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Cooperative High-Rate and Low-Latency Transmission, Employing Two-Tier Narrow-Band Internet-of-Things and Bluetooth Low-Energy Networks

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ABSTRACT Recently, narrowband Internet-of-Things (NB-IoT) networks have been on the rise in the IoT field due to their features like low power consumption and high penetration rate. However, NB-IoT's main drawbacks are its high delays and low data rates. To address these problems, in this paper, we present a two-tier cooperative solution to improve network throughput. Two-tier networks generally consist of cellular and device-to-device (D2D) communications. In this work, we use NB-IoT for cellular networks and Bluetooth low energy (BLE) for D2D communications. By leveraging these communications technologies, we enable idle nodes in a group to assist target nodes download and upload data. In doing this, we aim to maximize throughput, minimize consumed energy, and maximize the total remaining capacity of the node group batteries. To tackle the faced multi-objective optimization problem, we used the non-dominated sorting genetic algorithm (NSGA-II). Only one group gets selected from the candidate groups by adjusting the level of node participation. Simulation results show a 7.7-fold growth of throughput against only an 8 percent increase in energy consumption compared to the baseline download scenario and a 7.6-fold growth of throughput against just a 2 percent increase in energy consumption compared to the baseline upload scenario.

INDEX TERMS BLE, cooperative data transmission, D2D, NB-IoT, NSGA-II, two-tier networks.

I. INTRODUCTION

Over the last two decades, the Internet of Things (IoT) has been spreading rapidly, and the number of studies on this technology has been increasing steadily [1].

According to Transform a Insights' [2] total addressable market forecast database, 7.6 billion IoT devices were active at the end of 2019, which is expected to increase to 11.1 billion by 2030, with an annual growth of 11%. Short-range communications such as Wi-Fi, Bluetooth, cellular, public, and private networks are forecasted to change from 74%, 16%, and 10% in 2019 to 72%, 20%, and 8% in 2030, respectively [2], [3]. In the literature, the applications of fifth-generation cellular networks are divided into three main categories in terms of information transfer rates. First, Enhanced Mobile Broadband (eMBB) requires very high bandwidth, in the range of several gigabits per second. The second category is Ultra-Reliable Low-Latency Communications (URLLC), which is sensitive to latency, and the data must be delivered to the destination in a short period of time. The third category is Massive Machine-Type Communications (mMTC), which must connect and manage many IoT devices optimally and with low power consumption [4].

In this paper, the goal is to provide a solution for mMTC in which nodes can cooperate with each-other to send/receive data with higher data rate in limited time periods. So, the aim is to increase data rate efficiency, while other works in the literature have focused on different parameters (an example [5]). The proposed solution would be a necessity in the scenarios such as, Industrial Automation and Robotics, Smart Grid and Energy Management, Environmental Monitoring and Precision Agriculture, and Healthcare and Remote Patient Monitoring [6], [7], [8]. As an example, in Environmental Monitoring and Precision Agriculture, sensor nodes deployed in environmental monitoring networks and precision agriculture systems collect large volumes of data related to temperature, humidity, soil moisture, and crop health. High data rates are essential for transmitting sensor readings and images from remote field locations to centralized servers for analysis and decision-making. We have proposed a two-tier design, including Narrow-band IoT (NB-IoT) and BLE protocols which will be studied in this section in details, to increase the receiving data rate of each node. We have explained the basic information in the following paragraphs. The limited data rate of NB-IoT is inherently by its design since it wants to cover vast area with large number of nodes. The following paragraphs provide the necessary knowledge to understand the problem. It is worth mentioning that these paragraphs mainly focus on NB-IoT, BLE, and the challenges of combining them. The proposed solution will use a combination of NB-IoT and BLE.

For mMTC applications, NB-IoT is a promising new technology. The 3rd Generation Partnership Project (3GPP) introduced NB-IoT in its R13 standard in 2017 [1], [9]. The capabilities of NB-IoT in combination with other technologies such as D2D communications will lead to new features for IoT networks. In such two-tier networks, nodes take advantage of many of the features of D2D communication, such as low latency and high-speed communication technology [10], [11].

Since NB-IoT was initially intended to serve as precursor to and the cornerstone of 5G, its technological specifications will advance to the 5G future [12]. The 3GPP R13 version of NB-IoT is the most fundamental in terms of the technology's development. While R14 streamlined the delay and decreased power consumption, R15 increased its speed and improved its multi-carrier features. Additionally, R16 included a 5G core network-accessible increase in performance, and the R17 version has received formal approval. As NB-IoT has evolved, it has become a crucial part of 5G. During these updates, the observed time difference of arrival (OTDOA) (R14) and D2D communication have perhaps been the most important in their ability to expand NB-IoT use cases and increase the number of NB-IoT devices (R15). Further information about OTDOA and D2D was added in R16. The updates in R16 (Jun. 2020) were connected to improvements of earlier features: enhanced DL/UL transmission efficiency and user equipment (UE) power consumption, enhanced scheduling, enhanced network management, enhanced multi-carrier operation, enhanced mobility, and the investigation of the coexistence with new radio (NR). In addition, R17 is expected to support NB-IoT carrier selection based on coverage level and other specific requirements. It introduces support for a higher modulation (16 QAM) in the uplink and downlink, and reduces RRC re-establishment time with another cell. R17 is also expected to define signaling for neighboring cell measurements and the corresponding measurement triggering before radio link failure [13], [14].

NB-IoT is distinguished from conventional IoT technology by offering more extensive coverage than the latter, a higher number of connections, low speed, low cost, low power consumption, and superior design. As a result, NB-IoT significantly satisfies the varied needs and development requirements of ultra-long-distance communication technology while providing greater coverage and stability for the Internet of Things. IoT applications, such as remote meter reading, asset monitoring, smart cities, smart buildings, smart transportation, industrial Internet of Things, wearable technology, etc., are predicted to be extremely popular [15].

NB-IoT connects multiple devices and sensors, transmitting small data amounts over long distances. Based on the 3GPP standard, it operates in licensed spectrum bands. NB-IoT utilizes a 200 kHz bandwidth that can be allocated in three ways: standalone, LTE carrier, or LTE carrier's guard band. NB-IoT supports two duplex modes: half-duplex frequency division duplex (HD-FDD) and full-duplex frequency division duplex (FD-FDD). HD-FDD is ideal for devices without data transmission needs, while FD-FDD is ideal for bidirectional communication [16].

Bluetooth low energy (BLE) is another short-range technology used in D2D communications. The fifth version of Bluetooth uses 2 Msym/s modulation for low-energy mode to increase data transfer speed with 2 MHz bandwidth [17], [18]. NB-IoT, for its part, is an emerging technology that needs more attention. Our inspiration for this study comes from what NB-IoT can achieve in combination with BLE and D2D communications [19].

The modulation scheme used by BLE is Gaussian frequency shift keying (GFSK), which is identical to classic Bluetooth but with different symbol rate and deviation values. This leads to a decrease in power consumption and an increase in resistance to interference [18]. BLE supports four physical layer (PHY) modes: 1M, 2M, Coded S2, and Coded S8. The 1M and 2M modes use a symbol rate and a bit rate of 1 Mbps and 2 Mbps, respectively. The Coded modes utilize a lower symbol rate and bit rate of 500 kbps or 125 kbps. This is accomplished by employing a coding scheme that adds redundancy bits to every data bit. According to [20], the Coded modes offer improved range and reliability, but at the expense of lower data rates. Moreover, BLE supports two security levels: LE Legacy Pairing and LE Secure Connections. LE Legacy Pairing utilizes a temporary key (TK) for generating encryption and authentication keys, whereas LE Secure Connections employs an elliptic curve Diffie-Hellman (ECDH) key exchange for generating more robust encryption and authentication keys. Also, BLE supports two power saving mechanisms: connection intervals and advertising intervals. Connection intervals represent the time gaps between consecutive data transmissions in an established connection. In an unestablished connection, advertising intervals represent the time between two consecutive advertising packets. The application can adjust both mechanisms to balance power consumption and latency [18].

Combining BLE and NB-IoT offers certain benefits. BLE can be used for short-range communication between sensors and gateways, while NB-IoT can be used for long-range communication between gateways and cloud servers. BLE consumes less power and bandwidth than NB-IoT, resulting in more efficient and reliable data transmission. Additionally, NB-IoT provides better coverage and scalability compared to BLE. BLE enables device discovery and configuration [21], [22], while NB-IoT facilitates device management and control [23]. BLE allows for plug-and-play applications and easy deployment and updates of devices, while NB-IoT enables remote firmware updates and commands. Data collection and analysis can be done with BLE, while data transmission and storage can be done with NB-IoT. By using BLE, data processing and encryption can be done locally, while NB-IoT offers cloud-based alternatives for enhanced flexibility and security [24].

Knowing the challenges related to the problem, we summarize our contributions in this paper as follows:

- Proposing a novel cooperative solution aimed at enhancing the data send/receive rate of a node from the base station by leveraging assistance from neighboring idle nodes. We have used a two tier networks employing NB-IoT and BLE.
- We identify nodes that have the proper conditions to form a group. These conditions depend on the node's status at the group formation time.
- We consider three factors for selecting the nodes that constitute an optimal group, including maximum network throughput, minimum network power consumption, and maximum total remaining battery power of the selected nodes. We use a nondominated sorting genetic algorithm (NSGA-II) to solve this multi-objective problem.
- We introduced a coefficient (α) which is the contribution rate of each node that defines how much a node may participate in the process of upgrading other nodes download and upload.

The rest of the paper is organized as follows: Section II provides a review of relevant literature. Section III presents the system model, and then the problem is formulated. Section IV focuses on the algorithmic optimization of the NSGA-II, Section V provides a performance evaluation, and Section VI presents our conclusion.

II. RELATED WORKS

NB-IoT and BLE have attracted great attention these years because of their applications [25], [26]. In this article we address the challenge related to the integration of nodes in NB-IoT data networks, which often involves tasks such as forming a group by optimally matching the content requester (CR) nodes and the content provider (CP) nodes, and sharing base station (BS) by communicating directly with each other without interference. These tasks can be divided into three parts to classify the work done in the two-tier communication and cooperation for data transfer. It is worth mentioning that the proposed solution is novel, because no other research provides a solution to address the same problem. The problem is to cooperatively use two-tier NB-IoT and BLE networks to increase transmission efficiency of NB-IoT nodes. Transmission efficiency includes delay and energy. Efficiency will be higher since nodes will help eachother in transmitting data during their idle time.

Energy efficiency is an important parameter in NB-IoT and BLE systems. We first study some state-of-the-art works to understand the challenges. Reference [27] addresses the adaptation of non-terrestrial network for the random access (RA) step in NB-IoT systems, which is a challenging aspect in the NTN context. It has considered multiuser time-frequency synchronization and timing advance for data scheduling. Reference [28] provides a solution for distributed uplink power allocation under spatiotemporal fluctuation incorporating NB-IoT features.The features includes the number of repetitions, the data rate, the IoT device's energy budget, packet size, and traffic intensity. It uses stochastic geometry analysis and mean-field game (MFG) theory. Two testbeds have been used in [29] to conduct field measurements related to enhanced coverage levels selection. Measurement results provides a base to propose an adaptive radio access approach for user equipment, which includes two novel strategies for predictive enhanced coverage levels selection and opportunistic packet transmission.

Moreover, we will study a set of articles focused on data sharing through identifying and creating best matches between CR and CP nodes. The primary objective of the approaches in these articles is to improve the sharing of received node data with D2D communications.

Exploring the blind matching theory, the authors of [30] proposed a D2D content-sharing method based on the principle of mutual benefit. More specifically, they began by generating closed-form formulations of latency and reliability performance for D2D content-sharing scenarios. Next, the ultra-reliable low-latency communications (URLLC)-oriented joint optimization problem for provider-demander pairing and power control of potential providers was formulated as a two-sided one-to-one context-free matching game. This optimization problem involved a collection of aspiration levels agreement functions between demanders and potential providers and also involved a modified concept of pairwise stability as the solution. The authors of [31] proposed an energy-efficient content-sharing system based on D2D coordination multiple points transmission (D2D-CoMP) that exchanged data across numerous users to lower the power consumption per user device. There were three notable highlights in their work. First, their approach for matching suppliers with demanders subject to self-interference limitations was shown to be a classical maximum weighted matching issue. Using an efficient distributed algorithm, they showed that the best solution could be obtained when network-wide information was available. A second highlight was their approach to the problem of how many data packets each provider could transport. The authors overcame this problem by creating an effective packet-split method for D2D-CoMP that took both communication efficiency and energy usage into account. Third, they represented the collaboration demanders' file reconstruction problem as a shortest Hamiltonian path problem and showed the file reconstruction procedure. Another feature of this study was that the authors designed a framework for a distributed greedy method to locate the shortest file reconstruction path. In [32], the authors focused on the issue of optimizing cellular traffic offloading with D2D communication by selectively caching popular material locally and examining optimal matching for sender-receiver pairings. The authors of [33] explored the fundamental issues of how D2D communication enhances the system performance of cellular networks and what the potential impact of D2D communication using optimum solutions would be on system resource allocation and mode selection produced under realistic user and mobility scenarios.

The second set of articles we examined in our review sought to aggregate network nodes into groups that could interact with D2D technology directly, without intermediaries. These groups pursued a common goal. More specifically, the groups of network nodes that formed in each of these studies provided multiplayer content to CR nodes. The algorithm which is used for these scenarios is the coalition game.

The authors of [34] explored content-caching and user association problems for edge computing. In doing so, they developed a hybrid content-caching and user association optimization challenge to decrease delays for content downloading. They demonstrated that the combined optimization issue for content caching and user association is NP-hard. To minimize content download latency, their proposed method involved incorporating a smart content-caching policy and dynamic user association. Based on prediction results, the smart content-caching policy used exponential smoothing to anticipate the popularity of content and cache items. In [35], the authors propose an eco-friendly low resource security surveillance framework that aims to maximize the active participation of reusable low resource devices in generating reusable surveillance borders within a security district. The main problem is formally defined as the Reusable Surveillance Low Resource Device Participation Maximization (ReSLowPar) problem. The paper provides an ILP formulation for this problem and describes the main definitions used in the framework. Additionally, the paper presents the pseudocode for the Eco-friendly-System-Initialization algorithm, which is used for system activation. In [36], the authors used network coding and collaboration among user devices to tackle the challenge of reducing the latency of information delivery in a decentralized, partly D2D-connected network. Their proposed optimization approach considered user devices' acquired and missing contents, their restricted coverage zones, network coding, and the risk of content erasure. The optimization problem was treated as a coalition game with cooperative players, with the reward function deriving from the growing individual payoffs from the intended cooperative conduct. However, the formulation was unsolvable; therefore, the coalition game was modified into a coalition creation game. At each transmission, a distributed method for coalition creation based on merge-and-split criteria was created to address the relaxed problem. The authors of [37] constructed a user clustering problem to maximize the energy efficiency of a D2D multi-cast network, adopting both social tie information and a price strategy to encourage collaboration. The problem was split into two subproblems due to the NP-hardness. Specifically, a cluster head selection method based on maximal social weight was initially presented to distinguish the suitable cluster heads from numerous candidates and limit the maximum number of selected cluster heads. The authors then modeled the cluster formation process as a coalition-building game with non-transferable benefits. A distributed coalition-building method for cluster creation was presented on the basis of preference relationships and switch operations. In [38], the authors introduce a virtual emotion detection system for a two-way enabled multi-domain IoT environment, aiming to avoid detection holes in all IoT domains. The objective is to maximize the cumulative accuracy of detection holes by constructing barriers in every domain area. The problem is defined and solved using an ILP formulation, and the results are evaluated through extensive experiments. The authors of [39] investigated the issue of cooperative downloading through D2D communications. They presented a technique called cooperative content download-and-share (CoCoDaS) to encourage the demand for D2D communications by a simple pricing mechanism in cellular networks to unload the traffic burden from the base station. CoCoDaS enables users with the same content demand to download a massive file from the base station and exchange their downloaded content segments through D2D communications.

The third section is introduced as a supplementary part, which is one of the researches in the field of group communication in NB-IoT technology. In [40], an approach to group communication in NB-IoT introduced with the expansion of the NB-IoT frame and the introduction of an algorithm for the mechanism of multicast data transfer in NB-IoT technology.

Drawing on the foregoing literature review, we propose a novel cooperative solution aimed at enhancing the data send/receive rate of a node from the base station by leveraging assistance from neighboring idle nodes. Contributions of this article are explicitly expressed at the end of Introduction section.

III. SYSTEM MODEL AND PROBLEM FORMULATION

In this paper, we consider hundreds of nodes in a given environment receiving information or carrying out actions. Many of these nodes may send relatively large amounts of information (such as images, audio, etc.) at different times, or they may need to receive large amounts of information from the BS (databases, firmware, etc.). let us suppose that among the nodes in the network in an impassable environment, the software of some nodes needs to be updated or, it is necessary to update the local databases of some nodes alternately by the BS or other control center and analyze the environment of the nodes based on these databases.

To explain the scenario, let us consider an environment with n nodes. One of the nodes, which we designate the target node, wants to download or upload a large file (up to 10 MB). The BS has complete information about the nodes it covers. This information includes the percentage of battery power remaining at node i, the status of active sending or receiving data in node i, the activation of power saving mode (PSM) at node i, and the distance of node i from the target node. The BS performs a group formation operation by receiving the send request from the target node, according to the available information from the nodes.

The BS checks the request issued from the target node. The next step at the BS is to evaluate whether the request sent for the data download or upload falls into the category of large data. If the size of the data is not sufficiently large, it tells the node to send that data only through the NB-IoT connection. However, if the data is large, it will re-examine the request to determine if it should take action as cooperative download group (CDG) or cooperative upload group (CUG), based on the case. Depending on the specified operation type, the BS begins the initial process of forming the group. The requirements for membership in the cooperative group are explained in Section III-A and III-B.

As NB-IoT data rates can not exceed 160 and 130 kbps in upload and download, respectively [1], [41], it means that it takes longer to send and receive bulk data. To speed up the transfer of data in this system, we have used D2D communication with BLE technology.

Of the groups selected by the algorithm, only one group is selected on the basis of the contribution rate of nodes (α). Often, as the number of members in the group increases, the energy consumed and the throughput of the system increases. Generally, as α increases from zero to one, more nodes will contribute to the group.

Figure 1 shows an example of a cooperative download group and its function. As we can see, the blue nodes are auxiliary nodes and the gray node is the target node; this set constitutes a group. we depicted the BLE coverage area by a dashed circle. within the circle there are 3 different types of nodes colored as black, green and yellow. Black nodes are nodes in PSM nodes, green nodes are nodes in transfer for other data, and yellow nodes are nodes with a remaining battery level less than the specified threshold. NB-IoT data pieces are transmitted to group nodes, and auxiliary nodes transmit data pieces to the target node via BLE communication.

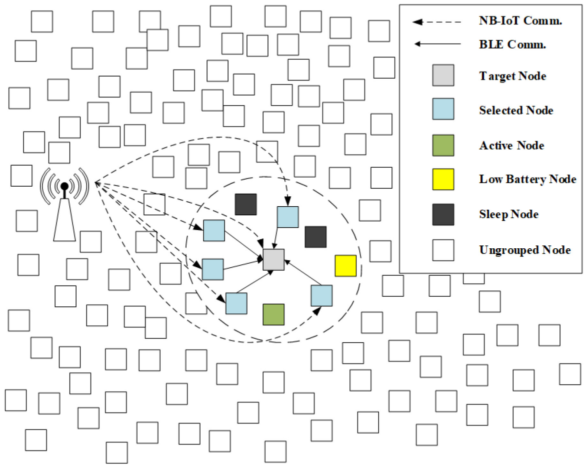

FIGURE 1. System environment and cooperative download group.

In this paper, we use an adopted version of an evolutionary algorithm called NSGA-II ([42]) to solve the multi-objective models. This algorithm was developed for such problems with a binary decision variable. Using the NSGA-II with objective functions aiming for cooperative downloading and uploading results in groups with different numbers of nodes. In each group, the energy consumed and the throughput obtained will differ. The algorithm prioritizes nodes with the most battery power for inclusion in groups. We will describe the NSGA-II based algorithm of solving the problem later in Section IV.

In overall, first, the download/upload request is sent from the target node. As transmitting the small size files do not need making groups, they will be transmitted via NB-IoT. In the download scenario, only nodes can become candidate for download group that are neither in PSM mode, nor in data transmission mode, nor with power less than the specified threshold and also in the target node BLE coverage range. Then, the NSGA-II algorithm runs with the defined goals of creating cooperative download group, and finds the optimal solutions. In the upload scenario, only nodes can become candidate for upload group that are neither in data transmission mode, nor with battery power less than the specified threshold and also in the target node BLE coverage range. Then, the NSGA-II algorithm runs with the defined goals of creating cooperative upload group, and finds the optimal solutions. After that, a parameter will be adjusted in the system based on determining the amount of nodes involved in the formation of the group, and the cooperative

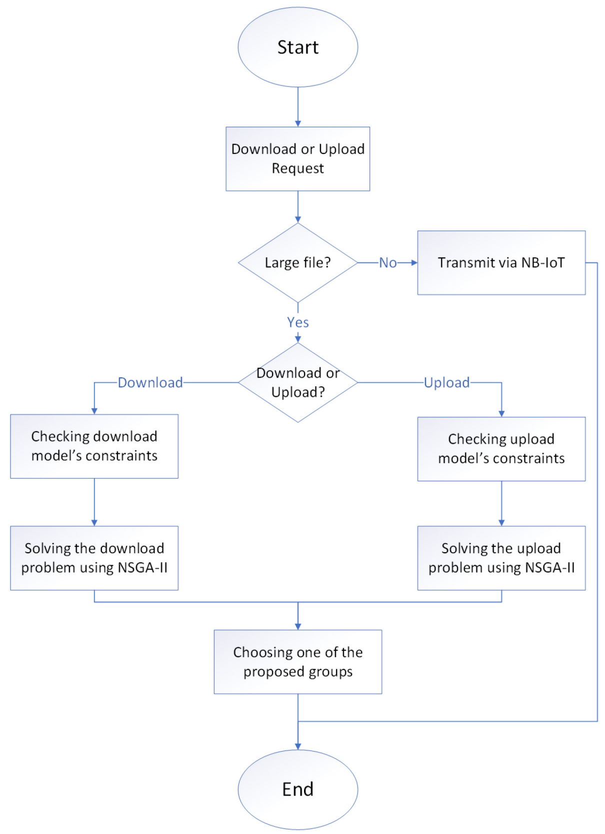

FIGURE 2. The flowchart of the proposed system.

TABLE 1. Symbols used in the download and upload group modeling.

Symbol	Description	Unit
X_i	Binary decision variable indicating whether node i is in the group	0 or 1
D_i	Distance of node i to the target node	m
B_i	Battery level of node i	0 to 1
PSM_i	Power saving mode status of node i	0 or 1
A_i	Active data transmission status of node i	0 or 1
E_{total}	Total energy consumption of the group	mJ
T_{total}	Total throughput of the group	kbps
B_{total}	Total remaining battery percentage of selected nodes	real positive number
$E_{helpers}$	Energy consumption of helper nodes	mJ
E_{target}	Energy consumption of the target node	mJ
E^h_{NB-IoT}	Total energy consumed by helper nodes for NB-IoT communication	mJ
E^h_{BLE}	Total energy consumed by helper nodes for BLE communication	mJ
$E_{merging}$	Energy consumption for merging all data fragments	mJ
$E_{splitting}$	Energy consumption for splitting all data	mJ
P^{max}_{CPU}	Maximum processor power consumption of nodes	mW
P^{rx}_{NB-IoT}	NB-IoT power consumption for receiving data	mW
P^{tx}_{NB-IoT}	Power consumed by nodes for transmitting data using NB-IoT	mW
P_{BLE}	Power consumption for data exchange using BLE	mW
$DataSize$	Total transferable data size	bit
$FileSize$	Size of the target file	bit
$Overhead$	Overhead of each data fragment	bit
t_{total}	Total time taken for the group to exchange data	s
t^{rx}_{NB-IoT}	Time taken to receive data using NB-IoT	s
t^{tx}_{NB-IoT}	Time taken to transmit data using NB-IoT	s
t_{BLE}	Time taken for data exchange using BLE	s
$t_{merging}$	Time taken to merge all data parts	s
$t_{splitting}$	Time taken to split data into fragments	s
b^{rx}_{NB-IoT}	Data receiving rate using NB-IoT	kbps
b^{tx}_{NB-IoT}	Data transmitting rate using NB-IoT	kbps
b_{BLE}	BLE data rate	kbps
b_{mem}	Data rate of main memory of nodes	kbps
m_c	Number of read or write operations in the main memory of nodes	real positive number
η	Number of nodes in the suggested group	real positive number

group will be selected. The flowchart of the whole process is shown in Figure 2. The process starts with a download or upload request. After that, it is checked whether the file size is large. If the file is large, it will be transmitted through NB-IoT. If the file is small, it is checked whether the request is to upload or download. Based on each request, the constraints of the proposed mathematical model are examined. Then, using NSGA-II, the problem of downloading or uploading is solved, and finally one of the proposed groups is selected through solving the problem.

In the following, we will explain the mathematical modeling of the cooperative formation of download and upload groups.

A. COOPERATIVE DOWNLOAD GROUP

Figure 1 shows an environment with n nodes. These nodes are equipped with NB-IoT and BLE communication modules. All nodes in this environment are in a set called I. One of these nodes, as the target node, requests the BS to download a large file. Then the download group formation process starts at the BS. As Table 1 describes the used symbols, in this model, the X_i variable will be the decision variable. X_i is a binary variable: it can be either zero or one; as such, it determines the absence or presence of node i in the download group.

The main goal of this model is to find and select nodes that create a higher throughput for the system with lower energy consumption. A secondary goal is to find and select the nodes that have the most remaining battery. Thus, implementing this model will not burden low-energy nodes and will move the nodes in the network to balance the battery level. So, as the multi-objective function in (1) describes, the goals are to minimizing the total energy consumed (E_{total}) from transferring a large file in the cooperative download group in joules (J), maximizing the total throughput (T_{total}) in kilo bits per second (kbps), and also maximizing the total percentage of battery power of the selected nodes (B_{total}) in the cooperative download group. In the following, we will describe how to calculate and optimize these terms. We have used the normalized version of each parameter in (1) by scaling each parameter to the range [0, 1] considering a maximum for each parameter.

In order for nodes to be able to join the group, the BS must check which nodes are within BLE coverage (ζ) range of the target node as (2) describes, where D_i is the distance between node i and the target node.

Next, the BS also needs to ensure that the node is not in PSM. Because in NB-IoT technology, whenever a node is in PSM, it shuts down its radio communication and cannot prepare to download data until it exits this mode [43]. The PSM_i symbol displays the saving mode status of each node i. PSM_i has a binary value of zero or one, which indicates that node i either is or is not in PSM, respectively. Therefore, for this condition, the equation must be established as (3).

Another important condition in this model is the inactivity of the node to data transfer (A_i). So, the value of A_i is zero if node i is not transferring any data. Vice versa, the value of A_i is one when node i sends or receives data. Thus, (4) can be expressed.

A condition for excluding nodes with battery power (B_i) below a critical threshold (B_{critical}) is given in (5). Therefore, the mathematical model is as follows:

$$\max \qquad \hat{T}_{\mathsf{total}} + \hat{B}_{\mathsf{total}} - \hat{E}_{\mathsf{total}}, \tag{1}$$

s.t.

$$D_i \times X_i \leq \zeta, \qquad i \in I, \tag{2}$$

$$\mathsf{PSM}_i \times X_i \leq 1, \qquad i \in I. \tag{3}$$

$$A_i \times X_i \leq 0, \qquad i \in I. \tag{4}$$

$$B_i \times X_i \geq B_{\mathsf{critical}}, \qquad i \in I. \tag{5}$$

The dependence of the objective function elements $\hat{T}_{\mathsf{total}}$, $\hat{B}_{\mathsf{total}}$, and $\hat{E}_{\mathsf{total}}$ on the control variable X_i will be expressed in details in (19), (21), and (6) (having (14) and (15)) respectively. To make it easier to calculate the amount of energy consumed and the total throughput in a group, we divide the nodes of a group into two categories: helper nodes and target node. E_{total} can be calculated from the sum of the energy consumed by the helper nodes (E_{helpers}) and the energy consumed by the target node (E_{target}) as follows:

$$E_{\mathsf{total}} = E_{\mathsf{helpers}} + E_{\mathsf{target}}. \tag{6}$$

The cooperative download model sends the data pieces simultaneously through the NB-IoT connection through different carriers to the helper nodes and the target node. The helper nodes then consecutively send the data pieces to the target node via the BLE connection. For the data pieces to be properly connected in the final step to form the original data, the number of pieces must be added to the data pieces. Also, in order for the helper nodes to be able to identify the target node and send the data pieces to it, the BLE address of the target node must be added to the data pieces. This additional information is added to the data pieces as an overhead. Figure 3 shows the bit share of each part of this overhead. 8 bits of overhead are for the data piece number, which can be a number up to 256. 48 bits of this overhead are for the Bluetooth MAC address, and the other 16 bits are for the CRC generated from the two parts and the main data piece to check for accuracy and error detection. Therefore, the overhead is added to the original data along with the other data pieces, and the total size the data to be transmitted is calculated as

$$\mathsf{Data}_{\mathsf{size}} = \mathsf{File}_{\mathsf{size}} + \mathsf{Overhead} \times \sum_{i \in I} X_i. \tag{7}$$

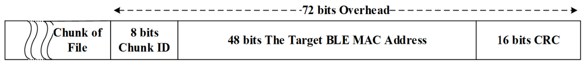

FIGURE 3. Data piece and its overhead.

The energy consumed by receiving each piece of data using NB-IoT is calculated as follows:

$$E^{rx}_{\mathsf{NB-IoT}} = P_{\mathsf{NB-IoT}} \times t^{rx}_{\mathsf{NB-IoT}}. \tag{8}$$

$E^{rx}_{\mathsf{NB-IoT}}$ is obtained by multiplying the power consumption of NB-IoT ($P_{\mathsf{NB-IoT}}$) by the time it takes to receive a piece of data with NB-IoT ($t^{rx}_{\mathsf{NB-IoT}}$).

Except for the target node, the rest of the nodes of the cooperative download group will be helper nodes. Therefore, to calculate the energy consumption of the NB-IoT by the helper nodes ($E^{h}_{\mathsf{NB-IoT}}$), (8) must be multiplied by the number of helper nodes as follows:

$$E^{h}_{\mathsf{NB-IoT}} = \left(P_{\mathsf{NB-IoT}} \times t^{rx}_{\mathsf{NB-IoT}}\right) \times \left(\sum_{i \in I} X_i - 1\right). \tag{9}$$

To calculate $t_{\mathsf{NB-IoT}}$, the size of each piece of data is divided by the NB-IoT data rate in the downlink $b^{rx}_{\mathsf{NB-IoT}}$ as follows:

$$t^{rx}_{\mathsf{NB-IoT}} = \frac{(\mathsf{Data}_{\mathsf{size}}) / \sum_{i \in I} X_i}{b^{rx}_{\mathsf{NB-IoT}}}. \tag{10}$$

The calculation of the energy consumed by sending each piece of data with the E_{BLE} relation can be given as follows:

$$E_{\mathsf{BLE}} = P_{\mathsf{BLE}} \times t_{\mathsf{BLE}}. \tag{11}$$

Moreover, P_{BLE} represents power consumption, and t_{BLE} designates the time it takes for each piece of data to transfer with the BLE connection. t_{BLE} can also be obtained by dividing the size of each piece of data by the BLE communication data rate (b_{BLE}). We can calculate b_{BLE} as follows:

$$t_{\mathsf{BLE}} = \frac{(\mathsf{Data}_{\mathsf{size}}) / \sum_{i \in I} X_i}{b_{\mathsf{BLE}}}. \tag{12}$$

The energy consumed by sending data to the target node with BLE communication using helper nodes is equal to the consumption of E_{BLE} by the number of helper nodes. E^{h}_{BLE} is calculated as follows:

$$E^{h}_{\mathsf{BLE}} = \left(P_{\mathsf{BLE}} \times t_{\mathsf{BLE}}\right) \times \left(\sum_{i \in I} X_i - 1\right). \tag{13}$$

E_{helpers}, which calculates the amount of energy consumed by the helper nodes, is obtained from the sum of the two Equations (9) and (13) as follows:

$$E_{\mathsf{helpers}} = \left(P_{\mathsf{NB-IoT}} \times t_{\mathsf{NB-IoT}} + P_{\mathsf{BLE}} \times t_{\mathsf{BLE}}\right) \times \left(\sum_{i \in I} X_i - 1\right). \tag{14}$$

According to (6), to calculate E_{total}, the total energy consumed by the helper and target nodes must be obtained.

Therefore, the energy consumed by the target node (E_{target}) will equal the sum of the energies consumed in these three operations. In the target node, one piece of data with NB-IoT connection is received from the BS, and other pieces of data are received from helper nodes with BLE connection. So, there will be E_{BLE} equal to the number of helper nodes and an $E^{rx}_{\text{NB-IoT}}$. The equation is as follows:

$$E_{\text{target}} = E^{rx}_{\text{NB-IoT}} + E_{\text{BLE}} \times \left(\sum_{i \in I} X_i - 1 \right) + E_{\text{merging}}. \tag{15}$$

To merge the two pieces of data, when the BLE connection receives the second piece, an in-memory process is performed. After receiving the next piece of data, the connection is made between the previously generated data and the newly received piece of data. This growth of data pieces will continue until the last piece is received. Therefore, a coefficient is obtained that indicates the number of repetitions of the read/write time of a piece of data in the main memory (m_c). In simple terms, the speed of reading and writing data from and to each node's main memory will be important in the in-memory processing. The main memory speed will determine the execution time of this process. Two pieces of data are read from memory and written to another part of memory and then merged and their overheads removed. Therefore, in each connection operation, the pieces of data are read and written once, which means that the connection time will be twice as long as the time it takes to read or write those pieces of data. m_c is calculated as follows:

$$m_c = 2 \times \sum_{k=2}^{\mu} k, \tag{16}$$

where μ indicates the number of selected members of the group; in other words, it indicates the number of pieces of data.

To obtain the processing time for merging the data, we multiply m_c by the time it takes to read or write a piece of data from or to the main memory (t_{mem}) as follows:

$$t_{\text{merging}} = m_c \times t_{\text{mem}}. \tag{17}$$

To calculate the energy consumption for merging the data pieces (E_{merging}), the power consumption of the merging processing must be multiplied by t_{merging}. For the sake of simplicity in the calculation, we consider the maximum power consumed by the processor of each node as the power consumption of this processing. We consider the worst-case scenario for this processing, which is a 100% load on the processor of the target node. Therefore, the merging processing power consumption will equal the target node's maximum processor power consumption ($P^{\text{CPU}}_{\text{max}}$), which is calculated as follows:

$$E_{\text{merging}} = P^{\text{CPU}}_{\text{max}} \times t_{\text{merging}}. \tag{18}$$

Therefore, according to Equations (14) and (15), the value of E_{total} will be calculated in (6).

Another goal of our approach is to maximize the throughput of the entire cooperative download group (T_{total}). The interval between the time data is sent to the nodes and the time that the target node reconstructs the original data from data pieces is called total transfer time (t_{total}). t_{total} consists of the time of receiving the data with the NB-IoT connection ($t^{rx}_{\text{NB-IoT}}$), the time of sending the data pieces from the helper nodes to the target node with the BLE connection (t_{BLE}), and the time of merging of the data in the target node (t_{merging}). The calculation of t_{total} is as follows:

$$t_{\text{total}} = t^{rx}_{\text{NB-IoT}} + t_{\text{BLE}} \times \left(\sum_{i \in I} X_i - 1 \right) + t_{\text{merging}}. \tag{19}$$

Since nodes receive pieces of data simultaneously from the BS with the NB-IoT connection, there will only be one $t^{rx}_{\text{NB-IoT}}$ at this time. Also, because the helper nodes will send the pieces of data consecutively (one after the other) to the target node, t_{BLE} will affect the number of helper nodes in the total time. The number of iterations for merging the data pieces is also obtained in (16), and the time it takes to merge all data pieces is in accordance with (17). To calculate the total throughput in the cooperative download group, the ratio of the total data size to the total data download time will calculate the data rate. The total throughput is calculated as follows:

$$T_{\text{total}} = \frac{\text{Data}_{\text{size}}}{t_{\text{total}}}. \tag{20}$$

As mentioned above, a secondary goal of our model is to maximize the total percentage of battery remaining nodes. This means that nodes with more battery storage are selected so that the probability of energy starvation of nodes generally becomes lower. B_{total} can be calculated as

$$B_{\text{total}} = \sum_{i \in I} (X_i \times B_i). \tag{21}$$

Now forming a cooperative download group with the proposed model will be possible.

B. COOPERATIVE UPLOAD GROUP

While most of the parameters and relationships will be the same for the cooperative upload model as they are for the cooperative download group, there are some notable differences due to the nature of data uploading.

The first difference between the upload and the download model is that there is no need to check the nodes for PSM mode. In NB-IoT, nodes for data upload can immediately exit PSM mode and start an upload operation. For this reason, Equations (2), (4), and (5) will be the conditions for the nodes to be nominated in the upload group.

In this model, the goals are similar to the cooperative download model ($\min E_{\text{total}}$, $\max T_{\text{total}}$, and $\max B_{\text{total}}$). There will be two different points in calculating the goals of the cooperative upload model than the previous model as follows:

- Divide the main data into pieces of data in the target node.
- Use uplink in NB-IoT connection which has different data rate than downlink.

The energy consumed by the target node (E_{target}) is calculated as follows:

$$E_{\text{target}} = E^{tx}_{\text{NB-IoT}} + E_{\text{BLE}} \times \left(\sum_{i \in I} X_i - 1\right) + E_{\text{splitting}}, \tag{22}$$

where $E^{tx}_{\text{NB-IoT}}$ is the energy used to send a piece of data with the NB-IoT. This value can be obtained as follows:

$$E^{tx}_{\text{NB-IoT}} = P_{\text{NB-IoT}} \times t^{tx}_{\text{NB-IoT}}. \tag{23}$$

In (23), there is value for the time it takes to send a piece of data with NB-IoT ($t^{tx}_{\text{NB-IoT}}$). The transmission time of a piece of data with an NB-IoT connection is determined according to the data rate of this technology in uplink. The calculation of $t^{tx}_{\text{NB-IoT}}$ is as follows:

$$t^{tx}_{\text{NB-IoT}} = \frac{\text{Data}_{\text{size}} / \sum_{i \in I} X_i}{b^{tx}_{\text{NB-IoT}}}. \tag{24}$$

The method of calculating E_{BLE} for a download group is stated according to (11). However, as in the previous model, it will be difficult to calculate the exact energy used to split the data pieces ($E_{\text{splitting}}$). Therefore, we estimated a worst-case scenario, which means that every part of the main data needs to be separated from it and formed into a piece of data. That part of the main memory is read first and then written in another part of the main memory. Therefore, for each data piece, two reading and writing operations are performed. For this reason, the criterion for calculating the processing time is the main memory speed of the nodes (b_{mem}).

Thus, b_{mem} is equal to the size of each piece of data at the time of reading or writing each piece of data in memory (t_{mem}), which must be repeated twice for each data. The value of t_{mem} can be obtained as follows:

$$t_{\text{mem}} = \frac{\text{Data}_{\text{size}} / \sum_{i \in I} X_i}{b_{\text{mem}}}. \tag{25}$$

The time required for generating data pieces from the original data to the number of group members ($t_{\text{splitting}}$), is estimated as

$$t_{\text{splitting}} = 2 \times t_{\text{mem}} \times \sum_{i \in I} X_i. \tag{26}$$

Also, to calculate $E_{\text{splitting}}$, the worst-case scenario to run this process is the maximum power consumption of the processor per node ($P^{\text{CPU}}_{\text{max}}$) must be available, and, like (27), the calculation of $E_{\text{splitting}}$ is as

$$E_{\text{splitting}} = P^{\text{CPU}}_{\text{max}} \times t_{\text{splitting}}. \tag{27}$$

By calculating these three components of energy consumption, E_{target} is calculated from (22).

According to the given explanations, E_{helpers} could be calculated as follows:

$$E_{\text{helpers}} = \left(E^{tx}_{\text{NB-IoT}} + E_{\text{BLE}}\right) \times \left(\sum_{i \in I} X_i - 1\right). \tag{28}$$

Like the cooperative download model, E_{total} is obtained from (6).

In calculating T_{total}, the value for the size of the data can be calculated from (20), but the t_{total} calculation differs from the download model. The time parameters used to calculate t_{total} in the cooperative upload model have already been introduced, and by calculating them, the t_{total} can be obtained as follows:

$$t_{\text{total}} = t^{tx}_{\text{NB-IoT}} + t_{\text{BLE}} \times \left(\sum_{i \in I} X_i - 1\right) + t_{\text{splitting}}. \tag{29}$$

As mentioned in (21), in the cooperative download model, B_{total} is calculated similarly in the upload model. The cooperative upload model is completed with the set of relationships expressed in this section.

IV. NSGA-II OPTIMIZATION

First, a screening operation is performed to enter candidate nodes into the algorithm. Screening operations are performed by applying the constraints introduced in Equations (2) to (5) on system nodes. In a multi-objective optimization problem, crowding distance is used to gauge the level of density among the solutions. It is frequently used to uphold diversity in evolutionary algorithms, such as NSGA-II, which aim to identify a collection of optimal solutions that balance various objectives. The concept of crowding distance entails assigning a numerical value to each solution, showing its proximity to neighboring solutions within the objective space. As the crowding distance increases, the level of isolation of the solution from others also increases. The solution becomes more crowded by others as the crowding distance decreases. Different ways of calculating crowding distance have been proposed in various studies. In this research, we used a method introduced in [44] to calculate the crowding distance. In this method, each chromosome on the same front is ranked using the crowding distance. On each front, the crowding distance value for the members with the highest and lowest value of objective functions will be equal to the infinite value, and for the other members of that front as follows:

$$\text{CD}_s = \sum_{o=1}^{n_{\text{obj}}} \left| \frac{f_o(i_s + 1) - f_o(i_s - 1)}{f_o^{\max} - f_o^{\min}} \right|, \tag{30}$$

where CD_s is the crowding distance of the chromosome s. $f_o(i_s + 1)$ is the value of the objective function o for chromosome one in the set after chromosome s. The chromosomes of each front are first sorted by their f_o, and then the crowding distance is calculated on the basis of the chromosomes arranged. $f_o(i_s - 1)$ is the value of the o^{th} objective function for chromosome one before s in the

Algorithm 1 Calculate Crowding Distance

procedure CALCULATECD($pop, fronts$)
  n_{pop} = length of pop
  $CrowdingDistance = \varnothing$
  for s in $1, \ldots, n_{pop}$ **do**
    f_s = members of $fronts(pop(s).rank)$, $cd = \varnothing$
    for o in $1, \ldots, n_{obj}$ **do**
      f_s = sort f_s by f_o
      i_s = index of s in f_s
      if s is upper or lower bound of f_s **then**
        $CrowdingDistance(s) = \inf$
      else
        $cd(o) = |\frac{f_o(f_s(i_s+1)) - f_o(f_s(i_s-1))}{f_o^{max} - f_o^{min}}|$
        $CrowdingDistance(s) = CrowdingDistance(s) + cd(o)$
      end if
    end for
  end for
  Return $CrowdingDistance$
end procedure

set. f_o^{max} and f_o^{min} are the upper and lower edges of the desired front. The number of objective functions is equal to n_{obj}. The values obtained for all objective functions must be added to calculate the crowding distance amount. Whatever the crowding distance value of one chromosome is bigger, the less congestion there will be in that chromosome region.

In Algorithm 1, *pop* and *fronts* variables are population of chromosomes and fronts, respectively. Since the operation of finding crowding distance will run for each chromosome, the procedure will be called according to the number of available population. The f_s set also includes chromosomes that are in front of the s chromosome. This set is sorted based on the desired objective function and the location number of the s chromosome is also stored in the i_s variable.

The decision variable in the cooperative download and upload group is binary. The range of variables in the NSGA-II algorithm is continuous. For this reason, when creating the first generation, crossover and mutation on chromosomes should be considered so that the variables are selected discretely. So, by applying this mode, the generation of new generations for the X_i will be done correctly. The steps of the NSGA-II algorithm are shown in Algorithm 2.

The NSGA-II algorithm introduces a set of answers based on the energy consumed and the group's throughput by selecting the nodes with the most battery power remaining.

To select a group or to display system performance, a parameter is needed that can be used to set the number of participating nodes. In this regard, the parameter α is introduced to determine the percentage of group nodes desired. In other words, the closer α is to zero, the lower the number of participating nodes in the group, and as a result, the throughput and energy consumption of the group will be lower.

Algorithm 2 NSGA-II Algorithm

procedure NSGA-II
  Candidates ← CandidateNodesSelection()
  n_{var} ← length of Candidates
  n_{pop} ← configured value for the number of populations
  $n_c \leftarrow \lfloor n_{pop} \times P_c \rfloor$
  $n_m \leftarrow \lfloor n_{pop} \times P_m \rfloor$
  i_{max} ← configured value for the iteration of NSGA-II
  for $j \in \{1, \ldots, n_{pop}\}$ **do**
    $pop(j)$ ← create a new genome and calculate its fitness based on the model objectives
  end for
  fronts ← find pop fronts with non-dominant sort
  CrowdingDistance ← *CalculateCD*(pop, fronts)
  pop ← sort pop with calculated CrowdingDistance
  for $i \in \{1, \ldots, i_{max}\}$ **do**
    popc ← crossover pop with number of n_c
    popm ← mutate pop with number of n_m
    pop ← merge pop, popc, and popm
    fronts ← find pop fronts with non-dominant sort
    CrowdingDistance ← *CalculateCD*(pop, fronts)
    pop ← sort pop with calculated CrowdingDistance
    pop ← select first n_{pop} members of pop
    fronts ← find pop fronts with non-dominant sort
    CrowdingDistance ← *CalculateCD*(pop, fronts)
    pop ← sort pop with calculated CrowdingDistance
    print pareto front
  end for
end procedure

To achieve this, first, the answer with the most throughput is chosen among the answers obtained after the implementation of the NSGA-II algorithm. The maximum number of nodes participating in the group is indicated by n_{max}.

The α will be an adjustable parameter. The multiplication of α by n_{max} determines the expected value of the number of nodes participating in the selected group (n_e), which is calculated as follows:

$$n_e = \alpha \times n_{\mathsf{max}}. \tag{31}$$

Then, we have to find among the group system answers with the closest number of participating nodes to the value of n_e, which is introduced as the selected group.

In 3, the chromosome number that has the highest transmissibility is placed in τ. Also, the distance between the expected number of nodes of the group and the number of members of each of the chromosomes of the output population in the NSGA-II algorithm is kept in δ. In γ, the chromosome number that has the smallest distance with the expected number of nodes for the group is placed,

Algorithm 3 Choosing Best Group Based on α

1: **procedure** SELECTBESTGROUP(α, pop)
2: $\quad n_{pop}$ = length of pop
3: $\quad \tau$ = find the index of maximum value of T_{total} in pop
4: $\quad n_{max} = pop(\tau).\eta$
5: $\quad n_e = \alpha \times n_{max}$
6: $\quad \delta = \varnothing$
7: $\quad$ **for** i in $1, \ldots, n_{pop}$ **do**
8: $\quad\quad \delta(i) = |pop(i).\eta - n_e|$
9: $\quad$ **end for**
10: $\quad \gamma$ = find index of minimum balue of δ
11: $\quad$ Return $pop(\gamma)$
12: **end procedure**

TABLE 2. Simulation initial parameters.

Parameter	Symbol	Value
Number of nodes	n	$1,500$
Environment size	u	250 m $\times$ 250 m
Power consumption of NB-IoT in downlink	$P^{rx}_{\text{NB-IoT}}$	213 mW [45]
Power consumption of NB-IoT in uplink	$P^{tx}_{\text{NB-IoT}}$	716 mW [45]
Power consumption of BLE for data transmission	P_{BLE}	65 mW [46]
Maximum power consumption of RPi 2B	$P^{\text{CPU}}_{\text{max}}$	3 W
Downlink data rate of NB-IoT	$b^{rx}_{\text{NB-IoT}}$	127 kbps [42]
Uplink data rate of NB-IoT	$b^{tx}_{\text{NB-IoT}}$	158 kbps [42]
Data rate of BLE	b_{BLE}	1.3 Mbps [47]
Speed of RPi 2B main memory	b_{mem}	2.4 Gbps
File size	File$_{\text{size}}$	16 Mb
Overhead size	Overhead	72 b

and the best group with the adjusted α value is the chromosome with γ number.

V. PERFORMANCE EVALUATION

To evaluate the performance of our proposed approach, we present simulated results for the proposed algorithm using MATLAB. We first discuss the simulated environment and the parameters used, and then we introduce the baseline solution against which our proposed approach is compared.

In the simulation of cooperative downloading and uploading, we randomly distributed $1,500$ nodes over a 250 square meter area. Node information was randomly generated. This information involved node location, node status in terms of activating the energy saving mode (PSM), node status in terms of data exchange, and node battery levels. Also, all of this information is available to the BS. The initial values for the simulation are shown in Table 2.

It is assumed that the nodes are based on the Raspberry Pi 2 board and the sensors and other IoT equipment in each node are connected to this board. This board has a 4-core processor with a frequency of 900 MHz and a main

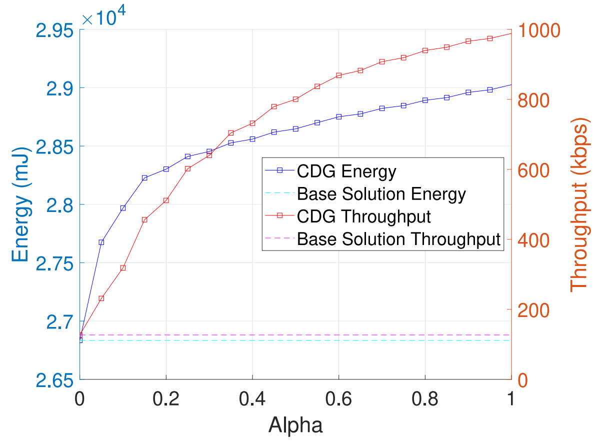

FIGURE 4. Throughput and energy consumption of the download group with different values of α.

memory of 1 GB with 450 MHz has by running benchmark software on the device in order to measure the speed of reading or writing in its main memory, the lowest value got from the data exchange rate in the main memory is over 300 MB/s or over 2400 It is megabit per second. Also, according to the information provided by the device manufacturer, the power consumption of 2 Raspberry Pi will reach about 3000 milliwatts in the maximum state. To simulate and solve the proposed method, we used an *Intel* Core i5 CPU with 12 MB DDR5 RAM. Also, the simulations were run on the MATLAB environment.

The nodes are assumed to be based on the Raspberry Pi 2B board, and each node's sensors and other IoT equipments are connected to this board. All information about the board was obtained by running benchmarking software on the board and the information provided by the manufacturer.

The nodes are positioned in fixed locations throughout the simulation environment. BLE communication interference is handled by BLE standards and no action was taken in this regard. At their baseline state, the nodes can send or receive data via NB-IoT without a D2D connection.

Also, the approach of the cooperative download or upload group has been evaluated from two perspectives. It is also simulated in two scenarios. The first scenario is related to the formation of the download group, as presented in the figure 5, where $\alpha = 0$, $\alpha = 0.3$, $\alpha = 0.6$, and $\alpha = 1$.

The second scenario is related to the formation of the upload group, as presented in the figure 6, where $\alpha = 0$, $\alpha = 0.3$, $\alpha = 0.6$, and $\alpha = 1$.

A. THROUGHPUT

Figure 4 shows the throughput and energy consumption of the cooperative download group with different values of α based on Table 3. As seen from Figure 4, with the participation of more nodes, increasing the throughput of the cooperative download group is logarithmic. The throughput at the baseline state ($\alpha = 0$) is equal to the data rate of NB-IoT in download, which is 127 kbps. The throughput with

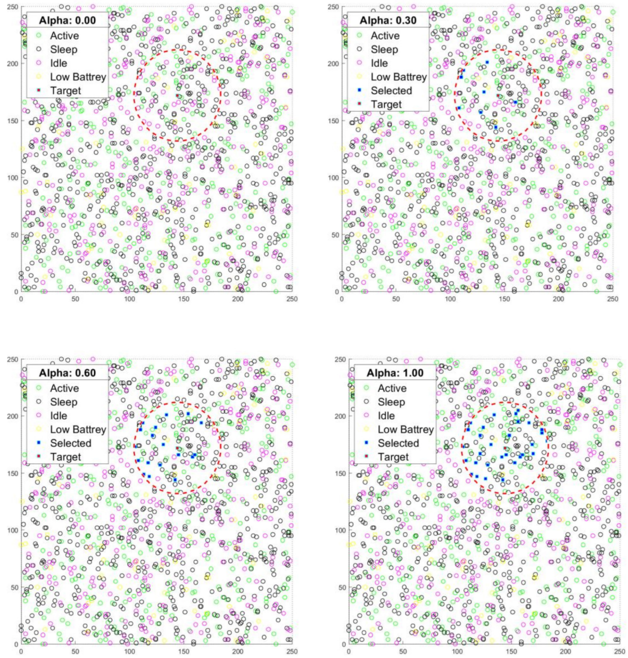

FIGURE 5. Formation of the download group.

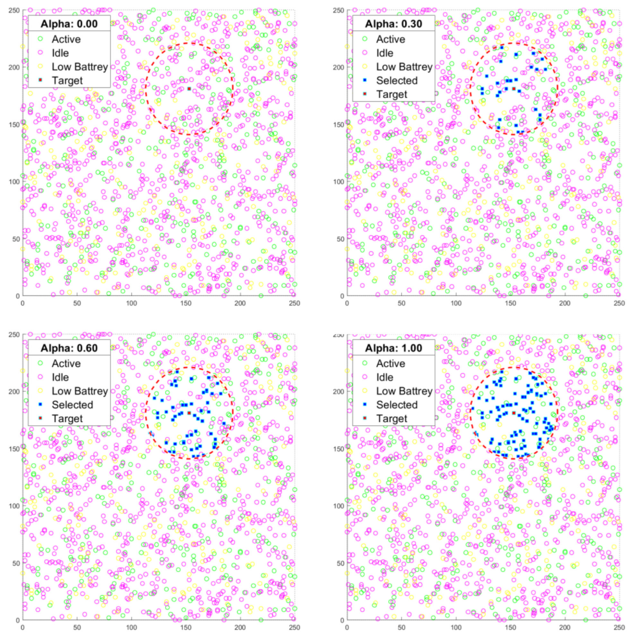

FIGURE 6. Formation of the upload group.

TABLE 3. Simulation results of forming a cooperative download group.

α	μ	t_{total} (s)	E_{total} (mJ)	T_{total} (kbps)	E_{target} (mJ)	$\frac{E_{\text{helpers}}}{\mu-1}$ (mJ)
0	1	125.98	26,834.766	127	26,834.766	-
0.2	6	31.3	28,227.28	456.09	6,119.06	4,605.9
0.4	12	21.87	28,526.96	704.2	3,403.32	2,303.01
0.6	19	18.42	28,750.78	868.46	2,568.36	1,454.58
0.8	25	17.03	28,892.29	939.65	2,360.051	1,105.51
1	31	16.19	29,025.79	988.41	2,278.85	891.56

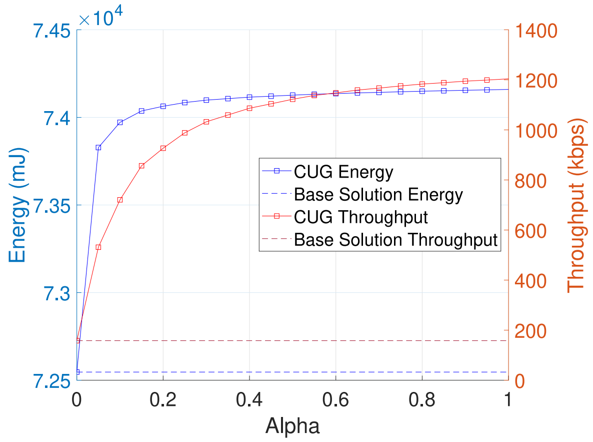

FIGURE 7. Throughput and energy consumption of the upload group with different values of α.

TABLE 4. Simulation results of forming a cooperative upload group.

α	μ	t_{total} (s)	E_{total} (mJ)	T_{total} (kbps)	E_{target} (mJ)	$\frac{E_{\text{helpers}}}{\mu-1}$ (mJ)
0	1	101.28	72,546.65	157.98	72,546.65	-
0.2	18	17.26	74,063.44	926.83	4,824.07	4,072.9
0.4	37	14.72	74,115.42	1,086.56	2,778.47	1,981.58
0.6	55	13.94	74,135.58	1,147.9	2,144.28	1,333.17
0.8	74	13.52	74,149.39	1,183.15	1,809.6	990.95
1	92	13.29	74,159.62	1,204.09	1,620.08	797.13

α values of 0.4, 0.6, and 1 is approximately 704.2 kbps, 868.4 kbps, and 988.4 kbps, respectively. Therefore, the maximum throughput to form a cooperative download group will be over 770% of the baseline state.

Figure 7 shows the throughput and energy consumption of the cooperative upload group with different values of α based on Table 4. The uplink throughput is equal to the NB-IoT data upload rate of 158 kbps. The throughput at α with values 0.4, 0.6, and 1 is approximately 1,086.5 kbps, 1,147.9 kbps, and 1,204.1 kbps, respectively. The throughput at $\alpha = 1$ is more than 760% of the throughput at the baseline state.

B. ENERGY

With the presence of intermediate nodes, the energy consumed for data exchange in the whole group will be more than the base state ($\alpha = 0$). However, the positive and vital point is that the energy consumed is distributed among the group nodes. For this reason, the power consumption of the target node and other nodes with more download or upload requests will be lower than the baseline state. Thus, the battery power of these nodes will be reduced along with that of other helper nodes. This distribution of energy

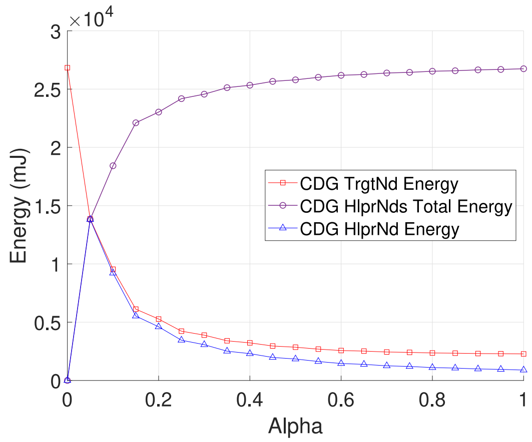

FIGURE 8. The energy consumption of the target node, each helping node, and the total energy consumption of the helping nodes in the download model.

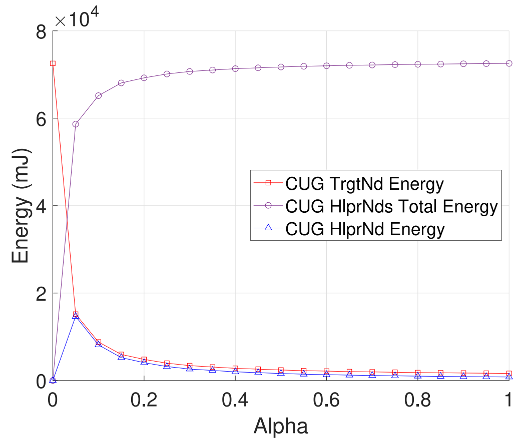

FIGURE 9. The energy consumption of the target node, each helping node and the total energy consumption of the helping nodes in the upload model.

consumption balances the battery consumption of network devices.

As shown in Figure 4, the energy consumption in the download group has a logarithmic growth like a throughput. However, according to Figure 7, the energy consumption for forming a cooperative upload group in the second scenario is the same.

According to the information in Table 3, the amount of energy consumed for the groups in which the participation rate of the nodes is 0.4, 0.6, and 1 is approximately 28, 527 mJ, 28, 751 mJ, and 29, 026 mJ, respectively. At the baseline state, however, the energy consumed equals 26, 835 mJ. When the node contribution is at its highest in the download model, the energy consumption will be 108% of the baseline energy consumption. But the energy consumed by the target node at $\alpha = 1$ is only about 2, 279 mJ, and the rest of the energy consumed is distributed among the nodes, which means that the target node consumes 8.5% of the energy consumed at the baseline state. There is the same condition in the second scenario. We see something similar for the upload model, as indicated by the energy consumption of the upload group shown in Figure 7. According to the information in Table 4, the energy consumption of the upload group with α values of 0.4, 0.6, and 1 is about 74, 115 mJ, 74, 136 mJ, and 74, 160 mJ, respectively. The baseline state in this model consumes about 72, 547 mJ of energy. In the highest degree of node participation, the uploading of data that consumes this amount of energy consumes only 2% more energy than the baseline state, where only 1620 mJ is consumed by the target node. Thus, the target node consumes 2.2% more energy than a traditional transfer. In Tables 3 and 4, the column $\frac{E_{\text{helpers}}}{\mu - 1}$ is the energy consumption of each helper node.

Figure 8, shows the energy used by the target node (CDG TrgtNd Energy), the total energy used by the helping nodes (CDG HlprNds Total Energy), and the energy used by each helping node (CDG HlprNd Energy) with different percentages representing the participation of different nodes (α). Figure 9 shows the energy used by the target node (CUG TrgtNd Energy), the total energy used by the helping nodes (CUG HlprNds Total Energy), and the energy used by each helping node (CUG HlprNd Energy). The second scenario is shown with different percentages of nodes participation. As both figures show, the helping nodes consume no energy with $\alpha = 0$, and as α increases, the energy consumed by the target and helper nodes decreases.

To sum up, our cooperative data transfer approach works well for the download model. In exchange for approximately 8% more energy consumption in the whole group, more than 770% of the baseline throughput is achieved. For the upload model, we saw that it consumes 2% more energy than the baseline state but offers 760% more throughput. A noteworthy point in energy consumption is the distribution of energy consumed among the nodes participating in the group. Therefore the energy consumption of the target node will be much less than the baseline state. So, for the download and upload models, this value represents 8.5% and 2.2% of the energy consumed by the target node using traditional data transfers, respectively.

To analyze the complexity of the Algorithm 1, we need to brake down the algorithm. The outer loop iterates over each individual in the population, with a complexity of $O(n_{pop})$. The inner loop iterates over each objective, with a complexity of $O(n_{obj})$. Finally, the sorting part in line 7, sorts the individuals based on a specific objective. This typically has a complexity of $O(n_{pop} * logn_{pop})$. Therefore, the overall time complexity of the algorithm is $O(n_{pop}^2 * n_{obj} * logn_{pop})$. However, it's important to note that the sorting operation is performed within the inner loop for each objective. This might lead to optimizations in practice, depending on the implementation. For instance, if the sorting results can be reused across objectives, the overall complexity could be reduced.

The complexity of the NSGA-II algorithm is primarily determined as follows: 1) Non-dominated sorting step which involves comparing each individual with all others to determine dominance. In the worst case, this is an $O(n^2)$ operation, where n is the population size. 2) Crowding distance calculation step which calculates the crowding distance for each individual, which typically involves sorting the population based on objective values. This can be done in $O(n_{pop}^2 * n_{obj} * logn_{pop})$ time which is approximately equal to $O(nlogn)$. 3) The complexity of crossover and mutation operations depends on the specific implementation, but they are usually $O(n)$ or less. 4) Selecting the best individuals based on non-dominated sorting and crowding distance can be done in linear time, $O(N)$. In conclusion, the dominant factor in the algorithm's complexity is the non-dominated sorting, which is $O(n^2)$.

The convergence of NSGA-II depends on several factors. A larger population size can improve exploration of the search space but increases computational cost. Crossover and Mutation Rates that control the balance between exploration and exploitation. Moreover, the selection mechanism determines how quickly the algorithm converges to the Pareto front. Also, the complexity and nature of the optimization problem significantly influence convergence.By preserving the best individuals in each generation, NSGA-II promotes convergence towards the Pareto front. Also, the crowding distance mechanism helps maintain diversity in the population, preventing premature convergence. Moreover, The Non-dominated sorting mechanism effectively identifies and selects superior solutions, accelerating convergence.

In conclusion, the provided NSGA-II algorithm has a time complexity of $O(n^2)$ due to non-dominated sorting. Its convergence is influenced by various factors, including population size, crossover and mutation rates, selection pressure, and problem characteristics. The algorithm's ability to maintain diversity and converge towards the Pareto front is primarily due to its elitism and non-dominated sorting mechanisms.

VI. CONCLUSION

The paper has proposed a novel two-tier cooperative solution to enhance the performance of narrowband Internet-of-Things (NB-IoT) networks, addressing the challenges posed by high delays and low data rates. Leveraging cellular and device-to-device (D2D) communications, we utilized NB-IoT for cellular networks and Bluetooth low energy (BLE) for D2D communications, enabling idle nodes to assist target nodes in data transfer. Through the application of the non-dominated sorting genetic algorithm (NSGA-II) to optimize multiple objectives problem, we achieved significant improvements in network throughput while minimizing energy consumption. Simulation results demonstrated that the paper has achieved its goals. Results highlight the efficacy of our approach in maximizing throughput and optimizing energy utilization, thereby paving the way for enhanced performance and wider adoption of NB-IoT networks across diverse IoT applications.

Testing the approach in different network scenarios and measuring its effectiveness is one of the proposed future works. Furthermore, another aspect to consider in future work is the support for various types of data, such as multimedia, and the examination of trade-offs among quality, efficiency, and throughput. Moreover, adding security and privacy features and assessing their impact on the performance of the proposed approach will be a valuable study in the future. The growth and development of NB-IoT is ongoing and still being improved by new 3GPP standards. With these new developments, new functions can be added to the cooperative data transfer approach.

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