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# Dragonfly-Based Joint Delay/Energy LTE Downlink Scheduling Algorithm

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**ABSTRACT** Managing radio resources in Long Term Evolution (LTE) networks is considered as one of the essential design factors for enhancing the overall system performance. Common approaches are introduced to either achieve fairness between network users or attain maximum spectral efficiency. However, these approaches do not consider optimizing energy consumption. Therefore, in this paper, a novel resource allocation algorithm based on the Dragonfly metaheuristic technique is proposed to allocate bandwidth to users. The new algorithm is called Dragonfly-based Joint Delay/Energy (DJDE) and considers the Quality of Services (QoS) requirements of the users while achieving a high level of energy efficiency. The proposed solution utilizes the Dragonfly algorithm to optimize the integration process of different scheduling policies. To evaluate the proposed algorithm, an extensive set of experiments are conducted to compare the proposed solution to the state-of-the-art techniques. Also, to assess the energy efficiency of the proposed method, another set of experiments are simulated to compare it with various algorithms that optimize energy consumption. The obtained results prove that the DJDE algorithm can satisfy the QoS requirements of the users while improving the overall system performance.

**INDEX TERMS** Dragonfly algorithm, LTE, resource allocation, scheduling.

### **I. INTRODUCTION**

With the growth of the demand for internet services, such as e-mail, file sharing, voice over IP, web browsing, video streaming, and wireless sensor networks, new challenges arise in the design of the cellular networks. As a result, the Long Term Evolution (LTE) was proposed to face some of these challenges and give an answer to these needs. LTE networks, based on Orthogonal Frequency Division Multiple Access (OFDMA), are designed to support a wide range of services of high rate, low latency multimedia Internet services with high mobility, and improved spectral efficiency [1]. In downlink/uplink transmission, the time domain is structured into frames, sub-frames, and slots. Each frame has 10 ms duration and 10 sub-frames. A sub-frame is formed by two adjacent slots of 0.5 ms each. The smallest time-frequency resource unit is known as a resource element. It is defined as one subcarrier in one OFDM symbol. A group of 12 contiguous subcarriers (180 kHz) over a one-time slot forms the Resource Block (RB) [1].

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To allocate resources to users, scheduling is performed in units of RBs. As a consequence of the limited availability of radio resources, the efficient use of these resources is inevitable. To achieve these requirements, many techniques are proposed to improve different network operations such as scheduling [2], Adaptive Modulation and Coding (AMC) [3], and resource sharing and optimization [4]. Although the radio resource management jointly exploits the advanced Medium Access Control (MAC) and physical functions, the scheduling is a MAC layer technique. Since the scheduling technique has no standard and is an implementation-specific, efficient scheduling technique is a crucial factor that affects the performance of different LTE network systems.

Also, the efficient use of radio resources is the main target of the system performance to meet user needs for specific Quality of Services (QoS). Since maintaining the bandwidth and guaranteeing the transmission parameters such as delay and bit error rate (BER) are considered as essential requirements to the applications, the QoS guarantee becomes necessary for communicating with different delay conditions. Therefore, different QoS-aware scheduling algorithms have been proposed to support real-time services among

applications. The packet scheduler at evolved NodeB (eNB) is used to assign portions of the shared spectrum among users according to certain strategies [5]. To achieve maximum spectral efficiency, the packet scheduler is used through an effective resource allocation technique. In fact, wireless channel quality is affected by several issues, such as fading, multipath propagation and Doppler effect and so on. In this sense, channel-aware scheduling and resource allocation algorithms [6] have been adopted in OFDMA systems by assigning RBs to users based on channel quality indicator (CQI) reports, which are regularly sent between User Equipments (UEs) to eNB. Alternatively, there are other techniques in which the packet scheduler tends to provide fairness among users regardless of the channel status [7] or achieve QoS requirements specified by the user [8]. Moreover, with the drastic increase in the number of UEs, the power consumption of the base stations has increased considerably, which negatively affects the operational cost. Therefore, other scheduling techniques investigate the performance of the packet scheduler in the downlink transmission and the energy consumption for different applications [9].

However, a closer look at these techniques shows a tradeoff between QoS requirements and energy consumption. For example, although many algorithms only consider QoS requirements [10]– [13], applying these policies can cause starvation of low priority classes, especially when real-time priority classes are crowded. Also, other techniques are proposed with the goal to optimize energy consumption [14]–[20]. However, most of the algorithms do not control or maintain the flow of traffic through the network. As a result, the network may not perform efficiently.

In this paper, an enhanced scheduling algorithm is proposed called Dragonfly-based Joint Delay/Energy (DJDE). The proposed algorithm is an optimization algorithm that simultaneously improves the QoS requirements and the overall system power consumption in an adjustable manner. It exploits the behavior of Dragonfly algorithm, which is a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems by cooperating and working together in groups [21]. Being an efficient algorithm especially with high-dimensional space, the Dragonfly algorithm is utilized in the proposed algorithm to execute the scheduling policy. The contributions of this paper can be summarized as follows:

- The paper introduces a new dynamic scheduling algorithm that takes into account allocating bandwidth to users. The proposed algorithm aims at satisfying the QoS requirements of the users while reducing energy consumption to achieve a profitable outcome in the cellular industry.
- The paper uses the Dragonfly algorithm optimization technique to adaptively integrate two scheduling policies. To decide the impact of each scheduling policy, the DJDE algorithm combines two mechanisms in a weighed manner, so the final policy is

customized to consider both QoS requirements and energy consumption.

• The paper presents an analytical framework to perform a comprehensive analysis of DJDE algorithm. It compares the proposed algorithm with other scheduling techniques and evaluates throughput, fairness throughput, and energy consumption.

The rest of this paper is organized as follows: Section II presents downlink resource allocation in LTE. Some related works are reviewed in Section III. Section IV introduces the original optimization algorithm used in the proposed method and discusses the Dragonfly optimization technique. Then, the proposed DJDE scheduling algorithm is explained in Section V. Section VI describes the simulation implementation of the proposed algorithm and compares it with other algorithms. Finally, Section VII is devoted to the main conclusion and future work.

## **II. DOWNLINK RESOURCE ALLOCATION IN LTE**

In LTE downlink/uplink transmission, access to the radio spectrum is based on OFDMA [2]. This allows the LTE system to support tremendous transmission rates, efficient bandwidth, and high immunity against fading. On the other hand, LTE networks still suffer from a considerable demerit, the lack of a standard resource scheduling technique to cope with the massive growth of inhomogeneous traffic. Therefore, the inconsistency between data rate and QoS requirements associated with different types of traffic is a challenging issue.

In the downlink air interface, i.e., from the eNB to UEs, the time domain is structured by frames, sub-frames, and slots. As mentioned before, each frame has 10 ms duration and 10 sub-frames. A sub-frame is formed by two adjacent slots of 0.5 ms each. The smallest time-frequency resource unit is known as a resource element. It is defined as one subcarrier in one OFDM symbol. A group of 12 contiguous subcarriers (180 kHz) over a one-time slot forms the RB. The smallest resource unit that can be allocated to a user during the transmission time interval (TTI) is a Scheduling Block (SB), which consists of two consecutive RBs as in Figure 1, it is the minimal quantity of radio resource that can be allocated to a UE [6].

In LTE network, each attached UE reports CQI via the uplink channel to eNB as an initial estimate of its link quality. For high data-traffic, the number of RBs is always less than the number of UEs. So, a scheduling process is then necessary. Since the eNB is responsible for all the scheduling and resource allocation functions, the eNB initiates the downlink packet scheduling process after receiving the instantaneous CQI feedback from the connected UEs. The CQI reports are usually pushed periodically with intervals of tens of TTIs.

In fact, the scheduling process must take the QoS-related parameters and fairness into consideration. According to these parameters, the scheduler ranks the attached UEs in a descending order to allocate the available RBs. This allocation tends to improve overall system performance [4].



**FIGURE 1.** Resource block and resource element definition.

## **III. RELATED WORK**

The primary focus of this research is to propose a scheduling algorithm that considers both the QoS requirements and the overall system energy consumption while optimizing the system throughput. Therefore, the related work looks into two main issues. While the main issue considers scheduling operations in downlink LTE networks, the second issue aims at optimizing the process of radio resource allocation.

As for the first issue, we classify the downlink scheduling algorithms into three categories, namely (i) QoS-unaware, (ii) QoS-aware, and (iii) Energy-aware algorithms. First, QoS-unaware based scheduling algorithms try to allocate RBs while taking the channel conditions into account. In these techniques, the eNB utilizes the CQI feedback from the UEs as indicators to the channel status. The collected feedbacks help the eNB to assess the data rate supported by the downlink scheduling. Many state-of-the-art scheduling algorithms fall into this category. For example, the work in [22] presents a Maximum Throughput (MT) algorithm that aims at enhancing the spectral efficiency by giving priority to the UEs with the best channel conditions. Then, the algorithm allocates the RBs to the UEs, to attain the highest throughput on a specific channel. The round-robin scheduler assigns the RBs in equal TTIs in an ordered manner. It allocates resources equally, regardless of the users' CQI.

Furthermore, authors in [23] presented the Proportional Fair (PF) scheme for the downlink direction. The proposed algorithm tries to balance between fairness and spectral efficiency, as it enhances fairness in terms of throughput among the UEs while retaining the spectral efficiency. Moreover, another fairness aware scheme is proposed in [24] to adopt fast variations in channel conditions. The proposed technique fairly allocates resources between UEs to enhance the performance of the cell edge users [24]. Nevertheless, these algorithms do not account for the QoS requirements for different UEs, which leads to performance degradation [25].

Second, there are many QoS-aware algorithms proposed to either support real-time services or provide fair allocations among traffic of UEs. For example, authors in [10] presented a scheduling algorithm that aims at satisfying

the QoS requirements. The technique exploits the concept of channel-aware service to rank guaranteed bit rate and non-guaranteed bit rate services from different QCIs. Moreover, a similar scheduling algorithm is proposed in [11] to avoid starvation of non- guaranteed bit rate flows and guarantees QoS of flows considering channel status, buffer size, packet delay, and QCI. Also, authors in [12] tried to find the trade-off between real-time applications and non-real time applications. The algorithm tries to classify the traffic into urgent and non-urgent ones. Similarly, a scheduling algorithm to allocate resources in multimedia applications is presented in [13]. As multimedia services require a high demand for network resources, the algorithm prioritizes real-time traffic by applying a delay priority function. However, although most of these algorithms [10]–[13] reach optimal QoS performance for real-time applications, they overlooked nonreal-time applications. Also, some of these approaches mentioned above could not satisfy different classes of QoS, which may be essential for the end-user. Furthermore, in some situations [26], these algorithms may fail to achieve fairness among UEs.

The third category represents a set of energy-aware algorithms that are used to optimize energy consumption in LTE networks. In general, the optimization of energy consumption can be accomplished by considering better energy efficiency (EE). This can be achieved by increasing the required bandwidth for each user data rate [14]. For instance, the work in [15] proposes a scheduling algorithm that analyzes the factors affecting transmission power. The proposed algorithm considers the throughput and fairness in a two-stage algorithm. While in the first stage, the algorithm handles the QoS requirements, the second stage aims at enhancing EE. Another work [16] presented an EE technique for low-load conditions by optimizing the energy bandwidth while considering the network load. The algorithm considers both the buffer status and the channel state while implementing the energy scheduler.

Also, aiming to reduce the energy consumption, authors in [17] proposed two scheduling algorithms that employ the channel conditions of the users to decide whether to offer them time slots or delate the transmissions. In [18], the authors have proposed a proportional-fair-energy policy available for both low and high load conditions. The proposed policy tried to balance two user prioritizations; namely, the user cumulative energy consumption ratio, and his current energy consumption ratio to enhance the energy performance. It focuses on improving energy performance at low and high load conditions as the two boundaries of the energy consumption range. Although previous works [14]–[18] tackled the problem of optimizing energy consumption. Most of these techniques show a trade-off between the energy cost and the overall system capacity, and hence, may not be effective in real-time environments.

Secondly, as for the issue of optimizing the radio resource allocation, previous research proposed the scheduling process as an optimization problem and tried to solve it while



**FIGURE 2.** Different states of Dragonfly swarm.

satisfying the QoS requirements of cellular networks. For example, work in [27] dynamically adapted to a variety of channel states. Since the optimized scheduling process is multifaceted and time-consuming, the research [27] treated the overall downlink scheduling as an NP-hard problem. Similarly, authors in [8] solved the optimization problem for throughput maximization and proposed a heuristic scheme with low complexity. However, the proposed solution resulted in an issue of fairness as the number of resources is not equally distributed among users.

Besides, in [28], an optimal heuristic algorithm for resource allocation in downlink LTE was proposed. The algorithm tried to maximize the overall users' throughput. However, other studies [29] stated that the computational complexity of the proposed method can be relatively high. Moreover, Iturralde *et al.* in [30] introduce two approaches; game theory and a virtual token to enhance the downlink scheduling process. The two-level algorithm tried to share the bandwidth between flow classes efficiently. Nevertheless, the proposed algorithm can be computationally expensive, especially when the number of users gets really high. Also, the work in [31] introduced a multi-level buffer to optimize network throughput. The algorithm split the users into a different buffer, considering the channel state. Although the algorithm aimed to enhance the system throughput, it did not take the QoS requirements into account. Therefore, to tackle some of the challenges mentioned above, in this research, a radio resource scheduling algorithm is proposed. It tries to solve the limitations of the previously mentioned algorithms.

## **IV. THE ORIGINAL OPTIMIZATION DRAGONFLY ALGORITHM**

Dragonfly algorithm (DA) is a metaheuristic optimization algorithm that simulates the Dragonfly behavior by adopting a static swarming for local hunting and a dynamic swarming for food search [32]. To result in a holistic solution, the algorithm exploits dynamic weights for each step. The algorithm considers the manner of the dragonflies to be one of five distinct stages, which are separation, alignment, cohesion, a distraction from the enemies, and attraction towards the food. These five situations are illustrated in Figure 2.

As a result, the algorithm defines five operations, where each operation expresses the corresponding state. Then, the algorithm uses these operations to find the solution in the search space. As shown in figure 2, the separation  $(S<sub>DA</sub>)$ state refers to the static behavior to avoid colliding with other neighboring dragonflies. The state can be formally modeled as [32]:

<span id="page-3-0"></span>
$$
S_{DA} = -\sum_{Neb=1}^{C_{Neb}} x_{DA} - x_{Neb}
$$
 (1)

where  $C_{\text{Neb}}$  represents the number of neighbors.  $x_{\text{DA}}$  and  $x_{\text{Neb}}$ define the place of the current Dragonfly and its adjacent individual, respectively.

Alternatively, the alignment  $(A<sub>DA</sub>)$  state is formulated as:

$$
A_{DA} = \frac{\sum_{N \text{eeb}}^{C_{N \text{eeb}}} v_{N \text{eeb}}}{C_{N \text{eeb}}} \tag{2}
$$

where  $v_{\text{Neb}}$  is the velocity of the neighboring Dragonfly's. ADAshows the consistency of the Dragonfly's velocity within the swarm [32].

Moreover, the cohesion  $(C<sub>DA</sub>)$  state of a given Dragonfly is defined as:

$$
C_{DA} = \frac{\sum_{Neb=1}^{C_{Neb}} x_{Neb}}{C_{Neb}} - x_{DA}
$$
 (3)

Also, since food is considered as a source of attraction for dragonflies, the food source  $(F<sub>DA</sub>)$  can be formally expressed as:

$$
F_{DA} = x_{food} - x_{DA}
$$
 (4)

where  $x<sub>DA</sub>$  defines the position of a given Dragonfly, and xfoodrepresents the position of the food source.

Also, the distraction  $(E_{DA})$  towards the enemy can be formulated as:

$$
E_{DA} = x_{\text{enemy}} + x_{DA} \tag{5}
$$

where  $x<sub>DA</sub>$  represents the position of a given Dragonfly and xenemy denotes the position of the enemy. Correspondingly, x<sub>food</sub> and x<sub>enemy</sub> represent the best and worst positions achieved by the swarm, respectively.

Finally, the position vector of a given Dragonfly during the time period between t and  $t + 1$  is formally defined as:

<span id="page-4-0"></span>
$$
X_{DA}(t+1) = X_{DA}(t) + \Delta X_{DA}(t+1)
$$
 (6)

where  $\Delta x_{DA}$  represents the direction of the Dragonfly's movement and can be formulated as [32]:

$$
\Delta X_{DA}(t+1) = (s \times S_{DA} + a \times A_{DA} + c \times C_{DA}
$$
  
+ $f \times F_{DA} + e \times E_{DA}$ ) +  $\omega \Delta X(t+1)$  (7)

where s, a, c, f, and e defines the weight assigned to the five states; namely separation, alignment, cohesion, food, and enemy, respectively,  $\omega$  denotes the inertia weigh, and t shows the iteration counter. It is essential to mention that this iterative process continues until the maximum number of iterations (It $r_{\text{max}}$ ) is reached [33].

#### **V. THE PROPOSED SCHEDULING ALGORITHM FOR LTE**

In LTE downlink transmission, the resource scheduler at eNB assigns the available RBs to the UEs, which need allocations. In this section, for simplicity, we assume a set of UEs in one eNB, where  $u \subset UEs = \{1, 2, ..., U\}$ . Moreover, RBs is the set of the assigned resource blocks, and it can be presented by the set rb  $\subset$  RBs = {1, 2, ..., RB}. Also, in our proposed model, TTIs is the set of transmission intervals and it is considered as  $n \text{ }\subset \text{T}$ TIs = {1, 2, ..., N}. In case of fewer resources than demand, the scheduler needs to run an assignment process to achieve a required goal. The state-ofthe-art scheduling algorithms usually try to either maximize the throughput or achieve user fairness [2].

Alternatively, the primary objective of the DJDE algorithm is to relax the delay requirements of UEs services to provide some QoS guarantees while considering the energy consumption in eNB. Therefore, in the proposed approach, an adaptive scheduling algorithm is proposed to integrate two scheduling policies to maximize the overall system performance. To control the trade-off between the QoS guarantee and energy consumption, the DJDE algorithm employs the Dragonfly algorithm to control the influence of each scheduling policy. The proposed algorithm regulates the effect of each policy based on the changes occurring in the network environment.

The proposed scheduling algorithm consists of three phases, namely, Network monitoring, Dragonfly-based scheduling algorithm, and Resource allocation. In the first phase, a preliminary process is conducted in which scheduling parameters are monitored and measured. Then, in the second phase, a Dragonfly-based optimization technique is



**FIGURE 3.** Proposed Dragonfly-based Joint Delay/Energy (DJDE) scheduling algorithm.



 $\blacksquare$ 



proposed to perform the scheduling process. Finally, in the third phase, the DJDE algorithm assigns RBs considering the bandwidth requirements. An overall view of the proposed algorithm is shown in Figure 3. The three phases are further explained in the following subsections. Also, the notations used in the mathematical analysis of the three phases are illustrated channel I.

#### A. PHASE 1: NETWORK MONITORING

This phase deals with collecting the scheduling parameters. So, for each UE, the proposed algorithm considers CQI feedback, buffer status, average delay, and energy consumption.

The CQI feedback indicates the Signal to Interference plus Noise Ratio (SINR) of each UE. Using the Shannon law, the maximum achievable throughput of the UE can be calculated on normalized bandwidth as follows [6]:

$$
d_{i,k}(n) = \log_2 [1 + SIR_{i,k}(n)]
$$
 (8)

When the scheduler receives an indication about available traffic flow to an UE, it updates the buffer status based on how much data can be sent. If the UE has a chance to be served, the scheduler assigns the RBs to the UE in current TTI, else it accumulates this traffic flow in the user's buffer.

The update process of the buffer status can be formally described as:

$$
b_i(n) = \begin{cases} 0, & \text{if } n = 0\\ b_i(n-1) - th_i(n-1) + Ar_i(n), & \text{if } n > 0 \end{cases}
$$
(9)

where  $Ar_i$  (n) is the arrived data size of the i<sup>th</sup> UE at the n<sup>th</sup> TTI, and th<sub>i</sub>(n-1) is the total throughput of the i<sup>th</sup> UE before the current TTI.

Let us assume that the weighted average delay of  $i<sup>th</sup>$  UE can be represented as  $D_i(n)$ . It involves two parts: the delay of the data in the buffer, including the delay of the buffered data  $D_i^b(n)$  and that for transmitted data  $D_i^{Ar}(n)$ .  $D_i(n)$  can be defined as [34]:

$$
D_i(n) = \begin{cases} D_i^b & \text{if } b_i(n) \ge \partial \\ \left[ 1 - \frac{b_i(n)}{\partial} \right] \times D_i^{Ar} + \frac{b_i(n)}{\partial} \times D_i^b & \text{if } b_i(n) < \partial \end{cases}
$$
(10)

where ∂ is the data window size to calculate the average delay, and  $D_i^b$  can be formulated as:

$$
D_i^b = \begin{cases} 0, & \text{if } n = 0\\ \frac{[D_i^b(n-1) + \tau] \times b_i(n-1)}{b_i(n)} & \\ -\frac{D_i(n-1) \times th_i(n-1)}{b_i(n)}, & \text{if } n > 0 \end{cases}
$$
(11)

where  $\tau$  is the time duration of a TTI and  $D_i^{Ar}$  is calculated

$$
D_i^{Ar} = \begin{cases} 0, & \text{if } n = 0\\ \left[1 - \frac{th_i(n-1)}{\partial - b_i(n-1)}\right] \times D_i^{Ar}(n-1) & (12)\\ + \frac{th_i(n-1)}{\partial - b_i(n-1)} \times D_i(n-1), & \text{if } n > 0 \end{cases}
$$

Also, the Energy Efficiency (EEi) is calculated (in Megabits/ Joule):

$$
EE_i(n) = \frac{th_i(n)}{P_i(n)}
$$
(13)

where th<sub>i</sub>(n) is the throughput of the i<sup>th</sup> user (in Megabits/s), and  $P_i(n)$  the total transmitted power (in W) in the  $n_{th}$ TTI [20].

## B. PHASE 2: DRAGONFLY-BASED SCHEDULING **ALGORITHM**

This phase aims at deciding on which UEs will receive resources. Dragonfly algorithm tries to maximize the overall performance of the system by imitating the dynamic social behavior of the Dragonfly swarms [33]. The algorithm mimics the static and dynamic behaviors of dragonflies in two main steps. In the first step, the algorithm imitates the flying behavior of dragonflies to create sub-swarms and explore various regions in a static manner. Consequently, in the second step, the algorithm exploits the static activities of the swarms to simulate dragonflies flying in larger swarms and heading towards one direction.

As a result, the algorithm can enhance the initial population for a given problem space and converge faster to the global optimum. Similarly, the DJDE scheduling algorithm applies the DA algorithm to rank the UEs based on their tolerable delay and total energy efficiency. To consider the effects of both the tolerable delay and the energy efficiency, the proposed algorithm introduces a metric  $(\alpha)$  to regulate the weighted effect of both parameters. The optimization process starts by creating a set of random solutions for finding the most suitable value for  $\alpha$ . The average delay and energy efficiency in UEs are combined according to a utility function, which can be formulated as:

<span id="page-5-0"></span>
$$
M_i(n) = \alpha \times D_i(n) + (1 - \alpha) \times EE_i(n) \text{ where } 0 \le \alpha \le 1 \quad (14)
$$

The range of  $\alpha$  is set to be [0,1]. When  $\alpha = 1$ , the proposed scheduling algorithm shows the same performance as other scheduling algorithms that are only impacted by the delay state. On the other hand, when  $\alpha = 0$ , the proposed scheduling algorithm depicts the behavior of the energy-efficient scheduling algorithms but does not satisfy QoS requirements. To find the most suitable value of  $\alpha$ , the DA algorithm is applied. In the DA algorithm, the position and step vectors of dragonflies are initialized by random values defined within the lower and upper bounds of the variables. In each iteration, the position of each Dragonfly is updated as in Equation [\(6\)](#page-4-0) [33].

A fitness function is used to evaluate  $\alpha$  with the constraints. It can be formulated as:

$$
\text{Fitness } f = \max \sum_{i=1}^{U} \sum_{n=1}^{N} M_i(n) \times th_i(n)
$$

Subject to:

$$
th_i(n) \le \sum_{j=1}^{rb} d_{i,j}(n) \quad \forall i \in U, n \in N, j \in RB
$$

$$
\sum_{i=1}^{U} \sum_{n=1}^{N} b_i(n) \le \text{Buffer\_size} \quad (15)
$$

where the first constraint limits the objective function only to allow the user to utilize channel bandwidth within the maximum bandwidth specified by Shannon law. Besides, the second constraint controls the size of the delayed data. So, it does not exceed the size of the buffer assigned to the user. Solving the fitness function results in the optimal value



**FIGURE 4.** Resource allocation process.

of  $\alpha$  that can be used to compute the utility function of UEs using the Equation [\(14\)](#page-5-0). Then, the scheduling algorithm uses the values of the utility function to rank UEs in descending order. Finally, the algorithm sends the ranked list of UEs to the third phase.

# C. PHASE 3: RESOURCE ALLOCATION

This phase is responsible for assigning RBs considering bandwidth requirements. It defines how much data should be transmitted by each data source scheduler. The scheduler takes the ranked list of UEs from the previous phase. Then, it assigns an integer value to the available RBs. The details of this process are illustrated in Figure 4 and are further explained next.

As the figure shows, the process starts by checking (Check I) whether there are available RBs and competing UEs try to downlink data traffic. In this case, the scheduler performs the second check (Check II) by examining the status of the buffer. In this step, if the buffer is not empty, the scheduler checks the number of competing UEs (Check III). If the number of UEs equals one, then all the RBs are allocated to this UE; otherwise, the scheduler proceeds with another check, which compares the number of UEs and RBs. On the other hand, in case the buffer was empty, the scheduler will continue checking the buffer status of the next competing UE.

Finally, in the fourth check (Check IV), the scheduler compares the number of RBs and UEs. If there are more RBs than UEs, then the scheduler allocates at least one RBs to each UE. On the other hand, if the number of UE is greater than the number of RBs, the scheduler utilizes the value of the utility function calculated in the previous phase to allocate the resource to each UE. After assigning all the available RBs, if there are any UEs left, the scheduler preserves them until the next TTI round of the scheduling process.

# D. THE TIME COMPLEXITY OF DJDE ALGORITHM

In this section, the complexity analysis for MT, PF, DBWPF, and the proposed DJDE algorithm is demonstrated based on the allocation time per TTI. Assume that, at an instant TTI, there is a number of U UEs' imposed to the scheduler seeking to be assigned to RBs for transmission. The complexity of the PF algorithm is calculated by the selection of the best metric for user u, and its scheduling complexity is given as O (RB log U).

The DBWPF algorithm adds a weighted average delay to the PF metric. However, its computational time differs from that of PF and chooses from several users. Hence, it has an allocation complexity of O (RB log U). Furthermore, the overhead scheduling complexity for the proposed DJDE scheduling algorithm is based on DA that regulates the weighted effect of both tolerable delay and total energy efficiency. The DA has time complexity just like most other optimization algorithms. It depends on the swarm size  $(C_{size})$ and the number of iterations ( $I$ t $r_{\text{max}}$ ), which could be considered as constants and not dependent on (RB, U). So, the overall complexity of the DJDA can be expressed as O(L RB log U)+O( $C_{size}$  × Itr<sub>max</sub>)  $\approx$  O(L RB log U)+O[\(1\)](#page-3-0), where the DA is executed every L TTIs. Based on the above complexity analysis, it is obvious that the DJDE scheduling algorithm has a minor overhead effect on the overall scheduling process.

## **VI. SIMULATION IMPLEMENTATION AND RESULTS**

To evaluate the efficiency of the DJDE, the experiments are two-fold. In the first part, we compare the performance of the proposed algorithm against state-of-the-art techniques, including MT [22] and PF [23]. The experiments also include the delay based weighted proportional fair (DBWPF) algorithm [34].

Since this algorithm prioritizes the UEs with the highest delay, comparing the DJDE algorithm with DBWPF is essential to evaluate the delay effect. Alternatively, in the second part of the evaluation, we compare DJDE with different algorithms that optimize energy consumption. The experiments include the PBWPF algorithm [35] from our earlier study and EEDSPF introduced in [36]. A.

# A. SIMULATION CONFIGURATION

The experiments consider the overall throughput, the throughput fairness, delay fairness [34], and energy efficiency. To implement the experiments and simulate the LTE scheduling procedures, we used MATLAB to record these evaluation metrics when the number of users increases. Table 2 shows the simulation environment of the proposed work.

# B. SIMULATION RESULTS

As for the first part of the comparison, Figure 5 represents the overall throughput achieved using MT, PF, DBWPF and the proposed algorithm for different numbers of users. As the figure illustrates, when the number of users is relatively small,

#### **TABLE 2.** Simulator environment.







all scheduling algorithms attain almost constant throughput levels. In this case, the available number of RBs is sufficient to transmit all queued data in buffers. Therefore, the overall throughput of the system is the same as the total users' traffic volumes. However, when the number of users increases, it is clearly shown that the MT algorithm achieves the maximum throughput since it selects the user with the most efficient channel and performs the transmission using this channel. Therefore, it manages to achieve maximum throughput and outperforms other scheduling techniques. Also, the proposed DJDE algorithm does not achieve the highest throughput, it manages to achieve high throughput compared to both PF and DBWPF algorithms, e.g., at  $U = 100$ , the proposed DJDE algorithm outperforms PF and DBWPF algorithms by 18.5% and 28.5%, respectively.

To evaluate the throughput fairness for the proposed algorithm as the number of users increases, Figure 6 compares DJDE with MT, PF, and DBWPF. As shown in the figure, the experimental results show similar behavior as the result of total throughput (Figure 5). Hence, the figure depicts,



**FIGURE 6.** Throughput fairness versus the number of users.



**FIGURE 7.** Delay fairness for different numbers of users.

when the number of users is relatively small, all scheduling algorithms achieve equal throughput fairness.

It is worth mentioning that any value of throughput fairness less than unity (i.e., maximum value) denotes that the active users do not obtain the same throughput. Since the data traffic volumes are not equal, each user has a different throughput value. On the other hand, when the number of users gets larger, the PF algorithm achieves maximum throughputfairness. However, although the proposed algorithm is outperformed by PF, it still manages to achieve comparable results and sustain competitive throughput fairness among other algorithms. Also, the figure demonstrates that, although MT managed to achieve the highest throughput (Figure 5) when considering the throughput fairness, it fails to outperform any of the comparing algorithms. Alternatively, the proposed algorithm manages to outperform MT by up to 25% when the number of users  $= 100$ . Moreover, when the value of U ranges between 60 and 100, both the DBWPF and the DJDE algorithms achieve a reasonable throughput-fairness level compared to the MT algorithm.

Similarly, Figure 7 describes the delay-fairness comparison between different scheduling algorithms for different numbers of users. The results obtained from the experiments show that the DBWPF algorithm outperforms all other scheduling algorithms by various margins. The DBWPF algorithm aims to give the priority of allocating radio RBs to the users with larger delays to reduce the system delay as much



as possible. Therefore, the DBWPF algorithm enhances the system delay fairness. However, the results also show that the DBWPF can only achieve a slight improvement when compared to the proposed algorithm. For example, the performance of DJDE only degrades by 6.4% for 80 users when compared to the DBWPF algorithm. It is worth mentioning that, when considering the delay fairness, the PF algorithm fails to outperform the proposed method. Even though, the PF algorithm managed to achieve the highest throughput fairness, when  $U = 80$ , 100, the proposed algorithm manages to enhance the delay fairness by 36% and 10% when compared to PF, respectively. Although the DBWPF outperforms the DJDE in terms of delay fairness, the DJDE aims to maintain a reasonable system delay fairness compared to MT, PF, and PBWPF algorithms while achieving a satisfactory level of energy efficiency.

Consequently, to evaluate the energy efficiency, Figure 8 compares DJDE to MT, PF, and DBWPF algorithms in terms of the amount of consumed energy with an increasing number of users. The figure demonstrates that when the number of users is relatively small, e.g.,  $K = 20$ , all scheduling algorithms have approximately equal energy efficiency, i.e.,  $EE \cong$ 60 kb/joule. Since the available RBs are sufficient to support most users' data, the scheduling is unnecessary; and hence, all algorithms show similar performance. Also, as the number of UEs increases, MT and DJDE outperform both PF and DBWPF algorithms because the EE is strongly affected by the gained throughput. On the other hand, when the number of users is relatively high, e.g.,  $K = 100$ , the proposed algorithm outperforms other scheduling algorithms, especially PF and DBWPF, in terms of energy efficiency.

The results empirically prove that when the number of users increases, the proposed algorithm can outperform other scheduling algorithms and achieve the least energy consumption (Figure 8), while sustaining comparable results for throughput, throughput delay, and fairness (Figures 5-7).

The proposed algorithm provides about a 20% increase in energy efficiency over PF and DBWPF algorithms. According to the optimized value of  $\alpha$  of the DJDE utility function, the proposed DJDE ensures the highest energy efficiency algorithm. Likewise, in the second part, the DJDE is compared with both the EEDSPF and PBWPF. The



**FIGURE 9.** The overall throughput per cell for a different number of users.



**FIGURE 10.** Throughput fairness versus the number of users.

results are illustrated in Figures 9-12. First, in Figure 9, the achieved throughput of EEDSPF, PBWPF and DJDE algorithms is reported for different numbers of users. Similar to Figure 5, the results show that for a small number of UEs, EEDSPF, PBWPF and DJDE algorithms acquire equal throughput. On the other hand, as the number of UEs increases, both PBWPF and DJDE achieve larger throughput than the EEDSPF algorithm. For example, when  $U = 100$ , both PBWPF and DJDE algorithms outperform the EEDSPF algorithm by 15% and 12.5%, respectively.

Also, Figure 10 represents the throughput-fairness for different numbers of users. The results show that DJDE achieves higher values of throughput-fairness when the number of users gets larger (for example, when the number of users is larger than 80). Besides, the proposed PBWPF algorithm achieves a reasonable throughput-fairness level compared to the EEDSPF algorithm. Moreover, Figure 11 provides the delay-fairness comparison between the contestant scheduling algorithms. Clearly, that the proposed algorithm outperforms EEDSPF, PBWPF algorithms by significant margins. According to the utility function Equation [\(14\)](#page-5-0), the DJDE algorithm succeeds to scale up the delay-fairness by utilizing the weighted average delay of each UE. As a result, DJDE can dramatically increase the delay-fairness up to 21.6% when compared to the EEDSPF algorithm for 100 UEs.

Finally, Figure 12 demonstrates the energy efficiency of the proposed algorithm compared to EEDSPF, PBWPF algorithms. It is interesting to observe that the proposed DJDE



**FIGURE 11.** Delay fairness for a different number of users.



**FIGURE 12.** Energy efficiency versus the number of users.

provides reasonable energy efficiency compared to EEDSPF algorithm, especially for a relatively large number of UEs. For example, when the number of users is greater than 80, the proposed algorithm attains  $EE \cong 100$  kb/Joule. In general, the insights obtained from the evaluation empirically prove that the proposed algorithm can satisfy the QoS requirements of the users while optimizing the energy consumption.

## **VII. CONCLUSION AND FUTURE WORK**

This paper presents DJDE, which is a novel scheduling algorithm for the downlink LTE channel. The algorithm aims at relaxing the delay requirements of UEs services while considering the energy consumption in eNB. The DJDE accomplishes such a goal in three phases. First, the algorithm monitors and records the scheduling parameters in a preliminary process. In the second phase, the algorithm optimizes  $\alpha$ that maximizes the fitness function. The optimized  $\alpha$  is used to calculate the utility function to rank the UEs in descending order. Finally, in the third phase, the scheduler assigns the available RBs according to the ranked list. These phases enable DJDE to dynamically enhance the overall system performance. The proposed algorithm is outperformed by other techniques when considering individual performance parameters. However, since we aim at presenting an optimization technique that tries to balance the QoS requirements and energy consumption, it is essential to consider multiple evaluation metrics at once. For example, even though the PF algorithm slightly surpassed the proposed algorithm when considering the throughput fairness, the proposed algorithm still managed to outperform the other algorithms including MT, and DBWPF. Moreover, the PF algorithm fails to achieve competitive results in delay fairness. Finally, when looking at the energy consumption, the algorithm shows significantly better results by outperforming all the other algorithms (when the number of users increases). As a whole, the experimental results demonstrate that the algorithm shows a balanced performance while sustaining the least power consumption, among other scheduling algorithms.

The insights obtained from the experiments prove that DJDE sustains a robust delay and throughput fairness. Besides, it provides the most energy-efficient algorithm considering acceptable delay fairness. For future work, the optimization procedure can be extended to accommodate other factors such as allocating radio resources to provide a satisfactory level of Quality of Experience. Moreover, another possible direction for improvement is to apply the proposed algorithm to advanced LTE or any 5G standards.

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