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Device-enabled neighborhood-slot allocation for the edge-oriented Internet of Things

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Internet of Things (IoT) has become an interesting research domain as numerous devices, preferably equipped with sensors, communication, and actuator modules, are deployed to capture real-time data in the different application areas, such as smart healthcare and industries. These devices have the built-in capacity to directly interact with the physical phenomenon and report any unusual situation within their respective coverage areas, i.e., monitoring a critical patient in the smart hospital but direct communication with a common destination module is not guaranteed and could possibly be very challenging if two or more devices, preferably those in closed proximity, are interested to transmit simultaneously. Therefore, in this manuscript, we are going to present a hybrid slot allocation approach, which is specifically designed for those devices resided in neighborhood and are eager to communication concurrently with a common destination device, i.e., server. In the beginning, the k-mean clustering algorithm is used to group these devices into clusters where server is forced to collect data from devices deployed in the respective coverage areas. Thus, every server generates dedicated slots for active devices and an additional slot for server(s). Similarly, the proposed neighborhood-enabled time division multiple access (TDMA) has the flexibility of assigning multiple slots to a requesting device if available, which is needed in scenarios, such as detection of pest in the field. Additionally, a member device is allowed to migrate (if needed and possible) from one server's coverage region to another. Simulation results confirmed that the proposed approach is better than the existing algorithms (opportunistic TDMA, hybrid TDMA, and non-orthogonal multiple access), particularly in terms of bandwidth, end-to-end delay, and empty slot utilization. The proposed scheme has improved bandwidth and empty slot utilization, which are approximately 15% and 12%, respectively, whereas it has achieved approximately 94.89% utilization of the available slots which was previously 93.4%.

KEYWORDS

Internet of Things, remote sensing, k-mean, clustering, time division multiple access (TDMA), communication

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1 Introduction

Internet of Things (IoT) is defined as a self-organized network of various devices C_i, i.e., things, which are dispersed either randomly or deterministically (if feasible) to periodically monitor a physical phenomenon, i.e., controlling manufacturing process in the hazard environment when entry of the human being is susceptible to possible danger (Song et al., 2020). These devices are attached directly to the equipment and programmed such that the required information is captured precisely and accurately after a fixed time interval (Alam et al., 2024). Furthermore, these devices C_i depend on the on-board battery that is most probably not rechargeable and equipped with transceiver module that has a limited coverage area, and thus, every device is not able to communicate directly with the base station (Nassereddine and Khang, 2024). It is important to note that these wearable devices C_i may be embedded with various application-dependent sensors and actuator modules in IoT networking infrastructures(Alshehri et al., 2018). Reliable and timely transmission of the capture data is one of the difficult problems with IoT networks (Wang et al., 2024). This captured data are either transmitted directly (if possible) or through multi-hop communication mechanism where a group of these wearable devices acts as relaying devices and is bounded to transmit data of the neighboring devices in addition to their own data (Gope et al., 2021). In these scenarios, it is high likely that multiple devices may be interested to communicate with a common destination module, i.e., server in this case.

Due to the concurrent communication in the IoT, the probability of collision among various packets is very high in industrial Internet of Things (IIoT) networks (Alshehri et al., 2019). Therefore, various simultaneous transmission-enabled communication approaches have been presented to guarantee concurrent transmission of packets from multiple wearable devices C_i to IIoT networks. These mechanisms are primarily based on the idea allocating dedicated sub-channels or a time slot or a separate code for the communication. Orthogonal Frequency Division Multiple Access (OFDMA) is one of the common mechanisms which is used to guarantee simultaneous transmission of multiple wearable devices C_i with a common receiver, i.e., server S_j in this case (Nguyen et al., 2020). OFDMA generates smaller frequency bands by dividing available bandwidth which is called sub channelization. These channels are assigned to various competing wearable devices preferably in first-come-first-serve or priority bases in IIoT networking infrastructures. Similalrly, OFDMA with a single carrier is presented to address concurrent communication of multiple devices through a hybrid of time and frequency domains. Apart from it, non-orthogonal multiple access (NOMA) was reported in the literature to enable packet transmission of multiple wearable devices C_i, concurrently using a shared medium of communication in the IoT networks (Khan et al., 2020). An extended version of the NOMA, i.e., power-enabled NOMA, was reported to address the aforementioned issue; power levels are utilized as a differentiating factor in the concurrent communication among multiple devices (Shahab and Shin, 2018; Sun et al., 2019). Wastage of the available bandwidth is among the core issues associated with these approaches, particularly in the IoT networks. In addition to these schemes, time division multiple access (TDMA)-based schemes were presented, where available sliding window (preferably time-based) is divided into various slots, and these available time slots are allocated to needy wearable devices either permanently or preemptive-based strategy (Johari and Krishna, 2020). A hybrid mechanism, i.e., TDMA and hierarchical, was reported in the literature to enable concurrent or simultaneous transmission of packets among multiple active wearable devices in the IoT networks. Although this mechanism has addressed various problems linked to the TDMA-based approaches, it is susceptible or vulnerable to the failure of a single point that is parent device C_i. Apart from these, neighborhood-based schemes have been presented for static and mobile IoT networks, respectively; however, both schemes do not consider applicability of the machine learning approaches, especially in scenarios where networks become mature (Khan et al., 2021, 2023). Therefore, an effective, reliable, and efficient wireless communication algorithm is required to be proposed that not only ensure simultaneous communication among multiple devices but also equally resolve the aforementioned issues.

In this study, we present a machine learning and neighborhood slot allocation-enabled wireless communication methodology that is particularly developed for the edge-enabled IoT infrastructure. In this approach, k-mean clustering (AI-based methodology) is utilized to organize randomly deployed wearable devices C_i into an operational hierarchical IIoT networks, where every server or cluster head (CH) has a specific set of member devices C_i. Second, every server S_j has been forced to form two groups of time slots, where one group, preferably large, is dedicated for the ordinary member devices C_i and other, particularly small, is reserved for server modules S_j, which are not able to transmit directly. The major contributions to the research community of the work presented in this study are as follows:

1. Machine learning and neighborhood slot allocation-enabled transmission for IoT networks with minimum possible communication overheads.
2. K-mean algorithm is used to ensure maximum possible utilization of the available bandwidth and empty slots in IoT.
3. Migration aware TDMA approach where wearable devices C_i may migrate from coverage area of a server to another, a common scenario in the smart hospitals.
4. A two tier machine learning-enabled slot allocation approach which is specifically designed for the hierarchical IoT networks.

The rest of the study is organized as follows. In Section 2, a brief but comprehensive literature review of the most relevant techniques is presented. In Section 3, we have focused on explaining how the proposed machine learning and neighborhood slot allocation-enabled mechanism are formed and how it is used to be applicable in the problem domain. In Section 4, a detailed and thorough analysis of the proposed and available schemes is presented in terms of numerous performance metrics. Finally, concluding remarks and future directions are presented.

2 Literature review

In this section, a brief literature review of numerous related approaches have been presented as complete review is beyond the scope of this study. Moreover, as existing approaches cover different research domains such as non-orthogonal multiple access (NOMA) and time division multiple access (TDMA), details of these schemes are shown in separate subsections.

2.1 Non-orthogonal multiple access-based approaches

Unlike single sub-carrier approach, where a high rate or power stream is transmitted to enable simultaneous wireless communication, a multiple sub-carrier concept is utilized in OFDMA. In this scheme, multiple small sub-carriers, preferably within the same single carrier stream, enable simultaneous communication among multiple interest devices in both traditional and constraint-oriented networking infrastructures (Nguyen et al., 2020). In OFDMA-enabled approaches, the available bandwidth (single stream) is divided into smaller multiple sub-carries or frequency bands which are allocated to those interested wearable devices. It is observed that these sub-carriers were bounded to transmit in parallel, where guard carriers are used to reduce channel interference and transmission delay. Similarly, vector OFDMA was reported which is based on the concept of multiple input and multiple output (MIMO), whereas flash OFDM is based on the concept of multiple tone and fast hoping to enable simultaneous wireless transmission among multiple devices. Single-carrier OFDMA is an alternative solution to the traditional OFDMA which has the capacity to allow more powerful transmitters. Additionally, NOMA scheme, that is a random access approach-based technique, has been reported in the literature to enable simultaneous transmission of multiple devices over a common channel (Khan et al., 2020). NOMA is reliable and has the ability to achieve expected goal of the 5G networks. In this scheme, every device is bounded to operate in the same frequency band, where power levels of every device are different from other, which is used as a differentiating factor at the destination module or device. Generally, NOMA utilized super position coding-enabled transmitters which are helpful to differentiate between down-link and up-link channels at the respective receiver that is a successive interference cancellation-enabled. An extended version of NOMA, that is power-enabled NOMA, was reported, where numerous devices use completely different power level in order to transmit data values (Shahab and Shin, 2018; Sun et al., 2019). Although these methods have addressed the communication problem (concurrent) with IoT networks, one of the frequent problems with these techniques is bandwidth waste.

2.2 Time division multiple access-based approaches

Contention-enabled multiple access approach, that is primarily a four-way hand shake approach, was presented to allow simultaneous transmission of more devices, preferably active and interested, with a common receiver. Furthermore, the situation becomes more and more complex only if devices have to utilize a common channel or medium for communication (Adame et al., 2014; Doost-Mohammady et al., 2016). Although this mechanism has resolved the collision issue, excessive time for registration is a challenging issue with this approach. Combined authentication/association (Shahin et al., 2016), distributed authentication control (Bankov et al., 2016), and centralized authentication control (Pawlowski et al., 2014) were reported in the literature to address numerous possible problems with the contention-enabled multiple access mechanism. Similarly, a reliable and efficient handshaking approach (four way), that is RTS and CTS which are used to represent request and clear-to-send, respectively, was presented specifically to resolve the challenging issue that is hidden terminal scenario (Chen et al., 2018). This mechanism ensure the reliability of an ongoing communication session by forcing other devices to hold their transmission until the session is completed. The exposed terminal scenario, where devices that can interact without interruption are constrained to wait for the successful conclusion of an ongoing communication session, is a strongly connected problem with this technique. Faruque (2019) have presented a TDMA-enabled communication mechanism to enable simultaneous transmission of multiple devices. In TDMA, the sliding window, time based, is divided into numerous slots, preferably of equal size. These available time slots are allocated to wearable devices on first-come-first-serve basis preferably in a non-preemptive manner. A member device must communicate (if it has data to send) in its dedicated slot, and slot is empty if a particular device does not have any data to send. In a dedicated TDMA approach, collision is completely avoided, but wastage of the available bandwidth is very high. Lee and Cho (2017) presented an alternative approach to the traditional TDMA scheme that is a hybrid scheme. TDMA and hierarchical approaches were integrated to form an exceptional communication scheme for the IoT network. However, single-point failure and transmission delay (maximum) are among the common issues associated with this approach. Similarly, a contention-free MA scheme was proposed by Zhai et al. (2016), to enable a proper schedule-based transmission of packets in time and frequency domains. It has used an automatic repeat request-based scheme to improve reliability and efficiency. However, specific hardware-oriented is one of the core issues associated with this scheme. Similarly, a slotted hybrid approach, that is based on CSMA/CA and TDMA, was presented by Shahin et al. (2018), to enable simultaneous transmission of multiple interested wearable devices preferably in their own time slot. This scheme is quite effective to address the excessive registration problem associated with the IoT networks. In this system, member devices are compelled to broadcast their authentication request messages via CSMA/CA, while association request messages are handled exclusively by TDMA. Batta et al. (2019a,b) have proposed various extensions to the traditional TDMA approach, especially distributed to improve latency in IoTs. A distributed and token-based mechanism was developed to resolve the hidden terminal scenario problem preferably in the IoTs and Mobile Ad Hoc Networks (MANETs) (Ye and Zhuang, 2017). Prolong end-to-end latency, concurrent packet transmission, and single-point failure are among the core problems with this scheme. Similarly, distributed TDMA was reported in the literature to minimize bandwidth wastage in the IoT networks, where slots are allocated to various devices using a mature scheduling policy

(Li et al., 2017). This scheme has used priority metric of a device to guarantee the allocation of a slot. However, starvation and simultaneous communications are not guaranteed, as time slot assignment strategy is prioritized. Thus, a low-priority device should wait longer. Similarly, a time slot assignment approach, which is based on the distributed TDMA, was presented by Bhatia and Hansdah (2013) where the allocation process of available slots is random. Synchronization is among the core problems, which is closely linked to this approach. A novel multi-channel hybrid approach was presented to resolve the aforementioned issue in IoMT (Ramachandran et al., 2020). On-board power efficiency and complexity are the main problems linked to this methodology. Similarly, topological orders-enabled TDMA scheme was reported in the study mentioned in the reference (nguyen et al., 2020), where wearable device maintained valuable information about the scheme, and it is very useful to get a time slot. However, slots' waiting time has a direct co-relation to the network density.

3 Proposed machine learning and neighborhood slot allocation-enabled communication scheme for Internet of medical things

A thorough and in-depth explanation of the suggested machine learning and neighborhood slot allocation-enabled communication technique is provided in this section. The proposed methodology is advanced enough to enable the transmission of packets, especially simultaneous of several devices, ideally close neighbors, to a single destination device, such as a server module or cluster head (CH) in IIoT networks. In the beginning, a hierarchical IIoT network is created using the K-mean clustering technique, one of the unsupervised learning and partitioning clustering mechanisms, where each member device is placed so that it may connect directly with the desired CH module in the IIoT networks. Below is a thorough explanation of the K-mean clustering method.

3.1 K-mean clustering in the proposed communication approach

Usually, k-mean clustering approach is used to divide data values (preferably non-labeled) into clusters, and it is high likely that data values belong to a particular cluster have the similar characteristics, particularly those on which clustering is performed. Initially, k-means clustering is bounded to randomly select K devices S_j, where K represents the expected number of clusters in the IoT networks as the intended CH S_j. In the proposed setup, CHs S_j are devices preferably with higher communication and processing capabilities than the ordinary devices C_i in the IoT networks. These devices S_jj may reside at different locations, as the deployment process or mechanism is random, and it is high likely that a balance clustering approach, where every cluster has similar member devices C_i, is not feasible. These cluster heads are deployed randomly using Equation 1, where every CH module S_j represents a particular centroid in the modified k-mean clustering approach as follows:

$$C_k = \frac{\sum_{j:(C(j))=k} CH_j}{N^k} \tag{1}$$

where k=1.....K clusters in the IoT network. In the second step of the k-mean algorithm, member devices C_i of every CH S_j are identified through a systematic processing that is using a well-known distance measure, such as Euclidean distance measure. Euclidean distance between a CH S_j and ordinary device C_i is calculated as described in Equation 2

$$Distance(S_j, C_i) = \sqrt{\sum_{l=0}^{n} (S_{1j} - C_{1i})^2} \tag{2}$$

where l represents various metrics used to calculate the distance between a particular CH and its neighboring devices preferably those reside in the coverage area of the communication module. Furthermore, a specific threshold value, i.e.„ $\delta = 0.05$ in this case, is assumed to divide member and non-member devices C_i using Equation 3 which is presented below.

$$\begin{cases} \forall_{j=0...m}\ D(S_j, C_i) < \delta \\ \exists_{i=0...n}\ D(S_j, C_i) == \delta \end{cases} \tag{3}$$

It is necessary to find the best possible set of nearest neighboring devices C_i for every CH module S_j in the IoT network. Additionally, every ordinary device finds the nearest CH module S_j, which is computed using Equation 4 as follows:

$$CH(j) = argmin_{j<k<K}[CH_j - C_i]^2 \tag{4}$$

where j=1 . . . m. Thus, a particular member device C_i joins the CH module S_j which is deployed at the least possible distance in the IoT networks.

Additionally, every CH module S_j is bounded to broadcast its location information to the neighboring devices C_i, which is quite similar to the process of computing a new centroid in the traditional K-mean clustering mechanism as given in Equation 5.

$$CH_j(a) = \frac{1}{n_{j:CH_j \leftarrow C_i}} \sum x_i(a) \tag{5}$$

where a represents the numerical or attribute value of possible set of member devices in the coverage area of a particular cluster head module S_j. It is noteworthy that a modified version of the traditional k-mean approach is used, where the cluster head selection process is repeatedly applied. However, in the proposed setup, CH modules are powerful devices, and the rotation process for the CH module is not needed. In this way, every device C_i becomes a member of the nearest possible CH module in the operational IoT networks. Furthermore, unlike balanced clustering mechanism where every cluster has similar number of member devices C_i, the proposed model adopts a non-balanced clustering methodology. It is due to the random deployment nature of these devices, i.e., C_i & S_j, where it high likely that a particular area may have dense deployment than other areas. As soon as the clustering formation mechanism is complete, the next process is to generate a dedicated time slot for every member device C_i in a particular CH module S_j.

4 Proposed neighborhood-enabled slot allocation approach for Internet of medical things

In this phase, it is assumed that every CH module S_j has completed the membership process of the ordinary devices C_i (preferably neighboring devices). Furthermore, a member device is bounded to be a part or member of a particular CH module S_j even though the another CH module is located in its coverage area. However, devices C_i reside on the edges of two or more clusters should keep the record of other CH modules S_{j+1}, which are at second and third (if any) positions as far as distance is concerned. Initially, every CH module S_j divides the allocated frequency domain (preferably radio) into time slots of equal size such that a particular time slot is sufficient for the transmission of data captured by a member device C_i. Moreover, every CH has to make sure that slots are allocated to those devices only which fall within the direct coverage area, i.e., having minimum possible distance. To understand the complete methodology, a detailed flow chart of the entire working process of the proposed neighborhood-enabled slot allocation scheme is shown in Figure 1.

Furthermore, a single device is allowed to transmit its data in a particular time interval, whereas other devices wait for their allocated time slots. Thus, the net rate of transmission in scenarios, where load remains constant, is shown in the following Equation 6.

$$\eta^{S}_{TDMA} = \frac{1}{M} \tag{6}$$

where M is the total number of member devices C_i in the coverage area of a particular CH module S_j. In the proposed TDMA approach, every CH module has a different number of member devices, and thus, it is high likely that the number of slots is different in every CH module S_j. For example, if a CH S_j has twelve (12) member devices, then it is forced to generate or divide the radio frequency into 12 equal time slots. Furthermore, these time slots are assigned in first-come-first-serve (FCFS) basis. Time slot T_1 is assigned to device C_i only if the time slot has reserved the device before other member devices $C_{i+...n}$ in a particular CH module S_j. It is important to note that spectral efficiency of the proposed TDMA scheme is computed using the following Equation 7.

$$\eta_a = \frac{\tau M_t}{T_f} \tag{7}$$

where metric τ represent the duration of a particular time slot, M_t is used to represent the total number of slots per frame, and T_f is used to depict the duration of a particular frame in the IoT networks. As soon as time slots are assigned to the member devices C_i, the next step is the transmission of data captured by these member devices. In the proposed neighborhood-enabled TDMA approach, it is possible that a particular CH module S_j has maximum number of member devices than other CH modules S_{j+1} in the networks. Therefore, a member device C_i in this particular CH is expected to wait longer for its particular time slots. For example, the n^th device C_n has to wait for ψ_n, which is represented by the following Equation 8.

$$\psi_n = \tau - Mod((\sum_{i=1}^{n} W_i + \frac{n-1}{\mu}), T) \tag{8}$$

where W_i and μ represent arrival and transmission time of a particular device C_i, respectively, in the proposed TDMA approach. Meanwhile, the serving time μ is represented by Equation 9.

$$\mu = \frac{1}{T} \tag{9}$$

where T represent the time interval of a particular time slot which is constant in the proposed mechanism. Thus, putting the value of μ in Equation 8, we get Equation 10 as given below.

$$\psi_n = \tau - Mod((\sum_{i=1}^{n} W_i + (n-1)T), T) \tag{10}$$

which is further simplified into the following Equation 11, as given below.

$$\psi_n = \tau - Mod((\sum_{i=1}^{n} W_i, T) \tag{11}$$

To resolve this issue, the proposed TDMA approach allows devices deployed on edges of two or more clusters to switch from one cluster to another. This process is applicable only if its waiting time interval with the first cluster is longer than its expectation. However, this shifting process is bounded by certain rules which are given below.

1. Migration is applicable in early stages of the IIoT and only once for every interested wearable device C_i.
2. slot waiting time or the expected value of ψ_n for a wearable device C_i is greater than the defined threshold value.
3. The number of wearable devices C_i in current cluster S_j should be greater than that of neighboring cluster S_{j+1} (if any exist).
4. A wearable device C_i, that is interested in migration, should be in direct communication range of the intended CH module $S_jj + 1$.
5. The intended CH module has not accepted any or at-most one migrated device C_i.

If a particular member device C_i fulfills the aforementioned restrictions, the proposed scheme allows this device to migrate from current CH module S_j to another CH S_{j+1}. For this purpose, this device C_i should inform the current CH module S_j before sending a cluster joining request to another CH module that is S_{j+1}. This previous information is helpful for the current CH; current CH S_j utilizes this time slot by assigning it to other member devices C_{i+1} or repeating the process of dividing the radio frequency into the time slots. However, it is noteworthy that the migration process of any member device C_i is possible until the network becomes fully operational.

When a device interested in migration sends a request to join cluster message to the intended cluster head, it waits for a certain time interval which is sufficient to receive response message from the expected CH module S_j, as described in Equation 12

$$T_b = rand(100 - 1000)\ microsec \tag{12}$$

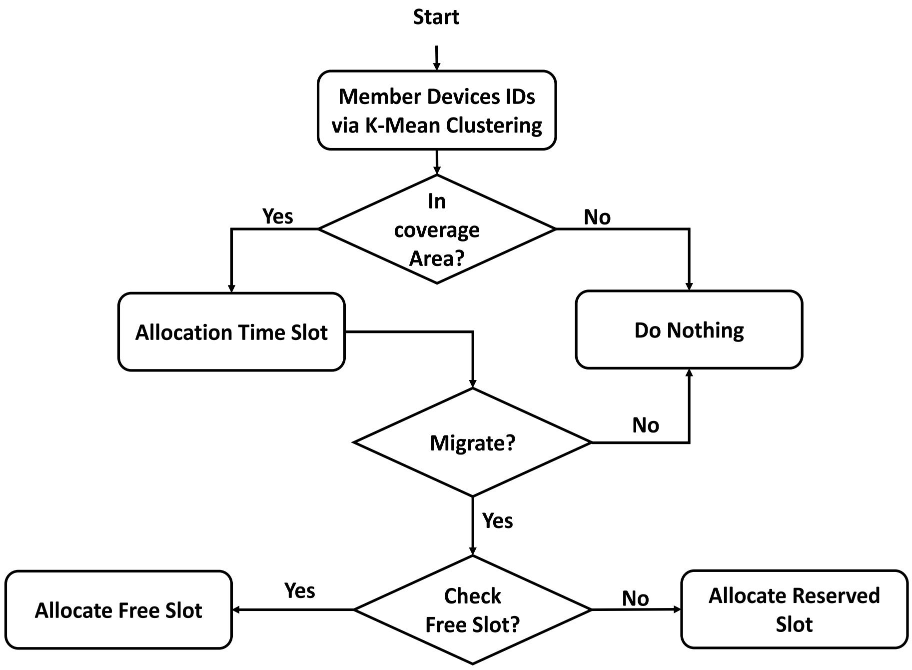

FIGURE 1
Flow chart of the proposed neighborhood-enabled slot allocation scheme.

where T_b represents back-off or waiting time interval of device C_i, which is interested in migration and joining another CH module S_j. The concerned CH module S_j generates time slot for the migrated device C_i by dividing the radio frequency domain into time slots. However, every CH module is bounded to repeat (if necessary) slot generation process once or twice, but it should be completed before the network becomes fully operational. Once time slots are generated, the alloted time slot is shared with the migrated device C_i in the IoT networks.

Migration activity of member device C_i from one CH to another is very helpful in the efficient utilization of the available bandwidth, maximizing throughput of the underlined networks. Apart from it, slot waiting time is reduced, which is directly proportional to the number of member devices in a particular CH module S_j. Additionally, the proposed TDMA approach allows a device C_i to hold multiple slots (if available) as long as other member devices C_{i+1} are not eager to communicate with the CH module S_j. However, a request should be sent by the concerned device C_i to the intended CH module S_j that multiple slots are required. For example, an IoT network is considered which has five CH modules S_j and fifty devices C_i where j=1.....5 and i= 1....50. Since the deployment process is random, it is quite likely that every CH module has different number of member devices. Apart from that, it is possible that a member device may be a part of two or more clusters, which is possible for those devices that are deployed on the edges of these clusters. However, unlike existing TDMA schemes, the proposed approach does not allow any device C_i to be a member of multiple cluster heads, resulting in data duplication and wastage of resources. Let us further assume that $CH_1, CH_2, CH_3, CH_4,\ and\ CH_5$ have 15, 10, 10, 7, and 8 member devices, respectively. Thus, cluster heads $CH_1, CH_2, CH_3, CH_4,\ and\ CH_5$ are bounded to generate 15, 10, 10, 7, and 8 time slots, respectively, and assign these slots to the member devices in FCFS. However, slot waiting time in CH_1 is approximately double than that of CH_4 and CH_5, respectively. Thus, as suggested in the proposed TDMA approach, if two devices are migrated from CH_1 to CH_4 and tow to CH_5, then waiting time interval in cluster head one,i.e., CH_1, is reduced considerably, which enhances throughput of the networks. Although slot waiting time intervals in both cluster heads, i.e., CH_4 and tow to CH_5, are increased approximately, its impact on overall waiting time of the member devices is less as member devices are less than other modules in the network. The proposed neighborhood-enabled slot allocation scheme bounds every CH to maintain a closed ratio with the number of available slots and member devices in the IoT. Additionally, every member device is bounded to communicate within its allocated time slot and more slots are required, these should be assigned based on their availability. Furthermore, reserve slots are utilized only if a new device enters in the coverage area of the respective CH, and free slots are not available. A complete description of this whole process is graphically presented in a diagram or system model, which is shown in Figure 2 .

5 Simulation results and discussion

In this section, a detailed analysis on the performance of the proposed machine learning and big data analytic-enabled approach in the light numerous evaluation metrics is presented. For this purpose, the proposed scheme along with the existing schemes is

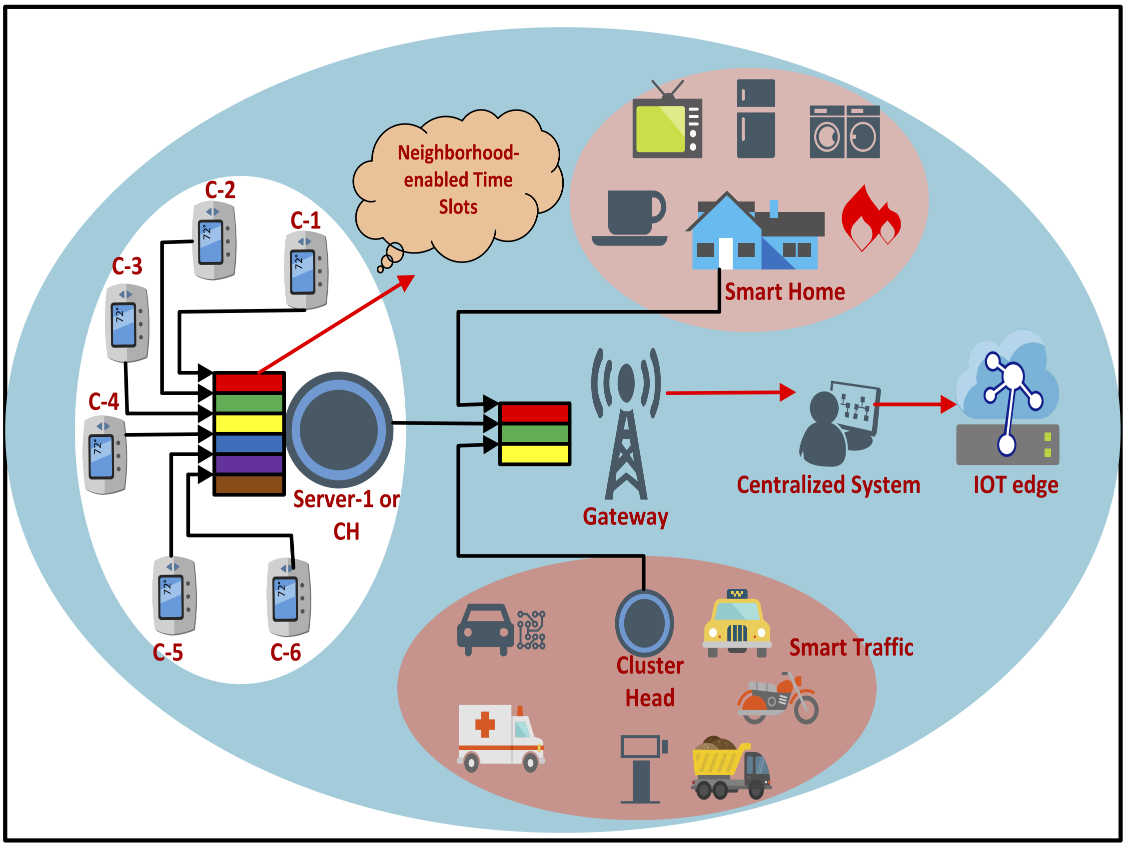

FIGURE 2
Graphical representation of the proposed neighborhood-enabled slot allocation scheme in the IoT.

implemented in OMNET++ (?), where the signal to noise ratio and interference are assumed to be constant. Every member device was assumed to have initial energy of 52000 mAh, which was similar to the capacity of WaspMote Technology Pro-board (?). Moreover, we have assumed that transmission and processing power of the CH module are far more greater than an ordinary device. Simulation parameters, which are used in conducting these experiments both for existing and proposed approaches, are shown in Table 1. In this simulation, the expected channel rate was assumed as 9600 and 2400 bps, where value of $\mu = 0.5$ *and* 2.8. For example, if channel rate is 9600 bps, then the length of a single packet is 86 * 8 bits $\Rightarrow$ approximate length of a single slot is $T_s = 64 * 8/9600 = 0.05$s. Now, if the total member devices in a particular cluster is 15, then the frame length $T_sM = 0.75\ s$. Apart from it, channel delay was assumed as constant in both schemes, i.e., proposed and existing. These algorithms are evaluated using different and well-known performance metrics, such as message or packet delay during transmission, packet loss ratio, slot waiting time, and utilization of the empty slots.

5.1 Average slot waiting time in the industrial Internet of Things

Usually in TDMA schemes, a shorter average waiting time for a respective slot (preferably for dedicated time slot of a particular device) of a particular member device is considered as the best possible solution in the IIoT networks. Slot waiting is the approximate time a device must be in the waiting state for the allocated time slot in every frame. Generally, slot waiting time has a direct proportionality ratio to member devices in a particular cluster or server device. Figure 3 shows that the proposed approach is a feasible solution than the existing approaches for the resource-constraint devices as it reduces the waiting time of a particular member device to an expected level. On X-axis, individual slot time, that is based on the number of devices in the coverage area of the respective server, is presented, whereas the Y-axis shows the approximate time required for a member device to wait for its dedicated slot in the IoT. Furthermore, the proposed scheme achieves this milestone without compromising on other performance metrics in the IIoT networks. Similarly, the proposed scheme outperforms than the existing scheme if migration of member devices, preferably from one cluster to another, is carried out properly, as shown in Figure 4.

5.2 Empty slot utilization in the industrial Internet of Things

In both traditional and IIoT networking, it is high likely that a particular device may not be interested in the transmission activity either due to non-availability of data or other issues. Thus, slots

TABLE 1 Simulation parameters of the Internet of medical things.

Parameters	Values
Area of deployment	900m * 900m
Ordinary devices	60, 120, 600, 1200
Cluster head S_j	five (05)
Preamble & header	15μs
T_b Waiting Time	random
Number of slot	member based
Time slot	50 us
Size of data	2000 bits
block size p	1 burst
Burst type	Synchronization Burst
Residual battery power (E_r)	E_i-E_c
Initial battery power (E_s)	52000 mAh
Channel delay (Ch_{delay})	10 milliseconds
Receiver energy consumption (P_{R_x})	59.1 mW
Transmitter energy consumption (P_{T_x})	91.4 mW
Energy consumption in idle mode	1.27 mW
Energy consumption in sleep mode	15.4 μW
XBee transceiver (T_i)	1 mW
Range of Xbee module (T_r)	500m
Transmission (blind) of physical layer S_j	28
Receiving power threshold (RTS_n)	1024 bits
Packet size (P_{size})	512 bits
Multi-frame	51
Distance between devices and CH	350m
Sampling interval	1, 2, 3,...10 seconds
Topological infrastructure	Static and Random
Carrier	BCCH

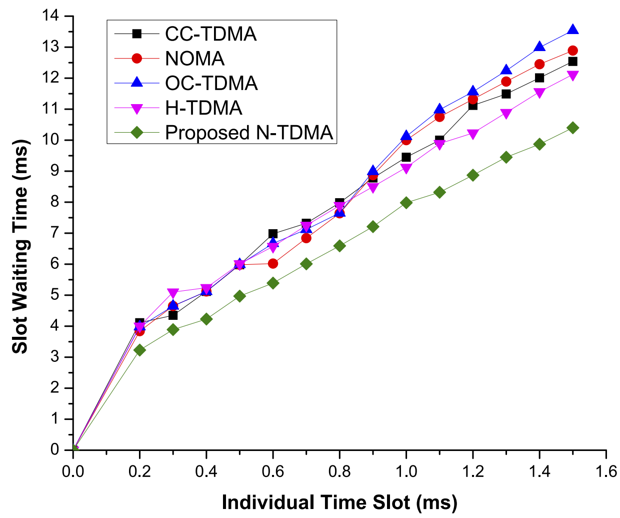

FIGURE 3
Proposed MLTDMA-based and field-proven approach evaluation (empty slots [without migration aware strategy]).

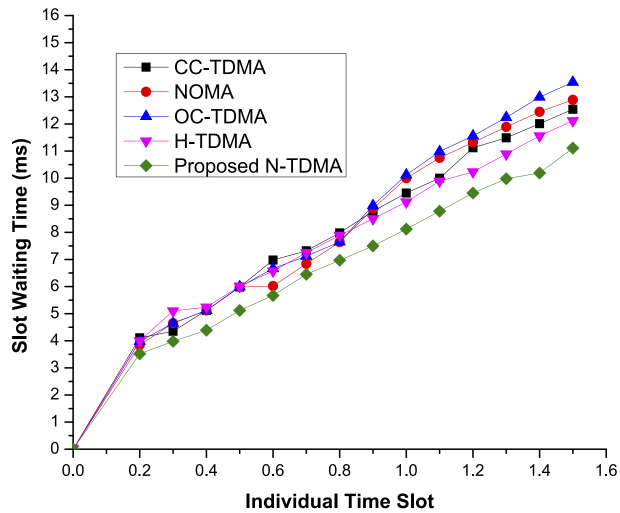

FIGURE 4
Proposed MLTDMA-based and field-proven approach evaluation (empty slots [with migration aware strategy]).

allocated to such type of devices are empty, i.e., no data values, which is a wastage of the valuable resources that are bandwidth in this case. To address this issue, the proposed machine learning and TDMA-enabled approach allowed a particular device to use two or more slots in a single frame if available. Figure 5 presents a comparative analysis of the proposed and existing approaches preferably how efficiently empty slots are utilized. On X-axis, individual slot time, that is based on the number of devices in the coverage area of the respective server, is presented, whereas Y-axis show the approximate time required for a member device to wait for its dedicated slot in the IoT. Similarly, in even-based application, it is possible that only those member devices are interested in communication, where the expected event is triggered in their vicinity. Figure 6 shows that the proposed scheme outperformed approximately all the existing schemes by allocated two or more slots (depending on their availability) to those devices, which are eager to communicate the expected event information.

5.3 Average packet transmission delay in the industrial Internet of Things

The performance of the proposed machine learning-enabled communication and existing approaches preferably with respect to the average packet transmission delay is shown in Figure 7, which clearly depicts that the proposed scheme has achieved the minimum possible transmission delay, where value of μ = 0.5. On X-axis, member devices belong to the internet of things and have an average transmission delay of 0.5 are represented, whereas on Y-axis, the approximate ratio of delay is encountered or observed during the whole communication process. The proposed approach has accomplished this minimum possible

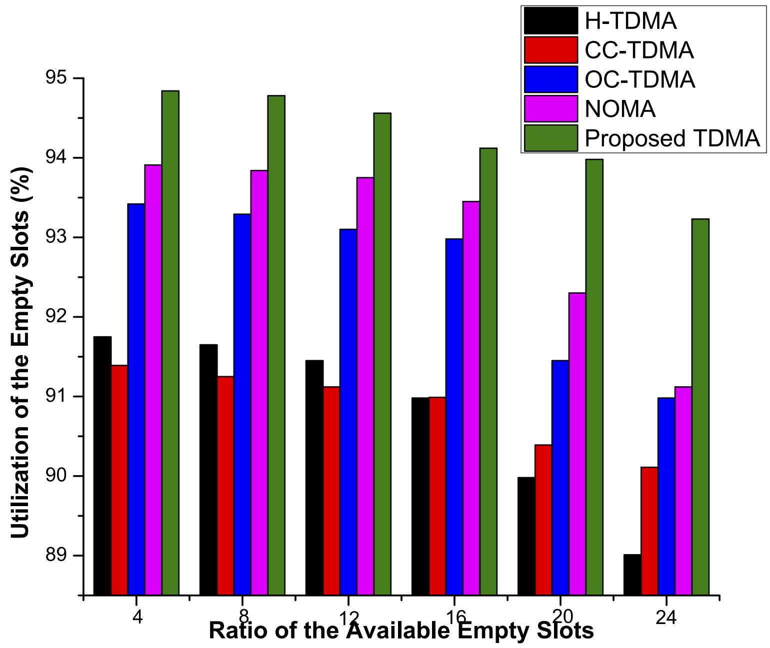

FIGURE 5
Proposed MLTDMA-based and field-proven approach evaluation (empty slots).

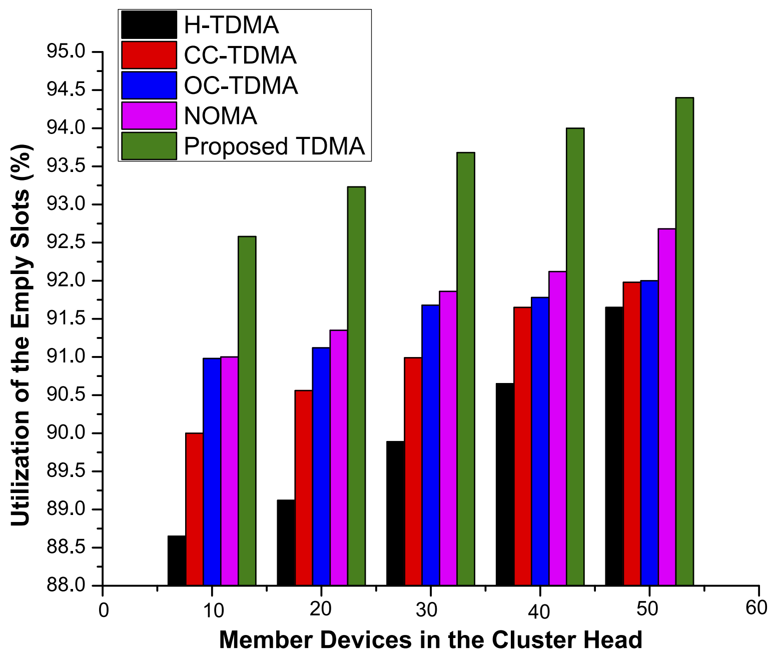

FIGURE 6
Proposed MLTDMA-based and field-proven approach evaluation (empty slots [event-based application]).

ratio due to the allocation of multiple slots and migration of member devices from heavy loaded clusters. Furthermore, processing delay at both ends, i.e., source and destination devices, is minimized due to availability of slot(s) in the IIoT networks. The proposed machine learning and big data analytic-enabled approach have reduced approximately 13% of the average packet transmission delay in an active IIoT networking infrastructure.

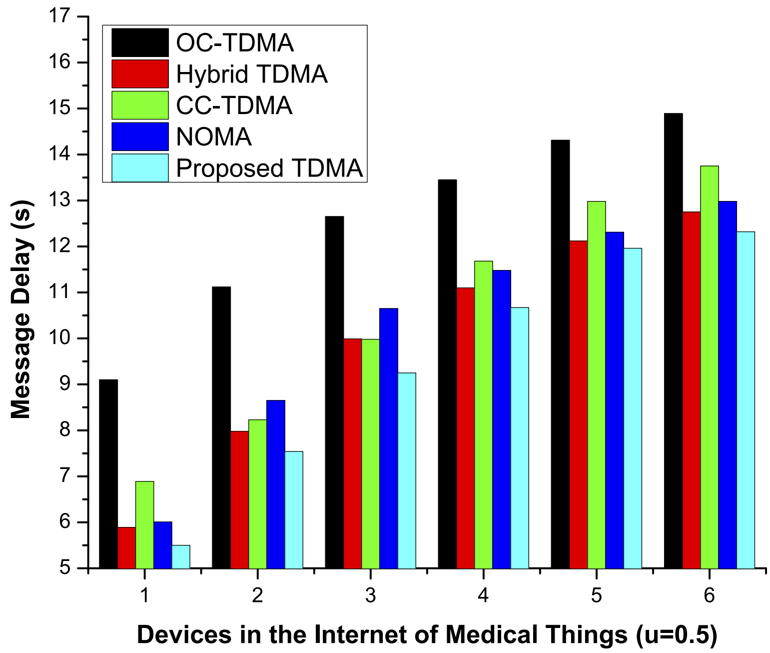

FIGURE 7
Proposed MLTDMA-based and field-proven approach evaluation (message delay).

5.4 Packet or frame loss ratio in the industrial Internet of medical things

Packet or frame loss ratio is one of the common evaluating metrics which is used by researchers and scientific organizations to judge the performance of a communication approach in the realistic environment of IIoT networks. APLR is defined as the possible ratio of the total transmitted packets to those which are delivered successfully to the server S_j. APLR is assumed as the challenging evaluation and effective metrics to judge the performance of a communication protocol, particularly in the IIoT networking infrastructures. Therefore, the proposed machine learning and big data analytic-enabled communication approach are compared with the existing approaches with respect to their performance while using APLR as evaluation metric. Figure 8 shows that the proposed scheme has the ability to maintain the lowest possible ratio of the average packets, which are lost during the communication process. On X-axis, member devices belong to the IoT are represented, whereas on Y-axis, the approximate ratio of those packets which are lost during the communication process is depicted. The proposed scheme has achieved this milestone by allowing member devices to migrate from heavy loaded, i.e., CH with approximately maximum members, clustering into others where load is minimum.

5.5 Computational complexity

Generally, every physical object is defined through time and space parameters. Similarly, efficiency of an algorithm is determined through the complexity of these two parameters, particularly time and space. Both of these parameters are very crucial particularly in situations where devices are resources-constraint, i.e., IoT. The time complexity of the proposed scheme is $\mathbf{O(n)}$ as compared to other algorithms, that is $\mathbf{O}\boldsymbol{n}^{\mathbf{2}}$ or even higher.

6 Conclusion and future directions

During the last two decades, the efficient utilization of resources, preferably bandwidth, was assumed as a challenging issue for communication approaches both in traditional and resource-constraint networks. In this study, machine learning and neighborhood slot allocation-enabled wireless communication approach were presented to address the aforementioned issue, particularly in the IoMT. Initially, uniform clustering is achieved through a modified k-mean clustering algorithm, where centroids were constants, i.e., cluster head in this case, which are approximately 5–10% of the ordinary devices. Then, a well-known distance measure was used to find member devices of every CH module, whereas devices reside on the edge of two or more CH modules were allowed to select any one of them. Furthermore, member devices are encouraged to migrate (in terms of membership not mobility) from one cluster to another cluster with certain rules and restrictions. Similarly, a member device was allowed to hold two or more slots if available in IIoT networks. Simulation results have verified that the proposed machine learning and big data analytic-enabled communication scheme are one of the best candidates than the existing approaches, especially IIoT networks. The proposed scheme has improved empty slot utilization ratio, approximately 13%, than the existing scheme with available resources.

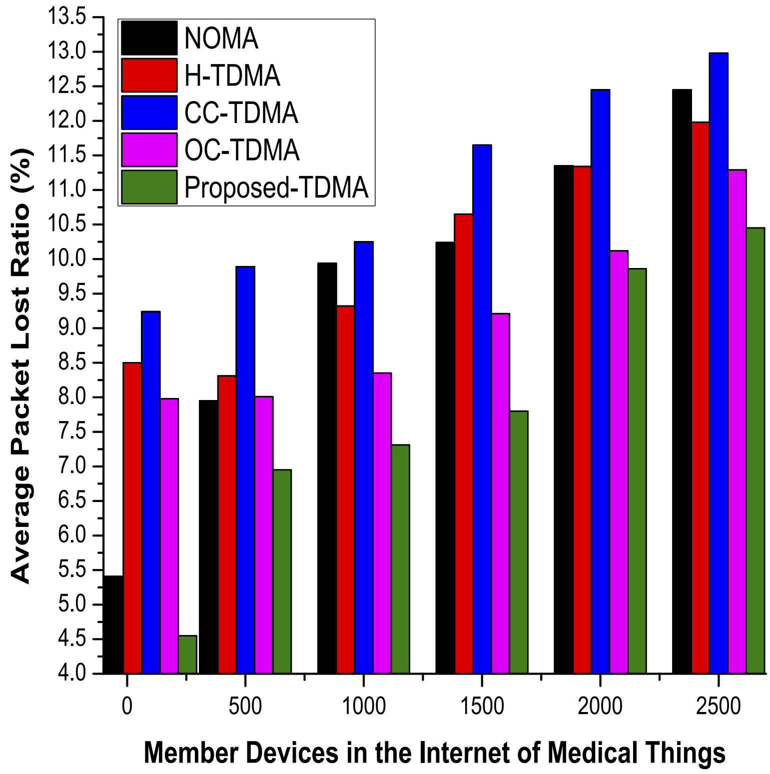

FIGURE 8
Proposed MLTDMA-based and field proven approach evaluation (APLR).

In future, we will investigate performance of the proposed machine learning and big data analytic-enabled approach in the IoMT environment, where wearable devices are mobile. Furthermore, it will be interesting to observe the results of the proposed scheme in those IoMT networks where both wearable devices and CH are mobile.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://home.uncg.edu/cmp/downloads/lwsndr.html.

Author contributions

RK: Investigation, Software, Supervision, Writing – original draft, Writing – review & editing, Conceptualization, Funding acquisition, Project administration. MK: Formal analysis, Software, Writing – original draft, Writing – review & editing, Conceptualization, Investigation, Methodology, Project administration, Resources. NS: Conceptualization, Data curation, Methodology, Supervision, Writing – review & editing, Formal analysis, Project administration, Resources, Software. AA-R: Formal analysis, Funding acquisition, Project administration, Validation, Visualization, Writing – review & editing. AK: Investigation, Methodology, Project administration, Software, Validation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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