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Dynamic Spectrum Sensing Under Crash and Byzantine Failure Environments for Distributed Convergence in Cognitive Radio Networks

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ABSTRACT In cognitive networks, efficient spectrum sensing is of great importance for communication of unlicensed secondary users (SU) without interfering with the communication of licensed primary users (PU). Such spectrum sensing requires robust and reliable communication between the SUs to sense the spectrum efficiently under different network circumstances and to make a quick decision for the data transmission. In this paper, we are proposing a decentralized cooperative algorithm for efficient sensing of spectrum in the networked cognitive radios. The proposed algorithm is investigated under crash and Byzantine failure environments to study their behavior and efficiency for consensus. Energy detector module is modeled for each cooperating SU in cognitive radio network for sensing the presence of PU in a dedicated spectrum. Moreover, SU is modeled as agents connected through undirected graphs to simulate communication among them related to the spectrum availability. Multiple simulation scenarios, based on autonomous SU using the proposed distributed consensus algorithm are presented to demonstrate the theoretical development of proposed algorithm to be visualized in real scenarios. The simulation results reveal that the proposed method provides a significant improvement in convergence rate, reliability, and in terms of various key performance indicators.

INDEX TERMS Multi-agent systems, energy model, distributed estimation, unreliable communication, distributed consensus control, crash and Byzantine failure, cognitive radios, spectrum sensing.

I. INTRODUCTION

With the emergence of wireless communication, radio spectrum has emerged as one of the most valuable resource, but unfortunately in the history of wireless communication, this resource is not fully utilized as it should be. In order to efficiently utilize the radio spectrum with limited radio resources, a new concept of cognitive radio was introduced with enhanced capabilities of spectrum sensing and spectrum sharing to overcome the issue of lack of spectrum availability [1]. Cognitive Radio (CR) is defined as a wireless technology that enables unlicensed user to work in a licensed band of frequency spectrum efficiently to overcome the shortage of availability of wireless spectrum [2]–[4] without disturbing the licensed user. In cognitive radios unlicensed users are active in the licensed spectrum, so such users are referred as SU and are on lower priority as compared to licensed users. The licensed users are referred as PU allocated for the frequency spectrum. The primary goal in cognitive radios is to minimize the interference ratio between the two classes of users in an efficient way [5], [6] to better utilize the available spectrum. It is important to mention here that there is no need for additional infrastructure and resources for the licence PU while working with unlicensed secondary users simultaneously. However, SU has some limitations in terms of power, energy, hardware, and in capabilities for signal processing for coordination in a network.

In cognitive radio networks, SU must be able to detect the active SU in the frequency spectrum to avoid interference in their communication continuously, and this concept is known as spectrum sensing. In other words, we can say that due to the lower priority of the SU, they must need to get the status

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of the available spectrum before starting any communication in a network [7]. Inaccurate sensing in frequency spectrum results in wastage of limited resources and causes interrupted interference amongst the PU. Spectrum sensing can be done in two possible ways, cooperative spectrum sensing or individual spectrum sensing. Cooperative spectrum sensing can be referred as a sensing of a spectrum by a group of SU and similarly, in individual or non-cooperative scenarios it is being done by the single individual SU. Spectrum sensing by a single SU can't be accurate and should be unreliable because of fading effect and shadowing, these factors can be reduced by the usage of spectrum sensing cooperatively for better results [8]. Cooperative sensing has several advantages over non-cooperative sensing [9]. For example, if an individual SU experienced a fading in a communication channel, chances are there that it cannot manage to distinguish between fading and white space from the effect of shadowing. But cooperative sensing works well for this scenario. Furthermore, another challenge for non-cooperative spectrum sensing is the issue of hidden terminal problem, it can be well dealt with cooperatively. Based on the last statement similar studies have been carried out by the authors in [10] by evaluating the performance of spectrum sensing cooperatively and proved the great results in their findings. Moreover different researchers [11] has produced better results for cooperative spectrum sensing considering different parameters based on the same problem.

Similarly, Probabilistic spectrum access (PSA) in the cognitive radio network is another solution to overcome the shortcomings in spectrum energy detection and studied by various researchers [12]–[16]. With this method, the channel detection determines the busy or empty status and frequentist inference is rummage-sale to predict channel status. However, the probabilities and uncertainties of false alarm cannot be addressed by common inferences when predicting channel status. In this research, we are proposing a solution for efficient spectrum sensing using consensus algorithm, which focuses on determining the existence of PU jointly by secondary users without using a common receiver in a communication channel and based on energy detection. The energy detection can better account for uncertainties and false alarm probabilities by taking into account the limitations of the spectrum detection results. The proposed algorithm is distributed in nature, final results for spectrum sensing is not depending on a common receiver in the communication channel. Moreover proposed consensus model is designed in such a way that SU collectively involve in decision-making and is inspired by bio-inspired consensus. The important characteristic of such an algorithm is the distributed coordination between the agents in a network with no central control for information exchange [17]. This research utilizes the basic concepts from graph and matrix theories and also a network topology is deployed with fixed and random connectivity.

The rest of the paper is organized as follows. Literature review is described in section II. In section III, we formulate the problem of the energy sensing model and present the proposed consensus algorithm. Simulation results are presented in section IV and section V concludes the paper.

II. LITERATURE REVIEW

Many researchers proposed multiple solutions for spectrum analysis in a cognitive radio network. The authors in [8] explored the problem of sensing throughput using a multi-mini-slot energy detection scheme to maximize SU throughput under the constraint that PU are adequately secured.

In various researches, two important techniques are used worldwide for spectrum sensing, one is with a common receiver which is known as a fusion center and the second is without a common receiver, mobile Ad hoc networks can be one of its examples. Various studies have adopted a centralized cooperative approach, utilizing the concept of a central fusion center for information sharing in spectrum sensing. In such scenarios cognitive radio in the network, shares the information of the PU and transmits this information to the cognitive radios to make a final decision [10]. A more alike solution for non-centralized spectrum sensing based on diffusion is studied by the researcher in [18] along with the consideration of the link failure in the cognitive radio network. Similarly, in a few proposed models for spectrum sensing, individual sensor collects the information of the other sensors in the network through a fusion center via feedback system [19]. Reporting of channel condition under deep fading environment between the cognitive SU and the common receiver is explored by [20]. A study is proposed to sense the spectrum in cognitive radios by exploiting the statistical old sensing information to enhance the efficiency of the spectrum sensing using noncooperative way in [21]. Zaeemzadeh et al in [22] introduced an approach for sensing the shared spectrum using the approach of Bayesian data-mining for heterogeneous cognitive radio networks.

One of the decentralized schemes for spectrum sensing is based on consensus algorithms, where information is exchanged between the SU to make decision [23], [24]. A similar approach is adopted by the authors in [25], where cognitive users reach a consensus value for spectrum sensing using their local values exchange without using a common fusion center. Another approach in cognitive radio is introduced by dividing the time slot of resource block into sensing and prediction of spectrum in a cooperative way for transmission of data [26]. Similarly, research is presented in a [27] by using an NCSS algorithm for non-cooperative spectrum sensing in cognitive radios. In this proposed scheme a node with the highest energy level is isolated from the prediction for the future computation. Moreover, many different approaches, based on cooperative spectrum sensing using consensus algorithms are proposed in [28], [29]. One of the major concerns faced by the distributed spectrum sensing is the security issues. Any malicious user can cause a wrong entry in spectrum sensing that leads to a critical threat in a network. Another approach is adopted by the author in [30], where a consensus base algorithm is used for energy computation, which later on communicated between the cognitive

TABLE 1. Comparision of sensing techniques in CRN.

References	Sensing Technique	Advantages	Limitations
[37]–[43]	Energy Detector	1. Less complex 2. Easy to design 3. No prior knowledge of PU 4. Non-coherent	1. Exposed to noise imprecision 2. Under perform in low SNR conditions 3. Poor in predicting noise and primary signal
[44]–[47]	Eigenvalue Based Detector	1. Non-coherent 2. Robust to noise 3. Work well in low SNR	1. Very high computational complexity
[48]–[51]	Matched Filter	1. High processing gain in less time 2. Optimal sensing for received SNR	1. Require prior knowledge of the PU 2. Complex design 3. Each SU require dedicated receiver for syncronization
[52]–[55]	Feature Detection	1. Robust to noise 2. Work well in low SNR	1. Require prior knowledge of the PU 2. Slow sensing of SU as compared to energy detector

radios to achieve final value. Another approach for sensing the spectrum sensing by the energy and first-order correlation of the signal received is studied and evaluated based on the detection of false alarms by the authors in [30]. Peng Hu et al in [31] proposed two schemes for achieving fairness in spectrum sharing based on local information in the cognitive radios. Similarly, last but not least author in [25] proposed a scheme, where SU in a channel coordinate with each other based on their local information without a centralized control using consensus to make the end decision. Also, it is proven in results, a significant decline in the probabilities of false alarms and wrong detection probabilities in a radio spectrum. Moreover, multiple schemes for the spectrum sensing in cognitive radios are proposed by many researcher [32]–[35].

There are two types of classes used for spectrum sensing, one is based on sensing and the other is based on monitoring [36]. As in this research, we are proposing an energy-sensing model so we focused on sensing rather than monitoring. A detailed comparison of various methods for spectrum sensing comprising of energy detector method, eigenvalues detector, matched filter method, and feature recognition methods are provided for deep insight in Table. 1.

SU achieve continuous spectrum detection in cognitive radio networks using one of the techniques described in Table 1. Cooperative spectrum recognition increases spectrum recognition performance by utilizing the three-dimensional diversity of SU. Most collaborative spectrum detection solutions are not distributed and share a mutual fusion centre, where it gathers verdicts from SU to finalize a conclusion on frequency tenancy. Now, distributed solutions have emerged due to their problem solving skills and robust nature to the worst channel conditions in achieving the desired goals. It is never be recommended to collect or gathered data on a common receiver, it causes a restriction in communication and this Fusion Centre can be the cause of single point of failure and becomes a bottleneck for the large data networks, where SU do not want to share their information with a single remote device. For this reason, this study focuses on a distributed solution for spectrum detection, as well as the implementation of the energy detection techniques in CRN. It is selected due to its minor complexity, it's easy-to-design approach, and because of no prior knowledge of the PU existence. A proposed design for SU communications to reach global agreement on the presence/absence of PU in a spectrum is based on a consensus algorithm. The proposed algorithm can work well in low SNR environments and more resistant to noise in an energy sensing.

A. WEIGHTS IN CONSENSUS ALGORITHMS

In literature, multiple weights are available to achieve the consensus agreement under diverse network topologies. Few of the weights extensively used for the dynamic topologies are the local degree and the metropolis hasting. In both techniques, they do not have a uniform weight for the agents associated with the networks. Both weights just depend on the availability of the local information of their neighborhood and that is one of the reasons that they are considered the best fit for the real-time applications.

1) LOCAL DEGREE WEIGHTS

One of the techniques in practice for designing weight matrix W is a local degree weight. The designing procedure involves the assignment of the weights on an edges based on the pair of vertices, depending on the largest out-degree of two connected agents for both transmitting and receiving edges [56]–[61]. In local degree weights, each agent must possess the knowledge of external degrees of all nearby agents. Mathematically, we can express local degree weights as:

$$W_{ij}(k) = \begin{cases} \dfrac{1}{\left(\left(max(d_i(k), d_j(k))\right)\right)} & i \neq j \\ 0 & otherwise \end{cases} \tag{1}$$

where $d_i(k)$ and $d_j(k)$ are the out degree of agent i and agent j respectively. Local degree weights are much similar to the max degree weights and adopted from the metropolis hasting algorithm based on Markov chain Monte Carlo distribution [62]–[64]. These weights are intended for taking the random sequence to converge them on particular common value and they also provide the surety of convergence in a graph where it is not bipartite. A bipartite graph can be defined as a graph which does not have any diverse size of sequences and undirected. Another important aspect for quick convergence by the local degree are the less complexity in computation of the

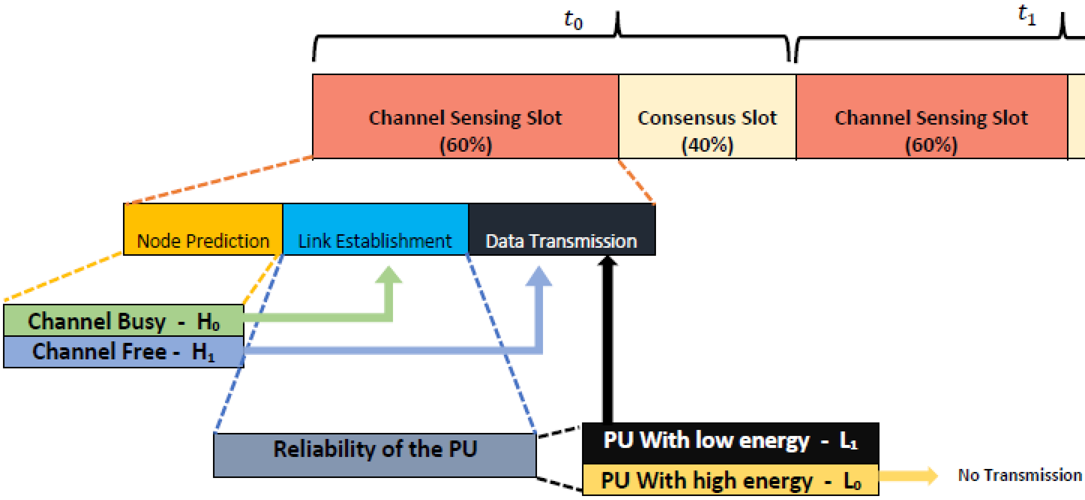

FIGURE 1. State diagram of a proposed Sensing model in order to Compute Energy utilization at each stage.

optimal value without prior knowledge of global information and the network topology [65].

2) METROPOLIS HASTING WEIGHTS

Well-known approach adopted by various researchers to design weight matrix W, addressing various applications is metropolis hasting weights [66]. Metropolis hasting weights have the ability to reserve the consensus on an average value, secondly they do not involves any complexity to compute, and finally metropolis hasting weights works well for the distributed sequence of the dynamic undirected graphs and guarantee to converge on an asymptotic average value with minimum convergence conditions. [61], [67]–[72].

Metropolis hasting weights is especially considerable for the networks experiencing unreliable communication within the network topology caused by dynamic or switching scenarios and even unreliability caused by a communication delay. In this weight, every agent determines the weight of its directly connected edges by only knowing the degree of their connected neighbors. The computation process of weights consists of two steps of communication between the pairs of the vertices in the connected neighborhood. Step one deals with the calculation of the degree of each agent by the initial count of the immediate neighbor. Likewise, in the second step already calculated degree of each agent is shared with all the instantaneous neighbors. In all this process, there is no requirement for the agents to have any information about the number of agents participating and similarly it is not required to have global knowledge of the complete communication network. In such weighting matrices, every agent knows out-degrees of all of its connecting neighbors that might be changing with every instant of time. Mathematically, it can be written as [73], [74]:

$$W_{ij}(k) = \begin{cases} \dfrac{1}{\left((max(d_i(k), d_j(k)))\right) + 1} & i \neq j \\ 0 & otherwise \end{cases} \tag{2}$$

Metropolis hastings weights are taken from the Metropolis algorithm [75], [76] based on Markov chain Monte Carlo [62]–[64]. This algorithm is specially designed for taking the random sequence of the distributed samples to compute the prediction or expected value. This algorithms performs well for the systems where the distribution of the samples are multi-dimensional and random.

III. PROBLEM FORMULATION OF ENERGY SENSING MODEL

Implementing the proposed consensus algorithm for the spectrum sensing in the cognitive radio networks required two basic steps. The first step is to identify the presence of the PU and the second step is to pass this information to the SU in the cognitive network to decide for further communication in the particular spectrum. Based on the information received in the first step, multiple agents in the cognitive radios will start exchanging the information with their neighborhood to make a local decision to achieve their global goal, if and only if the spectrum is sensed free. Here we denote the local measurement value of agent i as x_i. As in the previous sections, it is made clear that the consensus algorithm is based on the iterative process and the values of the state of all agents will update at all time iterations $k = 0, 1, 2, \ldots$, this process will continue until the entire agents in the network converge to a common value. So here in subsections, spectrum sensing energy and network model along with the consensus algorithm is presented to attain the desired goals.

In Fig. 1, we have provided detailed information about the design of the different steps involved in the proposed scheme. In the start we have divided the time into slots $t_0, t_1, t_2, \ldots$, we intentionally assigned the first part of the slot for channel sensing and, the next part of a time slot is occupied for the idle state, similarly, this will continue for the entire spectrum. The slots time cycle is 60% for sensing and 40% for idle considering the channel status. In the channel sensing time slot,

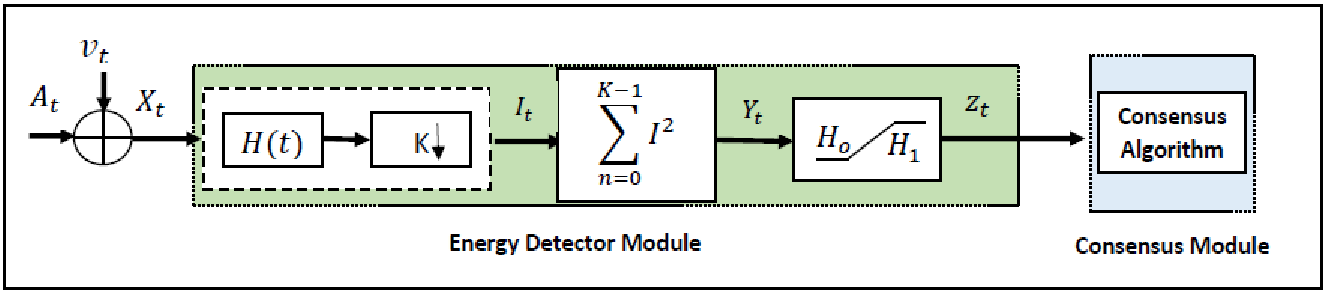

FIGURE 2. Block diagram of sensing model.

three important tasks will be carried out, first: channel status or prediction of PU presence, second: link establishment for the existing PU, and third: data transmission by the SU. In the first node prediction task, the spectrum will be checked for the existence of the PU by the energy detector installed in each secondary user as a primary task. If the users are traced then the spectrum is considered busy and SU cannot initiate their communication, so the available energy level is sent to the next stage of link establishment for various parameters checks such as the energy of transmission and reception, available throughput between the users and reliability of the energy level. So here in subsections, spectrum sensing energy and network model along with the consensus algorithm is presented to attain the desired goals. On the other hand, if no PU is detected then the spectrum is considered free and SU can initiate to establish a link to achieve their convergence goals.

A. PREDICTION OF PU IN COGNITIVE SPECTRUM

In Fig. 2 the energy-sensing model for the proposed system is provided. It mainly consists of two modules, the energy detector, and the consensus module.

Where A_t is the actual signal which is entering the system, while υ_t is the white Gaussian noise and X_t is the convolved signal. Mathematically, we can express X_t as in Eq.3:

$$X_t = A_t + \upsilon_t \tag{3}$$

In the energy detector module, we have defined convolution, sampling, energies of the signal, and the level of energy threshold. The output I_t after convolution and sampling of the received signal is given in Eq.4

$$I_t = X_t * H_t \tag{4}$$

Similarly, sum of all the energy of the received signal samples are presented by Y_t and mathematically expressed as $Y_t = \sum I_t^2$. And finally, the output of the energy detection module is denoted by Z_t. It can algebraically be written as in Eq. 5

$$Z_t = \left\{ \begin{matrix} Y_t \leq Z_t & H_0 \\ Y_t > Z_t & H_1 \end{matrix} \right\} \tag{5}$$

Here, we have introduced a threshold for energy levels $H_0 \& H_1$ for taking the decision based on piece-wise linear transformation function for prediction of primary user signal energy level. If the energy level H_1 (energy level is above noise energy level) is achieved, it means that the spectrum is busy and primary users exist in the system and vice versa for energy level H_0 (spectrum noise energy level). If the level H_0 is detected, then the system goes directly to the consensus process.

B. PROPOSED CONSENSUS ALGORITHM FOR SPECTRUM SENSING

This subsection will explain the proposed average convergence algorithm in this research. We will consider fixed and switching topologies along with the reliable and unreliable communication in the cognitive network. Moreover, convergence conditions of proposed distributed consensus algorithm is mathematically analyzed on the concepts of graph and matrix theories.

Proposed algorithm can be expressed mathematically as in Eq.6 & weighting factor as in Eq.7:

$$\alpha_i(t+1) = \alpha_i(t) + \sum_{j \epsilon N_i} \omega_{ij}(t) \left(\alpha_j(t) - \alpha_i(t)\right) \tag{6}$$

weighting factor ω can be computed as under, where $degree_i$ and $degree_j$ are the degree of agent i and agent j.

$$\omega_{ij}(t) = \begin{cases} \dfrac{degree_i(t) + degree_j(t))}{2degree_i(t)degree_j(t)} & i \neq j \\ 0 & otherwise \end{cases} \tag{7}$$

1) PROOF OF A PROPOSED CONSENSUS ALGORITHM FOR SPECTRUM SENSING

In the section above, a distributed algorithm is proposed with its weighting factor ω, which ensures the agreement of all the agents on common values. In this subsection, steps of expressions are provided to prove the said convergence.

Suppose

$$\Lambda(t) = \begin{bmatrix} \alpha_1(t) \\ \alpha_2(t) \\ \ldots.. \\ \ldots.. \\ \alpha_n(t) \end{bmatrix}, \quad \beta(t) = \begin{bmatrix} b_1(t) \\ b_2(t) \\ \ldots.. \\ \ldots.. \\ b_n(t) \end{bmatrix}$$

Moreover

$$\Lambda (t+1) = \begin{bmatrix} \alpha_1 (t+1) \\ \alpha_2 (t+1) \\ \cdots \\ \cdots \\ \alpha_n (t+1) \end{bmatrix}$$

To attain the convergence condition, we can draft the global state equation as:

$$\Lambda(t+1) = \Lambda(t) + \beta(t) \tag{8}$$

Universal input vector can be written after computing as:

$$\beta(t) = \omega_{ij}(t)(A - D)\Lambda(t) \tag{9}$$

where A is the adjacency matrix and D is the degree matrix.

Consensus on a common average value is achieved by computing the right weighting factor $\omega_{ij}(t)$ and then using this computed value in $\beta(t)$ in Eq.(9). Proposed method for calculating $\omega_{ij}(t)$ will surely contributes in explaining and achieving the main research objective that in $\alpha_i(t+1)$ for Eq.(6). For the agents in the network the same initial value are set as in the condition applied for convergence in the previous chapters, i.e. $x_1(0) = 1$ and $x_i(0) = 0 \; \forall i = 2, 3, 4 \ldots N$. Similarly graph $\mathcal{G}$ is considered as a connected graph with the spanning tree.

It is important to mention here since the network topology considered in this research is not reliable, so the weight matrix ω cannot be kept constant. It varies after every change of communication between agents. For this particular case, we use the algebraic notation $\omega_{ij}(t)$ in the equation (9).

If we substitute Eq.(9) in Eq.(8), we get

$$\Lambda (t+1) = \Lambda (t) + \omega_{ij}(t)(A - D)\Lambda(t) \tag{10}$$

We can further transform the expression by using Laplacian matrix i.e. $L = D - A$, in the following form:

$$\Lambda (t+1) = \Lambda (t) - L\omega_{ij}(t)\Lambda(t) \tag{11}$$
$$\Lambda (t+1) = (I - L\omega_{ij}(t))\Lambda(t) \tag{12}$$

Eq.12 implies for all $t = 0, 1, 2 \ldots$

$$\Lambda(t) = (I - L\omega_{ij}(t))\Lambda(0) \tag{13}$$
$$lim_{t\to\infty}\Lambda(t) = lim_{t\to\infty}(I - \omega_{ij}(t)L)\Lambda(0) \tag{14}$$

We know

$$lim_{t\to\infty}\Lambda(t) = lim_{t\to\infty}\omega(t)\Lambda(0) \tag{15}$$

Now equate the left sides of Eq.14 & Eq.15

$$lim_{t\to\infty}\omega(t) = lim_{t\to\infty}(I - \omega_{ij}(t)L) \tag{16}$$

From the mathematics, it is clear that it is one of the term which also guarantees the convergence of the agents in a network to reach consensus.

$$lim_{t\to\infty}\omega(t) = \left(\frac{1}{n}\right) 11^T \tag{17}$$

Substitute the value of Eq. 17 in Eq. 16, it gives us:

$$lim_{t\to\infty}(I - \omega_{ij}(t)L) = \left(\frac{1}{n}\right) 11^T \tag{18}$$

One of the objectives set in this research is the application of node counting, so here under unreliable communication topology we also consider grabbing that goal and for that particular purpose we took an infinite number of agents i.e. $n \to \infty$ in our communication network. We can mathematically express it as:

$$lim_{t\to\infty}(I - \omega_{ij}(t)L) = 0 \tag{19}$$

Here, we are assuming the degree of agent i that is $degree_i$ and its connected agent j with $degree_j$. $\omega_{ij}(t)$ the weighting factor in Eq. 20 is the key for the convergence, if it is perfectly computed then the whole system will reach the consensus under unreliable communication even when the connectivity of the network is limited or varying with time.

$$\omega_{ij}(t) = \frac{degree_i(t) + degree_j(t)}{(2degree_i(t)degree_j(t))} \tag{20}$$

IV. SIMULATION RESULTS

This section describes the basic simulation requirements for the proposed schema in the cognitive radio network. The energy measurement for the proposed energy model, along with the implementation of the consensus algorithm with dynamic and fixed network topologies, is presented among SU to achieve consensus. It also assigns SNR values that users dynamically change in each scenario to monitor the impact on network performance. Comparison results are also presented based on the most important performance parameters for different methods.

A. SIMULATION SETUP

In the proposed schema, we are assuming that the PU in the spectrum are dynamically connected and they can enter or leave the network at any time. Similarly, we have applied the same scenario for SU for group coordination and for achieving consensus. The total duty cycle of the time slot is divided into two parts. 60% duty cycle is reserved for the channel sensing and the rest 40% duty cycle is dedicated for idle mode or for consensus.

In the first stage of simulation, we have considered a Rayleigh noise added to the original signal for the PU. Later on, a band pass filter is applied for taking the decision based on piece-wise linear transformation function for prediction of PU signal energy levels H_0 & H_1 as in section 4.1. Every SU in the cognitive radio is equipped with an energy detector to calculate the received energy level for a quick decision. In the proposed energy model if the PU is absent in the spectrum only the noise level will come up which has assigned a threshold level and the spectrum is considered free while on the other hand if the threshold Z_t is greater than the noise level it means that PU are detected in the spectrum.

In the second stage of the simulation, if the energy level H_1 (energy level is above noise energy level) is achieved, it means that the spectrum is busy and PU exist in the system then this information is passed on to the network module, where an additional check of two energy levels is created for redundant check for measuring the signal strength named L_1 & L_0 based on logistic function curve. L_1 means the existing PU is available with a sufficient amount of energy for communication in the spectrum and similarly vice versa for L_0.

In the second stage proposed consensus algorithm is initiated if and only if, energy level H_0 (spectrum noise energy level) is received. In Fig. 3 we have presented the graphical presentation of an input signal, noise, energy levels of the convolutional signal, and the energy thresholds, where the signal is above the set threshold means PU exists in the spectrum and where this signal level is below the threshold level means no PU is detected. We do mention here that all the PU and SU are resource-constrained agents and they are unaware of their positions and their directional velocities because of their random network topology.

In our simulations, we have considered different network conditions for SU in the spectrum to attain consensus value. That includes the fixed and random network topologies along with the reliable and unreliable communication links. Furthermore, we have simulated this network model for pre-existing schemes for cooperative spectrum sensing based on metropolis [25] and local degrees. In the end, a detailed comparison is conducted by assuming different network scenarios and it validates the effectiveness of the proposed scheme by the results generated.

B. RELIABILITY IN CONVERGENCE ALGORITHMS

A major concern in distributed systems based on consensus algorithms is to attain complete network reliability in the existence of several defective or faulty agents. To attain reliability, the control inputs must achieve convergence. Such implementations allow the network to work in a corporative fashion despite the failures of the various agents in a network. In consensus-based networks, agents are supposed to agree on a single agreed value. During the communication phase, few of the agents may fail or can act in an unreliable way, so the control protocol used for the consensus must be fault-tolerant or robust. Though this failure of agents due to any reason may result in a skewed or delayed response and the desired consensus may not be achieved or may be computed incorrectly. When dealing with consensus algorithms, network reliability in terms of probabilities of failure can be undergone by two types of failures in a network:

1) Crash failure: This type of failure occurs in a network when an agent abruptly halts its communication a network and does not resume its communication again.
2) Byzantine failure: This is a type of failure, which occurs as a result of malicious actions of an agent in a consensus-based communication network or the second possibility is that after a long skew a non-communicating or sleeping agents resume their communication. Byzantine failures are considered much disruptive as compared to the crash failure. Therefore, a consensus protocol that bears Byzantine failure must support any possible failure that may experience by the communication network.

We proposed a consensus algorithm whose reliability in terms of probabilities of failure is adoptive. The proposed scheme can effectively acquire the convergence in reliable, unreliable, and asynchronous communication across distributed agent networks and it outperformed in reaching a consensus for both cases of failures as discussed above. In this research following networks configurations are considered to examine the reliability of the proposed algorithm in terms of probabilities of failure:

1) Fixed Network: In this configuration, there is no probability of link failure or agent failure. Communication links between the agents are all time available and communication amongst the agents is termed as reliable.
2) Dynamic Network: In this configuration, we have addressed the crash and Byzantine failures. All agents are connected through random directed or undirected graphs. An agent or communication link can be disconnected from the network or maybe it resumes its communication with the same communication edges. Furthermore, new agents may enter into the communication network and abruptly changes the topology of the network at any instance of time and such communication amongst the agents is termed unreliable communication. We have simulated the following scenarios:
   - Fixed network with random connectivity in an asynchronous communication network
   - Random addition and removal of agents in an asynchronous communication network
   - Random link failure and reconnection in an asynchronous communication network

In addition, the efficiency and performance of the proposed weighting matrix algorithm are compared with the existing metropolis method and local degree weights. In addition, four parameters are taken into account for the qualitative analysis in order to evaluate the productivity of the proposed method. The parameters considered are the number of iterations required to achieve complete convergence, the CPU processing time, the asymptotic convergence time, and finally the asymptotic convergence factor. We also present the comparison of different parameters using different methods in a tabular form. Moreover, consensus graphs and error plots are sketched for each scenario. All conditions are established as previously defined in terms of initial values and graph connectivity. It should be noted that the fault tolerance set for the network is $e = 10^{-15}$ in all cases. The sampling rate is set as one second per iteration.

where $e_i(t)$ can be expressed as:

$$e_i(t) = \sum_{j \epsilon N_i} |x_i(t) - x_j(t)|, \quad i = 1, 2, \ldots .n \tag{21}$$

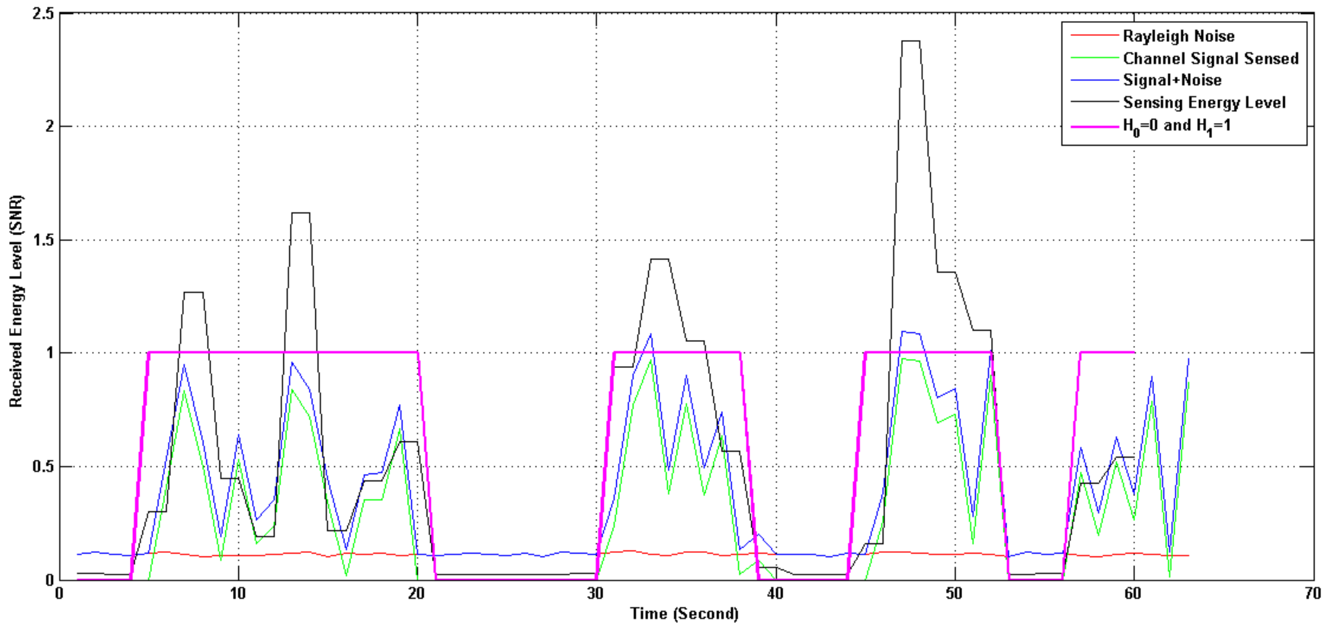

FIGURE 3. Communication spectrum sensing energy levels for predicting PU existence.

In all of the discussed scenario, it is confirmed that the spectrum of the channel is sensed free for communication by the SU without making any interference in PU intersection by satisfying the two threshold levels H_0 & L_0 in the proposed energy model.

1) CASE 1: FIXED NETWORK TOPOLOGY FOR SU IN COGNITIVE RADIO NETWORK WITH RANDOM CONNECTIVITY

In this scenario, we are assuming a fixed network topology consisting of 10 SU in a cognitive radio network under unreliable communication. We labeled SU as $i = 1, 2, 3, \ldots n-1$. An adjacency matrix is randomly selected, which eventually results in a change in the laplacian and degree matrix of the network. Signal to noise ratio (SNR) value for every SU is dynamically assigned, it variants between $5db$ to $10db$. The communication spectrum consisting of 10 SU with dynamic network topology under free channel is presented in Fig. 4. Total time required for achieving convergence for proposed, metropolis and local degree for communication spectrum of 10 SU with dynamic topology under free channel is provided in Fig. 5. In Fig. 5 it is seen that the proposed method is consuming less time in achieving the average consensus value as compared to the metropolis and local degree methods. Numerical results from the simulation are presented in a tabular form and presented in Table. 2 reflecting the various key indicators. Results indicate the effectiveness of the proposed consensus-based spectrum sensing algorithm for attaining convergence in fewer iterations of time as compared to the other known methods and performed best in other performance indicators.

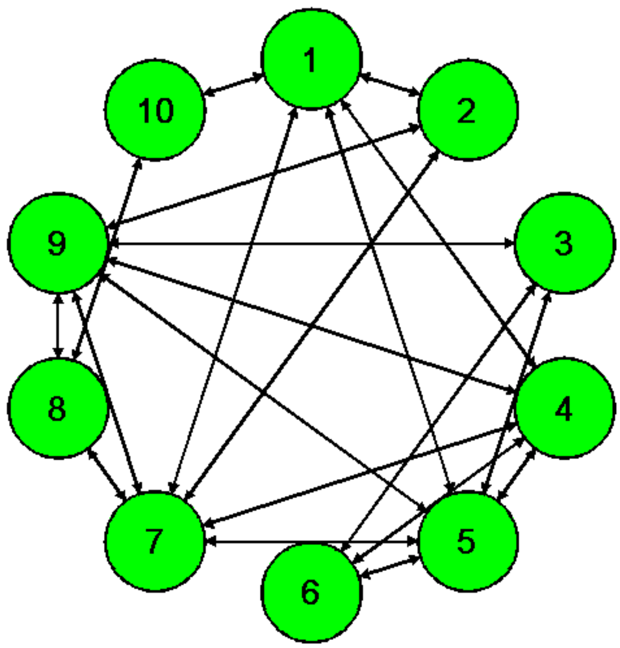

FIGURE 4. Communication spectrum consisting of 10 SU with dynamic network topology under free channel in case 1.

2) CASE 2: RANDOM ADDITION AND REMOVALS OF SU FROM THE NETWORK TOPOLOGY IN COGNITIVE RADIO NETWORK UNDER UNRELIABLE COMMUNICATION

In this case, we are considering the network topology between the SU as in the previous case, consisting of 10 SU. Once the convergence is achieved by the users in the cognitive radio

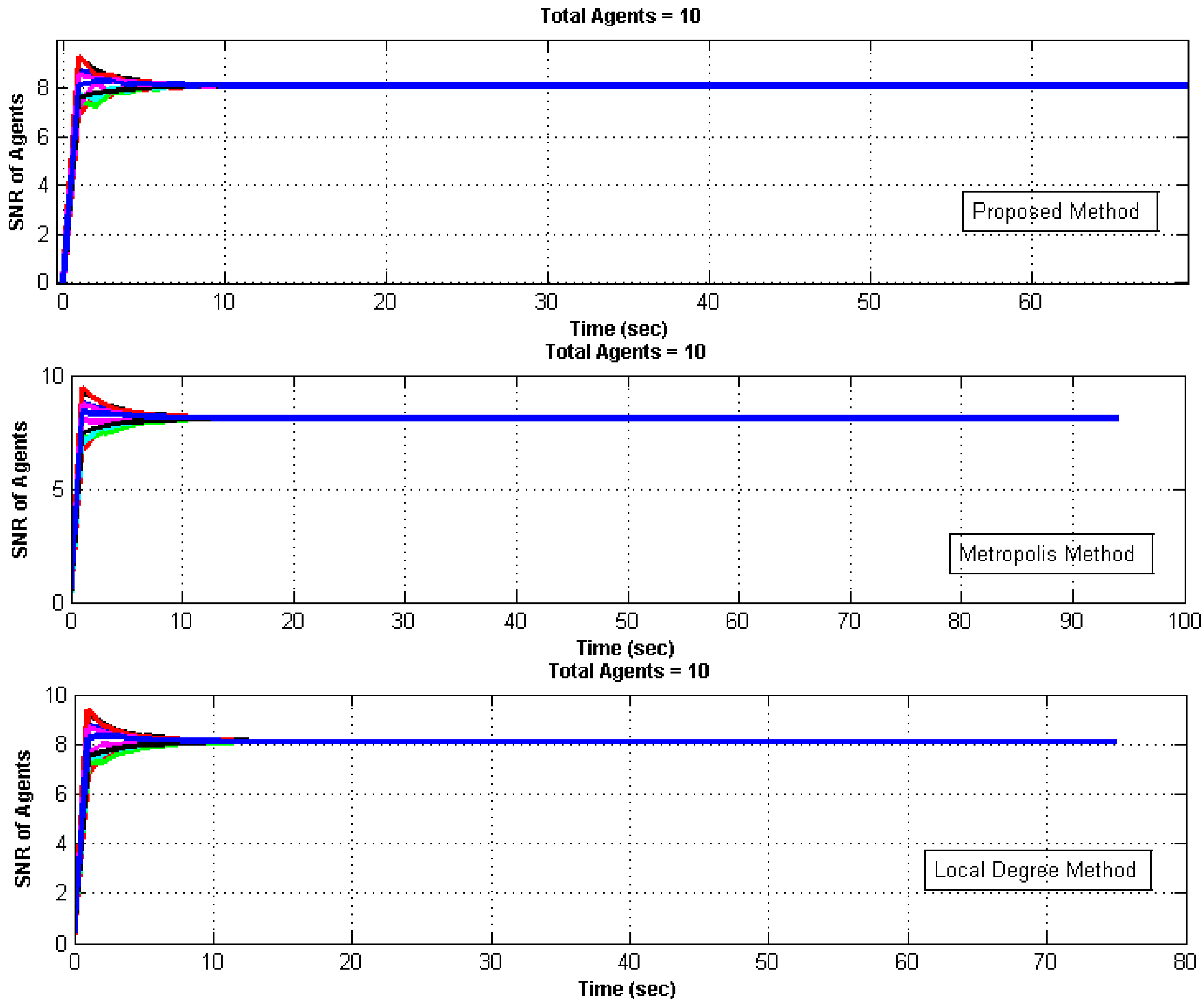

FIGURE 5. Consensus for proposed and existing methods for communication spectrum of 10 SU with dynamic topology under free channel in case 1.

TABLE 2. Comparison of proposed and existing methods for communication spectrum of 10 SU with dynamic topology under free channel in case 1.

	Proposed Method	Metropolis Hasting Method	Local Degree Method
Number of Iterations	70	95	75
CPU Processing Time (Min)	0.0267	0.0355	0.0328
Asymptotic Convergence Factor	0.6364	0.7655	0.7321
Asymptotic Convergence Time (Sec)	2.2131	3.7417	3.2072

network simultaneously 8 more SU enter randomly in the communication network after time $t = 20ms$. Here all the calculations regarding the matrices, connectivity, and communication between the SU will change and an algorithm will compute the convergence value again between the 18 SU to achieve the global goal. The proposed algorithm has produced very interesting and great results under such unreliable and switching network conditions and further, we have dynamically set the signal to noise ratio (SNR) for every secondary user, which is between $9db$ to $15db$. Furthermore, when this consensus is achieved by the 18 SU then after time $t = 30ms$ during the convergence process, 3 SU are eliminated randomly from the communication topology, which once again results in the change of adjacency and degree matrix which eventually affect the whole convergence process. Here, we can call this whole scenario as one of the most difficult convergence cases as a forced consensus. This whole cognitive network Scenario for random addition and removals of SU from the cognitive radio network experiencing unreliable communication is graphically presented in Fig.6. Initially,

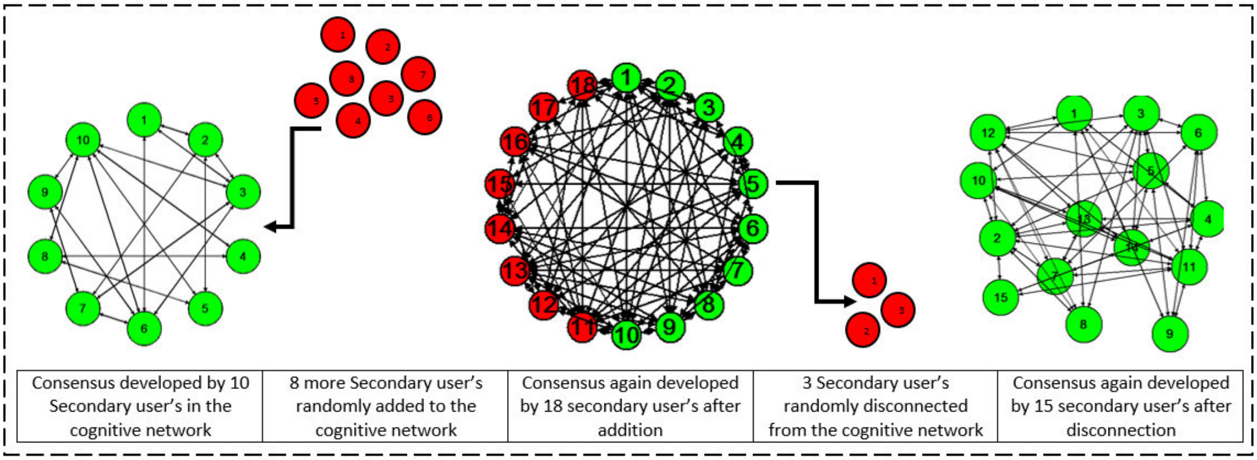

FIGURE 6. Scenario for random addition and removals of SU from the cognitive radio network experiencing unreliable communication in Case 2.

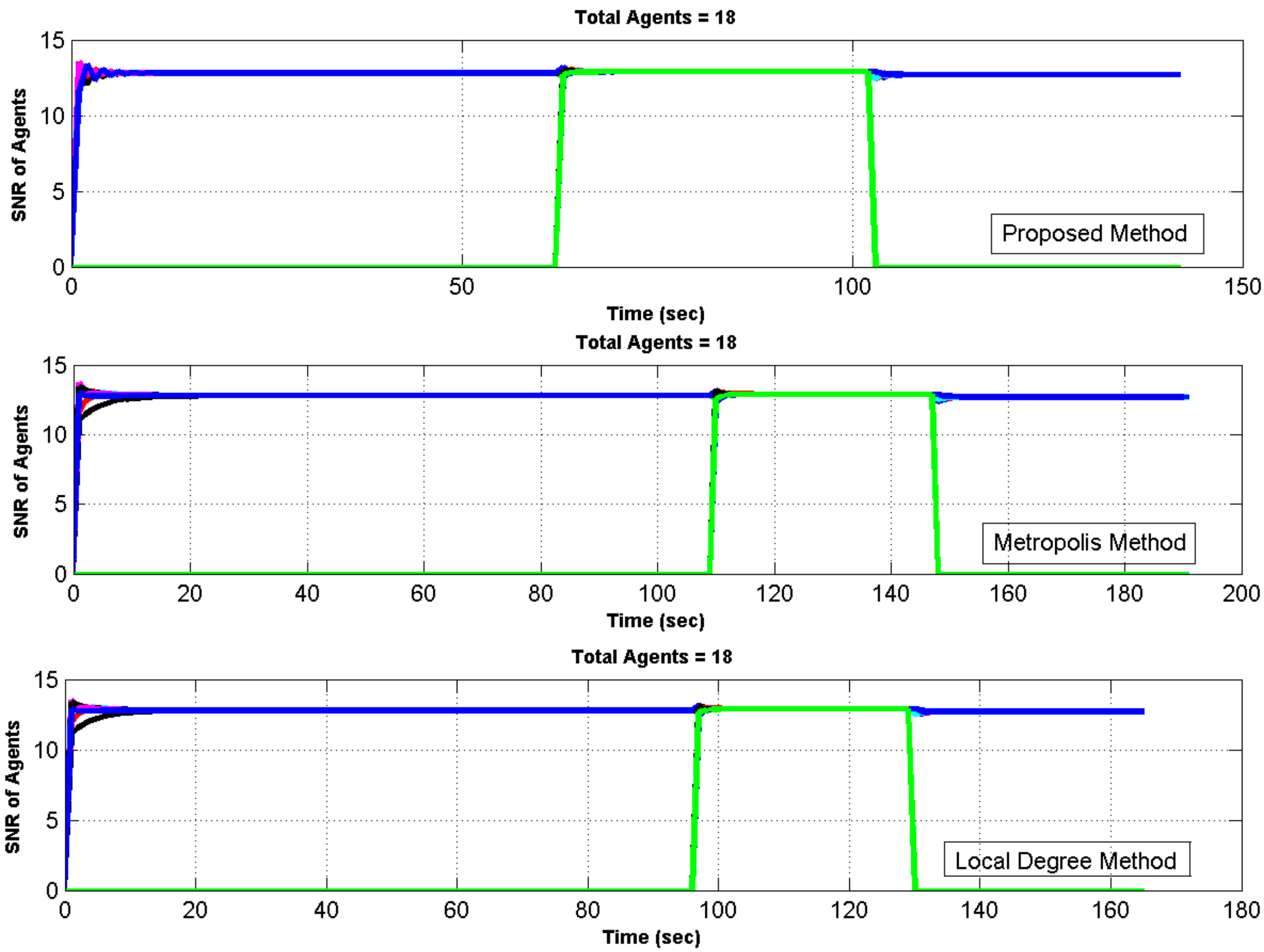

FIGURE 7. Convergence achieved by the proposed, metropolis and local degree methods for random addition and removals of SU in Case 2.

10 SU represented in green color connected through random network topology and reached their average consensus value. After time $t = 20ms$, 8 more SU entered into the communication network and they are presented by the red color. Now the network size changes from 10 to 18, again they will communicate through random network connectivity

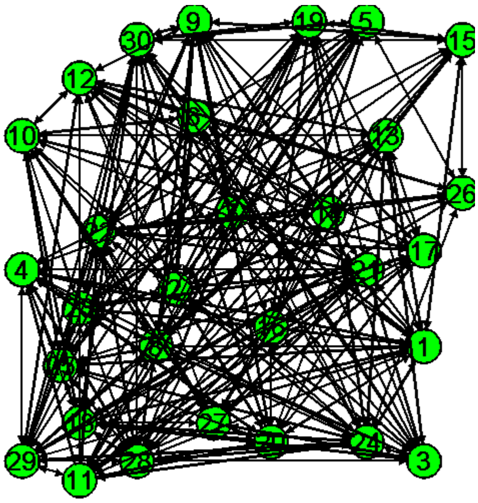

FIGURE 8. **Communication spectrum of 30 SU with a link failure and reconnection after few iterations with dynamic topology considered in Case 3.**

and reaches an average consensus value to achieve their local and global goal. Later on, after time $t = 30ms$ during the convergence process, 3 SU are eliminated randomly from the communication topology and shown in red color. Now the network size is limited to 15 agents, the algorithms will again compute the average consensus value and converge to the best optimal solution. As this case deals with the random addition and removal of the SU from the communication network so in Fig.7 convergence achieved by the proposed, metropolis and local degree methods is presented. The first part of the figure is showing the convergence time of the proposed system before addition or removal of the SU then convergence after addition of SU and finally convergence time after removal of SU from the network. And similarly, it is presented for metropolis and local degree simultaneously. It is quite obvious from the Fig.7 that in such a complicated scenario proposed method is reaching a point of convergence in a quicker way as compared to the rest of the method. Finally, the key performance indicators for the convergence algorithm for this scenario using the proposed and other well know methods are numerically presented in Table. 3. From the simulation results, it is clearly shown that the proposed method is performing best in all available solutions in terms of achieving convergence in fewer iterations, consuming the least CPU processing time, and attaining the best values for asymptotic convergence factor and asymptotic convergence time.

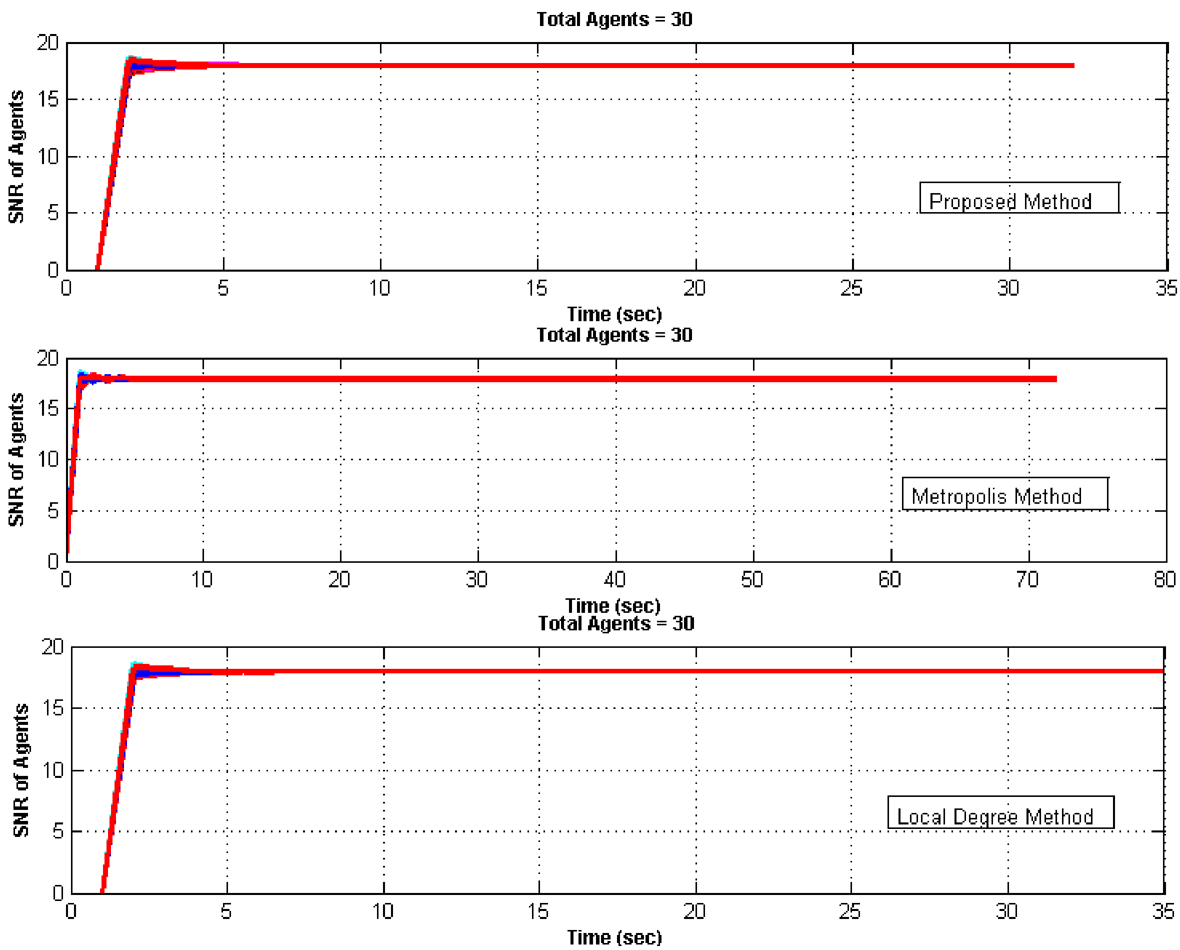

FIGURE 9. **Consensus graphs for proposed and existing methods for disconnection of SU with a link failure and reconnection after few iterations in Case 3.**

TABLE 3. Comparison of key performance parameters for random addition and removals of SU in Case 2.

	Proposed Method	Metropolis Hasting Method	Local Degree Method
Number of Iterations	140	195	165
CPU Processing Time (Min)	0.0796	0.1273	0.0986
Asymptotic Convergence Factor	0.6510	0.7526	0.7123
Asymptotic Convergence Time (Sec)	2.329	3.518	2.947

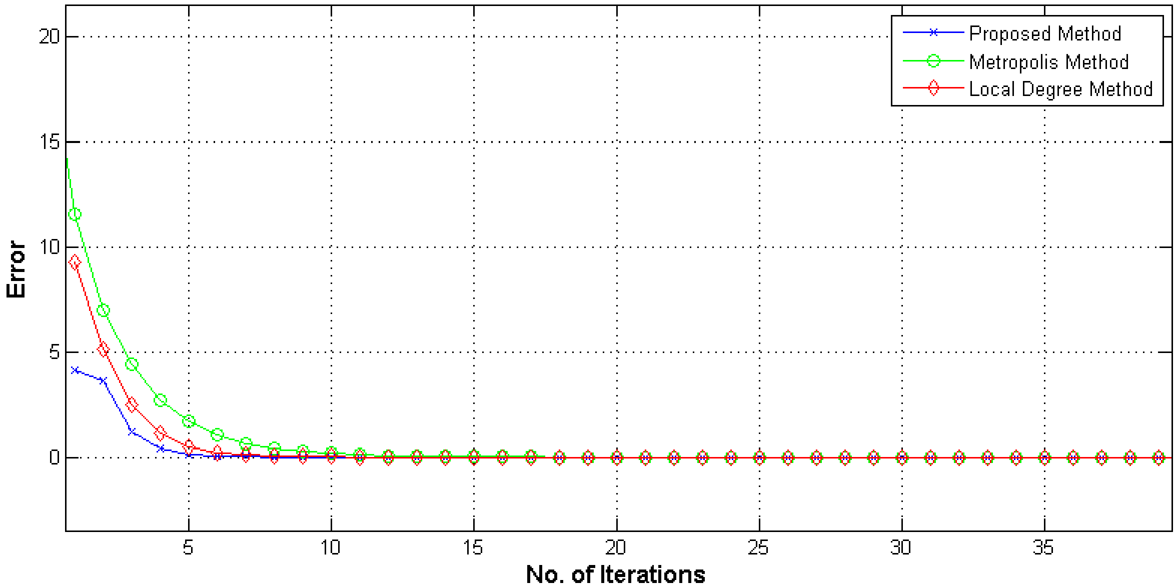

FIGURE 10. Error probability of proposed and existing methods for disconnection of SU with link failure and reconnection after few iterations in Case 3.

3) CASE 3: DISCONNECTION OF SU WITH A LINK FAILURE AND RECONNECTION AFTER FEW ITERATIONS IN THE CONSENSUS BASED COGNITIVE RADIO NETWORK UNDER UNRELIABLE COMMUNICATION WITH DYNAMIC TOPOLOGY

This scenario deals with a case when the spectrum is sensed free by the 30 SU and it is communicated in the network that no PU exist, so the SU go for the consensus agreement. As they achieved the consensus or during the process, few SU randomly disconnected from the communication network and it badly affects the link failure ratio, error metrics, neighborhood of the agents, and the degree of connectivity. The network will again go for the coordination process to achieve the convergence but during this phase of transition, the same disconnected SU active again and start communication in the network with the same linked neighborhood. Here we have set a condition in the simulation scenario that $2-8$ communication links for randomly selected agent breaks and disconnected from the network at any time during the convergence phase. Also, we have assigned a random distribution of SNR values for different SU that limits from $15db$ to $20db$. Very good results are generated from the simulations for the proposed spectrum sensing consensus-based algorithm for cognitive radio networks as compared to the existing algorithms in terms of the consumed number of iterations, the processing time for the algorithms, and convergence factors.

The Communication spectrum of 30 SU with a link failure and reconnection after few iterations with dynamic topology considered in this scenario is demonstrated in Fig. 8. Similarly, Consensus graphs for proposed and existing methods for disconnection of SU with a link failure and reconnection after few iterations are presented in Fig. 9. The first part of the figure is showing the convergence time of the proposed system for disconnection of SU with a link failure and reconnection after few iterations then finally convergence to a common value to reach a steady-state value. Similarly, it is presented for metropolis and local degree simultaneously in the second and third parts of the said figure. It is quite obvious from the Fig.9 that in this scenario, the proposed method is reaching a point of convergence in a hasten way as compared to the rest of the methods. Also, the plot of the error graph between the different states of the algorithm for the proposed and existing method is shown in Fig. 10. The mean square error for the proposed method is represented by a blue dotted line, it is reaching a zero error state in

TABLE 4. Comparison of key performance parameters for disconnection of SU with a link failure and reconnection after few iterations in Case 3.

	Proposed Method	Metropolis Hasting Method	Local Degree Method
Number of Iterations	32	71	36
CPU Processing Time (Min)	0.1568	0.2788	0.1948
Asymptotic Convergence Factor	0.4066	0.6199	0.4467
Asymptotic Convergence Time (Sec)	1.1112	2.0911	1.2410

TABLE 5. Overall average gain of different parameters for proposed method vs other methods in terms of % for the cases considered in this research.

	Proposed Method Vs Local Degree	Proposed Method Vs Metropolis Weights
Number of Iterations	18%	35%
Asymptotic Convergence Factor	10.22%	21.6%
Asymptotic Convergence Time (Sec)	21%	40.5%
CPU Processing Time (Min)	19%	35.3%

a very less number of iterations. Later on, in the graph, it is followed by the local degree method and then by the metropolis method. Finally Table. 4 reflects the results of the key performance parameters generated by the proposed and other considered methods during the simulation process. From the tabular results, the effectiveness and efficiency of the proposed algorithm are reflected as obvious evidence for the best performer to achieve the global convergence goal.

V. CONCLUSION

In this research, we modeled a spectrum measurement for cognitive radio networks as a cooperative control of a multi-agent system for the crash and byzantine failure environments. SU coordinate and exchange information based on their local measurements to achieve the convergence value. In this whole scenario, the PU can enter or leave the network at any time. Therefore, the algorithm proposed in this study is so efficient that SU can make a decision quickly and efficiently based on the energy measurements of the spectrum for random communication. The simulation results provide evidence to the claim above to show the effectiveness of the proposed energy model and the convergence algorithm.

Results in table 5 indicate the significant improvement in the numerical gain (in percentage) of the proposed method for all performance parameters compared to the other methods. The numerical values indicate that the proposed algorithm required less iteration, asymptotic convergence factor, CPU processing time, and asymptotic convergence time.

For future endorsement, we can extend the scope of the proposed algorithms in various new directions. This may include but is not limited to the following: One of the future enhancements of the current work is by extending the scope of the proposed protocol by introducing noise and interference factors to further enhance the performance of the protocol. Another factor that can be added to expand this work in the future is to make the system stabilize and converge as the system suffers jitters and unequal delays. When the network experiences jitters, the instability in the matrices and the calculations of the weighting factor increase surprisingly. This makes this scenario difficult and requires new design ideas to address this problem. Last but not the least, we can expand this model for network-aware and energy-efficient hierarchical routing in distributed convergence in wireless sensor networks (WSN) in the future by adding adaptive sampling, communication power control, energy consumption estimation, bandwidth estimation, and computation of link cost based on network topology.

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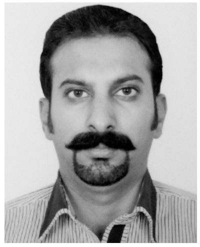

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