Utilizing Non-Orthogonal Multiple Access for Both Latency and Energy Efficiency Improvement in TSCH-Based WSNs

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ABSTRACT Non-Orthogonal Multiple Access (NOMA) is one of the promising technologies for wireless communication networks. Although NOMA was originally proposed in cellular networks, due to its strengths, it can also be used in other networks, such as wireless sensor networks (WSN). Massive connections and energy limitations are some of the challenges in the WSNs and NOMA can be used to improve spectral efficiency, reduce latency, and increase energy efficiency of the WSN. In this paper we investigate the effect of Power-Domain NOMA (PD-NOMA) on the performance of IEEE 802.15.4e Time Slotted Channel Hopping (TSCH)-Based WSNs. A clustered WSN is studied where sensor nodes send their data to their cluster heads using NOMA transmissions, where the cluster heads will also utilize NOMA for the transmission of their aggregated data to the sink node. A fair user grouping and power allocation scheme is proposed because of its great influence on the performance of the PD-NOMA, where users utilizing the channel simultaneously and their transmission power levels will be determined. A new clustering algorithm is also proposed to select the appropriate cluster heads for the NOMA transmission. Simulation results show that the proposed scheme improves energy efficiency, latency, and network throughput in IEEE 802.15.4e TSCH-based WSNs.

INDEX TERMS IEEE 802.15.4e TSCH, Non-orthogonal Multiple Access, Power Allocation, User Grouping, Wireless Sensor Network.

I. Introduction

Recently, NOMA has become a promising technology for improving system capacity, increasing spectrum efficiency, and reducing latency in the Internet of Things (IoT) and 5/6th generation (5G and beyond) cellular systems [1]. Unlike traditional Orthogonal Multiple Access (OMA), where resources are exclusively allocated to the users (such as Time Division Multiple Access (TDMA), Orthogonal Frequency Division Multiple Access (OFDMA), Code Division Multiple Access (CDMA), etc.), NOMA allows multiple users to share the same resource simultaneously [2, 3]. Simultaneous allocation of the resources to more than one user improves the spectrum efficiency, increases the overall system throughput, and supports more users compared to traditional orthogonal multiple access schemes. In general, dominant NOMA schemes are divided into the Power-Domain NOMA (PD-NOMA) and code domain NOMA. In PD-NOMA, multiple access is achieved by assigning different power levels to different users [4]. Code domain NOMA is similar to CDMA, in which different users use different codes for their transmissions over the same time-frequency resources [4].

Simultaneous use of a resource by the users causes intra-cell interference in NOMA. The Successive Interference Cancellation (SIC) technique is used in the receivers to eliminate this interference. In PD-NOMA's SIC technique, due to the different power levels of the users and their distinct channel gains, the Signal-to-Interference-plus-Noise Ratios (SINRs) of the received signals are different and this difference is exploited for the decoding of the received signals [5].

The key design aspect of the PD-NOMA is resource allocation, including user grouping, frequency resource assignment, and power allocation [6]. Since multiple users are admitted on the same frequency resource block in NOMA, the receiver complexity,
outage probability, and co-channel interference will increase. Therefore, grouping methods are suggested to reduce these issues. Grouping methods divide the users of a system into several groups where the users in each group are allowed to use the same resource. It means NOMA is implemented within each group, while the resources are allocated to different groups in an orthogonal manner. Therefore, grouping techniques limit the number of users that use the same resource. Also, channel gains of the users in each group must be sufficiently different to make an efficient SIC possible at the receiver. The minimum distinction of the channel gains is the criterion for the placement of the users in a group [7]. Thus, user grouping strategy has a significant impact on the performance of NOMA. Different user grouping methods have been proposed in the literature, e.g., [8], [9]- [14]. A traditional grouping approach is to group the user with the best channel conditions with the user with the worst channel conditions.

Besides user grouping, power allocation is also a key issue that affects the efficiency enhancement of PD-NOMA. In conventional PD-NOMA, more power is allocated to the user with weaker channel conditions to ensure fairness [15]. Other power allocation methods have also been proposed. For example, NOMA scheme with Fixed Power allocation strategy (F-NOMA) is a method in which the power allocation coefficients are predefined, and the user’s Quality of Service (QoS) or its required data rate cannot strictly be met [16]. Cognitive Radio inspired NOMA (CR-NOMA) has been proposed to consider the users’ QoS in the power allocation of the downlink transmissions. In CR-NOMA, the user with poor channel conditions is considered as a primary user in the cognitive radio network. Thus, the weak channel user receives enough power to meet its QoS needs, and if any power remains, service will also be provided for the users with better channel conditions [15]. Therefore, CR-NOMA will not be flexible enough to guarantee the QoS of all users [16]. Generally, user grouping and power allocation problems are jointly formulated as an optimization problem. Specifically, this optimization problem is known as Mixed-Integer Non-Linear Programming (MINLP) and is NP-hard (Non-deterministic Polynomial-time hard). Therefore, this problem is generally divided into two separate problems: user grouping problem and power allocation problem. Firstly, the user grouping problem is solved. Then, the users’ allocated power level will be determined based on the result of user grouping.

Although NOMA was originally proposed for cellular networks, it can be used in other networks such as wireless sensor networks (WSNs) due to its capabilities.

Wireless sensor networks consist of a large number of sensor nodes that are responsible for sensing and collecting environmental information. These sensors need to communicate with the sink to transfer the collected data. Therefore, many wireless transmissions have to be established [1, 17], and the available spectral bandwidth can be an obstacle for effective communications in WSNs. Furthermore, such a large number of wireless transmissions lead to high network latency if not managed well. Therefore, scalability (effective support of a large number of communications in the available bandwidth) and latency are the two main challenges in WSNs. One way to create more communications over a given bandwidth is to use effective multiple access techniques such as NOMA.

Clustering is another way to increase the scalability of WSNs. If direct communications are used on a large scale in WSNs, congestion will significantly increase in the channel access phase. As a result, bandwidth and energy will be wasted. Therefore, the clustering technique is used to deal with this issue. As shown in Fig. 1, the network is divided into several clusters through the use of a clustering scheme. Each cluster has a cluster head (CH), and the CHs are responsible for collecting the data of the sensor nodes within their clusters. They aggregate the collected data and send the aggregated data to the sink directly or through other CHs [18]. Some of the advantages of the clustering scheme are the reduction in the amount of information sent to the sink, increasing scalability, and increasing network lifetime. Various goals are considered for the CH selection, e.g. energy efficiency, network lifetime, delay, and so on. And many parameters, such as intra-cluster distance, sink
distance, residual energy, number of neighbors, and mobility degree can be considered to achieve these goals. So, Different clustering algorithms have been proposed, e.g. [18], [19-21].

IEEE 802.15.4 is one of the leading standards in the implementation of WSNs. However, its usage for industrial applications must be accompanied by providing high reliability and low latency. An expanded version, called IEEE 802.15.4e, has been introduced to provide these requirements. TSCH is one of the most popular modes of this standard, which is widely used in industrial and IoT applications (explained in Section IV.C). The TSCH Medium Access Control (MAC) mechanism is based on TDMA. Therefore, when the number of nodes increases, the nodes' latency increases as well. In this paper, we utilize PD-NOMA in the IEEE 802.15.4e TSCH based clustered WSNs, and we aim to improve the network performance in terms of spectrum efficiency, latency, and energy efficiency.

At first, CHs are selected based on a new clustering algorithm. In this algorithm, the cluster heads are selected so that they are capable of efficient NOMA transmission. Then, the sensor nodes are divided into clusters according to the selected cluster heads. They send their data to their cluster heads, using NOMA transmission. Cluster heads will also use NOMA for the transmission of their aggregated data to the sink node. A new user grouping & power allocation scheme is used in this step to group the sensors of the clusters/CHs and to assign their power levels.

**Paper Contributions:** The main contributions of this paper are:

- We investigate the usage of the PD-NOMA in the IEEE 802.15.4e TSCH-based clustered WSNs, and we reach improved spectrum efficiency, lower latency, and higher energy efficiency compared to the original IEEE 802.15.4e TSCH-based WSNs.
- We propose a new clustering protocol to select appropriate cluster heads to employ the NOMA technique for the transmission of their collected data to the sink.
- We derive a fair user grouping & power allocation scheme considering the users’ QoS to maximize fairness and overall system throughput. To achieve this, users’ QoS and the SINR differences are used to distribute the users in separate groups. Different power levels are assigned to different users in the user grouping algorithm based on their minimum required data rates.
- We propose a method for employing the NOMA technique in TSCH scheduling.

The remainder of this paper is organized as follows. Section II presents a brief survey of the related works proposed on NOMA usage in WSNs and also on user grouping in NOMA. Some preliminaries are discussed in Section III, and in Section IV, the background and system model are described. The proposed schemes are explained in Sections V and in Section VI, Particle Swarm Optimization (PSO) usage in the optimization problems is described. Section VII is allocated to the simulation and evaluation of our proposed scheme. Finally, the conclusion and future research directions are given in Section VIII.

**II. Related Works**

In this section, we briefly present the related works in two parts. Part A presents the works that use NOMA in WSNs, and in Part B, some user grouping methods are explained.

### A. NOMA usage in WSNs:

NOMA-based WSN is considered in [1] with a time-switching energy harvesting technique where closed-form analytical expressions are obtained for the outage probability and achievable rate.

In [8], the authors propose a fair NOMA-TDMA-DC scheme to be used in IoT. The proposed method aims to increase user fairness and spectrum efficiency, where the $\alpha$-fairness model is used for resource allocation. Different levels of fairness are achieved by changing the value of $\alpha$. Time slot allocation, power control, and user scheduling are formulated as an optimization problem to maximize the system's $\alpha$-fair utility under transmission power constraint and minimum rates. The formulated optimization problem is converted into the difference of two convex functions (D.C.) and is solved by the internal point method.

The authors in [17] use uplink NOMA with the cooperation of multiple relay nodes for WSNs, where a protocol to select the best cooperative relay based on channel state information is proposed, and a closed-form expression of outage probability is derived based on the SNR and SINR of the transmission links.

In [22], the authors propose three different energy harvesting (EH) protocols in NOMA-CRS (NOMA and the cooperative relaying systems) to increase the spectral and energy efficiency, where they analyze the achievable rate of NOMA-CRS with wireless power transfer (WPT) via simulation.

The application of the NOMA-based WSN for a smart agriculture system is investigated in [23]. The authors consider a relay-aided uplink NOMA for the transmission of the sensor nodes to the sink node to support more sensor nodes, and to increase the WSN's lifetime.
The authors of [24] consider a WSN based on NOMA, where Time-Switching-based Relaying WSN-NOMA (TSR WSN-NOMA) and Power-Splitting-based Relaying WSN-NOMA (PSR WSN-NOMA) protocols are proposed to deploy energy harvesting.

In [25], the authors propose an efficient energy resource allocation method in the NOMA-based Wireless Powered Sensor Network (WPSN). Sensor nodes obtain energy from the access point and utilize the harvested energy for the data transmission by the NOMA technique.

In [26], the authors use cooperative NOMA to transfer the wireless information and the power simultaneously. The network consists of a set of high-priority sensors, a set of low-priority sensors, a set of low-power relays, and a multi-antenna sink. First, the sink node selects its antenna, relay, and destinations based on the channel gain differences. Then, the cooperative transmission is done in two phases, using NOMA.

In [27], the goal of the authors is to minimize the total cost of radio resource usage, including channel usage duration and energy consumption of the sensors. For this purpose, a common optimization problem is formulated to determine the SIC decoding order, the power, and the nodes’ transmission time. As the problem is non-convex, the authors propose an efficient algorithm to find an optimal solution.

**B. User grouping in NOMA:**

In [9], the authors propose a method to improve grouping users with close channel conditions. If the grouping method places cell-edge users and cell-center users in a group, the users in the middle of the cell may not be put in any group. Therefore, two methods of user-grouping are proposed in this paper to relieve this issue.

The authors in [10] analyze the brute-force search method (BF-S) for the user grouping problem. The BF-S approach searches all feasible groups of users and generates the optimal user grouping and power allocation scheme that results in the highest throughput.

In [11], the authors propose a novel solution for the user grouping and power allocation problem. They make groups of the users that have different channel behaviors. Then, the power allocation problem is formulated as a variation of Knapsack Problem (KP), which is solved through a greedy method.

The authors of [12] propose a user grouping method that maximizes the physical distance of the grouped users. When the cell-edged users and cell central users are placed in the groups, the achieved rate enhancement will not be significant for almost half of the groups. However, D-NLUPA (Divide-and-Next Largest difference based User Pairing Algorithm) is proposed in this paper that ensures the rate enhancement for all of the groups.

In [13], a NOMA-based deep neural network (DNN) scheme is proposed for downlink transmission to model the nonlinear relation of the user grouping, channel diversity, and transmission power. They use the datasets generated by the brute-force search for the user grouping to train, validate, and test their scheme.

In [14], the proportional fairness (PF) metric is used in grouping the users and allocating the resources to the groups. In this process, a tradeoff will be established between the system’s total throughput and user fairness.

A hybrid NOMA-OMA scheme is considered in [28]. The authors formulate an energy-efficiency maximization optimization problem that aims at user grouping, channel assignment, and power allocation. Then, a low-complexity solution is proposed that obtains the optimal EE under any SIC order and an arbitrary number of users.

In [29], a power allocation method is proposed for a multiple-input multiple-output (MIMO) NOMA system with multiple users in a group. Power allocation is formulated as an energy efficiency maximization problem. Then, two solution methods are considered based on the transmit power. If the transmit power can satisfy the QoS of the users, a closed-form solution will be used for the corresponding maximization problem. Otherwise, a low complexity user admission scheme will be utilized.

In [30], the Minimum Distance-NOMA (MD-NOMA) scheme is proposed based on the grouping distance. The MD-NOMA aims to increase the number of grouped users that use NOMA transmission. Besides, the authors extend a joint power control scheme that considers the channel’s gain and allocates the power level so that the NOMA rate of the user becomes higher than its OMA rate.

According to the above-mentioned researches, in most of the reviewed methods, users’ channel gain is only considered for the user grouping. And in the user grouping algorithm, equal power levels are allocated to the users. However, as different users have various QoS requirements, their placement in different groups leads to different levels of interference, which affects their achievable rates (based on Equation (7)), and also their power consumption. Therefore, grouping based on the users’ channel gains may reduce the system’s fairness. Because all the users may need high bit rates in some groups, and this will increase the intra-cell interference. So, users of this group should consume
more power to overcome this interference and reach the minimum required data rate. Besides, their achievable rates are also decreased. However, such cases may not happen in other groups. Therefore, some users receive high interference, and others receive less. Therefore, considering only the channel gain causes the unfair distribution of users in groups. Furthermore, when the user grouping goal is to maximize the system’s total rate, the users with a high difference of channel gains will be placed in a group, and this may cause the users with similar channel gains to be deprived of the benefits of NOMA, and this issue reduces the fairness level of the system too. As a result, the approach of this study is the grouping of users according to the users’ minimum required data rate. Different power levels will also be assigned to the users based on their minimum required data rate.

III. Preliminaries

In this section, some preliminaries are provided. Jain index and Particle Swarm Optimization that will be used in our algorithm will be explained briefly.

A. Jain Index

Jain Index is a fairness metric that is used to specify whether users or applications are receiving a fair share of system resources or not. This metric is given by [31]:

\[
J(X) = \left( \frac{\sum_{i=1}^{N} x_i}{N} \right)^2
\]

(1)

where \( X \in \{ x_i \}_{i=1}^{N} \) and \( x_i \) is the gain received by the \( i^{th} \) user. The result of \( J(X) \) will be in the range of \( \left[ \frac{1}{N}, 1 \right] \). \( \frac{1}{N} \) refers to the minimum fairness in which only one user receives a non-zero gain, and 1 refers to the maximum fairness in which all users receive the same gain [31].

B. Overview of PSO

Particle Swarm Optimization (PSO) algorithm is a metaheuristic method derived from the behavior of biological societies such as flocks of birds. Therefore, PSO is a swarm intelligence-based algorithm that solves an optimization problem by iteratively improving the candidate solution [32, 33]. PSO has a linear time complexity, and will not be stuck in the local optimum points.

The steps of PSO implementation are described below.

a) The first step (initialization):

1. Several random solutions (particles) are generated (initial population). Each particle \( (Pop_i) \) has the position of \( XP_i \) and will move with the velocity of \( VP_i \) in the search space.
2. A fitness function is used to evaluate the quality of the solutions.
3. In this step, each particle is its own best, i.e., personal best \( (Pbest_i) \).
4. The particle with the best fitness is considered as the global best \( (Gbest) \).

b) The second step (Evolution): This step consists of algorithm iterations.

1. During each iteration, each particle \( (Pop_i) \) uses its \( Pbest_i \) and \( Gbest_i \) to update its velocity \( VP_i \) and its position \( XP_i \) using the following equations.

\[
VP_i(t + 1) = \omega \times VP_i(t) + c_1 \times rand_1 \times (XP_{Pbest_i} - XP_i) + c_2 \times rand_2 \times (XP_{Gbest_i} - XP_i)
\]

(2)

\[
XP_i(t + 1) = XP_i(t) + VP_i(t + 1)
\]

(3)

where \( \omega \in (0,1) \) is the inertia weight, \( c_1, c_2 \), \( 0 \leq c_1, c_2 \leq 2 \) are the acceleration coefficients.

2. When the new position is obtained, the particle \( (Pop_i) \) recalculates the fitness and updates its \( Pbest_i \) and \( Gbest_i \) using as

\[
Pbest_i = \begin{cases} Pop_i, & \text{if } \text{Fitness}(Pop_i) > \text{Fitness}(Pbest_i) \\ Pbest_i, & \text{otherwise} \end{cases}
\]

(4)

\[
Gbest_i = \begin{cases} Pop_i, & \text{if } \text{Fitness}(Pop_i) > \text{Fitness}(Gbest_i) \\ Gbest_i, & \text{otherwise} \end{cases}
\]

(5)

Finally, the particle corresponding to \( Gbest \) is returned as the best solution [18,32].

IV. Background and Network Model

In the following, some backgrounds are provided for a better understanding of the proposed scheme. Then, the network model will be explained.

A. Uplink-NOMA

In the uplink NOMA, each user can independently set its signal power level. So, the destination receives the users’ signals with different levels of power. The different channel conditions of the users are the reason for such a difference in the level of received power. This favorable difference can be adjusted to the
desired level with the help of suitable power control techniques. Power domain multiplexing (enabled by the different received power levels at the destination) is applied to superpose multiple signals, and a SIC mechanism is used at the receiver to decode the superposed signals. Since the received signal of the user with the highest channel gain is likely the strongest at the Access Point (AP), it is decoded first by the SIC. Therefore, the SIC decoding is in the descending order of the users’ channel gains in the uplink-NOMA. This means that the signal of the strongest user is decoded in each step, considering the other signals as noise. Then, the decoded signal will be subtracted from the received signal and this decoding process continues until the signal of the weakest user is decoded. Fig. 2 shows a simple 2-user uplink-NOMA with SIC at the AP.

Consider a group including \( n \) users with distinct channel gains. Channel gain of the \( i \)th user is \( h_i \), and \( |h_1| \geq |h_2| \geq \cdots \geq |h_n| \). Thus, for each \( i \leq n \), the \( i \)th user’s signal will be detected and removed from the received signal by the SIC technique. In each step of the decoding process, the signals of the weaker channel users are considered as noise.

In the uplink NOMA, multiple users (i.e., sensors) transmit data to a single receiver (i.e., sink) on the same resource block. Therefore, the received signal at the receiver can be expressed as

\[
Y = \sum_{i=1}^{n} h_i \sqrt{p_i} x_i + z \quad (6),
\]

where \( p_i \) is the \( i \)th user’s transmission power, \( z \) is the Additive White Gaussian Noise (AWGN) with zero mean and variance \( \sigma^2 \), i.e., \( z \sim \mathcal{CN}(0, \sigma^2) \), and \( x_i \) is the \( i \)th user’s transmitted signal. Therefore, the received SINR related to the \( i \)th user can be derived as

\[
\text{SINR}_i = \frac{p_i |h_i|^2}{\sum_{j=i+1}^{n} p_j |h_j|^2 + \sigma^2} \quad (7)
\]

In Equation (7), the denominator indicates the interference that the \( i \)th user receives from the users with the weaker channel conditions. Therefore, the achievable throughput of the \( i \)th user can be expressed as

\[
R_i = B \log_2 \left( 1 + \frac{p_i |h_i|^2}{\sum_{j=i+1}^{n} p_j |h_j|^2 + \sigma^2} \right) \quad (8),
\]

where \( B \) is the bandwidth of each resource block. So, the total achievable data rate in the group can be calculated using

\[
R_{\text{total}} = \sum_{i=1}^{n} B \log_2 \left( 1 + \frac{p_i |h_i|^2}{\sum_{j=i+1}^{n} p_j |h_j|^2 + \sigma^2} \right) \quad (9)
\]

B. NOMA Dominant Condition

The NOMA’s dominant condition refers to the conditions under which the spectral efficiency of NOMA is ensured to be higher compared to OMA.

\[
\forall i \text{ as a user } C_i^{\text{Oma}} < C_i^{\text{NOMA}} \quad (10)
\]

Therefore, appropriate users are grouped so that this dominant condition is met [34]. Consider a simple TDMA-based network with two users where, \( \text{user}_1 \) and \( \text{user}_2 \) are located at distance \( d_1 \) and \( d_2 \) from the AP, respectively (\( d_1 < d_2 \)). Therefore, their average channel gains are given by \( d_1^{-\alpha} \) and \( d_2^{-\alpha} \) (\( \alpha \) is the Path loss exponent). The channel gain of the \( \text{user}_1 \) is stronger than the \( \text{user}_2 \)’s. \( P_i \) is the normalized transmission power by the noise power spectral density at the receiver, i.e., \( P_i = \frac{P_i}{N_0} \), \( i = 1, 2 \), where, \( p_1 \) and \( p_2 \) are the transmission power levels of \( \text{user}_1 \) and \( \text{user}_2 \), respectively. Spectral efficiencies of \( \text{user}_1 \) and \( \text{user}_2 \) in NOMA and OMA are calculated using [34]:

\[
C_1^{\text{NOMA}} = \log_2 \left( 1 + \frac{P_1 d_1^{-\alpha}}{P_2 d_2^{-\alpha} + 1} \right) \quad (11)
\]

\[
C_2^{\text{NOMA}} = \log_2 \left( 1 + P_2 d_2^{-\alpha} \right) \quad (12)
\]

\[
C_i^{\text{OMA}} = 0.5 \log_2 \left( 1 + P_i d_i^{-\alpha} \right) \quad \forall i = 1, 2 \quad (13)
\]

In uplink transmission, NOMA always outperforms OMA for the weaker user (\( \text{user}_2 \)) because it does not face any intra-cell interference. However, \( d_2 \) can directly impact the performance of \( \text{user}_1 \). So if \( \text{user}_2 \) is located at a certain distance (\( R^{(UL)}_1 \)) from the AP, the NOMA’s throughput gain can also be guaranteed for
the stronger user \((\text{user}_1)\) [34]. Therefore, by applying the condition of \(C_i^{(\text{OMA})} < C_i^{(\text{NOMA})}\) for \(\text{user}_1\), \(R_i^{(\text{UL})}\) can be derived as [34]:

\[
R_i^{(\text{UL})} = \left(\frac{\sqrt{1 + P_i d_i^a}}{P_2}\right)^{-\frac{1}{a}}. \tag{14}
\]

We note that to ensure the NOMA efficiency for both users, user selection must follow the following conditions

\[
R_i^{(\text{UL})} < d_2 \tag{15}
\]

\[
d_1 < d_2. \tag{16}
\]

\section*{C. IEEE 802.15.4e TSCH}

As mentioned in Section I, an extended version of the IEEE 802.15.4 standard, called IEEE 802.15.4e, has been developed to explain a new Medium Access Control (MAC) suitable for the emerging needs of industrial applications [35]. TSCH is one of the most popular modes of this standard that aims to increase network capacity, improve reliability, and reduce power consumption and latency [36, 37]. The main feature of this standard is its possibility of multi-channel usage, based on the channel hopping technique. In TSCH, time is divided into time slots, and nodes use these slots to transmit their data. A set of these time slots is called slotframe, which is repeated over time [38]. The duration of time slots and the slotframe size is not specified in the standard. Slotframe size depends on the application, and its size can vary from 10 to 1000 time slots. Slotframe iterations at a given time will increase if the slotframe has a small size. In such a case, the nodes can achieve a higher bit rate. However, more power will also be consumed [39].

TSCH enables the nodes to schedule their transmissions on specific channels using a frequency hopping pattern. However, the channel/slot allocation algorithm is not pre-determined in the standard and can be specified based on the application. Scheduling algorithms determine the way by which the channel/slot is allocated to the nodes. Scheduling also specifies the way by which each node operates in each time slot (send, receive, or sleep), the neighbor to which the node should communicate, and also its channel offset. Network scheduling algorithms are divided into centralized and decentralized methods. In centralized methods, the network’s topology information is sent to a specific node, and this node creates, distributes, and updates the scheduling based on the received information. However, in the distributed methods, each node determines its scheduling based on the local information exchanged with the neighbors. Scheduling can be displayed as a two-dimensional matrix whose rows represent the channel offset, and the columns show the time slot number in the slotframe. A member of this matrix (a pair of slot/channel) is called a cell. Each cell can provide an opportunity for a node to communicate with its neighbors. There are two types of cells: dedicated cells and shared cells.

Each communication between two devices in a cell is defined as a link [40]. A dedicated cell is assigned to a single link, while shared cells can be used by multiple links (senders/receivers) [41].

\section*{D. Network model}

This paper deals with uplink transmissions in IEEE 802.15.4e TSCH-Based WSNs (shown in Fig. 1). The network consists of one sink, located in the center of the sensing field, and \(n\) sensors that are uniformly distributed in the area. All sensors and also the sink are equipped with a single antenna, and they are fixed without any mobility. Sensors perform sensing periodically, and always have data to send to their CHs or the sink. We assume that the sink has sufficient computing ability to execute clustering, user grouping, power allocation, scheduling, and SIC. Other assumptions are that the Channel State Information (CSI) is always available to the sensors and the sink, and the network synchronization is at the symbol level. A multi-level clustering is used in the network. At each level, the clusters will have CHs. Therefore, a cluster tree topology will be created. The sink runs user grouping & power allocation algorithm for the nodes of each cluster and also for the CHs. Therefore, the sensor groups, the CH groups, and also their transmission power levels will be determined. A centralized TSCH scheduling is used in this paper, where only the dedicated slots are considered [42]. However, unlike the traditional method, the resources are allocated to a node group instead of only one node. Therefore, each group of sensors or CHs can send their collected data according to the intended scheduling with the use of the NOMA technique.

In the next sections, CH selection, user grouping, and power allocation schemes will be explained. Finally, the implementation of NOMA in the TSCH standard will also be discussed.

\section*{V. Proposed scheme}

In this section, the proposed scheme will be explained. Relevant terminologies used in this section are provided in Table I.

\subsection*{A. Cluster head selection}

The clustering can be done in two ways. 1) The CHs are selected, then the clusters are formed according to
the selected CHs. 2) The clusters form and then CHs are selected for the clusters.

In this paper, the first scheme is used. So, for the CH selection phase, all the nodes (in the transmission range of the sink) send the information of their location and residual energy level to the sink. The sink finds the sensor nodes whose energy level is beyond the energy threshold. Then, the CHs will be selected from the nodes with a suitable level of energy. Finally, when the cluster heads are selected, the clusters will be formed. In this paper, we will select the cluster heads by adding the NOMA constraints, such that they can efficiently use NOMA for their transmissions to the sink node.

**NOMA constraints:** As mentioned in Section IV.B, the CHs that satisfy Equations (15) and (16) can be suitable to be paired for NOMA transmission. Consider \( m \) CHs are selected in each phase of CH selection. If the CHs are arranged in ascending order of their distance from the sink, they can be divided into two sets of \( G_1 \) and \( G_2 \) (the CHs with strong and weak channel conditions, respectively).

\[
\text{dis}(\text{CH}_1, \text{sink}) \leq \text{dis}(\text{CH}_2, \text{sink}) \leq \ldots \leq \text{dis}(\text{CH}_m, \text{sink}) \quad (17)
\]

\[
G_1 = \{\text{CH}_1, \text{CH}_2, \ldots, \text{CH}_{\lfloor m/2 \rfloor}\}
\]

\[
G_2 = \{\text{CH}_{\lfloor m/2 \rfloor + 1}, \text{CH}_{\lfloor m/2 \rfloor + 2}, \ldots, \text{CH}_m\} \quad (18)
\]

Table 1: Terminologies

| Term                      | Description                                      |
|---------------------------|--------------------------------------------------|
| \( h_i \)                | Channel gain of user \( i \).                    |
| \( P_i \)                | The transmission power level of user \( i \).     |
| \( P_t \)                | Maximum transmission power budget of each user.  |
| \( B \)                  | The bandwidth of the resource block.             |
| \( R_i \)                | Throughput of user \( i \).                      |
| \( \varphi_i \)          | The required data rate of user \( i \).          |
| \( \beta_{ij} \)         | The \( ij \)th element of the grouping relationship matrix. |
| \( n \)                  | The number of users.                             |
| \( \sigma^2 \)           | Noise power spectral density.                    |
| \( \alpha \)             | Path loss exponent.                             |
| \( \text{dis}(s_i, \text{CH}_j) \) | The distance between node \( s_i \) and \( CH_j \). |
| \( \text{dis}(\text{CH}_j, \text{sink}) \) | The distance between \( CH_j \) and the sink. |
| \( E_{\text{CH}_j} \)     | The current energy level of cluster head \( CH_j \). |
| \( m \)                  | The number of cluster heads.                     |
| \( l_j \)                | The number of sensor nodes in cluster \( j \).   |
| \( R_{\text{max}} \)     | Transmission range of the sink.                  |
| \( d_{\text{max}} \)     | Transmission range of the nodes and CHs.         |
| \( T_e \)                | The energy threshold.                            |
| \( \text{node degree} (\text{CH}_j) \) | The number of sensor nodes belonging to the \( CH_j \)'s cluster. |

The average CHs' distance from the sink for each set can be calculated as

\[
d_{1\Delta} = \frac{\sum_{k=1}^{m/2} \text{dis}(\text{CH}_k, \text{sink})}{\lfloor m/2 \rfloor} \quad (19)
\]

\[
d_{2\Delta} = \frac{\sum_{k=m/2+1}^{m} \text{dis}(\text{CH}_k, \text{sink})}{\lfloor m/2 \rfloor} \quad (20)
\]

To ensure NOMA efficiency, according to \( d_{1\Delta} \) and Equation (14), the CHs in \( G_2 \) should be located beyond \( R_t \) distance from the sink. Equation (14) can be rewritten as:

\[
R_t = \left( \frac{1 + R_0 \alpha}{P_1} \right)^{-\frac{1}{\alpha}} \quad (21)
\]

Here, \( P_t \) is the sensor's normalized transmission power, and it is assumed to be the same for all sensor nodes. Therefore, based on Equations (15) and (16) the NOMA constraints are expressed as:

\[
d_{2\Delta} > R_t \quad d_{1\Delta} < d_{2\Delta} \quad (22)
\]

In the following, based on the proposed scheme in [18], we formulate the CH selection problem as an optimization problem and based on intra-cluster distance, CHs' distance from the sink, and residual energy of the CHs by considering the NOMA constraint. The objective function is formed as a combination of distance and energy functions that will be explained below.

**Distance function:** Sensor nodes consume energy to send their collected data to the CHs, and CHs also need energy to send their collected data to the sink. The amount of energy consumption in transmission depends on the distance between the source and the destination. Therefore, the average intra-cluster distance (\( \frac{1}{l_j} \sum_{i=1}^{l_j} \text{dis}(s_i, CH_j) \)) and the average distance of the CHs from the sink (\( \frac{1}{m} \sum_{j=1}^{m} \text{dis}(CH_j, \text{sink}) \)) will affect their energy consumption. So, the selected CHs should be close to the sink and the cluster's members. As a result, Equation (23) is used in the objective function that selects the CHs to minimize the average intra-cluster distance and the average CHs' distance from the sink.
Objective 1:
\[
\text{minimize } f_1 = \frac{1}{m} \sum_{j=1}^{m} (\text{dis}(CH_j, \text{sink}) + \frac{1}{l_j} \sum_{i=1}^{l_j} \text{dis}(s_i, CH_j))
\]  
(23)

Energy function: As mentioned, the CHs are responsible for collecting the data from the sensor nodes within their clusters. Then, the CHs send the collected data to the sink. Therefore, the sensor nodes selected as CHs should have a high residual energy level. So, in an optimal CH selection, it is necessary to consider the total current energy level of the selected CHs \( (\text{Total energy} = \sum_{i=1}^{m} E_{CH_i}) \) that should be maximized. Therefore, the inverse of \( \text{Total energy} \) will be considered as the second objective that should also be minimized.

Objective 2:
\[
\text{minimize } f_2 = \frac{1}{m} \sum_{j=1}^{m} E_{CH_j}
\]  
(24)

The linear combination of the two objectives is finally assumed as the objective function of the CH selection problem (Equation (25)).

\[
\text{minimize } F = \delta f_1 + (1-\delta)f_2
\]  
(25)

Subject to:
\[
\begin{align*}
C_1 : \text{dis}(CH_j, \text{sink}) & \leq R_{max}, & \forall CH_j \in C \\
C_2 : \text{dis}(s_i, CH_j) & \leq d_{max}, & \forall s_i \in S_i, \ CH_j \in C \\
C_3 : E_{CH_j} & > T_H, & 1 \leq j \leq m \\
C_4 : 0 < \delta < 1 \\
C_5 : d_{2A} & > R_t \\
C_6 : d_{1A} & < d_{2A}
\end{align*}
\]  
(26)

Here, \( \delta \) is the weight factor \( (\delta \in (0,1)) \), and \( f_1 \) and \( f_2 \) are the distance and energy functions, respectively.

In Equation (25), Constraint \( C_1 \) ensures the CHs are in the transmission range of the sink, and Constraint \( C_2 \) ensures the members of a cluster are also in the transmission range of the CH. Constraints \( C_3 \) denotes that the residual energy of the CHs should not be less than the threshold \( T_H \) (that is assumed equal to the average energy of the sensor nodes), Constraints \( C_5, C_6 \) are the NOMA constraints. We now discuss the cluster formation algorithm.

Cluster formation

Once the CHs are selected, the sensors join them and form the clusters. Sensor node \( s_i \) will join \( CH_j \) if the following conditions are met:

1. \( s_i \) is in the transmission range of \( CH_j \)
2. \( CH_j \) has high residual energy \( (E_{\text{residual}}(CH_j)) \).
3. \( s_i \) is near the \( CH_j \) to consume low energy for its data transmission.
4. \( CH_j \) is near the sink to use low energy for its collected data transmission to the sink.
5. \( CH_j \) has a low node degree.

Therefore, the weight function for the cluster formation is defined as [18]:
\[
\text{CHWeight}(s_i, CH_j) \propto \frac{E_{\text{residual}}(CH_j)}{\text{dis}(s_i, CH_j) \times \text{dis}(CH_j, \text{sink}) \times \text{nodedegree}(CH_j)}
\]  
(26)

Each sensor node calculates the value of \( \text{CHWeight} \) for all the CHs in its transmission range and joins the one for which the highest weight is gained.

B. User grouping & power allocation scheme

In this section, user grouping and power allocation problems will be jointly formulated as an optimization problem to maximize both fairness and system throughput. Jain’s Index metric is used as the fairness parameter. It is worth noting that the groups are assumed to be consisting of two users in this paper. As the group size increases, complexity and outage probability in the detection of signals will increase. It is also important to note that when the group size increases, the obtained NOMA gain, in contrast to the increased complexity, is very small and negligible [43-47]. Therefore, the group size of two users is considered in this paper.

According to the above-mentioned issues, user grouping and power allocation optimization problems are formulated as
\[
\text{maximize } 1/2.J(X) + 1/2.NSTR
\]  
Subject to:
\[
\begin{align*}
C_1 : R_i & \geq \varphi_i \\
C_2 : P_i & \leq P_t \\
C_3 : \beta_{i,j} & \in (0,1), & 1 \leq i, j \leq n \\
C_4 : \beta_{i,j} = \beta_{j,i}, & 1 \leq i, j \leq n \\
C_5 : \beta_{i,j} = 0, & 1 \leq i \leq n \\
C_7 : \sum_{j=1}^{n} \beta_{i,j} = 1, & 1 \leq i \leq n \\
C_8 : \text{SNR}_i - \text{SNR}_j \geq th
\end{align*}
\]  
(27)
In Equation (27), \( J(X) \) is the metric of Jain Index, \( NSTR \) is the Normalized System's Total Rate, and \( \beta \) is a \( n \times n \) matrix representing the grouping relationship of the users where

\[
\beta_{i,j} = \begin{cases} 
1 & \text{user } i \text{ is grouped with user } j \\
0 & \text{otherwise,} 
\end{cases} 
\] (28)

In Equation (27), Constraint \( C_1 \) ensures the users' required data rate, Constraint \( C_2 \) denotes the power level limitation of the user, Constraints \( C_3, C_4, \ldots, \) and \( C_7 \) ensure that each user is only grouped with one other user. Finally, Constraint \( C_8 \) denotes SIC constraint in which \( \theta \) is the minimum power difference required for an efficient SIC. As mentioned in Section III.A, the value of \( J(X) \) is in the range of [0, 1], but System's Total Rate (STR) can take values much larger than one. Therefore, we use \( NSTR \) in the linear combination of the fairness and system's total rate. If \( R_i \) represents the achievable throughput of the \( i \)-th user, the system's total rate will be calculated by \( \sum_{i=1}^{n} R_i \). According to Section IV.A, \( R_i \) and \( \sum_{i=1}^{n} R_i \) can be calculated by Equations (8) and (9), respectively. So, \( NSTR \) can be calculated by

\[
NSTR = \frac{\sum_{i=1}^{n} B \log_2 \left( 1 + \frac{R_i |h_i|^2}{\sigma^2} \right)}{\sum_{i=1}^{n} B \log_2 \left( 1 + \frac{P_i |h_i|^2}{\sigma^2} \right)} 
\] (29)

In most methods, users’ access to the maximum possible data rate is assumed as the fairness indication. However, users require different data rates. It would not be a fair approach to allocate the network resources such that the same data rates are achieved. Therefore, we define that fairness will be established if all the users get their required data rate. The ratio of the user's achievable throughput (\( R_i \)) to the user's required data rate (\( \varphi_i \)) is assumed as the variable of Jain’s Index (\( X_i \)).

\[
X_i = \frac{R_i}{\varphi_i} 
\] (30)

Therefore, by using Equations (1), (8), and (30), \( J(X) \) can be calculated by

\[
J(X) = \frac{n}{\sum_{i=1}^{n} B \log_2 \left( 1 + \frac{R_i |h_i|^2}{\sigma^2} \right)} \left( \sum_{i=1}^{n} \frac{R_i |h_i|^2}{\varphi_i^2} \right) + 0.5 \cdot \frac{n}{\sum_{i=1}^{n} B \log_2 \left( 1 + \frac{R_i |h_i|^2}{\sigma^2} \right)} \left( \sum_{i=1}^{n} \frac{R_i |h_i|^2}{\sigma^2} \right) 
\] (31)

Finally, the user grouping & power allocation optimization problem can be written as (32).

As discussed above, unlike the exiting user grouping methods, we consider different transmission power levels for different users in our user grouping scheme. Different power levels are used because the strong user receives interference from a weak user in uplink NOMA transmission. Therefore, if the minimum required data rate of the weak user is high, its interference on the strong user will be high too. Therefore, the power consumption of the strong user needs to be high to overcome this interference. Besides, the signal strength of the grouped users must be sufficiently different so that the SIC technique can be applied at the receiver efficiently. Therefore, the minimum required data rate of the strong user (strong user's transmission power) and the SIC constraint limit the transmission power of the weak user. The weak user will be forced to use the power control method to reduce its interference. Therefore, weak and strong users should be grouped such that fewer restrictions will be applied to them. As a result, using channel conditions and users' minimum data rate requirements in grouping users prevent the grouping of the users with signal-to-noise ratios close to each other, and a fairer grouping result is obtained.

The transmission power of each user will be set such that the required data rate is provided when the user uses the allocated resource alone. This calculated power level will be the minimum value that users have
to take in their NOMA transmissions. In uplink-NOMA, the weaker user can reach its required data rate, using the above-mentioned power level because no intra-cell interference exists for the weaker user. However, the stronger user receives interference from the weaker user. Therefore, it has to use a higher power level to overcome the weaker user’s interference and to reach its required data rate.

The user grouping & power allocation algorithm can be summarized as follows:

1. The minimum transmission power of each user is calculated based on its required data rate.
2. The user grouping problem is solved with the use of the PSO algorithm and considering the users' channel gains and the calculated minimum power levels.
3. According to the determined groups in the previous step, power allocation is run to specify the users’ final power levels.

C. Implementation of NOMA in TSCH

As mentioned in Section IV.C, the scheduling algorithm specifies how the channels/slots are allocated. In the centralized scheduling methods, a central node performs scheduling based on the comprehensive information of the network topology and the nodes' traffic demands. In the scheduling process, the possible conflict and interferences in the wireless environment must be avoided. Therefore, two following constraints will be considered in the scheduling process.

- **Conflict constraint:** In IEEE 802.15.4e-based networks, all links are half-duplex. Therefore, a node cannot send and receive simultaneously. Furthermore, a node cannot receive signals of multiple nodes at the same time. So, the links that have a common node cannot be scheduled in a slot. For example, in Fig. 3, \(B \rightarrow A\) and \(D \rightarrow A\) are conflict links and cannot be scheduled in the same slot.

- **Interference constraint:** When two pairs of sending-receiving nodes that use the same radio channel are close to each other, the receivers can hear the transmission of both senders. The quality of the received signals decreases and may cause unsuccessful transmission. Therefore, the links that have interfering nodes should not be scheduled on the same channel at the same time slot. For example, \(A \rightarrow E\) and \(C \rightarrow D\) cannot use the same channel at the same time slot.

Therefore, we should care about the links with conflict and interference. However, according to the NOMA definition, a receiver node can receive signals of multiple nodes on a frequency band simultaneously. Therefore, a NOMA-based scheduling algorithm will be described in this section. Consider the network topology shown in Fig. 4. In this network, nodes are divided into clusters. Nodes of the clusters are grouped, and the members of each group send data to their corresponding CH simultaneously using NOMA. Besides, NOMA also helps CHs to send data to the higher level CHs simultaneously. But in this network, the nodes of each cluster cannot send in the same time slot due to the constraints of the scheduling problem. To solve this issue, the nodes of each cluster are divided into NOMA groups. Each group will be considered as a single node, and the network topology will be changed accordingly. Then, the scheduling
algorithm will be applied to the newly obtained topology. As shown in Fig. 5, the members of each cluster are divided into several groups (dash lines specify the groups). The defined groups are as follows:

\[
G_1 = \{a, b\} \quad G_2 = \{c, d\} \quad G_3 = \{g, h\} \\
G_4 = \{i, j\} \quad G_5 = \{l, k\}
\]  

(33)

Then after the grouping shown in Fig. 5, the topology changes to the one shown in Fig. 6 (Different groups are specified by different colors). If the results of the scheduling algorithm for this topology are according to Fig. 7-(a), by replacing each group with its members, the final scheduling will be according to Fig. 7-(b).

VI. PSO usage in the optimization problems

PSO algorithm is used in this paper to solve the optimization problems of the CH selection, and user grouping & power allocation.

In the problem of CH selection, Equation (19) is considered as the fitness function. Each initial particle shows the randomly selected CHs. Then, these random particles improve in the PSO’s finite iterations, and finally, the particle with the best fitness is returned as the selected CHs.

Complexity Analysis: Almost all metaheuristic algorithms are light in terms of complexity. The computational complexity of each iteration and the number of iterations (\(r\)) constitute the computational complexity of the PSO. Therefore, the complexity is in the linear form, and \(O(kr \cdot \log(k))\) (where \(k\) is equal to the initial population of the algorithm). As \(k\) is small (typically, \(k = 40\)), even if \(r\) is large (e.g. \(r = 5000\)), the computation cost will be almost light because the algorithm complexity is linear in terms of \(r\). Therefore, the main computational cost is because of the evaluation of the objective function. According to Equation (27), evaluation of the objective function in each iteration is performed with the computational complexity of \(O(n)\), where \(n\) is the number of sensors. Therefore, our user grouping and power allocation scheme has the complexity of \(O(nkr \log(k))\). Similarly, according to Equation (25), the complexity of our proposed clustering algorithm is \(O(nkr \log(k))\). The method proposed in [18] also uses the PSO algorithm to solve the clustering

![Figure 6. The topology after grouping.](image)

![Figure 7. (a) Group-based scheduling. (b) Final scheduling.](image)

![Figure 8. Convergence of the PSO algorithm.](image)
problem. So, its computational complexity is similar to our scheme.

The computational complexity of the method proposed in [8] (Referred to as the $\alpha$-fairness scheme) includes two parts: the computational complexity of each iteration and the number of iterations required for the algorithm convergence. In each iteration, the interior point method is employed with the computational complexity of $O(M^3)$, where $M = n^2 + 2n$ ($n$ is the number of users). Besides, the proposed algorithm converges linearly with a complexity of $O \left( \log \left( \frac{1}{\varepsilon} \right) \right)$, where $\varepsilon$ is the convergence accuracy of the algorithm. Therefore, the $\alpha$-fairness scheme has the complexity of $O \left( M^3 \log \left( \frac{1}{\varepsilon} \right) \right)$. Therefore, our scheme outperforms the proposed scheme in [8] in terms of computational complexity.

Convergence: The PSO algorithm is well-known for its fast convergence [48]. Besides, $\omega$ in Equation (5) is employed to control the impact of the previous history of velocities on the current velocity. Thus, $\omega$ influences the trade-off between global search and local search. A large $\omega$ facilitates global exploration, while a small $\omega$ tends to facilitate local exploration to fine-tune the current search area. Thus, by suitable adjustment of $\omega$ during the PSO execution, the PSO can have more global search ability at the beginning of the run and more local search ability near the end of the run [48]. Therefore, the PSO can converge to the optimal solutions in a small number of iterations. To show the convergence speed of our used algorithm, we presented the fitness function value of the PSO algorithm versus the number of iterations in Fig. 8. It is observed that after a certain (finite) number of iterations, the results converge to a suboptimal final value.

### Table II: Simulation parameters.

| Parameter               | Value   |
|-------------------------|---------|
| Time slot duration      | 10ns    |
| Minimum slotframe length| 10      |
| Number of channels      | 3       |
| The bandwidth of the channels | 333KHz |
| Simulation run time     | 500s    |
| Propagation model       | Two-Ray Ground Reflection Model |
| Noise power spectral density | -173 dBm/Hz |
| Uplink transmission power budget, $P_u$ | 24 dBm |
| SIC threshold, $th$     | 10 dBm  |
| $\alpha$                | 4       |

VII. Simulation and performance evaluation

The performance of the proposed scheme is evaluated through a comprehensive simulation study as presented in this section. In our simulation study, NS-2.31 and MATLAB 2018a are used to simulate the proposed CH selection, user pairing and power allocation schemes, and the proposed scheme of NOMA usage in a TSCH-based wireless sensor network. The following parameters are considered for the performance evaluation:

- Throughput: calculated by Equation (8).
- Power consumption: The total power consumed by the nodes for data transmission.
- Energy efficiency: The ratio of the overall system throughput to the total power consumption.
- Fairness level of the system: calculated by Equation (31).
- End-to-End Delay: The time interval between the production of data by the sender and the receipt of data by the destination.

To simulate the proposed scheme, we consider several sensor nodes (users) that are randomly distributed in a circular environment with a radius of 200m around the sink node. Sensors are clustered in multiple levels and send their information to the sink through their CHs. The CHs and the sensors will be grouped by using the proposed user grouping and power allocation scheme proposed in Section V.B. The number of selected CHs is equal to ten percent of sensor nodes. The scheduling algorithm used in this network is based on the proposed algorithm in [42]. Also, only dedicated slots of slotframe are considered. Since TSCH and NOMA techniques are jointly used, each channel in each time slot is assigned to more than one sensor (the nodes of a NOMA group). The simulation is repeated for 20, 30, 40, and 50 sensor nodes. The minimum required data rate of the sensors varies from 50 Kbit/s to 500 Kbit/s. In the PSO
algorithm, the initial number of particles and the number of iterations are set to 40 and 400, respectively. Also, the PSO parameters are set as defined in [18, 32] ($\omega = 0.7$ (inertia weight) and $c_1 = c_2 = 2$). Other simulation parameters are set according to Table II. To evaluate the proposed scheme, its performance will be compared to the TSCH standard, and our proposed CH selection scheme is compared with the proposed schemes in [18] (Referred to as the ECH Scheme) and [19] (Low Energy Fixed Clustering Algorithm: LEFCA). Furthermore, our user grouping and power allocation scheme is compared with the proposed scheme in [14] (Referred to as the PF scheme).

The end-to-end delay of the TSCH (clustered by our proposed CH selection and clustering algorithm) and our proposed scheme are shown in Fig. 9. TSCH and NOMA techniques are jointly used in our proposed scheme. Therefore, each channel is assigned to more than one node at each time slot. The number of sensors that are served in each time slot increases compared to the case where NOMA is not used. The length of the slotframe decreases, and thus, the number of slots assigned to a node in a certain period increases. As a result, the medium access time is reduced in our proposed schemes compared to TSCH. Therefore, as shown in Fig. 9, the end-to-end delay will be reduced. The end-to-end delay increases more significantly in the TSCH compared to our proposed scheme when the number of sensors increases. This is the result of the increase in the length of the slotframe.

It can be concluded from Fig. 9, that more sensors can be served in our proposed scheme (TSCH and NOMA jointly usage) considering a specific delay requirement.

Our CH selection and user grouping & power allocation schemes are evaluated against the PF, LEFCA, LEFCA+NOMA (grouped by our user grouping & power allocation scheme) and ECH schemes and the results are presented in Figs. 10-13, in terms of throughput, power consumption, energy efficiency, and spectrum efficiency, respectively, where it is shown that our scheme outperforms other schemes. The reason for the better performance of our scheme compared to the other schemes is that the NOMA constraint presented in Section V.A is applied in our scheme. CHs will be selected in a way that the minimum difference of the channel gains required for grouping is met. Therefore, they can use NOMA transmission efficiently. Besides, the intra-user/intra-cell interference will be reduced and the CHs consume less power to deal with these interferences. Furthermore, as the distinct minimum required data rates of the users are considered in the user grouping & power allocation problem, the groups are formed by the users that impose less interference on each other. This leads to low power consumption for the interference compensation.

Besides, as shown in Figs. 11, and 12, the proposed scheme outperforms the PF scheme in terms of power consumption and energy efficiency as the PF scheme
uses distinct channel gains for user grouping. When the number of users increases, the channel gains difference will reduce. Therefore, more intra-user interference will appear in the groups, and sensors should consume more power to compensate for the interference. Also, the intra-user interference affects the sensors' achievable data rates (based on Equations (7) and (8)). Thus, the throughput of the proposed scheme is higher than the PF, LEFCA, and ECH schemes. Consequently, the energy efficiency and spectrum efficiency of our proposed scheme are higher than other schemes.

As shown in Figs. 10 and 11, our proposed scheme, PF, LEFCA+NOMA and ECH reach a higher throughput compared to TSCH. However, the power consumption of these methods is higher than TSCH as the length of the slotframe reduces in these methods. Thus, the number of slotframe iterations increases at a given time, and more sensors will be served in each time slot. Consequently, throughput and energy consumption increase as well. On the other hand, the waiting time for medium access (Idle time) reduces in our proposed scheme, PF, LEFCA+NOMA and ECH due to the reduction of the slotframe duration.

Therefore, the energy consumption of the idle mode decreases too. However, due to the higher throughput of the proposed scheme compared to the others, the energy efficiency is also higher than TSCH, PF, LEFCA, LEFCA+NOMA, and ECH schemes, as shown in Fig. 12. Furthermore, the number of transmissions in the given spectral bandwidth is increased because more sensor nodes are served in each slot. So, according to Fig. 13, the spectrum efficiency increased in the proposed scheme compared to TSCH. In LEFCA+NOMA, due to random CH selection, NOMA conditions are less likely to be met than our CH selection scheme. Therefore, the sensors cannot be grouped properly, and intra-user interference will be high in the groups. As a result, power consumption increases and throughput decreases. Energy and spectrum efficiencies are also less than the other schemes.

To investigate the effect of the rate increase on the end-to-end delay, 266.6 kbps, 320 kbps, and 400 kbps data rates are assumed in a network with 50, 100, and 150 sensor nodes. According to Fig. 14, end-to-end delay increases as the data rate increases in the network. However, using NOMA jointly with the TSCH leads to the serving of more sensors even in
higher data rates. As mentioned above, the slotframe duration reduces in our proposed scheme that will result in an increase in the number of transmission of the nodes in a given time. Therefore, the queuing delay of the nodes and thus, the end-to-end delay will decrease too. Therefore, the NOMA technique can be used to support higher data rates in the network.

We further investigate the impact of using the non-orthogonal multiple access (NOMA) technique on TSCH capacity. For this purpose, the simulation is repeated for 12, 50, 150, and 200 sensor nodes. Then, the results of throughput and spectrum efficiency of the TSCH and our proposed scheme (TSCH and NOMA jointly usage) are compared. As seen in Figs. 15 and 16, when the number of sensors is low, the performance of both methods is the same, due to the low amount of traffic. All traffic will pass the network. However, throughput and spectrum efficiency increase rates slow down and gradually converge to a certain value (saturation condition) in the TSCH method with the increase of the number of sensors. This is due to the limited available resources that are allocated to the sensors orthogonally. So, the number of sensors that can be served simultaneously will be confined to the available resources. But, as shown in these figures, NOMA can increase the number of sensors that are served in a given bandwidth (or a given time) simultaneously. Therefore, throughput and spectrum efficiency increase proportional to the number of sensors. Throughput and spectrum efficiency convergence rates are slower than the TSCH case, and this convergence occurs in a higher number of sensors. Therefore, employing NOMA can increase the network capacity in the TSCH standard that can lead to the support of massive communications. Besides, we compared our proposed user grouping and power allocation scheme with the proposed scheme in [30] (clustered by our CH selection and clustering algorithm). In [30] (MD-NOMA), the grouping distance threshold (channel gains) is used for user grouping. So, when the number of users increases, the channel gain diversity decreases, the intra-user interference increases, and the throughput decreases. Besides, more users cannot be grouped because they cannot apply the NOMA technique. Therefore, fewer users will be served in a given bandwidth (or a given time) simultaneously, and this causes the network to reach saturation conditions in a fewer number of users. Throughput and spectrum efficiency also becomes lower than our proposed scheme.

To evaluate the fairness level of the proposed method, its performance is compared to the scheme proposed in [8] (α-fairness) and the PF scheme [14]. According to Fig. 17, the fairness level of the proposed scheme is higher than the α-fairness and PF schemes. Because in our scheme, users are grouped according to their minimum data rate requirements and channel gains, and this leads to the appropriate distribution of strong and weak users in the groups. Therefore, intra-cell interference decreases, and the ratio of the users' achievable data rate to the users' required data rate increases. The channel gain of users is considered for grouping in the PF and α-fairness schemes. Therefore, strong and weak users are not properly distributed in the groups, and the level of interference that occurs in the groups will increase. As a result, the achievable data rate of the users in the groups with high interference is low, and they cannot reach their required data rate in the given time. The more users, the more this problem occurs. However, in the proposed scheme, the users are grouped based on their required data rate and also their channel gain. Therefore, the inter-user interference and the number of groups with high levels of interference will be less than the PF and α-fairness schemes. Therefore, the sensors’ achievable data rate increases. More sensors will be satisfied and gain their required data rate. We refer to the sensors whose required data rate has been achieved as “satisfied nodes”. In the TSCH scheme, the number of satisfied nodes is less than the proposed
scheme, α-fairness and PF schemes, due to the orthogonal allocation of the resources.

Besides, as the number of users increases, the slot frame length increases as well. Thus, the number of transmitted bits in the given time reduces for each node, and the percentage of satisfied nodes reduces. Therefore, as shown in Fig. 18, the proposed scheme outperforms the other schemes in terms of the percentage of the satisfied nodes.

VIII. Conclusion

In this paper, PD-NOMA based scheme was proposed to improve scalability and latency in IEEE 802.15.4e TSCH based clustered WSN. In this scheme, a new clustering algorithm is proposed to select appropriate CHs such that the selected CHs can be grouped for efficient NOMA transmission. Efficient user grouping and power allocation strategies, which are key design issues for successful operations of NOMA systems are formulated as an optimization problem. The optimization problem aims at maximizing fairness and overall system throughput under the constraints of transmission power budget, minimum data rate requirements of the users, and SIC constraints. In the proposed user grouping algorithm, unlike other existing schemes, users' QoS and the SINR difference are used to distribute the users in the groups, which imposes low interference on them. So, users consume less power to overcome this interference, improving energy efficiency. The simulation results showed that our user grouping & power allocation scheme performs well in terms of fairness, throughput, power consumption, and energy efficiency. Furthermore, the proposed scheme outperforms the TSCH scheme in terms of delay, throughput, and also spectrum and energy efficiencies. The performance of the proposed schemes can be investigated in a MIMO system as a future work. Furthermore, our proposed user grouping scheme can be studied for the groups with various number of users. The effect of mobility on the performance of the proposed scheme is another research direction that can be handled by suitable dynamic user grouping methods (Dynamic user re-grouping and resource allocation).

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