and GBR
[25]	Whale optimization algorithm-based resource allocation scheme	-	-	✓	✓	-	-	✓	Resource allocation based on MTC devices with single cell	CQI
[28]	Energy efficient RA method by combination of PSO, FLC with Taguchi method	✓	✓	✓	-	✓	-	-	Allocation of resources for IoT devices	Statistical QoS
[29]	RSMA technique with Han–Kobayashi scheme for RA in multicell mm-Wave environment	✓	✓	✓	-	✓	-	-	D2D communication in a multicell environment for an uplink channel	QCI and Max weight
[30]	Red–black tree building TDPS classifier by combining channel quality and application priority as an allocation metric	✓	✓	✓	-	✓	✓	✓	Resource allocation based on HTC devices with macro/femto cell	QCI and GBR
[26]	Three-step genetic-based metaheuristic RA in mixed traffic environments	-	✓	✓	-	-	-	✓	Resource allocation based on MTC devices and UE with single cell	QCI and GBR
[18]	Matching-based cross-layer resource allocation	-	✓	✓	-	-	-	✓	Resource allocation based on MTC devices and UE with single cell	QCI and GBR
[27]	Sliding window-based RA algorithm for Hybrid eMBB and URLLC Services	✓	✓	✓	-	✓	-	-	Resource allocation based on MTC devices and UE with single cell	QCI and GBR
[24]	Amended barnacles mating optimizer-based RA algorithm	-	✓	✓	✓	-	✓	✓	Resource allocation based on HTC devices with macro/femto cell	GBR and Max weight
[31]	FVI based RA algorithm by combining Lagrange dual method and improved PSO with matching.	✓	✓	✓	-	✓	-	✓	Resource allocation based on HTC devices with macro/femto cell	GBR and Max weight

system capacity can be denoted as:

$$\underset{E_m^l,\alpha_{mn}^u,\,E_n^k}{Max} \sum_{n\in N}\sum_{m\in m} C_{UE,M2M}^{Uplink} \tag{6}$$

Such that:

$$\Gamma_{n,UL}^i \geq \Gamma_{\min}^i \,\&\, \Gamma_{m,UL}^j = \Gamma_{\min}^j, \quad \forall n \in N \,\&\, m \in M \tag{7}$$

$$0 \leq E_n^k \leq E_{\max}^k \,\&\, E_m^l \leq E_{\max}^l, \quad \forall n \in N \,\&\, m \in M \tag{8}$$

$$\sum_{n\in N} \alpha_{mn}^u \leq 1 \,\&\, \alpha_{mn}^u \in \{0,1\}; \quad \forall n \in N \,\&\, m \in M \tag{9}$$

$$\left(\sum_{n\in N} \alpha_{mn}^u\right)\left(\sum_{m\in M} \alpha_{mn}^u\right) = 0; \quad \forall n \in N \,\&\, m \in M \tag{10}$$

where $\Gamma_{\min}^i$ & $\Gamma_{\min}^j$ denotes the minimum value of SINR of UE and M2M users respectively. $E_{\max}^k$ & $E_{\max}^l$ denotes the maximum transmitted energy of the UE and M2M users respectively. According to the Constraints developed, the Equation (6) represents the QoS requirements of the UEs and M2M Pairs. The constraint developed in (7) assures maximum energy transmitted in the uplink channel of Cross-layer environment. The constraint developed in (8) and (9) assures the assumed condition, that each uplink channel of UE can be shared only by one spectrum of M2M users in the same channel. The constraint developed in (10) assures that the M2M pair can share only one spectrum in the uplink channel of UE. The next section describes the energy-efficient resource allocation algorithm according to the developed constraints.

To reduce the computational complexity of the proposed algorithm, the objective function is decomposed into two terms. So, the first objective for the constraint developed in (5) is to maximize the energy transmission between the M2M allocated pairs and its shared resource by the UE in uplink channel. The second objective in the constraint developed in (5) is allocating resources to UE and M2M users using the dragonfly optimization algorithm. When the mth M2M device pair reuses the uplink channel of the nth UE, the energy optimization problem can be remodelled as:

$$\underset{E_m^l,E_n^k}{Max}\left\{\log_2\left(1+\frac{E_n^k G_{nUE}}{\beta^2+\sum_{m\in M} E_m^l \alpha_{mn}^u y_{mn}}\right) + \log_2\left(1+\frac{E_m^l G_{m,M2M}}{\beta^2+\sum_{n\in N} E_n^k \alpha_{mn}^u y_{mn}}\right)\right\} \tag{11}$$

Such that, $\Gamma_{n,UL}^i \geq \Gamma_{\min}^i$ & $\Gamma_{m,UL}^j \geq \Gamma_{\min}^j$; $\forall n \in N$ & $m \in M$ $0 \leq E_n^k \leq E_{\max}^k$ & $0 \leq E_m^l \leq E_{\max}^l$; $\forall n \in N$ & $m \in M$.

To provide stringent QoS requirements, the value of SINR for M2M pairs and U∈'s should be higher than that of minimum designed value. Hence energy transmitted by M2M devices and U∈'s will not exceed the minimum value. Therefore, the energy of M2M pair, E_m^l should lie between the lower limit of energy defined as E_{Lower}^{UL} and the upper limit energy E_{Upper}^{UL} and can be denoted as:

$$E_{Lower}^{UL} = \max\left\{0,\ \frac{\Gamma_{\min}^j\left(\beta^2 + E_n^k y_{mn}\right)}{G_{M2M}}\right\} \tag{12}$$

$$E_{Upper}^{UL} = \min\left\{0,\ \frac{E_n^k G_{nUE} - \Gamma_{\min}^i \beta^2}{\Gamma_{\min}^i y_{mn}}\right\} \tag{13}$$

When there are huge number of resources available, to determine the resource allocation between M2M devices and UE, the optimal M2M and UE pairing solution can be given as:

$$\underset{\alpha_{mn}^{UE},\ \alpha_{mn}^{M2M}}{Max}\left\{\sum_{n\in N}\sum_{m\in m}\left(\alpha_{mn}^{UE}\ C_{UE,M2M}^{Uplink}\right) + \left(\alpha_{mn}^{M2M}\ C_{UE,M2M}^{Uplink}\right)\right\} \tag{14}$$

Such that,

$$\sum_{n\in N} \alpha_{mn}^{UE} \leq 1 \,\&\, \sum_{m\in m} \alpha_{mn}^{M2M} \leq 1$$

$$\alpha_{mn}^{UE}\,\alpha_{mn}^{M2M} \in \{0,\ 1\} \quad \forall n \in N \,\&\, m \in M$$

$$\left(\sum_{n\in N} \alpha_{mn}^{UE}\right)\left(\sum_{m\in m} \alpha_{mn}^{M2M}\right) = 0; \quad \forall\, n \in N \,\&\, m \in M$$

4 | RESOURCE ALLOCATION ALGORITHM

4.1 | Stage I: Modelling of the environment—MTCDs with HTC UEs

In a cross-layer network, the parameters specified for resource allocation energy efficiency should be defined in the network modelling stage. The scheduling algorithm proposed here addresses channel quality Indicators, Buffer status, average delay, and energy consumption. As this algorithm provides cross-layer scheduling with m number of UE and n number of M2M devices, the M2M devices transmit $K{\times}DT_m$ times to the BS, and we require a P number of modulation coding schemes to transmit, which are identical to each other. Considering this scenario, it can be treated as a multiobjective knapsack problem. Therefore, the total number of resource blocks generated by the UE and M2M devices are considered knapsack, and we define all the data transmitted as items. The priority factor for each UE can be denoted as:

$$PF_n = \begin{cases} D_{HoL}\,\theta_n\left(\dfrac{\gamma_{GBR} * \gamma_n(t)}{\gamma_n^k}\right)^{\alpha} + S_n;\ \text{When } UE \in GBR \\ \eta_n\left(\gamma_{NGBR} + S_n\right);\ \text{When } UE \in Non-GBR \end{cases} \tag{15}$$

where D_{HoL} denotes the head of line delay of n^{th} user, θ_n denotes the factor to reduce the power consumption of the device, γ_n (t) is the rate of the n^{th} channel measured at t for UE, γ_n^k represents the average data rate of the nth UE at time t for k^{th} sub-channel, α is exponential factor and S_n denotes the buffer status of each UE for i^{th} service. The nth user equipment with the best channel quality can be defined as:

$$UE_n = \arg \max_n \left\{ Pn.\exp\left(\frac{q_n.\, p_d\ (t)}{d_n + \sqrt{\left(\frac{1}{R\,Tm}\right) \sum_m p_m(t)}} \right) \delta \text{n} \right\} \quad (16)$$

P_n, q_n, and d_n are the adjustable parameters which can be modified in order to attain the best channel quality among various UE and $P_d(t)$ represents the packet delay for each UE which can be represented as:

$$P_d\ (t) = \sum_m \left\{ \frac{-\left(\log \frac{\Delta m}{\beta m}\right)}{RT_m} \right\} \quad (17)$$

where Δm denotes the probability packet delay threshold level, δn denotes the spectral efficiency of a channel for user equipment, RT_m denotes the amount of real time flows, β_m denotes the delay target of UE_n. Each data has some contribution related to the energy efficiency and if the transmitted resource block data is X_m, M2M is transmitted by pth MCS for given slot t, where of knapsack capacity can be given by:

$$\left(1,\ \left\lceil \frac{size\ of\ \left(X_{m,n,i,j}\ \right)}{R_{m,n,i,j}} \right\rceil \right) \quad (18)$$

And its contribution to the energy efficiency can be given by,

$$\frac{size\ of\ data(X_{m,n,i,j})}{\left\lceil \frac{size\ of\ data\ \left(X_{m,n,i,j}\ \right)}{R_{m,n,i,j}} \right\rceil \times f_{m,n,i,j}} \quad (19)$$

From the above relations, a variable $Z_{m,n,i,j}$ is defined and it's clear that data $X_{m,n,i,j}$ is transmitted in t with modulation coding scheme. When $Z_{m,n,i,j}$= 1 otherwise $Z_{m,n,i,j}$= 0. Therefore, the energy optimization be transformed into a 2D knapsack problem and are defined as NP-hand problem. To arrive solution for this NP-hand problem we first reformulate the above condition as the constraint in which the resource blocks are owed in one-time slot, such that it cannot exceed a function S.

$$\sum_{n=1}^{N} \sum_{m=1}^{M} \sum_{i=1}^{DT_i} \sum_{j=1}^{DT_j} \left(Z_{m,n,i,j} * \left\lceil \frac{size\ of\ data(X_{m,n,i,j})}{R_{m,n,i,j}} \right\rceil \right) \le S \quad (20)$$

And the energy distributed for any single resource block (both M2M and UE) must attain the MCS constraint such that,

$$\left\{ \begin{array}{l} \mathrm{E}_{m,n,l,j} + 10\ \log \left\lceil \frac{size\,of\ data\ \left(\mathrm{X}_{m,n,i,j}\right)}{R_{m,n,i,j}} \right\rceil + \\ (\gamma - 1) \times pathlosscomponent \end{array} \right\} \ge (SINR)_{i,j,m,n} \quad (21)$$

The scheduler changes the buffer state depending on the size and information that can be transmitted. If there is any probability that the data from the UE can be associated with the current transit time interval, then the data from UE will be allocated, otherwise any data from M2M devices can be shared in that spectrum. The status of the buffer should be updated on every transmit time interval and it can be defined as:

$$BS(k) = \begin{cases} 0; & if\ k = 0 \\ BS(k-1)\ -\ \eta_m(k-1)\ +\ ds_m(k); & if\ k > 0 \end{cases} \quad (22)$$

where $ds_m(k)$ denotes the data size of the m^{th} UE and k^{th} TTI; $\eta_m(k-1)$ represents the total throughput of the m^{th} user equipment at the past TTI. Let $W_m(k)$ denotes the weighted mean delay of m^{th} UE. w_m^{bd} denotes the buffered data and w_m^{bd} denotes the transmitted data then:

$$W_m(k) = \begin{cases} w_m^{bd} & BS(k) \ge \phi \\ \left(1 - \frac{w_m^k}{\phi}\right) \times w_m^{td} + \frac{w_m(k)}{\phi} \times w_m^{bd} & BS(k) < \phi \end{cases} \quad (23)$$

where φ denotes the size of the window. In order to determine the mean delay, $w_m^{bd}\ (k)$ can be determined as:

$$w_m^{bd}\ (k) = \begin{cases} 0 & for\ k = 0 \\ \frac{\left[w_m^{bd}\ (k-1)\ +\ t\ \right] \times\ BS\ (k-1)}{BS\ (k)} - \frac{w_m\ (k-1)\ \ \eta_m(k-1)}{BS\ (k)} & for\ k > 0 \end{cases} \quad (24)$$

$$w_m^{td}\ (k) = \begin{cases} 0 & for\ k = 0 \\ \left[1 - \frac{\eta_m(k-1)}{\phi - BS(k-1)}\right] \times w_m^{td}\ (k-1) + \frac{\eta_m(k-1)}{\phi - BS(k-1)} \times w_m(k-1) & for\ k > 0 \end{cases} \quad (25)$$

where η_m represents the throughput of the m^{th} UE device and w_m represents the weighted mean delay of the mth UE device.

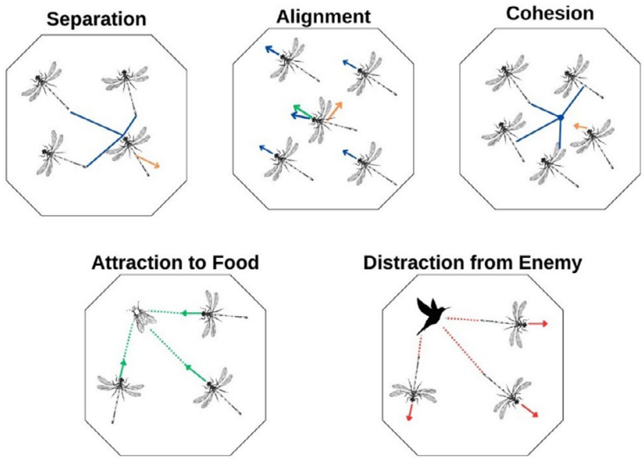

FIGURE 2 Behaviour of dragonfly swarm.

4.2 | Stage II: Levy flight Brownian-based dragonfly optimization

The nature of a dragonfly is that they make small pairs among themselves to pursue and kill other flying insects for their food and separate among themselves to distract their enemies. These two behaviours of dragonflies are identical to two states of optimization procedure using meta-heuristics named exploration and exploitation. To make this dragonfly operation artificial and to create mathematical expressions for solving these optimization problems, there are five weights: separation weight S_{LD}, alignment weight A_{LD}, cohesion weight C_{LD}, food factor weight F_{LD}, enemy factor weight E_{LD}, and inertia weight W_{LD}. These five stages of operation are expressed in Figure 2, in which the objective would be the dragonfly gets attracted to the food and distracted from their enemies.

To obtain the results in the search space, we define various possible dragonfly behaviours. The first step denotes the separation weight, and this behaviour represents the Collison avoidance with the nearest dragonfly. So, if we consider X as the data to be transmitted, then this behaviour infers the avoidance of Collison from the nearest UE and M2M devices. This state is marked as:

$$S_{LD} = -\sum_{g=1}^{M+N} X_{LD} - X_g^{(m+n)} \tag{26}$$

where $M+N$ represents the maximum devices available in the entire single cell scenario and g represents the number of neighbours around the devices. The second step refers to the alignment in which all the neighbouring dragonflies will be matched with the other flies. This refers to the alignment of UE and M2M devices according to the traffic in the network. The alignment can be represented as:

$$ALD = \sum_{g=1}^{M+N} -\left(\frac{V_{mn}}{MN}\right) \tag{27}$$

where m_n represents the product of number of UE and M2M devices and V_{mn} denotes the velocity of transmission of UE and M2M devices. The cohesion factor of the optimization algorithm be defined as:

$$C_{LD} = \frac{\sum_{g=1}^{M+N} X_g^{m+n}}{MN} - X_{LD} \tag{28}$$

The cohesion factor C_{LD} represents the dragonfly sticking together depending upon different scenarios. In cross layer optimization, C_{LD} represents UE and M2M devices sticking together in a giving bandwidth by sharing the same spectral resource. The dragonfly also tends to attract themselves towards their identified food factor and this can be represented as:

$$F_{LD} = X_{Fo} - X_{LD} \tag{29}$$

where X_{Fo} represents the location of the food availability and available of the dragonflies and this compares with the availability of the resource block at the user end for allocating the availability resources according to their priority. XLD represents the amount of resource blocks which are to be transmitted by each UE and M2M devices. The dragonflies tend to repel away from their enemies, and this can be represented as enemy factor weight,

$$E_{LD} = X_{en} + X_{LD} \tag{30}$$

The factors described by food X_{fo} and enemy Xen describe the best and worst positions of the dragonflies. The position of UE and M2M devices can be updated according to the results obtained from the food factor and enemy factor,

$$X_{LD}(t+1) = X_{LD}(t) + \Delta X_{LD}(t+1) \tag{31}$$

where ΔX_{LD} be movement of dragonfly or it is compared with the movement of UE and M2M devices. It is very important to note the moving direction of the flies or the direction of movement of UE and M2M devices and it can be represented as,

$$\Delta X_{LD}\,(t+1) = \begin{pmatrix} a.S_{LD} + b.A_{LD} + c.C_{LD} \\ + d.F_{LD} + e.E_{LD} \end{pmatrix} + \theta \times \Delta X\,(t+1) \tag{32}$$

where a represents a factor related to the separation, b represents a factor related to the alignment, c represents a factor related to the cohesion, d represents a factor related to the food, and e represents a factor related to the enemies, θ represents a factor related to the variation in data resources and t represents the number of iterations. When there are no neighbour dragonflies, they search the pairs around the space by using Levy flight and the position can be updated as,

$$X_{t+1}^{LD} = X_t^{LD} + Levy(f).X_t^{LD} \tag{33}$$

where f denotes the frequency factor of the updated dragonfly position and this can be represented as,

$$Levy(f) = 0.28 \times \frac{g_1 \times \beta}{|g_2|^{\frac{1}{\alpha}}} \tag{34}$$

where g_1 and g_2 represents the random value which varies as (0,1) and α represents a constant value which can be 1.46 here and β is represented as,

$$\beta = \left(\frac{\Gamma\ (1+\alpha) \cdot \sin\ \left(\frac{\pi}{2}\right)\alpha}{\Gamma\ \left(\frac{1+\alpha}{2}\right) \cdot\ \ \sqrt{\frac{\alpha}{2}} \times 2^{(\alpha-1)}} \right)^{\frac{1}{\alpha}} \tag{35}$$

where $\Gamma(\alpha) = (\alpha - 1)!$. The DELFDO algorithm proposed in this work to rank the UE and M2M devices not only based upon their QCI values but also based upon their urgency factor and priority factor with lower energy devices available in cell. To provide energy efficiency and allocate resource for UE and M2M devices according to the DELFDO algorithm. A Levy flight factor β is proposed to adjust the priority factors among the users in base sectors. The value of β should be carefully selected to rank with the UE and M2M devices according to the priority factor, low delay, and low power consumption. This situation can be elaborated by defining utility function of DELFDO algorithm,

$$L_m\,(k) = \beta \times W_m\,(k) + (1-\beta)\,E_m\,(k)\ ; \quad 0 \leq \beta \leq 1 \tag{36}$$

where $E_m(k)$ denotes the energy efficiency, and the value of F varies from 0 to 1. When the value of β is set to 0 and 1, then the algorithm does not provide the energy Efficiency and QOS constraints are not resolved. The Levy flight dragonfly algorithm is proposed to optimize the value of β and at each step the location of the UE and M2M devices are updated. The periodic motion of the dragonflies is spread over time with a normal distribution, involving sudden jumps and random motions resembling vibrations. The Brownian motion steps are determined using a Gaussian distribution, and the equation is adjusted based on the algorithm's agent size and number, thereby finalizing the Brownian motion. The updated position can be given as,

$$X_{t+1}^{LD} = X_t^{LD} + \sqrt{\frac{T}{M}}\,rand() \ *\ \frac{1}{b\sqrt{2\Pi}}e^{\left(\frac{V_D - A_G}{2b^2}\right)} \tag{37}$$

The symbol T represents the time period for the motion of a dragonfly, set at 0.01 in this work. In Equation (37), the term M indicates the proportion of sudden motions for the same agent over time. V_D stands for dimensions, and A_G represents agents.

To validate the β in our proposed DELFDO algorithm, we define a fitness function F is given by,

$$F = \max \sum_{m=1}^{M} \sum_{n=1}^{N} (L_m\,(k) \times \eta_m) + (L_n\,(k) \times \eta_n) \tag{38}$$

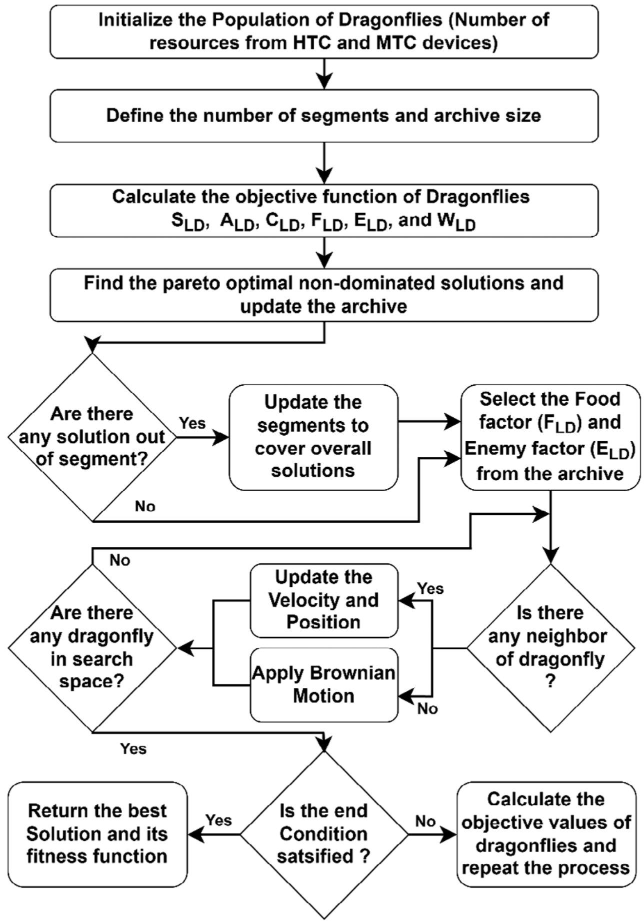

FIGURE 3 Flowchart representing the operation of Levy flight Brownian-based dragonfly optimization.

where η depends on the throughput of the UE and M2M devices and the condition can be described as,

$$\eta\,(k) \leq \sum_{m=1}^{RB} \sum_{n=1}^{RB} W_{m,n}\,(k)\,; \qquad i,j \in RB \tag{39}$$

$$\sum_{m=1}^{M} \sum_{n=1}^{N} B_s\,(k)\ \leq\ size\ of\ buffer\ in\ resource\ block \tag{40}$$

Buffer status reports depend upon the size of buffer. When there is no delay in transmitting data then the size of buffer will also be decreased, and this describes the optimal value of β by evaluating the fitness function. Once the value of β is evaluated then according to the estimated utility function and priority value, ranks will be allocated to the UE and M2M devices.

Figure 3 represents the step-by-step optimization process using Levy flight Brownian-based dragonfly optimization. In multiobjective optimization, we start by placing dragonflies randomly in the search space. We set the maximum archive size and define the number of segments. Using their current positions, we generate solutions that do not dominate each other. If the archive is full, we remove some solutions and add new ones. The hypersphere is updated to cover all solutions if needed. For dragonflies with neighbours, we calculate the velocity vector and update the position. If there are no neighbours, we use Brownian motion to find a solution and adjust the position. We then check if the dragonflies are within the search space. The best and worst solutions in the archive are chosen as nutrient sources and enemies, respectively.

4.3 | Stage III: Resource allocation

This stage represents the allocation of resources to UE and M2M devices based upon the proposed DELFDO algorithm by considering their bandwidth requirements. The algorithm begins by examining the availability of resource blocks from the UE and M2M devices and scheduler. When the resource blocks are found at the input, the algorithm explores whether there are starving UE and M2M devices by considering the priority factor of the available resources. The second step in the resource allocation algorithm examines the buffer status report. δ_f the buffer status is empty and continuous to check whether there are striving UE and M2M devices. When the buffer status is not empty the algorithm checks the quantity of resources available. When the resource availability is for only one UE, then the radio resource blocks are all allocated to the specified UE and M2M devices. When there are a greater number of resource blocks for multiple UE and M2M devices the scheduler proceeds with the next step. In the third step the scheduler calculates resource blocks and the availability of UE and M2M devices. For the number of UE and M2M devices less than that number of resources, the resources are allocated to the users based upon round robin fashion. When the number of UE and M2M devices are greater than the number of resources, the resources are allocated to the users based upon the calculated utility function in phase 2. The remaining unallocated resources to the UE and M2M devices are again fed to the first round of the scheduler.

The complexity of the proposed DELFDO algorithm is analyzed based upon the resource allocation time per transit time interval. The parameter to calculate the time complexity of DELFDO algorithm includes the size of dragonfly (D_s) and the maximum number of redundant bits (r_{max}) which does not vary by the increase of resource blocks. The time Complexity of DELFDO algorithm can be given as O (PRB log UE) + O (Ds $\times$ r_{max}) for every transit time interval. From this analysis, it is predicted that the time complexity of DELFDO algorithm has minimum effects on the entire resource allocation process.

5 | RESULTS AND DISCUSSION

The performance evaluation of the proposed optimal algorithm in terms of throughput, average PDBV of MTCDs, Energy efficiency, Resource block utilization, fairness index, packet loss ratio and percentage of unserved resources in delay were discussed in this section. Discrete event simulation without inter-cell interference is conducted where M2M communication consists of one eNodeB and N MTCDs. The theoretical and practical values are validated by just substituting the arrival rate of MTCDs/UEs in the derived equations. The distribution of the arrival rate of users is uniform with the values as in Table 2. Outcomes of the proposed scheme is compared with HORA and CRBA algorithm [20]; whale optimization algorithm (WOA)-based resource allocation scheme [25]; RSMA technique with Han–Kobayashi scheme for RA in multi-cell mm-wave environment [29]; amended barnacles mating optimizer-based RA algorithm(ABMO) [24] and energy-aware mode selection for D2D resource allocation using Hungarian algorithm [19]. Unit cell that are uniformly distributed MTCDs and H2H UEs are considered. Due to the presence of additive white Gaussian noise (AWGN) path loss and shadowing effect takes place. SNR at receiver projects that value of CQI is determined by schedulers. Voice-over-IP (VoIP) and video applications are respectively sources of H2H traffic and M2M traffic as shown in Table 2.

TABLE 2 Simulation parameters.

Parameter	Value
Cell radius	500 m
Number of eNB	1
Simulation period	1000 TTIs
Distances between MTCDs and eNB	20–300 m
Transmitter power	23 dBm
Noise figure	18 dB
H2H arrival rate	64, 128, 256 kbps
M2M arrival rate	10, 20, 30, 40 kbps
Distribution of MTCDs/UEs	Fixed and uniform
Delay bound	0.2 ms
Bandwidth	20 MHz
Number of PRBs	180
Number of sensor types on each MTCD	5–12
Maximum PDBV	10%
Propagation loss	Urban macro cell model
Placement of HTC UES and MTC devices	Random

Figure 5 shows the comparison of energy efficiency for the proposed DELFBDO technique by varying the HTC UEs from 10 to 70 with fixed MTC devices as 10 and by varying the HTC UEs from 10 to 70 by varying the MTC devices from 10 to 70. When the value of MTCDs increases, communication is scattered, which consumes higher energy. Because of the increase in MTCDs the available RBs are in scarceness to convey all the sensory data and hence few may be lost. By proper scheduling of data packets to MTCDs, the proposed scheme helps to achieve higher energy efficiency. The average energy efficiency for a fixed number of MTC device as 10 and number of HTC UEs as 10 of the proposed the proposed DELFBDO technique is 2.8% higher than the Hungarian algorithm, 6.7% higher than the HORA and CBRA algorithm, 12.2% higher than the WOA, 17% higher than the ABMO, 24.8% higher than the RSMA technique. When the number of HTC UEs increase to 70 with a fixed number of MTC devices as 10, the proposed DELFBDO technique is 2.3% higher than the Hungarian algorithm, 4.9%

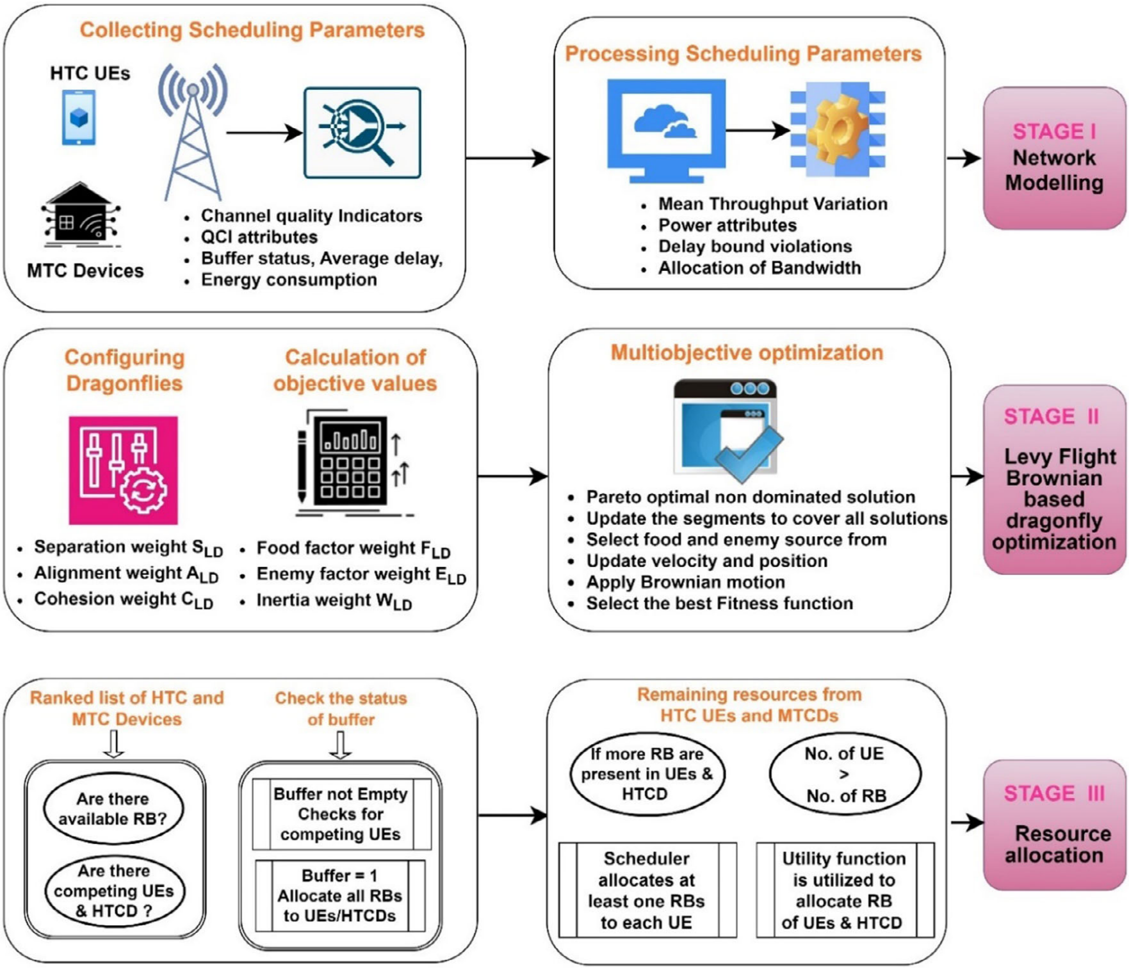

FIGURE 4 Resource allocation process in a cross-layer environment by using Levy flight Brownian-based dragonfly optimization algorithm for HTC-UEs and MTC devices.

higher than the HORA and CBRA algorithm, 8.1% higher than the WOA, 10.1% higher than the ABMO, 12.5% higher than the RSMA technique. When the number of HTC UEs increase to 70 with an increase in number of MTC devices as 70, the proposed DELFBDO technique is 2.2% higher than the Hungarian Algorithm, 5.9% higher than the HORA and CBRA algorithm, 10.5% higher than the WOA, 12.7% higher than the ABMO, 20.9% higher than the RSMA technique. The practical results demonstrate that the proposed DELFBDO technique outperforms alternative scheduling algorithms by achieving the lowest energy consumption.

Figure 6 shows the comparison of Average system throughput for the Proposed DELFBDO technique by varying the HTC UEs from 50 to 300 with fixed MTC devices as 50 and by varying the HTC UEs from 50 to 300 by varying the MTC devices from 50 to 300. Mean throughput variation refers to the statistical measure of how the achieved data throughput fluctuates or changes over time. It is commonly expressed as the standard deviation or variance of the data throughput values obtained during a certain period. The average system throughput for a fixed number of MTC devices as 50 and number of HTC UEs as 50 of the proposed DELFBDO technique is 30.4% higher than the Hungarian algorithm, 16.2% higher than the HORA and CBRA algorithm, 8.8% higher than the WOA, 20.7% higher than the ABMO, 2.6% higher than the RSMA technique. When the number of HTC UEs increase to 300 with a fixed number of MTC devices as 50, the proposed DELFBDO technique is 29.3% higher than the Hungarian algorithm,41.7% higher than the HORA and CBRA algorithm, 27.5% higher than the WOA, 13.9% higher than the ABMO, 6.9% higher than the RSMA technique. When the number of HTC UEs increase to 300 with an increase in the number of MTC devices as 300, the proposed DELFBDO technique is 25% higher than the Hungarian algorithm, 16.2% higher than the HORA and CBRA algorithm, 30.2% higher than the WOA, 5% higher than the ABMO, 13.4% higher than the RSMA technique. With a small number of users, all scheduling algorithms exhibit consistent throughput, utilizing sufficient RBs to transmit queued data. However, as the user count increases, the proposed DELFBDO technique stands out by achieving maximum throughput, selecting the most efficient channel for transmission.

Figure 7 shows the comparison of Fairness Index for the Proposed DELFBDO technique by varying the HTC UEs from

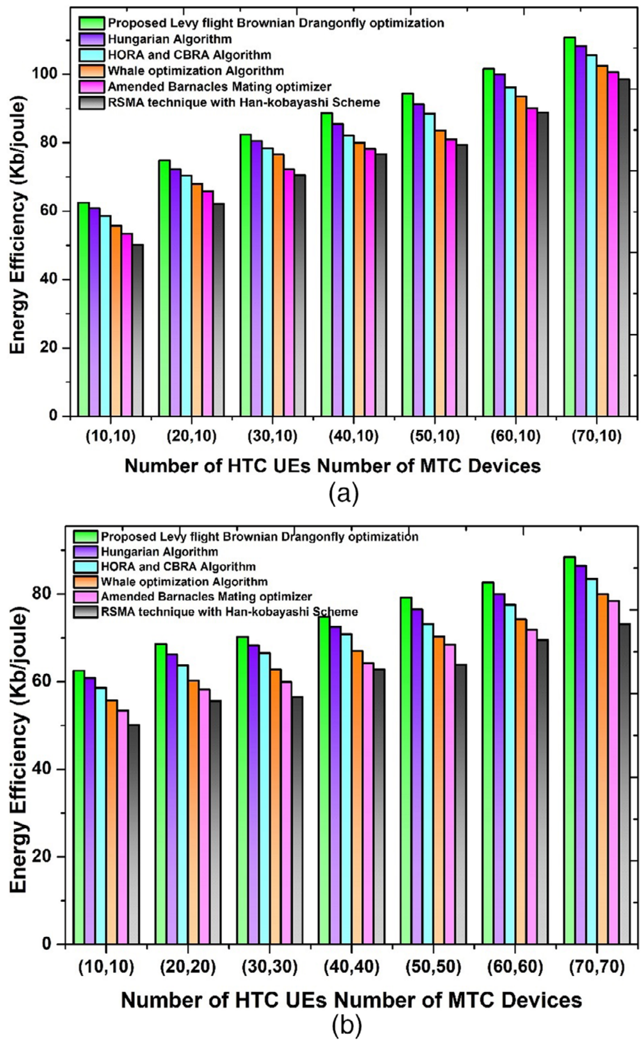

FIGURE 5 Comparison of energy efficiency for the proposed DELFBDO technique. (a) When number of HTC UEs are varied by fixing the MTC devices to 10. (b) When number of HTC UEs are varied by varying the MTC devices.

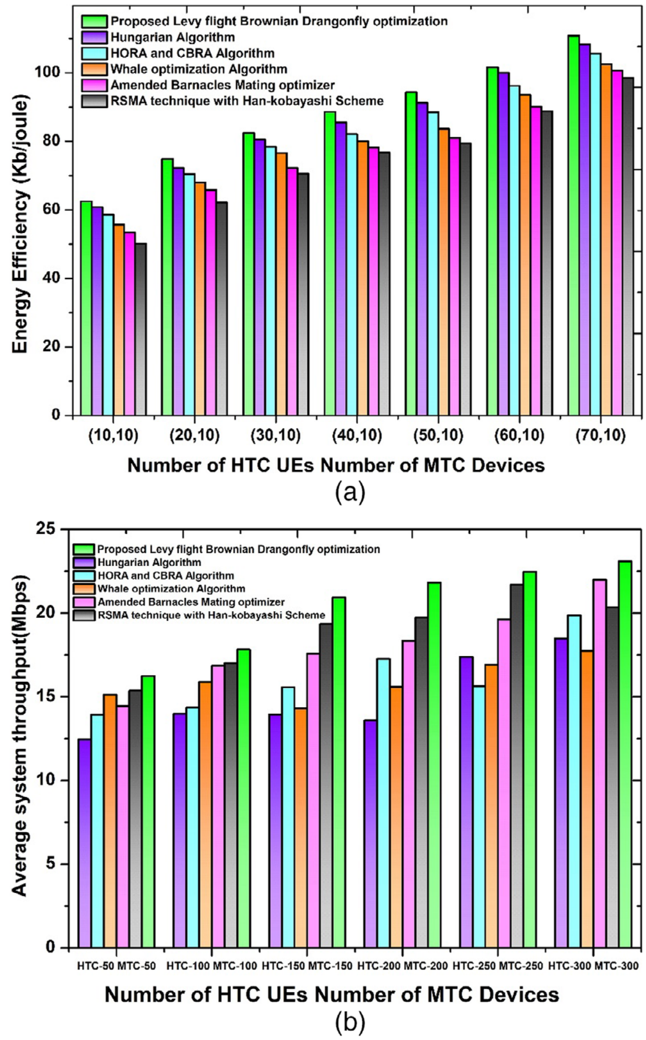

FIGURE 6 Comparison of average system throughput for the proposed DELFBDO technique. (a) When number of HTC UEs are varied by fixing the MTC devices. (b) when number of HTC UEs are varied by varying the MTC devices.

10 to 100 with fixed MTC devices as 10 and by varying the HTC UEs from 10 to 100 by varying the MTC devices from 10 to 100. Jain's fairness index is used to calculate the fairness index of the user. It quantifies how equitably the available radio resources are distributed among users, ensuring that no user experiences significant disadvantage in terms of data rate or QoS. Index varies from 0 to 1 with 1 to be the highest. The average Fairness Index for a fixed number of MTC devices as 10 and number of HTC UEs as 10 of the proposed the proposed DELFBDO technique is 3.1% higher than the Hungarian algorithm, 8.7% higher than the HORA and CBRA algorithm, 16.3% higher than the WOA, 23.5% higher than the ABMO, 31.6% higher than the RSMA technique. When the number of HTC UEs increase to 100 with a fixed number of MTC devices as 10, the proposed DELFBDO technique is 10% higher than the Hungarian algorithm, 22.2% higher than the HORA and CBRA algorithm, 37.5% higher than the WOA, 46.7% higher than the ABMO, 69.2% higher than the RSMA technique. When the number of HTC UEs increase to 100 with an increase in the number of MTC devices as 100, the proposed DELFBDO technique is 14.3% higher than the Hungarian algorithm, 27% higher than the HORA & CBRA algorithm, 33.3% higher than the WOA, 45.5% higher than the ABMO, 77.8% higher than the RSMA technique. The proposed scheduler achieves a balance among various QCI, enabling improved response times for individual applications, with simulation results demonstrating superior fairness compared to conventional schedulers.

Figure 8 shows the comparison of resource block utilization for the proposed DELFBDO technique by varying the HTC UEs and MTC devices from 100 to 700 with an increment of 50 users. The resource block utilization for when the number of both HTC UEs and MTC devices is 100 for the proposed the proposed DELFBDO technique is 4.7% higher than the Hungarian algorithm, 8.7% higher than the HORA and CBRA algorithm, 17% higher than the WOA, 23.5% higher than the ABMO, 29.9% higher than the RSMA technique. When the

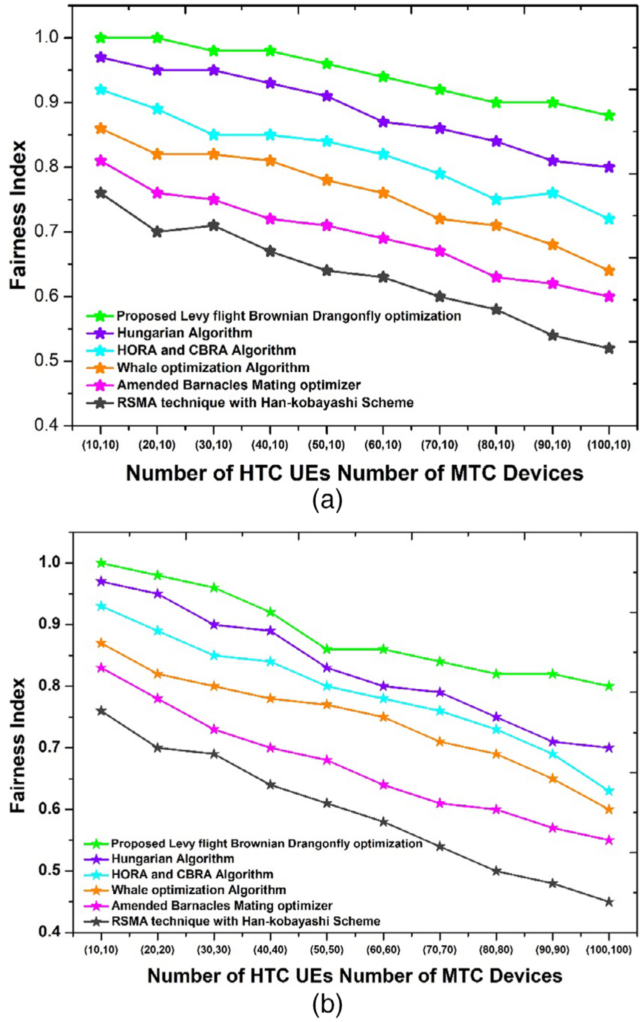

FIGURE 7 Comparison of fairness index for the proposed DELFBDO technique. (a) When number of HTC UEs are varied by fixing the MTC devices. (b) When number of HTC UEs are varied by varying the MTC devices.

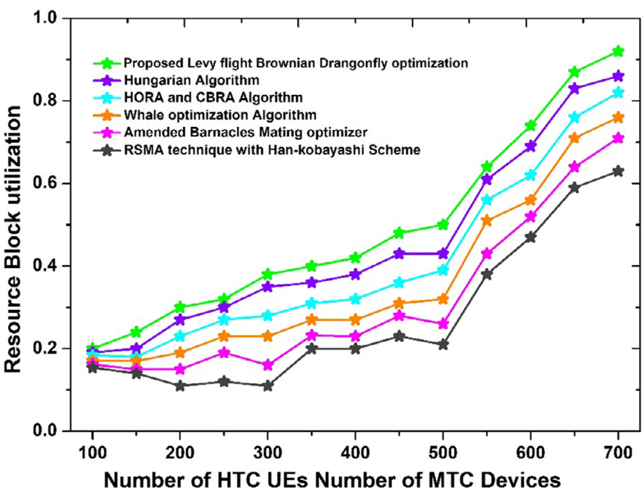

FIGURE 8 Comparison of Resource block utilization for the proposed DELFBDO technique when number of HTC UEs and MTC devices increases from 100 to 700.

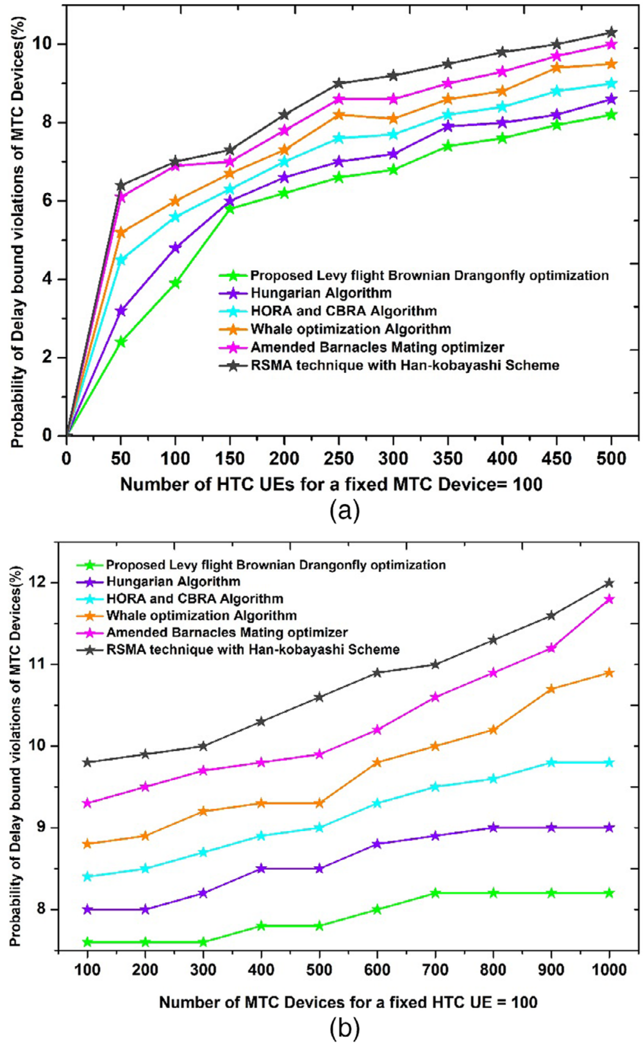

FIGURE 9 Comparison of average PDBV for the proposed DELFBDO technique. (a) When number of HTC UEs are varied by fixing the MTC devices. (b) When number of HTC UEs are fixed by varying the MTC devices.

number of HTC UEs and MTC devices increases to 700, the proposed DELFBDO technique is 7% higher than the Hungarian algorithm, 12.2% higher than the HORA and CBRA algorithm, 21.1% higher than the WOA, 29.6% higher than the ABMO, 46% higher than the RSMA technique.

Figure 9 shows the comparison of average probability of delay bound violation (PDBV) for the proposed DELFBDO technique by varying the HTC UEs from 50 to 500 with fixed MTC devices as 100 and by fixing the HTC UEs as a constant of 100 users with the variation in MTC devices from 100 to 1000. This metric represents the average potential benefit in terms of delay reduction or network performance improvement that can be achieved by scheduling critical MTCDs at specific times. In the context of LTE-A, critical MTCDs could be high-priority data packets, real-time communication, or tasks with strict latency requirements. The average PDBV for a fixed number of MTC devices as 100 and number of HTC UEs as 50 for the proposed the proposed DELFBDO technique is 25% higher than the Hungarian algorithm, 46.7% higher than the

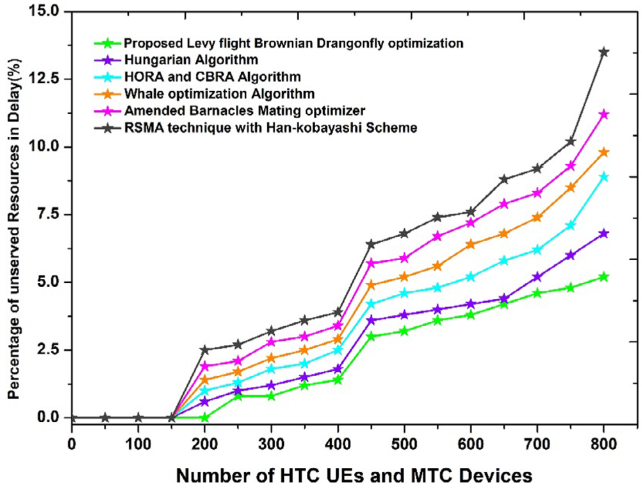

FIGURE 10 Comparison of percentage of unserved resources in delay for the proposed DELFBDO technique when number of HTC UEs and MTC devices increases from 100 to 800.

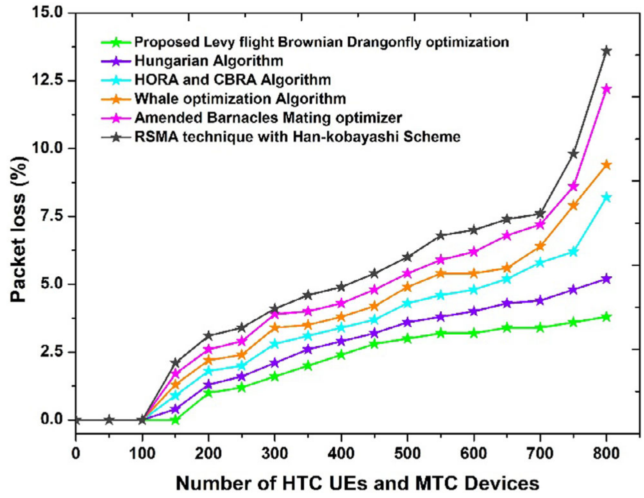

FIGURE 11 Comparison of Percentage of packet loss for the Proposed DELFBDO technique when number of HTC UEs and MTC devices increases from 100 to 800.

HORA and CBRA algorithm, 53.8% higher than the WOA, 60.7% higher than the ABMO, 62.5% higher than the RSMA technique. When the number of HTC UEs increase to 500 with a fixed number of MTC devices as 100, the proposed DELFBDO technique is 4.7% higher than the Hungarian algorithm, 8.9% higher than the HORA and CBRA algorithm, 13.7% higher than the WOA, 18% higher than the ABMO, 20.4% higher than the RSMA technique. On the other hand, when the number of HTC UEs is fixed to 100 with an increase in the number of MTC devices as 100, the proposed DELFBDO technique is 5% higher than the Hungarian algorithm, 9.5% higher than the HORA and CBRA algorithm, 13.6% higher than the WOA, 18.3% higher than the ABMO, 22.4% higher than the RSMA technique. When the number of HTC UEs is fixed to 100 with an increase in the number of MTC devices as 1000, the proposed DELFBDO technique is 8.9% higher than the Hungarian algorithm, 16.3% higher than the HORA and CBRA algorithm, 24.8% higher than the WOA, 30.5% higher than the ABMO, 31.7% higher than the RSMA technique. Higher availability of users allows for better optimization of resource allocation and scheduling of critical MTCDs, leading to a higher potential for delay reduction and improved network performance. On the other hand, low availability of users may limit the potential benefits of scheduling techniques, impacting overall network efficiency and latency.

Figure 10 shows the comparison of percentage of unserved Resources in delay for the proposed DELFBDO technique by varying the HTC UEs and MTC devices from 100 to 800 with an increment of 50 users. The percentage of unserved nodes in delay refers to the proportion of user equipment (UEs) or nodes that experience delays beyond a certain threshold or fail to receive service within an acceptable time frame. Mathematically, the formula for calculating the percentage of unserved nodes in delay is percentage of unserved nodes in delay = (number of unserved nodes/total number of nodes) × 100. The percentage of unserved nodes in delay when the number when the number of both HTC UEs and MTC devices is 300 for the proposed DELFBDO technique is 33.3% higher than the Hungarian algorithm, 55.6% higher than the HORA and CBRA algorithm, 63.6% higher than the WOA, 71.4% higher than the ABMO, 75% higher than the RSMA technique. When the number of HTC UEs combined with MTC devices increases to 800, the proposed DELFBDO technique is 23.5% higher than the Hungarian algorithm, 41.6% higher than the HORA and CBRA algorithm, 46.9% higher than the WOA, 53.6% higher than the ABMO, 61.5% higher than the RSMA technique. Proposed algorithm provides the best performance in serving LTE-M devices due to their urgency consideration in scheduling.

Figure 11 shows the comparison of percentage of packet Loss for the proposed DELFBDO technique by varying the HTC UEs and MTC devices from 100 to 800 with an increment of 50 users. Monitoring and managing the packet loss rate is essential for LTE-A network operators to ensure reliable data transmission and a satisfactory QoS for users. It refers to the statistical measure of the percentage of data packets that are lost or discarded during transmission between the user equipment (UE) and the eNodeB. The percentage of packet loss when the number of both HTC UEs and MTC devices is 300 for the proposed DELFBDO technique is 23.8% higher than the Hungarian algorithm, 42.9% higher than the HORA and CBRA algorithm, 52.9% higher than the WOA, 59% higher than the ABMO, 61% higher than the RSMA technique. When the number of HTC UEs combined with MTC devices increases to 800, the proposed DELFBDO technique is 26.9% higher than the Hungarian algorithm, 53.7% higher than the HORA and CBRA algorithm, 59.6% higher than the WOA, 68.9% higher than the ABMO, 72.1% higher than the RSMA technique.

6 | CONCLUSION

Joint delay and energy aware Levy flight Brownian movement-based dragonfly optimization scheduling algorithm for uplink

LTE channel is presented. The proposed algorithm targets energy consumption in eNB at trade off with the delay requirements of UEs. This is achieved in three processes. First, the scheduling parameters are obtained and checked. In the next phase, the algorithm optimizes α which is used in the calculation of utility function to rank UEs in an order that maximizes the fitness function. Finally, the scheduler allocates the available RBs based on a ranked list. These make the DELFBDO algorithm to dynamically improvise overall system performance. The proposed algorithm is outperformed by other techniques when considering individual performance parameters. But it is essential to consider multiple evaluation metrics at once for all proposed schemes. In a generic way, the simulated results demonstrate proposed algorithm shows a balanced performance among other scheduling algorithms by sustaining least power consumption. By intelligently allocating resources, these algorithms can enhance network performance, improve user experience, and efficiently utilize available network resources.

AUTHOR CONTRIBUTIONS

The authors of this paper contributed to the research and preparation of the manuscript in the following ways: **Leeban Moses:** Conceptualization; methodology; software; data curation; writing—original draft. **Perarasi Sambantham:** Methodology; formal analysis; supervision. **Muhammad Faheem:** Software; data curation; data validation; review and editing. **Shoukath Ali:** Investigation; visualization; data validation; project administration. **Arfat Ahmad Khan:** Conceptualization; data curation; data validation; review & editing.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

FUNDING INFORMATION

The authors would like to thank their affiliated institutes for supporting this study.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available upon request from the corresponding author. Due to privacy and ethical considerations, the datasets generated and/or analyzed during the current study are not publicly available. However, the authors are committed to facilitating access to the data for replication, validation, and further research purposes.

ORCID

Leeban Moses https://orcid.org/0000-0001-7468-1660
Muhammad Faheem https://orcid.org/0000-0003-4628-4486
Shoukath Ali K https://orcid.org/0000-0001-9256-373X

REFERENCES

1. González, E.E., Estrada, Y., Garcia-Roger, D., Monserrat, J.F.: Performance evaluation and optimal management of mode 2 V2X communications in 5G networks. IEEE Access 11, 128810–128825 (2023). https://doi.org/10.1109/access.2023.3333680
2. Mai Do, H., Tran, T.P., Yoo, M.: Deep reinforcement learning-based task offloading and resource allocation for industrial IoT in MEC federation system. IEEE Access 11, 83150–83170 (2023). https://doi.org/10.1109/ACCESS.2023.3302518
3. Li, J., Guan, W., Tang, Z.: A Resource allocation scheme for packet delay minimization in multi-tier cellular-based IoT networks. Mathematics 11(21), 4538 (2023). https://doi.org/10.3390/math11214538
4. Camargo, J.S., et al.: Dynamic slicing reconfiguration for virtualized 5G networks using ML forecasting of computing capacity. Comput. Networks 236, 110001 (2023). https://doi.org/10.1016/j.comnet.2023.110001
5. Mughees, A., et al.: Energy-efficient joint resource allocation in 5G HetNet using multi-agent parameterized deep reinforcement learning. Phys. Commun. 61, 102206 (2023). https://doi.org/10.1016/j.phycom.2023.102206
6. Guo, Q., Tang, F., Kato, N.: Resource allocation for aerial assisted digital twin edge mobile network. IEEE J. Sel. Areas Commun. 41(10), 3070–3079 (2023). https://doi.org/10.1109/JSAC.2023.3310065
7. Elsayem, M., Abou-Zeid, H., Afana, A., Givigi, S.: Intelligent resource allocation for grant-free access: a reinforcement learning approach. IEEE Networking Lett. 5(3), 154–158 (2023). https://doi.org/10.1109/lnet.2023.3299182
8. Hegde, A., Song, R., Festag, A.: Radio resource allocation in 5G-NR V2X: a multi-agent actor-critic based approach. IEEE Access 11, 87225–87244 (2023). https://doi.org/10.1109/ACCESS.2023.3305267
9. Bruun, R.L., Santiago Garcia, C.M, Sorensen, T.B., Pratas, N.K., Madsen, T.K., Mogensen, P.: Signaling design for cooperative resource allocation and its impact to message reliability. IEEE Access 11, 103569–103584 (2023). https://doi.org/10.1109/ACCESS.2023.3317269
10. Eswaramoorthi, R., Leeban Moses, M., Sahul Hameed, J.B., Ghanti, B.: Deep graph neural network optimized with fertile field algorithm based detection model for uplink multiuser massive multiple-input and multiple-output system. Trans. Emerg. Telecommun. Technol. 33(12), e4614 (2022). https://doi.org/10.1002/ett.4614
11. Shirkolaei, M.M., Jafari, M.: A new class of wideband microstrip falcate patch antennas with reconfigurable capability at circular-polarization. Microwave Opt. Technol. Lett. 62(12), 3922–3927 (2020). https://doi.org/10.1002/mop.32529
12. Shirkolaei, M.M., Ghalibafan, J.: Scannable leaky-wave antenna based on ferrite-blade waveguide operated below the cutoff frequency. IEEE Trans. Magn. 57(4), 1–10 (2021). https://doi.org/10.1109/TMAG.2021.3060683
13. Maleki, A., Oskouei, H.D., Mohammadi Shirkolaei, M.: Miniaturized microstrip patch antenna with high inter-port isolation for full duplex communication system. Int. J. RF Microwave Comput. Aided Eng. 31(9), e22760 (2021). https://doi.org/10.1002/mmce.22760
14. Aziz, W.A., Ioannou, I.I., Lestas, M., Qureshi, H.K., Iqbal, A., Vassiliou, V.: Content-aware network traffic prediction framework for quality of service-aware dynamic network resource management. IEEE Access 11, 99716–99733 (2023). https://doi.org/10.1109/ACCESS.2023.3309002
15. Paymard, P., Amiri, A., Kolding, T.E., Pedersen, K.I.: Optimizing mixed capacity of extended reality and mobile broadband services in 5G-advanced networks. IEEE Access 11, 113324–113338 (2023). https://doi.org/10.1109/ACCESS.2023.3323815
16. Sultan, M.T., El Sayed, H.: QoE-aware analysis and management of multimedia services in 5G and beyond heterogeneous networks. IEEE Access 11, 77679–77688 (2023). https://doi.org/10.1109/ACCESS.2023.3298556
17. Moses, M.L., Kaarthick, B.: Multiobjective cooperative swarm intelligence algorithm for uplink resource allocation in LTE-A networks. Trans. Emerging Telecommun. Technol. 30(12) (2019). https://doi.org/10.1002/ett.3748
18. Abdelsadek, M.Y., Gadallah, Y., Ahmed, M.H.: Matching-based resource allocation for critical MTC in massive MIMO LTE networks. IEEE Access 7, 127141–127153 (2019). https://doi.org/10.1109/ACCESS.2019.2939120
19. Tsai, H.C., Kao, S.J., Huang, Y.L., Chang, F.M.: Energy-aware mode selection for D2D resource allocation in 5G networks. Electronics 12(19), 4054 (2023). https://doi.org/10.3390/electronics12194054
20. Kukade, S., Sutaone, M., Patil, R.: Optimal performance of resource allocation in LTE-A for heterogeneous cellular network. Wireless Networks 27(5), 3329–3344 (2021). https://doi.org/10.1007/s11276-021-02635-w

21. Abdelsadek, M.Y., Ahmed, M.H., Gadallah, Y.: Cross-layer resource allocation for critical MTC coexistent with human-type communications in LTE: A two-sided matching approach. IET Commun. 14(18), 3223–3230 (2020). https://doi.org/10.1049/iet-com.2019.0944
22. Gatti, R., Shankar, S.: Bidirectional resource scheduling algorithm for advanced long term evolution system. Eng. Rep. 2(7), e12192 (2020). https://doi.org/10.1002/eng2.12192
23. Liu, J.S., Lin, C.H.R., Hu, Y.C.: Joint resource allocation, user association, and power control for 5G LTE-based heterogeneous networks. IEEE Access 8, 122654–122672 (2020). https://doi.org/10.1109/ACCESS.2020.3007193
24. Mohammadnejad, Z., Al-Khafaji, H.M.R., Mohammed, A.S., Alatba, S.R.: Energy optimization for optimal location in 5G networks using improved barnacles mating optimizer. Phys. Commun. 59, 102068 (2023). https://doi.org/10.1016/j.phycom.2023.102068
25. Sing, R., Bhoi, S.K., Panigrahi, N., Sahoo, K.S., Jhanjhi, N., AlZain, M.A.: A whale optimization algorithm based resource allocation scheme for cloud-fog based IoT applications. Electronics 11(19), 3207 (2022). https://doi.org/10.3390/electronics11193207
26. da Mata, S.H., Guardieiro, P.R.: Resource allocation for the LTE uplink based on Genetic Algorithms in mixed traffic environments. Comput. Commun. 107, 125–137 (2017). https://doi.org/10.1016/j.comcom.2017.04.004
27. Sui, W., Chen, X., Zhang, S., Jiang, Z., Xu, S.: Energy-efficient resource allocation with flexible frame structure for hybrid eMBB and URLLC services. IEEE Trans. Green Commun. Networking 5(1), 72–83 (2021). https://doi.org/10.1109/TGCN.2020.3028202
28. Chen, Y.-L., Lin, Y.-H., Chen, H.-Y., Hung, K.-C.: Energy efficient resource allocation algorithms combining PSO with FLC and Taguchi method in hybrid opportunistic networks. Appl. Soft Comput. J. 148(129), 110717 (2023). https://doi.org/10.24433/CO.0
29. Sarma, S.S., Hazra, R., Goswami, P.: Power optimization in a multicell D2D communication for smart city in an mm-wave cellular network: an mIoT perspective. IEEE Internet Things J. 10(21), 18686–18694 (2023). https://doi.org/10.1109/JIOT.2023.3262577
30. Singh, U., et al.: Scalable priority-based resource allocation scheme for M2M communication in LTE/LTE-A network. Comput. Electr. Eng. 103, 108321 (2022). https://doi.org/10.1016/j.compeleceng.2022.108321
31. Cao, Y., Zhong, Y., Peng, X., Pan, S.: Energy efficiency maximization for hybrid-powered 5G networks with energy cooperation. Electronics 11(10), 1605 (2022). https://doi.org/10.3390/electronics11101605

How to cite this article: Moses, L., Sambantham, P., Faheem, M., Ali K, S., Khan, A.A.: Joint delay and energy aware dragonfly optimization-based uplink resource allocation scheme for LTE-A networks in a cross-layer environment. J. Eng. 2024, e12353 (2024). https://doi.org/10.1049/tje2.12353