DFPC: Dynamic Fuzzy-based Primary User Aware clustering for Cognitive Radio Wireless Sensor Networks

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ABSTRACT

Clustering-based routing solutions have proven to be efficient for wireless networks such as Wireless Sensor Networks (WSNs), Vehicular Ad Hoc Networks (VANETs), etc. Cognitive Radio WSN (CR-WSN) is a class of WSNs that consists of several resource-constrained Secondary Users (SUs), sink, and Primary Users (PUs). Compared to WSNs, there are several challenges in designing the clustering technique for CR-WSNs. As a result, one cannot directly apply the WSN clustering protocols to CR-WSNs. Developing a clustering protocol for CR-WSNs must address challenges such as ensuring PU protection, and SU connectivity, selecting the optimal Cluster Head (CH), and discovering the optimal cluster size. Present CR-WSN clustering solutions failed to resolve the trade-off among all essential clustering objectives. To address these challenges, this study presents a novel approach called Dynamic Fuzzy-based PU aware Clustering (DFPC) for CR-WSNs. DFPC uses a dynamic approach to discover the number of clusters, a fuzzy-based algorithm for optimal CH selection, and reliable multi-hop data transmission to ensure PU protection. To enhance the performance of CR-WSNs, an effective strategy was designed to define the optimal number of clusters using the network radius and live node. Fuzzy logic rules were formulated to assess the four CR-specific parameters for optimal CH selection. Finally, reliable intra- and intercluster data transmission routes are discovered to protect the PUs from malicious activities. The simulation results showed that the DFPC protocol achieved an improved average throughput of 48.04 and 46.49, a PDR of 93.36 and 84.37, and a reduced delay of 0.0271 and 0.0276 in static and dynamic topologies, respectively, which were better than those of ABCC, ATEEN, and LEACH protocols.

Keywords-ant colony optimization; artificial bee colony; cognitive radio; clustering; energy efficiency; fuzzy logic

I. INTRODUCTION

A Wireless Sensor Network (WSN) consists of tiny, low-cost sensor devices that are used in hazardous environments where it is difficult to recharge sensor device batteries [1-2]. The Internet of Things (IoT) is a concept in which things are wirelessly connected to computers for several reasons, some of which include Big Data [3-5]. The expansion of this concept has been driven by the relatively low cost of sensor devices. These applications call for the transfer of enormous volumes of data, the creation of a hierarchical structure, the provision of low-latency services, an increase in spectrum availability, and low levels of power consumption. For instance, the 2.4 GHz frequency range is already occupied by various wireless applications such as Bluetooth and Wi-Fi. Fifth-generation network technology is also on the horizon, which calls for cautious planning for spectrum availability. In recent times, much focus has been given on the application of cognitive radio to WSNs [6]. Building an effective cognitive radio WSN for spectrum access to an underutilized band licensed to a Primary User (PU) presents several problems.

Cognitive Radio (CR) networks could potentially address the spectrum access challenge for the future IoT technology, which is envisioned to be built on cognitive networks. Cognitive Internet of Things (CIoT) solutions for WSNs offer a higher level of intelligence to improve data sensing and processing. It is vital to have an intelligent and upgraded Medium Access Control (MAC) architecture that allows the presence of sensor networks to coexist with the existing wireless infrastructure [7], as it is required for the complete integration of CIoT into WSN. To adequately incorporate CIoT, there is a need to address cognition in spectrum access. In simpler terms, while most of the spectrum is used sporadically, specific portions remain consistently engaged.

There are situations, both manufactured and natural, in which spectrum is scarce and require the most efficient spectrum use. The strategy known as Opportunistic Spectrum Access (OSA) or Dynamic Spectrum Access (DSA) can be applied to alleviate spectrum inefficiencies. OSA is essential for CR because it enables wireless devices to observe, learn, and adapt to their environments. On the other hand, CRSN contributes to improving both the performance of IoT networks and the requirements of their users. Sensor devices use energy to perform spectrum detection and sharing to meet the criteria of quality of service and high throughput imposed by applications [8]. Due to the lack of knowledge of the network, these applications must have access to scattered channels. A concept resembling this was recently suggested for single-user and multi-user cognitive users. On the other hand, this cutting-edge technique causes a network collision when applied to a situation with several users. Priority, random access, and fair resource allocation models have been presented as ways to reduce the risk of crashes caused by interference and the inconsiderate actions of certain users of CR-WSN [9]. However, these models can only provide a single channel to a cognitive individual at any moment. As a result, if the preferred channel is already occupied, they must wait for the next available slot. Similarly, if multiple channels are unoccupied simultaneously, the spectrum goes to waste, even if only one channel can be used.

A precise channel model is constructed to evaluate the signal intensity in various sections of a complicated interior environment. A discrete event simulator is then used to compare the performance of the recommended routing protocol and the performance of two alternative routing techniques. A single cognitive radio source-destination environment may have many amplify-and-forward relays, emphasizing the most effective approach for allocating power to them. The problem may be theoretically expressed as reducing total energy consumption while considering sensor reliability in terms of detection and likelihood of false alarms, secondary user throughput, and interference threshold of the primary user. Then, there is the concept of assigning uneven amounts of electricity to relays based on clusters. In recent years, the use of licensed spectrum has been shallow, leading to a significant waste of spectrum resources [10]. The limited spectrum problem can be adequately addressed by CR-WSN, which combines sensor networking with cognitive technology [11].

Cognitive users take advantage of unoccupied frequencies to maximize spectrum use. Both routing and spectrum are considered the most critical research hotspots in CR-WSNs [12]. Clustering-based WSN algorithms are not compatible with CR-WSNs and hence cannot be used with them directly. On the other hand, the Low-Energy Adaptive Clustering Hierarchy (LEACH) was implemented in CR-WSN without regard for how to use energy efficiently. One of the downsides of CR-WSNs is that node energy cannot be conserved, which is one of the reasons why it is limited. It is essential to use an efficient routing protocol to increase the energy economy of CR-WSN and extend the time it can remain operational. For CR-WSN, it is necessary to have a reduction in the amount of energy used during data transmission.

Clustering algorithms originally developed for WSNs face significant challenges when applied to CR-WSNs. In contrast to traditional WSNs, developing a suitable clustering technique for CR-WSNs presents many complexities and hurdles. This study aimed to address these clustering issues and improve the overall performance of CR-WSNs beyond previous attempts. Although optimization methods have demonstrated their effectiveness in WSNs [13-17], adapting such approaches to CR-WSNs could potentially lead to an increase in the computational overhead associated with the clustering process. In contrast, compared to optimization-focused techniques, fuzzy-based solutions [18-20], offer a more lightweight and efficient alternative for addressing clustering challenges in CR-WSNs. These unique challenges serve as the driving force to propose an innovative clustering solution and provide a robust and efficient method explicitly tailored to the distinctive characteristics and requirements of CR-WSNs.

This study developed the novel Dynamic Fuzzy-based PU aware Clustering (DFPC) protocol to address the challenges of current clustering solutions for CR-WSNs. The DFPC protocol has multiple objectives: dynamic discovery of the optimum number of clusters, optimal Cluster Head (CH) selection using CR-specific parameters, and PU protection from malicious SU data. According to these objectives, the novelty of DFPC is highlighted as follows:

- A novel dynamic mechanism is proposed to discover the optimal number of clusters in the network using the SU node's Maximum Connectivity Frequency (MCF) to compute each cluster's Upper Bound (UB). According to the UB, the number of clusters for the CR-WSN was discovered.
- For each cluster, the optimal CH node is selected using a fuzzy logic mechanism to evaluate each SU by computing their CR-specific linguistic parameters such as the distance from the SU to the Sink, the SU residual energy, the

mobility of the SU, and Signal-to-Noise-Ratio (SNR) of the SU.

- An algorithm of reliable route formation for inter- and intra-cluster data transmissions to protect the PU from malicious users or unauthorized access was designed.
- The DFPC protocol was modeled, simulated, evaluated, and compared with previous clustering protocols for static and dynamic network scenarios.

II. RELATED WORK

The issues of constructing mobile and static CR-WSNs using the clustering mechanism have been recently studied, as clustering has been proven effective for WSN routing. Because WSN clustering is ineffective for CR-WSNs, clustering intellectual WSNs should be an NP-complete problem. Several CR-WSN routing strategies were reviewed and analyzed, highlighting current research problems that need to be addressed for a future roadmap in this sector.

A. State-of-the-Art Solutions

In [21], a clustering method for CR-WSNs was presented using physical layer data while keeping the component of arbitrary CH selection in LEACH. The objective was to shift CHs to more appropriate locations while reducing their number to the absolute minimum. In [12], the current literature on this rapidly growing application area of CR-WSNs was reviewed, analyzing previous studies and introducing outstanding questions from recent efforts. The use of Energy-Aware Clustering (EAC) routing can improve spectrum detection while reducing energy consumption [22]. In this study, an energy expenditure model was presented that included spectrum detection and cluster energy consumption before determining the optimal number of clusters for the organization's activities. It is necessary to evaluate the value of direct assets in reducing energy consumption, using the lopsided clustering technique to regulate energy consumption among CHs under multiple bounce transmission conditions [23]. In [24], LEAUCH was proposed, considering channel resources and uneven clustering for balancing energy consumption. In [25], Hybrid Data-type Clustering (CR-HDC) routing was suggested to improve the organization lifespan of CR-WSNs, identifying the appropriate transmission scope of a sensor hub for both cases when spectrum handoff is applied and when it is not by analyzing the general energy usage of CR sensor hubs under a range of scenarios. In [26], spectrum-aware clustering routing was introduced to elucidate the challenges of portable CR-WSNs in coordinating communication to a sink node during deployment. This process involved two steps: first, evaluation of the eligibility of hubs for clustering and, subsequently, forming clusters among those hubs based on vacant spectrum groups. The possibility for normal re-clustering, the anticipated cluster inclusion zone, and the most extreme age recurrence for energy-producing activities were all considered as variables in the routing selection. In [27], the prerequisites for CR-WSNs and the benefits of hub clustering were investigated, underlining the differences between WSNs and CR-WSNs with hub clustering. In addition, the characteristics, engineering, and geographic distribution of CR-WSNs were discussed.

In [28], a unique Artificial Bee Colony Clustering (ABCC) technique was proposed to cope with the energy consumption of CR-WSNs. A restricted clustering strategy was developed for CR-WSNs to boost sufficiency, flexibility, valuable spectrum of heads, and correspondence overhead while minimizing the data transmission. In [29], event-based clustering was proposed using Ant Colony Optimization (ACO) to improve energy efficiency. In [30], a localized clustering algorithm was proposed, where each center point calculates and distributes its weight to its one-hop neighbor, and the center point with the most weight becomes CH. In [31], an Advanced TEEN (ATEEN) clustering-based routing was proposed for CR-WSNs, forming a limit delicate energy-effective sensor organization that was both delicate and effective for stable clustering and energy efficiency. In [32], three distinct CR-WSN cluster structures were explored: an adjusted single-jump structure, a multibounce cluster structure, and a half-and-half cluster structure. At the first site, the impact of three buildings in various configurations on the movement of the defined region was investigated. According to [33], each CH in CR-WSNs should have a separate fixed channel to reduce difficulties. The segregated nodes of the layer take on the role of CH, use the asset assigned to each CH, and send the information to the next leap CH in the chain. In [34], Multiple Revealing Channels (MRC) were used for cluster-based CR-WSNs to increase the potential to use the detail time allocation by extending the detection season of optional customers. To expedite the execution of spectrum detection and minimize the delay in revealing periods for all CHs, this method introduced multiple announcing channels based on frequency division and incorporated multiple access. In [35], the Modified Adaptive Cluster-Based Heuristic Approach (MACHBA) was proposed to solve the optimal spectrum identification problem in various applications. In [36], a localized clustering approach was proposed to promote stability, effective spectrum management, scalability, and reduced communication overhead. Each node computes its weight and communicates it to its one-hop neighbors, and the node with the greatest importance is designated as the CH.

B. Motivation

Establishing a clustering mechanism for CR-WSNs is more complex than in WSNs due to difficulties in PU security, SU connection, spectrum collisions, optimal cluster discovery, etc. This study aims to fill these research gaps:

- Optimization-based clustering protocols report insufficient use of techniques for optimal CH selection in CR-WSNs.
- As the optimal CH selection was achieved using traditional WSN parameters, the performance trade-off has not been achieved in static and mobile CR-WSNs.
- There is a lack of a multiple-purpose CR-WSN clustering protocol to satisfy essential requirements such as optimal cluster discovery, optimal CH selection using CR-specific parameters, and PU protection.
- Existing clustering approaches for CR-WSNs incorporate the PU, significantly undermining its security.

The proposed DFPC protocol aims to overcome the above challenges.

III. DFPC METHOD

Figure 1 shows the overall architecture of the DFPC protocol, which consists mainly of three phases: cluster numbers, optimal CH selection, and PU protection. The cluster number phase is launched after the network deployment to discover the optimal number of possible clusters in the network. Using MCF and UB, k clusters are initially formed. After discovering k optimal clusters, the next phase is a selection of the optimal CH for each cluster. The optimal CH selection is periodically evaluating each cluster for re-clustering, performing operations such as selecting new stable CH with joining and disjoining Cluster Members (CMs) due to their mobilities. A fuzzy logic approach was used to evaluate each SU in the network using four different linguistic input variables mapped to an integrated fuzzy score for CH selection. Finally, the last phase belongs to PU protection by forming a reliable route for inter- and intra-cluster data transmission. CMs periodically sense and transmit data to the associated CH, which then transmits periodically collected information to the intended sink node. The data will then be distributed from the sink to the connected PUs. A reliable route formation approach was used to prevent malicious data transmission and ensure integrity and security in the PUs.

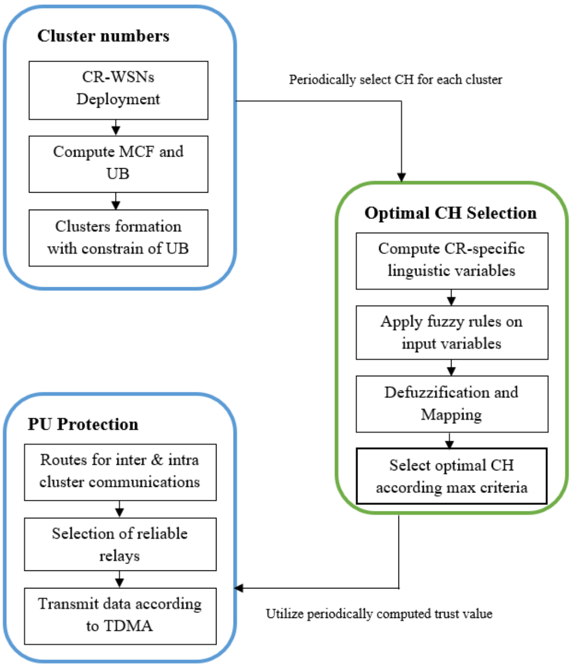

Fig. 1. The graphical abstract-proposed DFPC protocol for CR-WSNs.

A. System Model

Suppose a CR-WSN deployed in an area of $X \times Y$ network size with n SUs, $SU = \{su^1, su^2, \ldots, su^n\}$, and one sink. The initial k groups formed using the K-means clustering algorithm after discovering the optimal number clusters k is $C = \{c^1, c^2, \ldots, c^k\}$. For each j^{th}, $j \in k$, cluster c^j, the proposed optimal CH selection algorithm is applied to maximize energy efficiency and Quality of Service (QoS) with PU protection. A fuzzy logic-based approach was used to solve this optimization problem for optimal CH nodes for each cluster and reliable route formation. The proposed clustering protocol is based on the following assumptions:

- All SUs are static and move randomly with resource limitations.
- PUs are assumed to be outside entities and will not be considered parts of the clustering protocols.
- The sink node is placed outside the network with all security provisions and without resource limitations.
- The distance parameter was measured using the Received Signal Strength Indicator (RSSI).

B. Optimal Clusters Discovery

The ideal number of clusters in cluster-based CR-WSN is a problem. Due to the significant number of clusters, extensive paths are established that incur more delay. On the other hand, a limited number of clusters depletes the CH's energy and results in inefficient spectrum sharing. An effective technique should be developed to determine the optimal number of clusters and improve the performance of CR-WSN. At first, the network's total number of clusters and CHs was computed. The cluster size was optimized proportionally to the CR-WSN size. The proposed clustering method populates every cluster as much as possible in order to reduce the total number of clusters in the network. However, oversizing the cluster also has a significant impact on CH performance. For a CR-WSN with n nodes in a network area of $X \times Y$, the MCF for each SU is estimated in meters as follows:

$$MCF = \pi . r^2 \quad (1)$$

where r represents the specific distance in meters. This calculation determines the network's radius, typically half its height or width, following standard conventions. The radius r is crucial in estimating the MCF and UB. The value of r was set equal to $X/2$. The primary objective is to determine MCF for each SU within the network. To achieve an optimal clustering of SUs, it is essential to identify SU groups that share similar connectivity frequency characteristics. Consequently, the most effective approach to ensure an optimal number of clusters is to estimate the MCF. Subsequently, appropriate actions can be taken to discover the ideal number of clusters within the deployed network. CH forms the connectivity p using the node density parameter, calculated as [36]:

$$p = \frac{n}{X^2} \quad (2)$$

Thus, the maximum SUs in each cluster are calculated as [36]:

$$UB = p . \pi . r^2 \quad (3)$$

UB indicates the maximum allowable SUs in each cluster in the network, makes the cluster formation process efficient, and reduces the burden of finding the number of clusters at every interval. The initial step in determining the network's UB involves computing MCF. Estimating the connectivity frequency for each SU in the network is essential to calculate the UB. Leveraging the MCF, the maximum count of SUs that can be accommodated within a single cluster is identified based on the input network's characteristics. This is based on a combination of the MCF and the node density parameters. The UB, derived from the MCF, ensures an accurate assessment of the number of SUs accommodated within a cluster, accounting for their density and connectivity frequency attributes. Subsequently, once the UB is determined, the network can be optimally partitioned into the ideal number of clusters. Identifying the optimal cluster count through UB and MCF directly influences the overall improvement in performance in the proposed protocol. Therefore, the number of clusters is calculated using UB as [36]:

$$k = \left|\frac{n}{UB}\right| + 1 \tag{4}$$

where the addition of 1 represents the reliability of cluster formation to prevent the condition of non-clustered SUs in the network.

C. Optimal CH Selection

The optimal CH selection is launched for each cluster in the network after network deployment and clustering. First, the CH selection method is performed using the fuzzy model. The type-2 fuzzy rules aim to choose the best CH node from a set of nodes. The rules combine four language input variations: distance (*f*1), residual energy (*f*2), SNR (*f*3), and speed (*f*4). In addition to residual energy and distance parameters, CR-specific metrics were evaluated, such as the speed and SNR of each SU node in the proposed protocol.

Algorithm 1: Optimal CH Selection using Fuzzy Logic

```
Inputs:
k: number of clusters
CM: set of nodes in a cluster
RT: routing table for each node
T: Total network duration

Output:
CH: set of CHs at current cycle
While (T)
  For each cluster c⇦1:k
    Compute the number of nodes in the cluster:
    m ⇦ size(CM(c))
    For each SU ⇦ 1:m
      Compute linguistic inputs:
      f1 ⇦ getDist(su^i, sink)
      f2 ⇦ getEnergy(su^i)
      f3 ⇦ getSNR(su^i)
      f4 ⇦ getSpeed(su^i)
      DF(i) ⇦ T2FIS(f1, f2, f3, f4)
      Updated routing table entry:
      RT(CM(c, su^i)) ⇦ update(DF(i))
    End For
    Optimal CH selection for current cluster c:
    CH(c) ⇦ index(max(DF))
  End For
T--
Return CH
End While
```

Algorithm 1 shows the functionality of the suggested fuzzy logic-based optimum CH selection process. For each cluster $c \in k$, the number of Cluster Members (CMs) is first discovered. These CM values are different for each cluster, thus, for the *m* CMs belonging to the current cluster *c*, they are analyzed using the fuzzy logic technique. Before applying the Type-2 fuzzy model for the optimal CH selection, the four parameters of each SU node $su^i \in m$ are calculated. The linguistic variables *f*1, *f*2, *f*3, and *f*4 for each $su^i \in m$ are then entered into the Type-2 Fuzzy Interference System (T2FIS) function. Then, fuzzy if-then rules map the inputs to the fuzzy output, comprising linguistic control rules. The FIS replicates human decision-making using fuzzy if-then rules for the language factors shown in Table I. The defuzzifier takes the aggregated linguistic values of the FIS and creates a nonfuzzy control output that picks the best CH for each cluster. The next section presents the computation of four linguistic variables and the design of the fuzzy logic model.

- Distance: This parameter ensures clustering and data transmission phase reliability by assisting in selecting the SU as the CH for each cluster with the shortest geographical distance to the sink node. RSSI was used to estimate the geographical distance between the su^i to sink node at time *t*, as follows:

$$f1\left(su^i(t)\right) = [dist(su^i,\ sink) < rssi] \tag{5}$$

where $dist(su^i, sink)$ represents the geographical distance between two nodes, and *rssi* is the communication range of su^i. As the proposed objective function is maximization-based, it can be rewritten as:

$$f1\left(su^i(t)\right) = \left(\frac{1}{[dist(su^i,sink)<rssi]}\right) \tag{6}$$

The higher the value of $f1(su^i(t))$, the better its chances of becoming CH.

- Residual Energy: This parameter is extensively used in various WSN clustering methods and intends to guarantee that nodes with more residual energy consume less and have a longer network lifespan. The $f2(su^i)$ at time *t* is computed as:

$$f2\left(su^i(t)\right) = \frac{E_{residual}(su^i(t))}{E_{initial}(su^i)} \tag{7}$$

where $E_{initial}(su^i(t))$ represents the initial energy of the node su^i and $E_{residual}(su^i(t))$ represents the remaining energy of the node su^i at time *t*. The node with higher $f2(su^i(t))$ is an excellent candidate to become CH.

- SNR: The SNR level of SUs is another vital parameter to suppress the challenges of spectrum efficiency and interference mitigations in CR-WSNs. The calculation of SNR requires both information on the *rssi* and the noise power (*np*) at the receiver. The node with a higher SNR will be a good candidate for the optimal CH selection. The SNR fitness value $f3(su^i(t))$ at time *t* is computed by:

$$f3\left(su^i(t)\right) = 1 - \left(\frac{1}{[rssi(su^i)+np(su^i)]}\right) \tag{8}$$

The node with higher $f3(su^i(t))$ is an excellent candidate to become CH.

- Speed: Because CR-WSNs are static or dynamic, mobility becomes critical in ensuring dependable and optimum CH selection. The SU with the slowest mobility will be a viable contender for achieving energy-efficient and stable clustering in the network. The present moving speed of SUs is calculated using a simplified location differentiation technique between the two relevant time intervals, *t*-1 and *t*. The $f4(su^i)$ at time *t* is computed by:

$$f4\left(su^i(t)\right) = \left(\frac{1}{mobility\left(su^i(t-1), su^i(t)\right)}\right) \qquad (9)$$

The node with higher $f4(su^i(t))$ is an excellent candidate to become CH.

Figure 2 shows the T2FIS() fuzzy model, which accepts the fuzzy inputs ($f1, f2, f3$, and $f4$) and is forwarded to Madani FIS via the fuzzy rule set. The purpose of establishing these value thresholds is to categorize these parameters into three distinct levels: low (below 0.25), medium (ranging from 0.25 to 0.65), and high (above 0.65). These linguistic variables were used within the context of a fuzzy logic system to facilitate mapping based on the categorization mentioned above. The implementation of these value limits showed improved simulation results when experimenting with various thresholds.

TABLE I. MEMBERSHIP FUNCTIONS FOR FUZZY INPUTS

Variable	**"far"**	**"medium"**	**"near"**
Distance	$f1 \leq 0.25$	$f1 > 0.25$ && $f1 < 0.65$	$f1 \geq 0.65$
Variable	**"low"**	**"medium"**	**"high"**
Residual Energy	$f2 \leq 0.25$	$f2 > 0.25$ && $f2 < 0.65$	$f2 > 0.65$
Variable	**"sparse"**	**"medium"**	**"dense"**
SNR	$f3 \leq 0.25$	$f3 > 0.25$ && $f3 < 0.65$	$f3 \geq 0.65$
Variable	**"fast"**	**"average"**	**"slow"**
Speed	$f4 \leq 0.25$	$f4 > 0.25$ && $f4 < 0.65$	$f4 \geq 0.65$

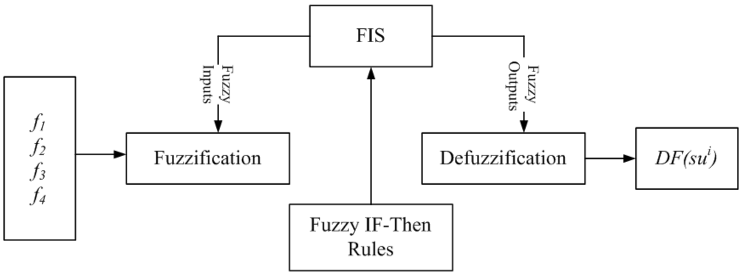

Fig. 2. The proposed fuzzy model for each SU evaluation.

The output was then defuzzified to generate $DF(su^i)$. The defuzzification result indicates the fitness score of each SUs. After computing the value for each SU in the current cluster, the SU with the highest DF value is chosen as the best CH for this cluster. This method is performed for each TDMA slot to update and maintain each cluster. Table I shows the definition of the membership functions for each linguistic variable. Using these variables, 48 fuzzy rules were designed to evaluate the linguistic output of each SU. During the defuzzification process, the input membership functions, shown in Table I, are applied, and accordingly, the output mappings are performed for each input SU. That mapping is either of three classes: "worst", "good", or "best". The defuzzification mappings are extended to a unique integrated score for each SU. In the defuzzification phase, FIS established at each of the SU in the CM set can be expressed as:

$$DF(su^i) = \text{defuzzification}(f1, f2, f3, f4) \qquad (10)$$

The result of the fuzzy logic approach *DF* is in the range of 0 to 1, where a value close to 1 is the preferable option for optimal CH selection. In this process, four linguistic variables ($f1, f2, f3$, and $f4$) are used as input to the Type-2 fuzzy logic system. This system determines the optimal CH node among the available SUs within the current cluster. The result produced by the T2FIS is also a numeric value that falls from 0 to 1, and again a value closer to 1 indicates the most suitable candidate for CH selection. Fuzzy rules guide the transformation of linguistic input into linguistic output during the defuzzification process, ultimately aiding in selecting the ideal CH for the cluster.

D. PU Protection

The problem of PU protection was formulated using a reliable route formation algorithm for intra- and inter-cluster data transmissions. The reliable forwarding relay is selected by evaluating each SU candidate via their calculated trust value during the CH selection phase. Algorithm 2 outlines the procedure for safeguarding PUs through a robust route discovery method. It is important to note that PUs are external entities and do not play a role in clustering and routing algorithms. Several previous studies integrated PUs into routing strategies, but this approach was vulnerable to security threats. This study chose to omit PUs from the clustering process. Instead, the routing algorithm shown in Algorithm 2 focuses primarily on preventing PUs from being inadvertently incorporated into the routing process, improving security and reliability.

Algorithm 2 shows the reliable routes for any source node *s* (CM or CH node) and its corresponding destination node *d* (CH or BS). The forwarding relay is selected by fetching and comparing its periodically computed DF value. The node with a higher DF value is selected as the forwarding relay *f*. This process continues until the destination is reached. This reliable route formation ensures stable routes on the network that do not transmit insecure or malicious information to the BS node. Therefore, it protects the PU connected to the BS as well.

Algorithm 2: PU Protection via Reliable Route Formation

```
Inputs:
s: source code, s ∈ CM || CH
d: destination node, d ∈ CH || BS
RT: routing table for each SU
Output:
Reliable route formation

s ⇦ broadcast(RREQ, d)
q ⇦ getResponse(RREP)
For each i ∈ q
  temp(i) ⇦ RT(DF(i))
End For
If (f == d)
  Return R
Else
  s ⇦ f, continue
  // update routing table with currently selected
  // forwarding relay
  R ⇦ update(s, f)
End If
Return (R)
```

IV. RESULTS AND DISCUSSION

The proposed DFPC protocol was compared with three existing protocols. ABCC [28], ATEEN [31], and conventional LEACH [21]. ABCC and ATEEN have recently been proposed for CR-WSN clustering using optimization algorithms. These protocols were implemented and tested under identical simulation parameters, detailed in Tables II and III, using the NS2 tool version 2.34 on an Ubuntu 12.04 OS using a VMware workstation with 4GB RAM, 80 GB hard drive, Intel Core-i3 processor, and an Intel graphics card. Two network types were used to assess the reliability and efficiency of the clustering protocols: one with varying SU density and static topology and the other with varying SU density and dynamic topology. In the static topology, the position of each SU is fixed. In the dynamic topology, each SU moves randomly across the network with speeds ranging from 2 to 10 m/s. Moving sensor nodes are nothing more than moving CR users, such as in healthcare applications. The performance of each protocol was evaluated using the average throughput, Packet Delivery Ratio (PDR), average energy consumption, average delay, and communication overhead. The primary variable of interest is the number of SUs. Values ranging from 50 to 200 were considered, encompassing a low- to high-density spectrum to assess the scalability and reliability of the protocols.

TABLE II. SIMULATION PARAMETERS FOR STATIC CR-WSNs SCENARIOS

Number of SU sensors	50-200 (50, 80, 120, 150, 200)
Number of channels	6-10
MAC	802.11
Queue limit	50 packets
Simulation time	100 s
Transmission range	250 m
Clustering protocols	LEACH
Traffic type	CBR
Number of connections	5
Network size	500 m × 500 m
Sink position	Center of the network
Packet size	512 bytes
Initial energy	0.5 nj
Transmitter energy consumption	16.7 nj
Receiver energy consumption	36.1 nj

TABLE III. SIMULATION PARAMETERS FOR DYNAMIC CR-WSNs SCENARIOS

Number of SU sensors	50-200 (50, 80, 120, 150, 200)
Number of channels	6-10
MAC	802.11
Queue limit	50 packets
Simulation time	100 s
Transmission range	250 m
Clustering protocols	LEACH
Traffic type	CBR
Number of connections	5
Network size	500 m × 500 m
Sink position	Center of the network
Packet size	512 bytes
Initial energy	0.5 nj
Transmitter energy consumption	16.7 nj
Receiver energy consumption	36.1 nj
Mobility speed	2-10 m/s
Mobility model	Random Waypoint

A. *Simulation Results for Static Topology*

This section presents the simulation results for static CR-WSNs with a density variation scenario. Figures 3 to 7 show the results of average throughput, PDR, average delay, routing overhead, and average energy consumption for each clustering protocol. The results show that increasing SU density harms network performance. With increasing SUs, average throughput and PDR performance degraded, while average delay and routing overhead increased. The average energy consumption is the only parameter that is efficient against the increased SU density.

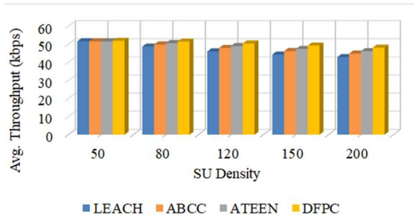

Fig. 3. Average throughput analysis for static CR-WSNs.

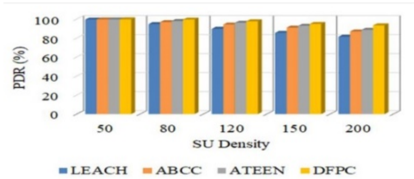

Fig. 4. PDR analysis for static CR-WSNs.

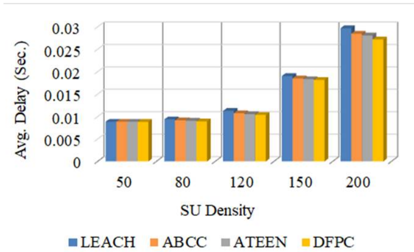

Fig. 5. Average delay analysis for static CR-WSNs.

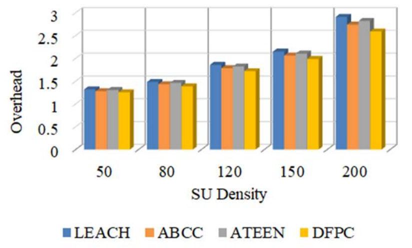

Fig. 6. Routing overhead analysis for static CR-WSNs.

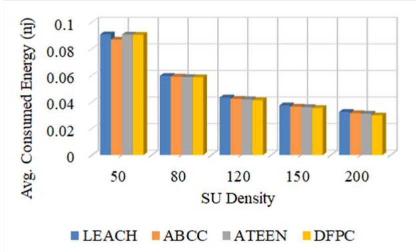

Fig. 7. Average energy consumption analysis for static CR-WSNs.

The average throughput, PDR, delay, and overhead became worse with increasing density as a result of the increased routing operations in the network. For average throughput and PDR, DFPC significantly outperformed the other protocols, the leading causes for this being the designed mechanisms for optimal clusters, optimal CH selection, and reliable route formation. Apart from this, the higher PDR directly affected the lower communication delay and overhead in the network when using the DFPC protocol, because DFPC requires fewer clustering rounds and packet retransmissions than the other protocols, reducing average delay and overhead performance. On the other hand, since the existing LEACH, ABCC, and ATEEN protocols relied heavily on static clustering with conventional WSN parameters for optimal CH selection, they resulted in lower performance. Consequently, the reduced clustering rounds and retransmissions reduce energy consumption.

B. Simulation Results for Dynamic Topology

Figures 8-12 show the results for average throughput, PDR, average latency, average used energy, and communication overhead, respectively. The networks were built with different SUs, such as 50, 80, 120, 150, and 200. The mobility speed of the SUs in each network ranged from 2 to 10 m/s. The results show that increased density reduces throughput and PDR performance. This is mainly due to the growing number of communication lines and interference in CR-WSNs. Figures 10 and 11 show that increasing SU density negatively influenced average latency and communication overhead. As the density of SUs increased, frequent clustering and routing processes led to a significant escalation in communication latency and overhead. On the other hand, as shown in Figure 12, increasing SU density had a beneficial influence on average energy usage due to the huge number of idle SUs in the network.

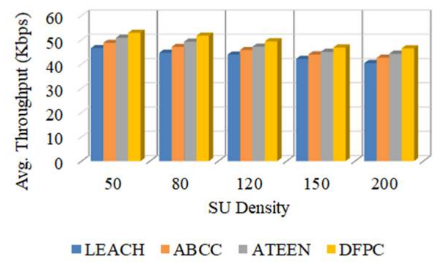

Fig. 8. Average throughput analysis for dynamic CR-WSNs.

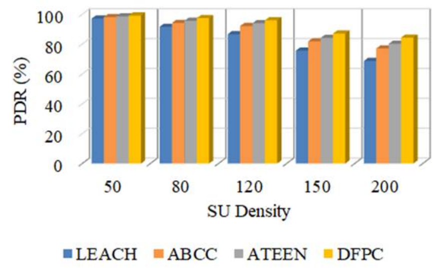

Fig. 9. PDR analysis for dynamic CR-WSNs.

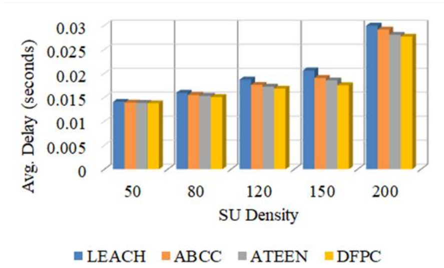

Fig. 10. Average delay analysis for dynamic CR-WSNs.

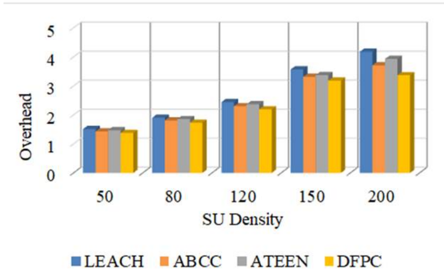

Fig. 11. Overhead analysis for dynamic CR-WSNs.

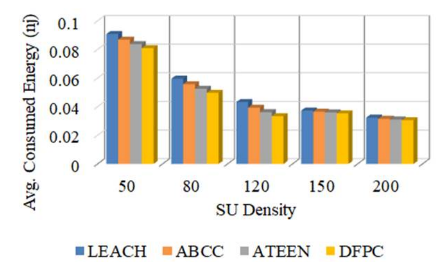

Fig. 12. Average energy consumption analysis for dynamic CR-WSNs.

The results show the efficiency of the proposed DFPC compared to the other protocols. The main reasons are the dynamic discovery of the number of clusters, the optimal CH selection considering speed as one of the parameters, and the reliable route formation. These characteristics are missing in the three existing protocols. Among them, the ATEEN protocol outperformed LEACH and ABCC in terms of throughput, PDR, latency, energy consumption, and communication overhead. The ATEEN protocol outperformed LEACH and ABCC because it employs a better data-transfer mechanism based on TEEN's thresholding approaches. Compared to ABCC and ATEEN protocols, the traditional LEACH procedure performed the poorest, since it relies on the only known energy parameter for clustering. Optimization methods with updated fitness functions were used in both the ABCC and ATEEN protocols. Table IV shows a qualitative comparative analysis of the proposed protocol, indicating that it is the best candidate for use in CR-WSNs.

TABLE IV. QUALITATIVE COMPARATIVE ANALYSIS OF THE PROPOSED METHOD

Static CR-WSN with SU density 200					
Contribution	**Avg. throughput**	**PDR**	**Avg. delay**	**Overhead**	**Avg. energy consumption**
LEACH [21]	42.82	81.45	0.0297	2.91	0.03243
ABCC [28]	44.74	86.94	0.0284	2.74	0.03153
ATEEN [31]	46.12	88.8	0.0280	2.822	0.03112
Proposed	48.04	93.36	0.0271	2.588	0.02993
Dynamic CR-WSN with SU density 200					
LEACH [21]	40.42	68.75	0.0299	4.173	0.03243
ABCC [28]	42.61	77.08	0.0291	3.709	0.03153
ATEEN [31]	44.25	80.2	0.0280	3.927	0.03112
Proposed	46.49	84.37	0.0276	3.366	0.03049

Compared to the other protocols, the experimental results consistently demonstrate that the proposed DFPC protocol stands out as the most effective choice. Several key factors contribute to its superiority. First, the DFPC protocol dynamically determines the optimal number of clusters, a feature that distinguishes it from other protocols. Additionally, it excels at selecting CHs by factoring in speed as one of the critical characteristics, ensuring an efficient and reliable clustering process. Moreover, it excels at establishing reliable routes for data transmission. The efficacy of DFPC depends on its innovative processes to achieve these ideal clusters, select the most suitable CHs, and construct robust routes. The multifaceted approach differentiates DFPC from previous single-objective clustering protocols.

Security threats were not adequately considered during the evaluation of the DFPC protocol. To improve its robustness and credibility, it should be subjected to a comprehensive assessment that includes various security threat scenarios. Neglecting to address security concerns may significantly limit its viability and adoption.

V. CONCLUSIONS AND FUTURE WORK

The design of clusters for CR-WSNs is one challenging research problem considering essential requirements such as optimal deployment, the optimal number of clusters, CR-specific CH selection, and protection of PUs from malicious activities. This study proposed a novel CR-WSN clustering solution to address these challenges and lead to improved performance. The proposed DFPC protocol mainly consists of an optimization mechanism of the number of cluster formations, fuzzy-based optimal CH selection, and a reliable route formation for PU protection. The proposed approach produced a better clustering solution for CR-WSNs. DFPC was simulated, evaluated, and compared with the LEACH, ATEEN, and ABCC protocols using static and dynamic CR-WSNs. For both scenarios, the DFPC outperformed the other clustering protocols. The average throughput and PDR performance of DFPC were improved by approximately 9.45% and 11.21%, respectively. The average delay, energy consumption, and overhead performance of the DFPC protocol were reduced by 7.8%, 12.3%, and 13.2%, respectively. In the future, the performance of the proposed DFPC protocol can be verified by introducing different CR-WSN threats, the use of optimization algorithms, and AI.

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