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Fully Automated Multi-Resolution Channels and Multithreaded Spectrum Allocation Protocol for IoT Based Sensor Nets

TAIMUR HASSAN¹, SALEEM ASLAM¹, AND JU WOOK JANG², (Member, IEEE)

¹Department of Electrical Engineering, Bahria University, Islamabad 44000, Pakistan

²Department of Electronic Engineering, Sogang University, Seoul 04107, South Korea

Corresponding author: Ju Wook Jang (e-mail: jjang@sogang.ac.kr).

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ABSTRACT Internet-of-Things (IoT)-based sensor networks have gained unprecedented popularity in recent years and they become crucial for supporting high data rate real-time applications. For efficient data transmission within IoT networks, it is necessary that each IoT node learns and adapts itself to recent time/spectral characteristics of channels to maximize the throughput and perform channel swapping wherever required. Many researchers have proposed channel allocation and channel quality measurement protocols within multichannel sensor networks. However, to the best of our knowledge, there is no literature available that proposes an automated and adaptive protocol that can learn and adapt according to changing channel characteristics in IoT network for achieving maximum data transmission and throughput. Therefore, this paper proposes a fully automated self-learning and adaptive protocol which can automatically transmit multiuser data by efficiently utilizing channel time/spectral characteristics. The proposed protocol is unique as it learns and adapts itself to the increasing network density based upon the network metrics. It also allows each node within IoT network to automatically detect the neighboring channel attributes so that they can swap channels to achieve maximum data transfer. This is accomplished by continuously extracting distinct features from the network topology. After extracting these features, the proposed protocol efficiently selects the best channel for an incoming node, provides the best channel utilization based upon its time/spectral attributes, and detects and allocates the unused spectrum of neighboring channels through multistage Gaussian radial basis function and multilayer perceptron-based nonlinear support vector machines classification model. Simulation results demonstrate the supremacy of the proposed protocol in terms of throughput, successful reporting probability, average blocking probability, fairness, and classification accuracy.

INDEX TERMS Internet-of-Things (IoTs), wireless sensor networks (WSN), support vector machines (SVM), spectrum allocation.

I. INTRODUCTION

Internet-of-Things (IoTs) based wireless sensor networks (WSNs) are becoming one of the key element for implementing different applications related to healthcare and surveillance [1]–[4]. IoT network can be thought as the combination of objects, sensors, and devices, interrelated with different kinds of controllers, armed with transceivers, and embedded with protocols for the distribution of their sensing and control information [5]. IoT networks (nets) consist of multiple sensor nodes that have the capability to sense their neighboring environment however; they have a finite amount of energy, processing unit and memory [4].

One of the key tasks within sensor nets is to determine the route taken between source and destination for effective data transmission [2], [3]. Many researchers have worked on improving the energy consumption in each sensor node in order to maintain high data transmission rate [5]. Also, there has been a paradigm shift in WSNs which allows each sensor node to effectively transmit a large amount of data without notable delay [6]–[8]. Furthermore, different methods have been proposed which employs multichannel protocols for effective communication over WSNs. Apart from this, different hybrid channel partitioning protocols are also proposed that utilizes fixed slots based time/frequency

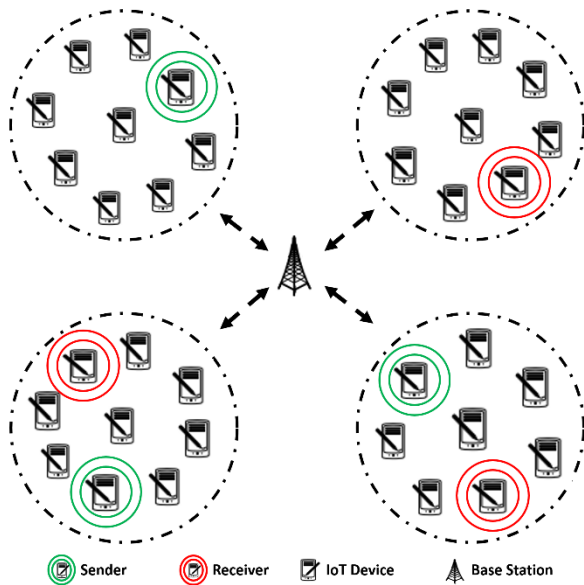


FIGURE 1. Proposed system model.

attributes for efficient channel utilization. Figure 1 shows a typical IoT based sensor network in which IoT nodes are deployed within the regional cluster where different channels provide high-speed data transmission in a single tier based IoT network. Two adjacent nodes are connected to each other via an active path that is formed by selecting the best available channel. Apart from this, each node is equipped with the decision support system so that it can swap to nearby channels by continuously learning the network metrics and the network topological conditions. Unlike conventional WSNs, multichannel based IoT networks need a mechanism to determine which channel is to be selected for transmitting the potentially large amount of data. Data can also be prioritized as some nodes might have higher priority data for transmission as compared to others. So, each IoT node must be able to detect the neighboring channel congestion as well as channel load to throughput (LTR) for effective data transmission. Many researchers have proposed different protocols to measure channel quality and stability in a multichannel environment [8]–[16]. Some of those protocols utilize single radio per node [17]–[21]. If the spectral bands at transmitting and receiving end vary then they may be additional power dissipation overheads along with channel switching delays [21]. Due to these switching delays, there may be the loss of data during high data rate transmission [21], which ultimately affects the performance of the whole system. Therefore, instead of packet-based channel assignments, stream-based channel assignment protocols are proposed under such circumstances [22], [23].

Apart from this, many researchers have proposed multiple hybrid channel partitioning protocols that utilize fixed slots based time/frequency attributes for efficient channel utilization. Shahid *et al.* [24] proposed a potential game (PG) approach for joint resource and power allocation (JRPA) that

improves the performance of femtocell capacity by minimizing interference and maintaining the macrocell performance. Yu *et al.* [25] proposed a multichannel protocol in which each node keeps a utility function and a performance matrix based on past information to predict network topological information. This protocol assigns channels based on past information and does not consider the current channel quality indicator (CQI). Saleem *et al.* proposed a channel selection and allocation in cognitive radio networks by ranking the statistics of PU usage. Apart from this, many multichannel protocols within sensor networks do not employ any channel quality measurement protocols, such as Lagrangian relaxation (LGR) algorithm [28]–[30]. Furthermore, several efforts have been done in exploiting the quality service aware channel allocation in cognitive radio based networks [31]–[33] and many researchers proposed medium access control (MAC) layer protocols for the single hop [34] and multi-hop networks [35]. However, these protocols are not self-aware in terms of learning the changing network metrics and most of the work has been done in formulating a good CQI metric for best channel assignment rather than developing a fully automated channel partitioning and spectrum allocation protocol that can automatically detect channel time/spectral attributes for efficient data transmission in a multiuser environment. Therefore, this paper presents a fully automated protocol that can transmit multiuser data efficiently based on channel time/ spectral characteristics. The proposed protocol is unique in a way that it can learn and adapt to increasing network density based upon the network metrics. The main contributions of this paper can be summarized as follows:

- This paper presents a fully automated network-aware channel allocation protocol that automatically learns the network dynamics and topological information to transmit the maximum amount of data.
- The proposed protocol is first of its kind that employs Gaussian radial basis function and multilayer perceptron-based non-linear support vector machines within each IoT node to detect neighboring channel quality for autonomous channel switching.
- Furthermore, this paper proposes a multi-resolution hybrid channel partitioning protocol which automatically analyzes the varying time/ spectral characteristics of a channel for efficient data transfer in a multiuser environment.
- The proposed protocol significantly outperformed other state of the art solutions in terms of mean throughput, mean channel blocking probability, channel fairness, successful reporting probability and achieved up to 50% better classification accuracy as compared to existing decision support system based spectrum detection and allocation protocols.
- The proposed protocol is extremely robust and provides high transmission rate up to 43.5 Mbps over a single multi-resolution channel.

The paper is structured in such a way that section II explains the underlying system model and the supervised decision

TABLE 1. Symbols and notations.

Symbols	Description
ϑ	Multi-resolution Channel
\emptyset	Multi-resolution Channel Capacity
K	Number of Multi-resolution Channels
N	Number of IoT Nodes
x	IoT Node Baseband Signal
φ	Modulated Signal
σ_φ^2	Channel Variance
ϑ_L	Lower Decomposed Channel Band
ϑ_H	Higher Decomposed Channel Band
$L_{PF}(2n)$	Decimated Low Pass Strainer
$H_{PF}(2n)$	Decimated High Pass Strainer
f	Fused Feature Vector
f_1	Number of Nodes
f_2	Number of Messages
f_3	Channel Load to Throughput Ratio
f_4	Channel Blocking Probability
f_5	Jain's Fairness Index
N	Number of IoT devices
ϑ_T	Total Channel Bandwidth
ϑ_N	Channel ϑ utilized by N IoT Devices
K	Depicts Number of Folds during Cross Validation
α	Classification Accuracy
τ_p	True Positive Rate/ Sensitivity
τ_N	True Negative Rate/ Specificity

support system. Section III presents the detailed performance evaluations of the proposed protocol along with its comparison with state of the art techniques. Section IV presents the discussion and Section V highlights the conclusion and future directions. Apart from this, Table 1 describes different symbols and notation that are used in the paper. IoT nodes and sensor nodes are used interchangeably in this paper for reflecting IoT devices.

II. SYSTEM MODEL

A. NETWORK MODEL

We propose an IoT based sensor network that consists of N sensor nodes over K multiresolution channels as shown in Figure 2. For the sake of simplicity and illustration purpose, the channels in the proposed protocol are modeled using Additive White Gaussian Noise (AWGN). The proposed protocol employs a supervised decision support system which

automatically allocates the channel's time frame or spectral bandwidth to the incoming nodes depending upon the channel load as well as the size of the packet. The proposed system achieves efficient channel utilization based on network density. If there are more users and each user having large packet size to deliver, then the proposed protocol assigns each user a specific portion of the spectrum for transmission. Similarly, if there are fewer users or the packet chunks are smaller in length, then the channel allocates equal time frame to each user for transmission. Apart from this, the proposed protocol allows each node to detect the unused spectrum of neighboring channels as well as the channel throughput, then the node computes the LTR (i.e., it is the CQI that defines the load versus quality of the channel). If the LTR of a neighboring channel is low, then the respective node swaps the channel by sending two-way handshaking process. The spectrum allocation in the proposed protocol is accomplished by extracting distinct features from the network statistics and these features are passed to the proposed classification system embedded within each IoT node, which tells each node whether to request for channel swapping or not. The details of each respective section of the proposed protocol are discussed below:

1) NETWORK-AWARE MULTI-RESOLUTION CHANNELS

We employed K multi-resolution channels in the IoT network where the proposed protocol automatically allocates channel time frame or spectral attributes to all IoT nodes. The core benefit of utilizing multi-resolution channels is that they provide the least corruption and better transmission rate due to their ability to generate optimal time/frequency localization (the depiction that at what time the particular frequency occurs and how the information at particular time instance is encoded in the frequency domain) as shown in Figure 2. The proposed protocol modeled each multi-resolution channel ϑ using AWGN as expressed through (1)-(3):

$$\begin{bmatrix} \varphi_0 \\ \vdots \\ \varphi_{i-1} \end{bmatrix} = \begin{bmatrix} \alpha_0 \cos \left(2\pi \sum_{k=0}^{N-1} (f_c + \Delta_0 x_0(k)) \right) \\ \vdots \\ \alpha_{i-1} \cos \left(2\pi \sum_{k=0}^{N-1} (f_c + \Delta_{i-1} x_{i-1}(k)) \right) \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} \vartheta_0 \\ \vdots \\ \vartheta_{j-1} \end{bmatrix}_{\vartheta_j} = \begin{bmatrix} \varphi_0 + \frac{1}{\sqrt{2\pi}\sigma_0} e^{-\frac{\varphi_0}{2\sigma_0^2}} \\ \vdots \\ \varphi_{i-1} + \frac{1}{\sqrt{2\pi}\sigma_{i-1}} e^{-\frac{\varphi_{i-1}}{2\sigma_{i-1}^2}} \end{bmatrix} \quad \forall i \neq j \quad (2)$$

and

$$\emptyset_j = \frac{1}{2} \log \left(1 + \frac{\frac{1}{N} \sum_{k=0}^{N-1} |\varphi_j(k)|^2}{\sigma_{\varphi_j}^2} \right) \quad (3)$$

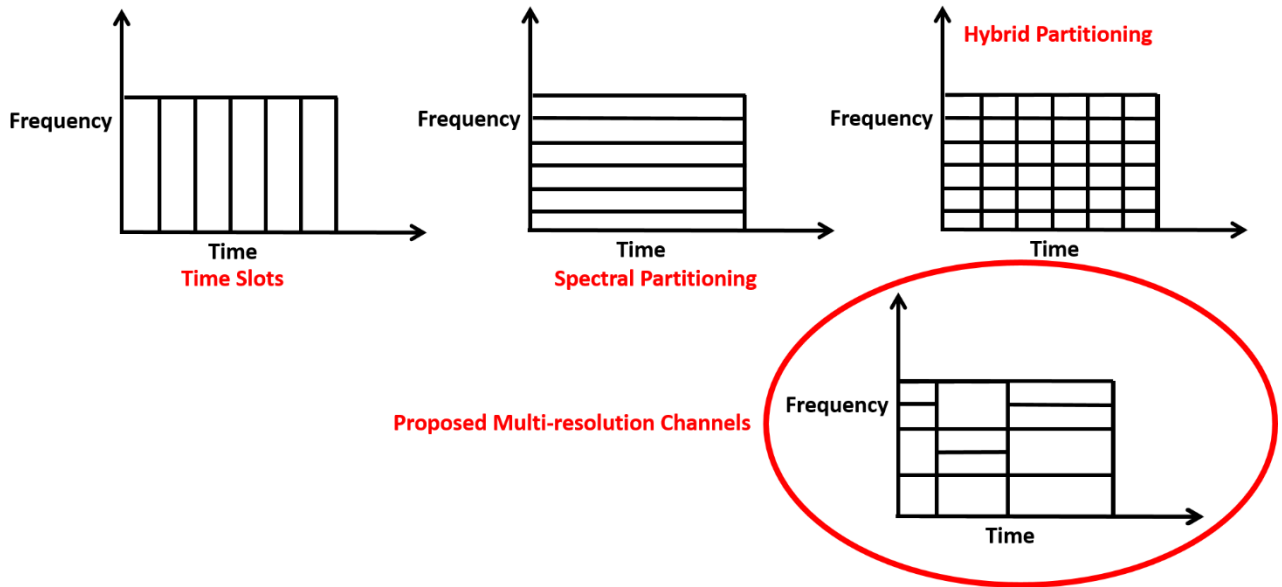


FIGURE 2. Hybrid multi-resolution channels.

where $x_i(k)$ is the baseband signal of sensor node i , α_i is the carrier amplitude for the message signal of IoT node i , Δ is the frequency deviation, φ_i is the modulated signal of IoT node i , $\sigma_{\varphi_j}^2$ is the variance of load on channel j and ϑ_j is the output constraint of channel j by the channel capacity θ_j . The multi-resolution analysis of ϑ is performed through Daubechies Type-II based wavelet packet decomposition which decomposes the channel model into its higher and lower spectral bands through (4) - (6):

$$\begin{bmatrix} \vartheta_0 \\ \vdots \\ \vartheta_{j-1} \end{bmatrix} = \begin{bmatrix} \langle \vartheta_L^0, \vartheta_H^0 \rangle \\ \vdots \\ \langle \vartheta_L^{j-1}, \vartheta_H^{j-1} \rangle \end{bmatrix} \quad (4)$$

and

$$\vartheta_L^i = \sum_{k=0}^{n-1} \vartheta_i(k) L_{PF}(2n - k) \quad (5)$$

$$\vartheta_H^i = \sum_{k=0}^{n-1} \vartheta_i(k) H_{PF}(2n - k) \quad (6)$$

where ϑ_i is the i^{th} channel output, $L_{PF}(2n)$ is the decimated low pass filter, $H_{PF}(2n)$ is the decimated high pass filter, ϑ_L^i is the lower decomposed band and ϑ_H^i is the higher decomposed band.

B. HYBRID CHANNEL PARTITIONING PROTOCOL

The proposed protocol is first of its kind that allows efficient data transmission by learning the channel attributes. Each IoT node within the network is equipped with Gaussian radial basis function and multilayer perceptron-based non-linear SVM that takes a 2D feature vector $f = [f_1, f_2]$ as an input and gives a decision whether to utilize channel's

time or spectral characteristics. The detailed description of each feature is presented below:

1) NUMBER OF NODES (f_1)

The first feature is the number of IoT nodes within the IoT sensor network. The total count is calculated periodically through (7) - (8):

$$N = \{n_1, n_2, n_3, \dots, n_k\} \quad (7)$$

$$f_1 = \sum_{k=0}^{N-1} N_k \quad (8)$$

2) NUMBER OF MESSAGES (f_2)

The second feature f_2 is extracted by measuring the length of total messages which needs to be transmitted through the respective channel. f_2 is measured in unit of samples/second (9).

$$f_2 = \sum_{K=0}^{N-1} \sum_{j=0}^{K-1} x_i(j) \quad (9)$$

These features are extracted periodically by each IoT node to determine whether to use channel time frame or spectral bandwidth for data transmission. If the number of nodes and the data is lesser, then the respective channel utilizes time slots for data transmission. Contrary to this, if there are many nodes that are transmitting a large amount of the data, then the channel will use its spectral bandwidth for transmission as shown in Figure 3. The proposed protocol utilizes multistage decision support system for autonomous channel partitioning and channel swapping. In the first stage, it is used to determine the channel utilization through time or spectral characterization using f_1 and f_2 . In the second stage, it is used by the

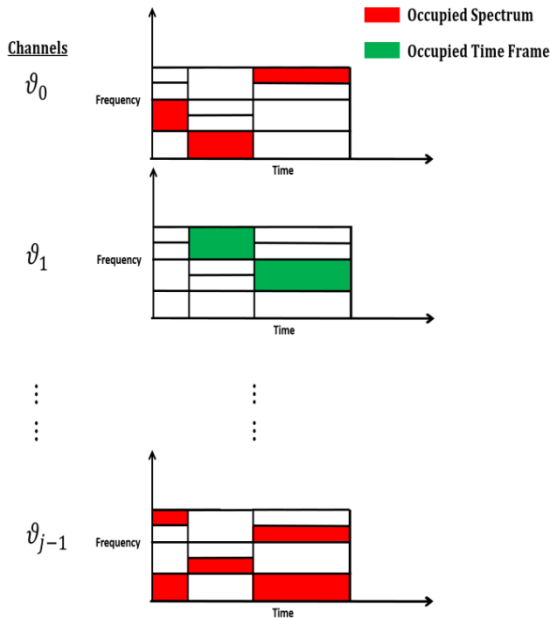


FIGURE 3. Multichannel data transmission of IoT sensor nodes.

sensor nodes to determine channel swapping mechanism. If it is decided by the Stage-I SVM that the underlying channel must be partitioned w.r.t time then channel swapping takes place by measuring the channel LTR and if it is decided by Stage-I SVM to partition channel w.r.t frequency then the proposed protocol employs Stage-II SVM for channel swapping using f_3, f_4 and f_5 . The Stage-I classification model in a proposed protocol is trained on a custom prepared dataset. Some of the randomly selected samples from the dataset for each category along with their mean and standard deviation (STD) is also shown in Table 2.

From Table 2, it can be observed that the extracted features are quite discriminating from each other for the automated selection of channel time or spectral attributes. In a dense IoT network where each IoT node sends a large amount of data, the channel is partitioned based upon its spectral bandwidth. However, if the devices are less in numbers or the numbers of messages are minimal then the channel is partitioned into time frames. Apart from this, each node computes LTR on neighboring channel to take the decision about swapping the channel. The LTR of a neighboring channel is computed through (10):

$$LTR = \frac{\sum_{K=0}^{N-1} \sum_{j=0}^{K-1} x_i(j)}{\frac{1}{2} \log \left(1 + \frac{\sum_{k=0}^{N-1} |\varphi(k)|^2}{\sigma_\varphi^2} \right)} \quad (10)$$

If the LTR is less than a threshold τ then the node sends a two-way handshake request and on receiving the acknowledgment, the node swaps the channel as shown in Figure 4. The value of τ was empirically found to be 0.3 through logistic regression modeling [36] as expressed by (11) - (13):

$$\tau = \frac{1}{1 + e^{-\gamma}} \quad (11)$$

TABLE 2. Randomly selected samples from stage-I training dataset.

Type	Cases	Features	
		f_1 (IoT Devices)	f_2 (Samples/Sec)
TIME PARTITIONING	Case-1	8 devices	8000
	Case-2	10 devices	1000
	Case-3	15 devices	5000
	Case-4	3 devices	1000
	Case-5	2 devices	2000
	Mean	7.6	3400
STD	5.3	3050	
SPECTRAL PARTITIONING	Case-1	45 devices	20000
	Case-2	100 devices	10000
	Case-3	100 devices	1000
	Case-4	50 devices	5000
	Case-5	65 devices	7000
	Mean	72	8600
STD	27	7162.4	

$$\gamma = \beta_0 + \beta_1(z) \quad (12)$$

$$\beta = [\beta_0, \beta_1] = \left[f(z_k), \frac{df(z_k)}{dz_k} \right] \quad (13)$$

where γ is the first order polynomial computed over the range of $0 \leq z \leq 1$ and z_k is the difference between two extremes of z .

C. ROBUST SPECTRUM ALLOCATION

The key feature of the proposed protocol is that it allows each node to detect the real-time state of neighboring channel during channel congestion. This allows each node to transmit data efficiently by channel swapping. This is unrelated to

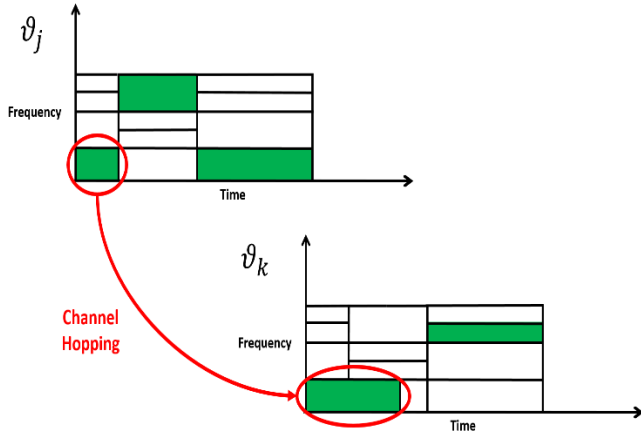


FIGURE 4. Swapping between time based channels.

conventional spectrum sensing concept for two-tiered cognitive radio networks where a secondary user can temporarily occupy vacant spectrum bands in the absence of a primary user.

Each node within a network computes 3 distinct features, forming a 3D feature vector, which is passed to Stage-II classification model to decide whether to switch the channel or not. The detailed description of each feature is depicted below:

1) LOAD TO THROUGHPUT RATIO (LTR) (f_3)

LTR measures the neighboring channel utilization and it is computed using (10). A lower value of LTR indicates that the channel capacity is underutilized and it can accept more data to transmit. Higher LTR indicates that the channel is mostly occupied.

2) BLOCKING PROBABILITY (f_4)

Blocking probability (P_B) indicates that whether the neighboring channel will block the data transmission after channel swapping. It is calculated through (14):

$$f_4 = P_B = \frac{\left(\frac{\vartheta_T}{\vartheta_N} - \sum_{K=0}^{N-1} \sum_{j=0}^{K-1} x_i(j) \right)}{\frac{\vartheta_T}{\vartheta_N}} \quad (14)$$

where $\frac{\vartheta_T}{\vartheta_N}$ is the bandwidth chunk allocated to each node, ϑ_T is the total channel bandwidth and ϑ_N are the total nodes transmitting data using the ϑ channel.

3) CHANNEL FAIRNESS (f_5)

The proposed protocol employs Jain’s Fairness Index to measure the neighboring channel fairness for transmission. Jain’s Fairness Index is computed through (15) [36]:

$$f_5 = \frac{\left(\sum_{K=0}^{N-1} \vartheta_N^i \right)^2}{N \sum_{K=0}^{N-1} (\vartheta_N^i)^2} \quad (15)$$

Each node periodically extracts these features to determine channel switching state and the extracted features are passed to the Stage-II SVM model. SVM is trained on the custom

TABLE 3. Randomly selected samples from stage-II training dataset.

Type	Cases	Features		
		f_3	f_4	f_5
CONTINUE TRANSMISSION	Case-1	0.45	0.41	0.80
	Case-2	0.59	0.26	0.84
	Case-3	0.85	0.15	0.73
	Case-4	0.71	0.28	0.85
	Case-5	0.53	0.31	0.78
	Mean	0.62	0.28	0.80
STD	0.15	0.09	0.04	
SWAP CHANNEL	Case-1	0.13	0.17	0.91
	Case-2	0.23	0.06	0.97
	Case-3	0.17	0.14	0.98
	Case-4	0.04	0.26	0.92
	Case-5	0.16	0.08	0.90
	Mean	0.14	0.14	0.93
STD	0.06	0.07	0.03	

prepared training dataset and 5 randomly selected samples of each class are also shown in Table 3. If the SVM within the respective node decides to swap channel then two-way handshake process is initiated.

The proposed protocol utilizes SVM based decision support systems because it is fast and it provides the best accuracy for binary classification [37]–[40]. Figure 5 depicts the training phase of SVM at both stages. The training samples of stage I consist of two features (f_1, f_2) whereas training samples of stage II are represented by three features (f_3, f_4, f_5), respectively. The performance of SVM at both stages is measured through k -fold cross-validation. We cross-validated the SVM for different values of k and computed the overall accuracy. The best accuracy was achieved for $k = 10$ as shown in Table 4. Moreover, the complete flow diagram of the proposed protocol is shown in Figure 6 in which the proposed protocol continuously learns from the network metrics to utilize channel time or spectral bandwidth and it also senses the neighboring channel quality for possible channel swapping.

III. SIMULATION RESULTS AND ANALYSIS

The proposed protocol is modeled on a machine with Core i5 processor and 4GB DDR3 RAM and its performance is

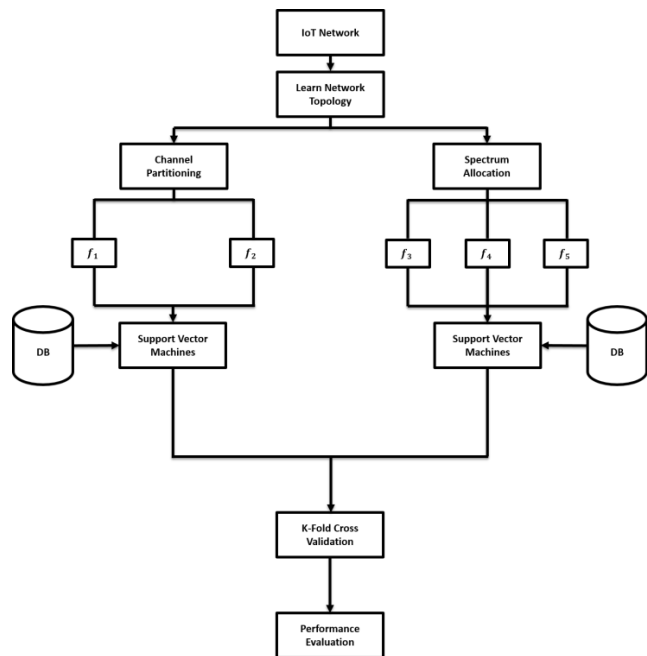


FIGURE 5. Training phase of proposed classification system.

TABLE 4. k-fold cross validation

Stage	k	Accuracy
STAGE-I	2	0.931547619
	4	0.952380952
	6	0.931547619
	8	0.952380952
	10	0.958333333
STAGE-II	2	0.931547619
	4	0.958333333
	6	0.952380952
	8	0.931547619
	10	0.979166667
	12	0.952380952

compared with the state of the art solutions against various metrics. The simulation results are achieved using MATLAB R2017a where different simulation parameters are depicted in Table 5. Apart from this, all the nodes employ SVM based decision support system that has been implemented using Gaussian radial basis function (RBF) and multilayer perceptron (MLP) based non-linear kernels. At each classification stage, a decision boundary is computed by varying the number of cross validation splits and this process is iterated until the accuracy of 90% or above is achieved in each split. The simulation environment that is used to compute the performance of classification model was MATLAB R2017a and Weka.

The simulation results are obtained by employing a multithreaded architecture with the utilization of up to 4 CPU

TABLE 5. Simulation parameters.

Parameters	Values
IoT Sensor Nodes	100
Multi-resolution Channels	110
Simulation Time Frame	1800 Seconds
Number of Cores in Parallel Computation	4
Computational Cluster	1
Channel Modeling	AWGN
Noise Variance	0~0.81
Modulation Protocol	Parallellized FM
Total Folds	6
Folds Range	[2:2:12]
Dataset Shuffle	Random
SVM Kernels	[RBF, MLP]

TABLE 6. Proposed system performance.

Stage	Correctly Classified Samples	Accuracy	Sensitivity	Specificity
STAGE-I	43 / 45	95.55%	100%	90.48%
STAGE-II	98 / 99	98.98%	100%	97.95%

cores yielding the time performance of 2 seconds on average for channel partitioning decision and 3 seconds on average for the channel allocation including the hopping latency. Table 6 shows the receiver operator characteristics (ROC) ratings of the non-linear SVM based classification system at both stages. From Table 6, it can be observed that the proposed system is quite robust in utilizing channel resources for efficient data transmission.

The aim of the proposed protocol is to provide high data rate while balancing the load between different channels. Apart from this, the proposed protocol also makes sure that each IoT device gets the best available channel where all channels continuously learn from their load characteristics to define their mode of transmission for achieving maximum throughput. For this, different performance metrics have been

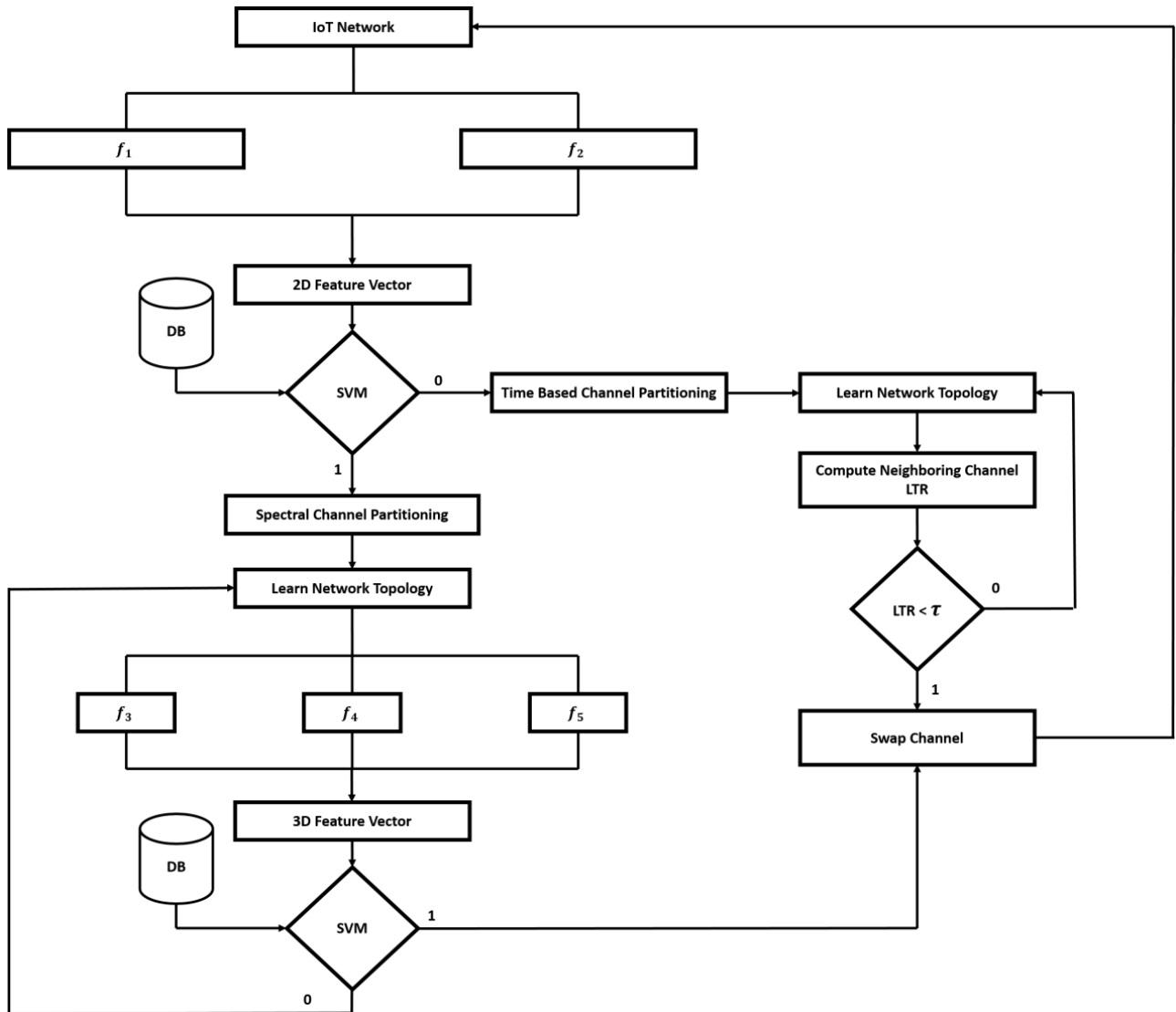


FIGURE 6. Flow diagram of proposed protocol.

computed for the proposed protocol such as mean throughput, average blocking probability, channel fairness, successful channel reporting probability, signal power levels at the receiver end and the performance of employed classification model through receiver operator characteristics (ROC). Average blocking probability represents the possibility of channel blockage, channel fairness depicts whether the channel provides equal transmission rate to all IoT devices, successful reporting probability describes the performance of channel in successfully transmitting data within IoT network. These performance indicators have also been compared with other state of the art protocols. Figure 7 shows the mean throughput trend of proposed multiresolution channels. The throughput curve is computed by measuring the throughput of 110 multiresolution channels for the different number of IoT devices and then taking their average.

Figure 7 also show the throughput comparison of proposed protocol with random, greedy and particle swarm

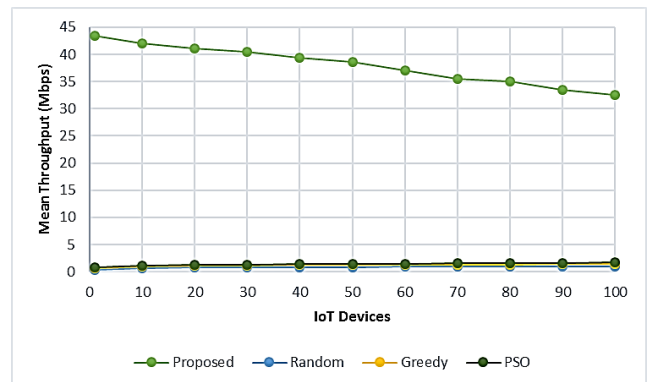


FIGURE 7. Mean throughput versus different number of IoT devices.

optimization (PSO) based protocols [31] and it can be observed that the proposed protocol outperforms others in terms of providing high data rate in a dense IoT network. It is also evident from Figure 7 that the proposed protocol

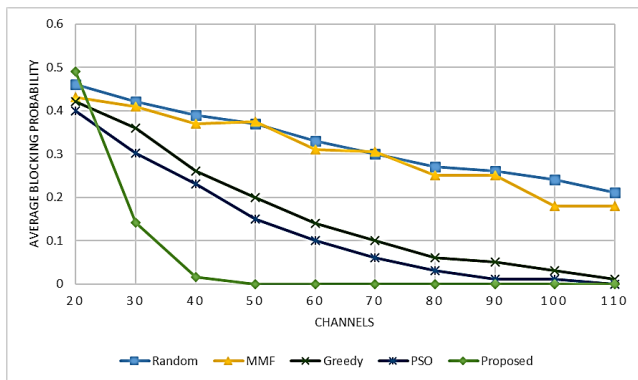


FIGURE 8. Comparison of mean blocking probability with different number of channels.

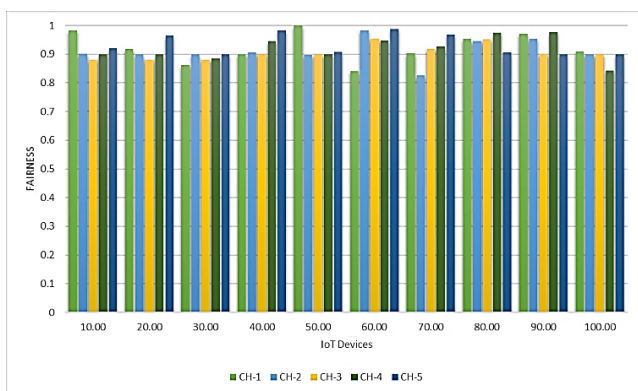


FIGURE 9. Jain's fairness index for randomly selected channels employing various IoT devices.

is quite robust in providing high data rate even with heavy load e.g. the average data rate is around 38.55 Mbps against 50 IoT devices over the proposed multiresolution channels. The transmission rate is highly reliant on channels blocking probability and Figure 8 highlights the neighboring channel blocking probabilities under the proposed protocol. Furthermore, Figure 8 compares the blocking probability of proposed protocol with random, min-max fair (MMF), greedy and PSO based protocols [31]. The channels were varied from 20 to 110 where the proposed protocol produces minimal blocking probability as number of channels increases and it is worth noting that the blocking probability decreases exponentially as compared to other protocols e.g. the blocking probability is around 0.15 when employing 30 channels and it decreases to 0.01 when the channels are increased to 40.

The channel fairness is also another important criterion to measure the efficiency of data transmission. For this, the proposed protocol employs Jain's Fairness Index [36] to model the fairness among 110 deployed multiresolution channels. Figure 9 shows the channel fairness of 5 randomly selected channels from the channel pool and the fairness index was extracted for IoT devices ranging from 10 to 100. It can be observed from Figure 9 that the fairness among multiresolution channel under the proposed protocol is quite

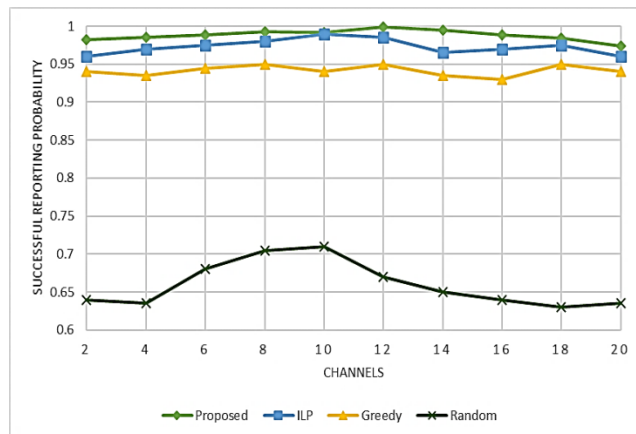


FIGURE 10. Comparison of reporting probability across different channels with different protocols.

high providing fair share of channel utilization among dense IoT networks. The efficiency of the proposed system was also tested by measuring successful channel reporting probability and it is compared with the other state of the art protocols. Figure 10 shows the comparison of successful channel allocation probability for an IoT network consisting of 2 to 20 channels and it is compared with the greedy, random and integer linear program (ILP) [5] based protocols.

The proposed protocol outperforms others yielding the most optimal results for the different number of channels. For example, an IoT network consisting of 10 channels and having random channel allocation protocol has a reporting probability of around 0.710, the greedy protocol has a reporting probability of around 0.940, ILP based protocol [5] has a reporting probability of 0.980 whereas the proposed protocols give a successful reporting probability of around 0.985. In order to measure the transmission power level by the proposed protocol, different receivers operating at 700 MHz, 900 MHz, 1800 MHz and 2100 MHz spectral bands are deployed at different geographical distances which vary from 250 to 3000 meters as shown in Figure 11. It can be observed that the power levels decrease when the distance is increased however the transmission at higher spectral band has lesser power loss.

Furthermore, the proposed protocol has been compared with the state of the art machine learning (ML) based spectrum occupancy detection protocols [41] where each protocol employs Naïve Bayes Classifier (NBC), SVM with linear hyperplane, Linear Regression (LR), Decision Trees (DT) and Hidden Markov Models (HMM). The performance of ML-based protocols for spectrum detection and allocation are validated by measuring the probability of correctly identifying the vacant channels which is known as classification accuracy ' α ' [41]. Therefore, this paper also utilizes the same metrics for measuring the performance of spectrum occupancy by the proposed protocol. Figure 12 shows the comparison of the proposed protocol against state of the art

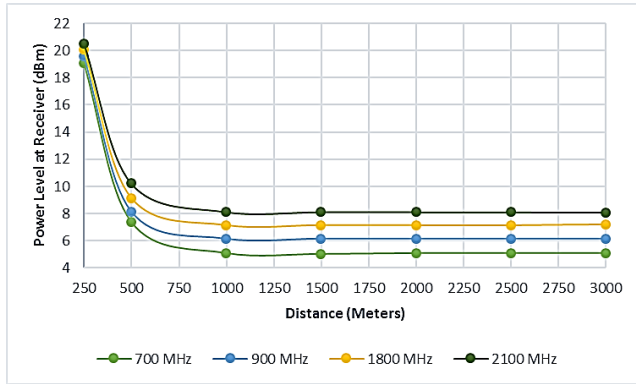


FIGURE 11. Received signal power from different spectral bands. IoT receivers are deployed at various geographical locations.

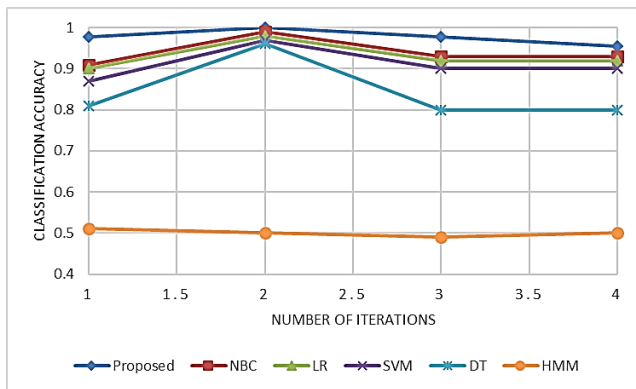


FIGURE 12. Comparison of proposed protocol with state of the art ML based spectrum occupancy detection using 55 fold cross validation

supervised and unsupervised ML-based spectrum occupancy detection protocols [41] by varying number of iterations from 1 to 4 and keeping the value of k in k -fold cross validation to 55 [41].

Figure 13 shows the comparison of the proposed protocol against state of the art ML-based spectrum occupancy detection approaches [41] by varying number of iterations from 1 to 30 however, now the value of k in k -fold cross validation is kept to 192 [41]. From Figure 12 and 13, it can be clearly observed that the proposed protocol is extremely robust in detecting unused spectrum for possible allocation. It should also be noted that the SVM model in Figure 12 and 13 is different than the SVM model which has been incorporated within proposed protocol as the proposed protocol adapts non-linear SVM model with Gaussian radial basis function and multilayered perceptron based kernels as compared to linear SVM [41].

Figure 14 and Figure 15 show the ROC performance ratings of the proposed classification system at both stages against different number of folds. As we can see from Figure 14 and Figure 15 that the proposed classification system is quite robust in correctly classifying test samples at different fold levels. These performance metrics are

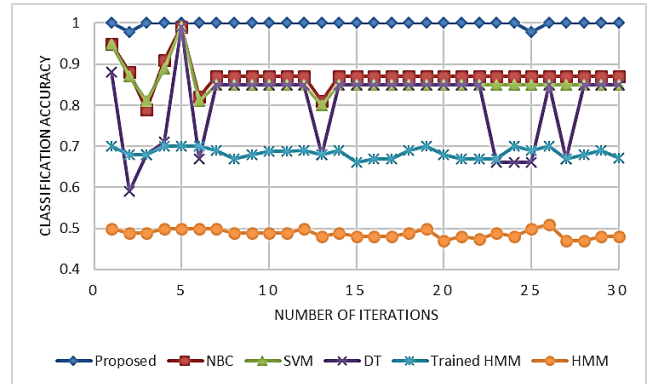


FIGURE 13. Comparison of proposed protocol with state of the art ML based spectrum occupancy detection using 192-fold cross validation.

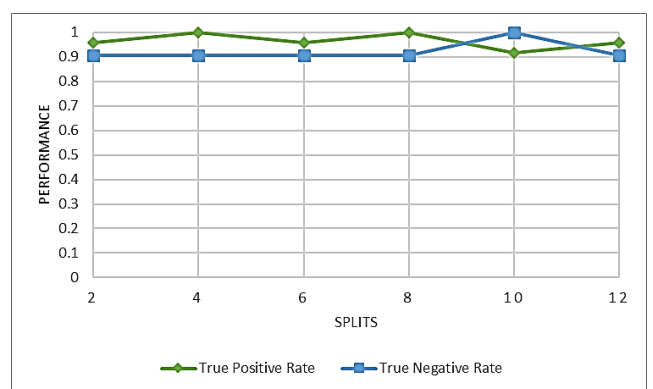


FIGURE 14. ROC performance ratings of stage-I classification system.

mathematically in (16) – (18):

$$\alpha = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad (16)$$

$$\tau_\rho = \frac{T_P}{T_P + F_N} \quad (17)$$

$$\tau_N = \frac{T_N}{T_N + F_P} \quad (18)$$

where T_P are true positives, T_N are true negatives, F_P are false positives, F_N are false negatives, α represents the classification accuracy, τ_ρ represents the true positive rate and τ_N represents the true negative rate. Apart from this, the overall performance of the proposed classification system is depicted in Table 6.

IV. DISCUSSION

This paper introduces a fully automated network-aware channel allocation protocol for high-speed transmission within IoT sensor nets. The proposed protocol assures the optimal channel allocation to IoT devices where IoT devices continuously learn from their load characteristics to define their mode of transmission for achieving maximum throughput. To validate the proposed protocol, the results are compared with existing ones which reveal that proposed protocol outperforms across different metrics such as mean throughput,

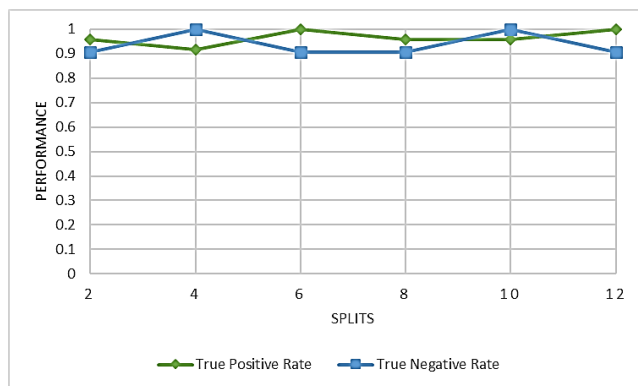


FIGURE 15. ROC performance ratings of stage-II classification system.

mean channel blocking probability, channel fairness, and successful reporting probability. For example, the proposed protocol shows 8%, 11% and 25% better performance gain over CRN, greedy and MMF protocols, respectively in terms of average blocking probability. And, 11%, 12%, 15%, and 50% better classification accuracy compared to existing, NBC, SVM, DT and HMM. Similarly, the performance gain across other matrices is also significantly higher. Furthermore, the proposed protocol exhibits a very low computational complexity as it takes around 2 seconds on average for channel partitioning decision and 3 seconds on average for channel allocation including the hopping latency by developing a multithreaded architecture utilizing 4 cores of Intel i5 processor. Although the proposed protocol is targeted for IoTs, it is equally applicable to 5G cellular, ad hoc and device to device communication paradigms for achieving fast, reliable and fully automated spectrum allocation.

V. CONCLUSION AND FUTURE WORK

This paper proposed fully automated channel detection and allocation protocol that automatically learns channel attributes for efficient and high-speed data transmission. Furthermore, the proposed protocol uses multi-resolution channels to provide efficient localization of channel time/frequency characteristics. The proposed protocol is extremely unique as it automatically learns the network density as well as number of messages which each IoT user sent. Based upon these characteristics, it automatically chooses channel time or spectral bandwidth for maximum data transfer. The proposed protocol falls into the category of hybrid channel partitioning protocols but its first of its kind to have Gaussian radial basis function and multilayer perceptron-based non-linear SVM classification model to detect channel time/ spectral characteristics for high-speed transmission as well as for autonomous channel swapping during channel congestion. The proposed protocol has also been compared with the state of the art solutions against different metrics where the proposed solution significantly outperforms them against different performance metrics. The proposed protocol is extremely robust and it provides high data rate (up to 43.5Mbps) to each IoT node. The proposed

protocol is applicable to wide range of medical applications especially in telemedicine systems where a highly fast and reliable transmission rate is required for sending patient history and diagnostic reports in between hospitals and remote units. Also, the proposed protocol can be utilized in defense sector to provide high-speed and reliable communication link between army troops. In future, this work can be extended to take the energy variations in consideration with the spectral efficiency of the proposed protocol. Also, the proposed protocol can be extended by incorporating decision support systems to detect fraudulent, spam and redundant messages to save channel space and to automatically prioritize user data for more active transmission.

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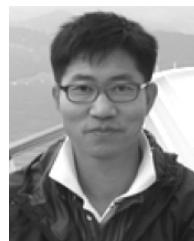
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TAIMUR HASSAN received the B.S. degree in computer engineering from Bahria University, Islamabad, in 2013, and the M.S. degree in computer engineering from the Center for Advanced Studies in Engineering, University of Engineering and Technology, Taxila, in 2015. He is currently pursuing the Ph.D. degree in computer engineering with the College of Electrical and Mechanical Engineering, National University of Sciences and Technology, Islamabad. He is a Lecturer with the Department of Electrical Engineering, Bahria University, Islamabad. His research interests lie in the field of medical image analysis, machine learning, embedded systems, and wireless communications. He was a recipient of many national and international awards.



SALEEM ASLAM received the B.S. degree from the University of Engineering and Technology, Taxila, Pakistan, in 2006, the M.S. degree from the National University of Sciences and Technology, Islamabad, Pakistan, in 2008, and the Ph.D. degree from Sejong University, Seoul, South Korea, in 2013. From 2007 to 2011, he was a Lecturer with the National University of Computer and Emerging Sciences, Islamabad. From 2011 to 2013, he was a Research Assistant with the Network Research Lab, Sejong University. During 2014–2015, he was a Post-Doctoral Fellow with the Wireless Communications and Signal Processing Laboratory, Queens University, Kingston, ON, Canada. During 2016–2017, he was a Visiting Post-Doctoral Fellow with the Mobile Networks Lab, Sogang University, Seoul. Since 2015, he has been with Bahria University, Islamabad, where he is currently an Assistant Professor and the Head of the Electrical Engineering Department. His research interests include spectral and energy efficient solutions for next-generation cellular, sensor, smart building networks, and Internet of Things.



JU WOOK JANG received the B.S. degree in electronic engineering from Seoul National University, Seoul, South Korea, the M.S. degree in electrical engineering from the Korean Advanced Institute of Science and Technology, and the Ph.D. degree in electrical engineering from the University of Southern California, Los Angeles, CA, USA. From 1985 to 1988 and from 1993 to 1994, he was with Samsung Electronics, Suwon, South Korea, where he was involved in the development of a 1.5 Mb/s video codec and a parallel computer. Since 1995, he has been with Sogang University, Seoul, South Korea, where he is currently a Professor. He has also built systems for videoconferencing, streaming, home networks, and ad hoc networks using protocols like real-time transport protocol, session initiation protocol, Internet-of-Things and Blockchain. His current research interests include WiMAX protocols, mobile networks, and next-generation networks. He was a recipient of the LG Yonam Overseas Research Grant in 2001.

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