IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 13, 2020, accepted August 30, 2020, date of publication September 3, 2020, date of current version September 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3021507

A New Bio-Inspired for Cooperative Data Transmission of IoT

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This work was supported by Penerimaan Negara Bukan Pajak Universitas Negeri Malang (PNBP UM), Indonesia under Grant Number 12/2020.

ABSTRACT The original queen honey bee migration (QHBM) was developed for independent action on solving efficient mobile routing in WSN. In this article, we enhanced the original QHBM using Binary testing injection on the cooperative node's selection on IoT system. We also added a new cost function for making nodes' coalition, implementing the threshold value for modified QHBM (mQHBM for short), and demonstrating the mQHBM-CMIMO in fair comparison with another previous algorithms. Our research portrayed that mQHBM can perform better than its competitors such as Fuzzy- BT, Neuro Fuzzy and PSO in terms of network lifetime and the end to end delay.

INDEX TERMS Binary testing, cooperative nodes, CMIMO, IoT, QHBM.

I. INTRODUCTION

Recently, Wireless Sensor Networks (WSNs) have been utilized for various applications such as military operations, health care, surveillance systems, and Intelligent Transport Systems (ITS), etc. [1], [2]. The WSN network is formed from several nodes with the role of the sensor. The development of the routing protocol is quite rapid, where energy efficiency is the main attention due to the sensor nodes supplied from batteries.

One of the routing protocols developed by researchers [1] is the low energy adaptive clustering hierarchy (LEACH), which is adaptive in cluster formation by relying on probability theory. Routing in LEACH is divided into two phases, namely the phase of cluster formation and the phase of data transmission. FIGURE 1 shows the LEACH protocol, where nodes form clusters, and the data communication is done hierarchically, from nodes to CH, then forward to sinks [2], [3]. LEACH is simple and relatively easy to develop an effective saving energy nodes in close transmission distances. For a decade, LEACH has become prevalent, and many of the previous works have demonstrated another approach in cluster formation by introducing the remaining energy parameters, RSSI, etc. [2]–[18] also in data gathering [50]–[52].

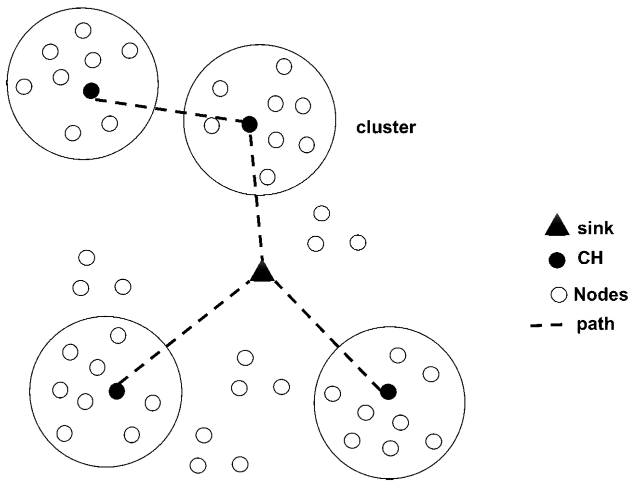

FIGURE 1. Cluster-based data transmission.

The weakness of this LEACH is that the cluster head (CH) nodes require extra energy for clusters formation and data gathering of all members, which make the CH nodes depleted their energy. Moreover, data communication task in WSN and IoT encompasses a direct impact on energy consumption [1], [50].

A hierarchical design based on a clustering algorithm could manage the data communication and save energy in WSNs [50]–[52]. In particular, Researchers have considered

The associate editor coordinating the review of this manuscript and approving it for publication was Yu-Huei Cheng.

the length of data communication paths to improve clustering schemes that perform better both in heterogeneous and homogenous networks [50]. Energy consumption may impact on network lifetime; thus, the network lifetime of hierarchical networks is extended by using a sleep-wake up the mechanism for overlapping neighbouring nodes [51]. The CH could reduce data redundancy, which in turn it could extend network lifetime.

The enhancement and application of intelligent systems such as GA [12]–[14], Fuzzy [7], [9]–[11], NN [16], [17], and PSO [16], [17] are enacted in subsequent developments. Besides, according to [7], [9]–[11], Fuzzy application can improve data communication performance in topology clustering, which is supported by [50], revealing that the application can improve the energy saving and lifetime of the hierarchical WSN.

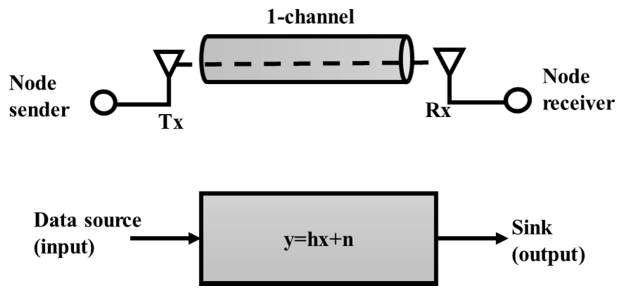

FIGURE 2. SISO channel.

Most of the previous works [1]–[17] used the single output single input (SISO) model for transmitting data. This SISO system is shown in FIGURE 2. Although a single channel system makes data communication easier and faster, SISO results in poor throughput, so it is not suitable for applications that require priority data and isolated nodes. The idea to improve the SISO system's throughput while saving energy for long-distance transmission has emerged since the beginning of the decade, namely by developing multiple antennas. Nodes that are equipped with multiple antennas can open multiple channels to communicate, thereby increasing throughput. This system is known as the MIMO, as depicted in FIGURE 3.a. [19]–[21]. In this system, nodes are equipped with multiple antennas, so there are several possible channel states such as FIGURE 3.b. [22]. Hardware, which is more complex and expensive, is the main obstacle in implementing MIMO systems in various applications, given the number of nodes that can reach hundreds or even a thousand [23], [25]–[30].

However, the multi-channel formation stage involves complex computation on a logical MIMO system or extra hardware for the physical MIMO system. Furthermore, cooperative MIMO (CMIMO) comes as a more adaptive solution to hardware nodes, where this system does not require additional physical antennas [21]–[27]. The MIMO system is formed virtually by utilizing a coalition of nodes to form a cooperative node (CN) so that it is considered a virtual

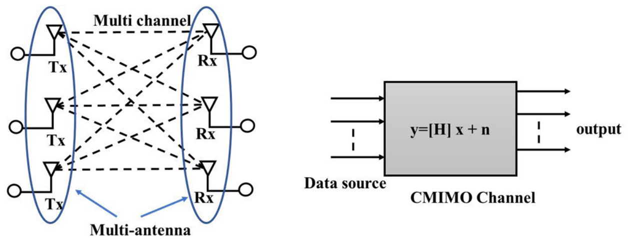

FIGURE 3. CMIMO model. a. cooperative nodes transmission, b. CMIMO channel.

hardware unit. CN has the role of providing multiple channels for nodes to send data to the server [36], [37].

Like WSN, nodes in IoT use batteries, so attention to energy savings is crucial. On the other hand, data communication requires a lot of energy slots. The hardest working nodes will quickly run out of energy. Internet of Things (IoT) technology has gradually shifted its older sibling wireless sensor network (WSN). IoT is featuring node as a sensor, actuator, or both, meanwhile, WSN' node serves as a sensor [26], [39]–[43]. Moreover, in both IoT and WSN, a node could set as relay nodes. Currently, IoT is applied in various fields such as healthcare, smart home, and smart grid. It has also been more prevalent than WSN. The communication platform, such as Zigbee, Bluetooth, and WIFIs supported by both WSN and IoT [1], [42], [43]. Since those are closely related, a mismatch or overlap in definitions exists. However, the well-developed WSN routing could be adopted to IoT.

Researchers began to think about developing a virtual MIMO, in which a coalition of several nodes became a single unit as cooperative nodes (CN) that formed multiple virtual antennas [19]–[23]. This system is known as the MIMO cooperative (CMIMO). CMIMO has been widely applied to WSN and IoT. It has also been suggested to be a good protocol in increasing throughput and more efficient for long-distance transmission [27], [32]–[34]. CMIMO operates on a logical layer where several nodes are recruited as cooperative nodes (CN) to open the virtual communication channels resembling a multi-input multi-output system (MIMO). Thus, cooperative nodes can receive multiple data and relay multiple data at once. The discussion about CMIMO is mostly geared on the selection of nodes as candidates for CNs [32] and channel state estimation models [27], [30]–[34]. The selection of CNs has been very diverse, starting by utilizing intelligent systems such as GA, PSO, Fuzzy, and NN [7], [26], [29], [33], [39], [40], [51].

The channel state estimation model is common and adopts MIMO real hardware models. Nonetheless, the approach can vary; for example, it utilizes residual energy, link credibility, and other parameters that can be accessed from nodes. Until today, the study of cooperative routing generally deals with channel problems and the selection of cooperative nodes [20]–[33]. The study of channels is carried out to strengthen the argumentation of virtual methods or logical channels that are more flexible than creating physical channels that require more complicated and sophisticated hardware. Fortunately, cooperative diversity as a core technique brings a solution to this problem. To take advantage of this technology in the MIMO system, cooperatives MIMO (CMIMO) are created in collaboration with the individual antenna presented. In long-distance transmission, CMIMO has been proven to defeat SISO in energy reduction performance. Besides, it can achieve real MIMO excellence. However, CMIMO channel interference and synchronization are the main problems that make applying CMIMO [29], [33], [38].

Typical CMIMO [19]–[33], CMIMO-SM [27], and CMIMO-STBC [34] were developed as variants for studies that are more inclined to energy efficiency. Besides, scholars discussed the relationship between BER and energy consumption and did not discuss the end to end delay or lifetime. The improvement of the energy efficiency of a wireless sensor network has been a great concern nowadays. For the improvement of energy efficiency, we use spatial modulation (SM) along with CMIMO to make a new technique called CMIMO-SM. The simulation shows that significant energy efficiency enhancement and reduction of energy consumption employed the CMIMO-SM technique.

An earlier study of package error rate (PER) and energy consumption in CMIMO, where CMIMO nodes energy is mostly spent on intra-cluster and inter-cluster, has been carried out [27]. Furthermore, CH nodes coalesce with nearby nodes to form multi-channels in forwarding data to the destination. Peng *et al.* [34] have developed a new CMIMO based on spatial modulation (SM) on an ad hoc network, where this method is also used to optimize energy on the network. CN nodes are formed on the internal cluster. In addition to energy consumption, the number of hops and bit error ratio (BER) has become a consideration in the analysis. Further research related to CMIMO should be directed to investigating the optimization aspect of selecting CNs.

We have found a bio-inspired optimization method called queen honey bee migration (QHBM), which has proven to be feasible for WSN routing optimization [5], even, it can be used for maximum power tracking (MPPT) [49]. This method was adopted from the behavior of young queens on honeybee colony who wander to make their own hives. In contrast to the bee colony (BC) or artificial bee colony (ABC) using swarm intelligent, the decision making on QHBM is carried out entirely by the queen. The movement of the queen not only follows the instructions of the scouts but also evaluates environmental factors such as wind. Then, the queen movement is adjusted using a compass [5].

The success of this QHBM motivates us to research CN optimization problems in CMIMO on the IoT system. In CMIMO, the transmitter N_T attempts to send independent data x[k] simultaneously to the receiving nodes. The receives signal at k-th receiver node is given as [7]:

$$\mathbf{y}_k = \mathbf{H}\mathbf{x}_k + \mathbf{n}_k, \quad k = 1, 2, \ldots . K \tag{1}$$

where $\mathbf{H}$ is a square matrix indicating CMIMO communication channel gains, and $\mathbf{n}_k$ is a vector, representing the noise in the channel. Matrix H is given by:

$$\mathbf{H} = \begin{bmatrix} h_{11} & h_{12} & \ldots & h_{1j} \\ h_{21} & h_{22} & \ldots & h_{2j} \\ \vdots & \vdots & \vdots & \vdots \\ h_{i1} & h_{32} & \ldots & h_{ij} \end{bmatrix} \tag{2}$$

where h_{ij} is the CMIMO link between i-th N_T and j-th M_R. The previous works [7] used the largest distance of neighbors as the main parameter to increase the communication quality in CMIMO for the unknown channel state information (CSI). However, this method gives a trade-off in energy costs for data communication. Taking the example for 2 × 2 MIMO transmission, we get:

$$y_1 = h_{11}x_1 + h_{12}x_1 + n_1 \tag{3}$$

$$y_2 = h_{21}x_2 + h_{22}x_2 + n_2 \tag{4}$$

Given the inconclusive reviews of recent research on CN optimization problems in CMIMO on the IoT system, we conclude that:

- CMIMO was developed at WSN [19]–[39], whereas we were more interested in IoT as suggested by [41]–[48].
- Most IoT systems enacted by studies of [41]–[48] did not take into account the role of nodes as actuators, where these nodes requisite to receive commands from the cloud downloaded by sink. Meanwhile, we used IoT where nodes can act as sensors, actuators, or both.
- In a similar idea of research done by [1], [3]–[18], we also used random techniques in the cluster formation phase, but we added the remaining energy constraint to the CH selection.
- Most recent studies did not explain implicitly or explicitly the initial conditions of energy in nodes, whereas we applied the same initial energy to all nodes.
- In response to [6]–[40], we used optimization methods in CN selection, and we also employed QHBM for solving the CN selection problem. Moreover, if compared to the original QHBM [5], the modified QHBM has added the binary testing ability to the queen for Channel State Estimation. Thus, the time slot per iteration of mQHBM is longer than the original QHBM.
- Unlike studies carried out by [27], [28], [30], [32]–[38], in the present study, we introduced a new evaluation function in the CN optimization study, which considers the link quality (q_e) and residual energy (r_e).

Our contributions in this article are outlined in the following points:

- We developed a new hybrid bio-inspired by modified QHBM and adapted the Binary Testing so that the proposed method called modified QHBM (mQHBM) for CMIMO data transmission on IoT system.
- We established a cost function for evaluating candidate CNs based on the weighted RSSI values as the link quality parameter (q_e) and residual energy (r_e), where

the proportion of residual energy influence greater than RSSI. The value of this cost function is evaluated using mQHBM.
- We demonstrated a comparison of the performance of this hybrid method with several additional methods in the introduction section.

Finally, section 2 will briefly describe WSN routing, including CMIMO, as well as bridging adaptations to IoT. Section 3 presents the modelling of the system covering the network, energy, and the proposed methods. The results of testing and performance analysis are described in section 4. Lastly, section 5 summarizes the discussion in this article.

II. SYSTEM MODELLING

A. GENERAL ASSUMPTIONS

At the outside, the number of nodes that have equal initial energy is deployed in L^2 area. A node may serve as sensor, actuator, or both, which are known as the entity in terms of IoT. The majority of energy consumption in a node is data communication, denoted as e_c, where e_c is the total of energy for data transmission (e_{Tx}) and data reception (e_{Rx}). Let d be the distance between two nodes deployed in the field with L^2 area. Suppose that all information about nodes' position and distance receives signal strength indicator (RSSI) and residual energy (r_e) of all nodes, these are reported to the router.

B. THE PROPOSED MODEL

We developed CMIMO, a multi-channel data communication model for an IoT system. The proposed CMIMO model consists of 3 stages, such as cluster formation, coalition, and data communication.

1) CLUSTER FORMATION

In the initial stage, the sink divides the IoT area into a smaller region called clusters where the cluster radius is R_c limited to 0.15L. L is the length of IoT field in meters. For example, L = 100 m, the cluster radius is R_c = 15 m. This consideration was carried out based on RSSI measurements in our previous paper [3], where the effective distance to maintain link quality is around 0.15L in the case of a square field. Sink seems to form a travelling wave, like a splash of water in a pond (see FIGURE 4), while circular waves leave the center and grow bigger ($R_c \lll nR_c$). The dashed-circle in FIGURE 4 is the border for creating clusters. FIGURE 5 shows the clusters formed in each border, so that the distance of the clusters' center could be nR_c, where n = 1, 2, 3, . . . is the perimeter of the n-th wave.

2) COALITION

The second stage is the formation of cooperative nodes. In each cluster, the agent queen (coalition coordinator) will evaluate the surrounding nodes to become cooperative nodes based on the following cost function. FIGURE 6 shows

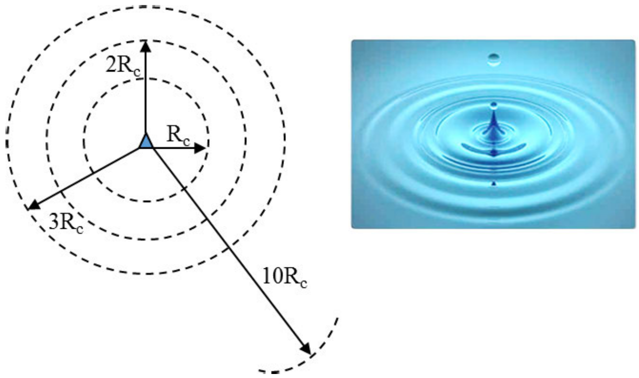

FIGURE 4. Sink reach the nodes like water splash.

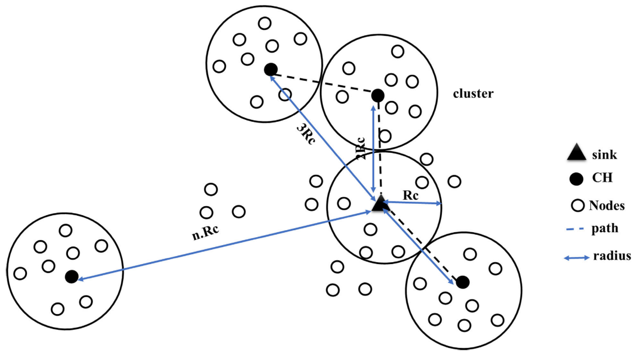

FIGURE 5. QHBM clustering.

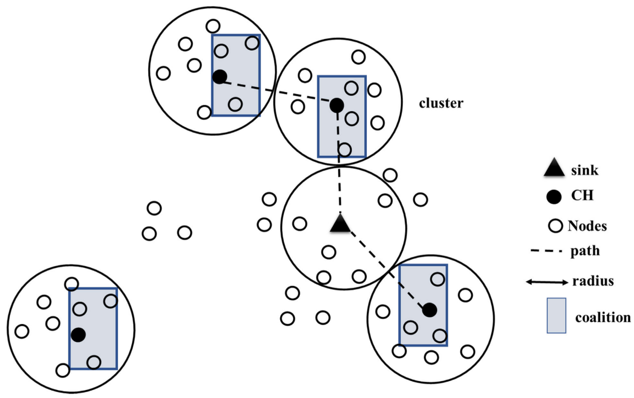

FIGURE 6. CN nodes formation and possible routing.

the coalition process.

$$f_c^{(k)} = \beta.(q_{e_k}) + \gamma.\frac{r_{e_k}}{\sum_{k=1}^{n} r_{e_k}} \tag{5}$$

where $f_c^{(k)}$ is the cost function of k-th node in cluster C, q_{e_k} denote the Receive Signal Strength Indicator in the k-th node, and r_{e_j} is the residual energy in the j-th node, and $\beta + \gamma = 1$.

3) CHANNEL STATE ESTIMATION

The third stage is channel state estimation, wherein this article adopts the binary testing technique to obtain the probability of false alarms. Subsequently, the queen in each cluster will send beacons to the nodes, so they get the state of the empty channel to send or receive data from the cloud. Then, the queen will evaluate in the next iteration; the process is repeated from stage 1 to 10% of the nodes have run out of energy.

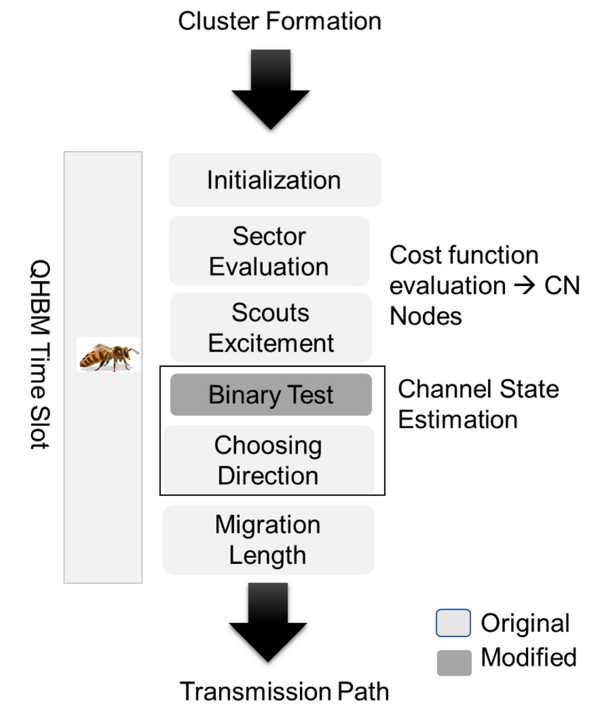

FIGURE 7. **The mQHBM process.**

First, it is the formation of CNs nodes using mQHBM. mQHBM selects nodes by evaluating two parameters for CNs formation, namely RSSI and residual energy (r_e) of candidate CNs. Second, it is channel selection using BT. BT will provide a binary decision for each CNs channel and generate channel state information, i.e., Used or Not Used for every request ($\mathrm{req_i}$) from nodes. Furthermore, the node can use the free channel to send or receive data. The $\mathrm{C_i}$ compress and split those data into k partitions, then broadcast them to i numbers of $\mathrm{CN_i}$. FIGURE 7 shows the mQHBM process.

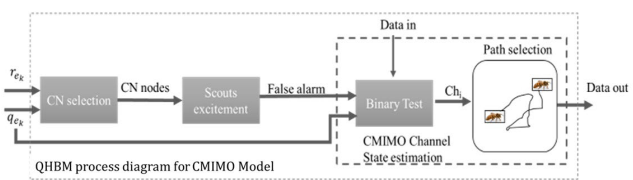

FIGURE 8. **CMIMO model.**

FIGURE 8 depicts the CMIMO model using mQHBM. Channel State Model. Binary testing used to decide either channel j is used or not by evaluating the link credibility of the channel. The CSI is decided locally in corporative receivers by the following binary hypothesis testing adopted from [7]:

$$\mathrm{H_1} : \mathrm{y_k} = h_{\mathrm{ij}}\mathrm{x_k} + \mathrm{n_k} \tag{6}$$

$$\mathrm{H_0} : \mathrm{y_k} = \mathrm{n_k} \tag{7}$$

where $\mathrm{H_0}$ and $\mathrm{H_1}$ represent the hypotheses of available and unavailable channels, respectively, $\mathrm{y_k}$ is the received signal at the $\mathrm{CNg_k}$ as $\mathrm{N_R}$ in cluster $\mathrm{C_j}$ and $\mathrm{a_k}$ is the amplitude of the emitted signal by the transmitter and received at $\mathrm{CNg_k}$ as $\mathrm{N_R}$ in cluster $\mathrm{C_j}$ recalling that (2) it always gives the best link quality among $\mathrm{N_R}$ and $\mathrm{M_R}$ with the highest remaining energy. A given threshold value δ_k used for local decision in $\mathrm{CNg_k}$ is either to accept H1 or reject it [11]:

$$\mathrm{H_i} = \begin{cases} \mathrm{H_1} : & \mathrm{w_k} < \delta_\mathrm{k} \\ \mathrm{H_0} : & \text{otherwise} \end{cases} \tag{8}$$

To reduce the complexity, it is assumed that all corporative nodes ($\mathrm{CN_g}$) use the same threshold value δ_k in making decisions. An optimal decision will be made by the receiving $\mathrm{CNg_{(k)}}$ in neighbours. We denote the binary decision to become 1 is a detection; otherwise, it becomes 0.

The credibility of each CN is evaluated by an mQHBM comprehensive evaluator. This evaluator has two inputs that are the probability of detection and the probability of false alarm. The output of the evaluator, Cre, is the credibility of the cluster that is being evaluated.

The final decision will be made based on the CN decisions and their corresponding weight values. The decision from a cluster with higher credibility gets a greater weight and vice versa. From this aspect, the weight $\mathrm{w_j}$ of the j-th cluster is obtained by normalizing the credibility as follows:

$$\mathrm{w_j} = \frac{\mathrm{Cre_j}}{\max(\mathrm{Cre_j})} \tag{9}$$

where $\mathrm{Cre_j}$ is the credibility of the j-th cluster, $\mathrm{Cre_{max}}$ is the maximum credibility among k CN:

$$\mathrm{Cre_{max}} = \begin{matrix} \max(\mathrm{Cre_j}) \\ \mathrm{j} \in [1, \mathrm{K}] \end{matrix} \tag{10}$$

In conclusion, the final decision is made based on the following simple weighted OR rule:

$$H = \begin{cases} \mathrm{H_1}, & \text{if} \sum_{\mathrm{j}=1}^{\mathrm{K}} \mathrm{w_j D_j} \geq 1 \\ \mathrm{H_0}, & \text{otherwise} \end{cases} \tag{11}$$

where $\mathrm{D_j}$ is the decision of the j-th CN, $1 \leq \mathrm{j} \leq \mathrm{K}$. $\mathrm{D_j}$ becomes 1 if there is detection; otherwise, $\mathrm{D_j}$ becomes 0.

III. SIMULATION SETUP

In this article, n number of static nodes are considered to be located randomly in $\mathrm{L^2}$ square area of interest. A static IoT sink is placed in the right corner of the area. To improve the scalability, feasibility, and effectivity of the proposed method, the number of nodes and the size of the area of interest are varied. In addition, the initial battery energy in all nodes is 1 J. The complete simulation parameters are listed in Table 1.

TABLE 1. Simulation parameters.

Parameters	Values
Number of Nodes	10, 50, 100, 200, 250, and 300
Area of Interest	Square
Sensing area (L × L)	100 m × 100 m, 200 m × 200 m
Sink position (Xs, Ys)	(50, 50), (100,100)
Number of nodes (N)	100
The initial energy of node	1 J
Electronic energy (E_{elec})	50 nJ.bit^{-1}
Energy for data aggregation (E_{DA})	5 nJ.bit^{-1}
ε_{fs}	10 pJ.bit^{-1}.m^{-2}
ε_{mp}	0.0013 pJ.bit^{-1}.m^{-4}
Distance threshold (d_0)	75 m
Packet size (b)	10 kbits

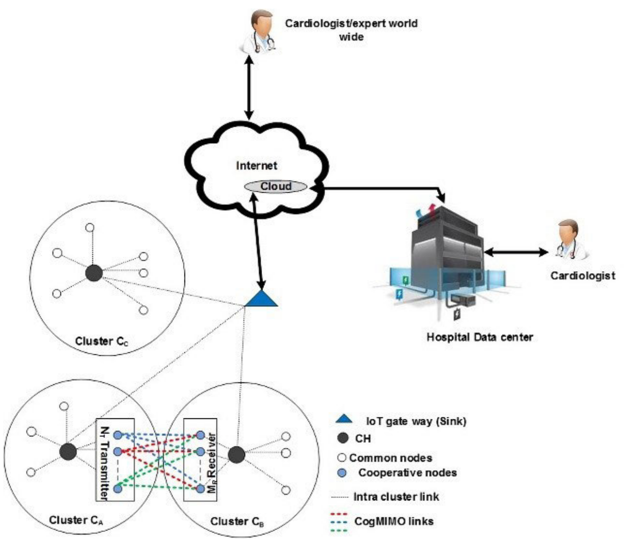

FIGURE 9. Case study: IoT for remote health care.

FIGURE 9 shows a block diagram of the logical view of IoT for remote healthcare, which is used as the case sample. In the bottom layer, we assume that the data are recorded for 5 minutes, repetitively, and some actuator, e.g., automatic door/valve, is well set up. In the middle layer, the high priority packets, such as heart sounds (from 10 kb to 200 kb), relay through the CN and, at the same time, the actuator, i.e., oxygen valve received data through CNs. CNs forward data to the top layer, keep on Cloud Database, and finally, it is used by medical operators, doctors, or cardiologist. The example of the open virtual multi-channel on CMIMO is illustrated by red, blue, and green dashed lines, respectively.

We developed our own functions to create a simulation environment using MATLAB® that suitable for testing and fair comparison with competitor protocols. MATLAB® has features for designing up the IoT prototype that supported prebuilt features and functions IoT protocols such as REST, MQTT, and OPC UA, including models analytic and IoT algorithm [53].

Two simulation scenarios were conducted to test the proposed mQHBM and validate it through a fair comparison with the former algorithms.

- Scenario 1: The number of nodes was 10 nodes located on 100 m × 100 m area of interest. Each node generates data packet per second and data relay by using CMIMO. During the simulation, the packet drop, lifetime, and the number of CN nodes are calculated. Each plot represents 10 simulations times. The same condition is also applied in running CMIMO by Fuzzy Binary Testing (Fuzzy-BT) [7], PSO [17] and Neuro-Fuzzy [48] to guarantee comparative fairness. Then, the simulation repeated for testing the performances of the proposed algorithm in a large number of nodes.
- Scenario 2: The area of interest is enlarged to 200 m × 200 m, and the other steps are the same as the first scenario. The results are also compared with former mention algorithms. As listed in Table 1, the number of nodes changes to 50, 100, 150, and 200 nodes, whereas the size of the region is maintained constant.

IV. RESULTS AND ANALYSIS

A. NETWORK LIFETIME

A lifetime network is used as a metric to measure the network longevity, which defines the time or round when the first node dies in the network during the simulation. FIGURE 10 shows the performance results of the proposed CMIMO and the former algorithms in terms of the lifetime. Based on the analysis, the CMIMO returns the longest lifetime for all given node diversities. The life of nodes can be maintained because of the corporative works between CN nodes to handle the data communication, which distributes the energy consumption to all members of the corporation.

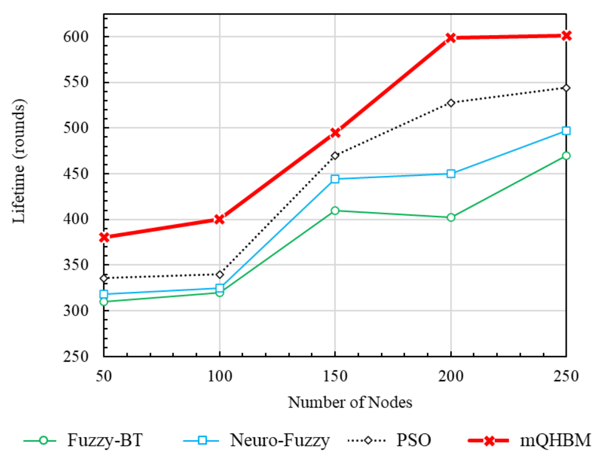

FIGURE 10. Lifetime comparison for fixed network size 100 × 100 m^2.

In FIGURE 10, while the number of nodes are increased to 250 nodes in the same region of interest, the lifetime of Fuzzy-BT is increased to 470 rounds. This means that the first node depleted its energy after 469 rounds. At the same number of nodes in 100 m × 100 m area, the lifetime of Neuro-Fuzzy was 497 rounds. The mQHBM is making the first node extending to 544 rounds. Compared to all previous methods, the mQHBM improved lifetime in the network until 601 rounds. In summary, the trend of lifetime graph in FIGURE 10 is risen as the increment of the number of nodes in the field. As the number of the node is increased, the distance among nodes is shorter, which varies the node density in the field. This condition made the node required a smaller amount of energy for data gathering.

The lifetime extension is a metric that defines the lifetime gap among methods which can be calculated as following [2]:

$$L_{extra} = \frac{L_{CMIMO} - L_x}{L_{CMIMO}} x100\% \qquad (12)$$

where L_{extra}, L_{CMIMO}, and L_x represents the lifetime extension, lifetime given by mQHBM, and lifetime provided by other methods, respectively. Besides, x = 1, 2, 3; where 1 is Fuzzy-BT, 2 is Neuro-Fuzzy, and 3 is PSO.

The mQHBM can extend the lifetime of an IoT network consisting of 50 nodes in 100 × 100 m^2, which used Fuzzy-BT until 18.55%. The lifetime given by mQHBM is 16.31% longer than neuro-Fuzzy for 50 nodes in the same field size. The mQHBM provides 11.81% longer lifetime than PSO. The average lifetime for network size 100 × 100 m^2 is extended by mQHBM from Fuzzy-BT is 22.06%. The extended network lifetime in the same condition given by mQHBM is 17.46% and 10.62% compared to neuro-Fuzzy and PSO.

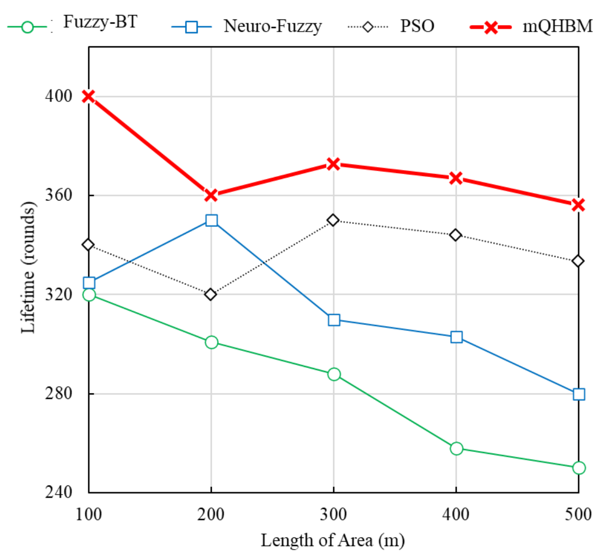

FIGURE 11. Lifetime comparison for different network size (n = 100 nodes).

FIGURE 11 shows the lifetime comparison in the diverse simulation area while the node number is 100, and the network size is varied. The trend of a lifetime is reduced in the larger area because the fixed number of nodes are spared in the larger distance. The mQHBM surpasses the other method in all network sizes. The shortest lifetime is provided by Fuzzy-BT. As the length or area is 500 m, the network lifetime given by Fuzzy-BT is 20% shorter than mQHBM. The Neuro-Fuzzy makes the lifetime 18.75% shorter than mQHBM, whereas the lifetime by using mQHBM is 15% shorter than PSO.

The energy consumed by nodes is the main cause of the energy depletion in the first node. Compare to the Fuzzy-BT transmission, the distance between transmitters is longer than in Neuro-Fuzzy, which relays the data to other clusters. Since the distance is shorter, thus, the energy consumption is reduced. This condition makes the lifetime of IoT in the mQHBM scheme is longer than the other schemes. Besides, the proposed mQHBM effectively chooses the CN node for data gathering. Thus, it can make the lifetime of the IoT network longer.

B. END TO END DELAY

The high priority data requires a certain delay to be received by the sink or IoT hub. This delay depends on the engagement between the transmission and receiver. In the first condition, when the network size maintains the same for all simulation, that is 100 m × 100 m and the number of nodes, it is varied from 50 to 250 nodes. The number of CN nodes, the combination of the transmitter (M), and receiver (N) are varied for demonstrating the results of CMIMO with different modes, such as (1) SISO-like CMIMO where CN = 2, M = N = 1, (2) MISO-like CMIMO where CN = 2, M = N = 1, and CMIMO in are normal mode.

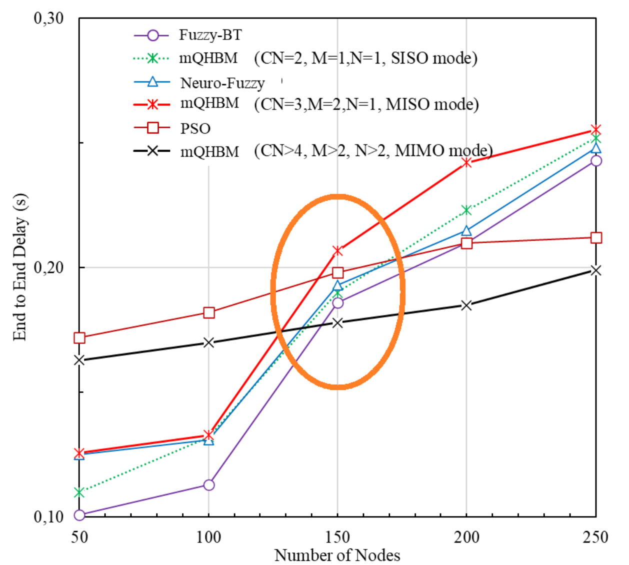

FIGURE 12. Delay comparison in IoT network of 100 × 100 m^2 (n is varied).

FIGURE 12 shows the results of an end to end delay (in seconds) for the aforementioned scenario. For a small number of nodes in the field, i.e., 100 and 150, the Fuzzy-BT, Neuro-Fuzzy, and even the mQHBM in SISO and MISO mode are faster than the Neuro-Fuzzy and PSO. In the low density of nodes in the region of interest, the HS data gathering takes a short time and may skip the routing problem. However, in a dense network, the routing problems exist in the SISO and MISO, and the high traffic causes the packet drop and prolong the end to end delay. When the region of 100 × 100 m^2 is filled by 100 nodes, at the points marked with the dashed-ellipse, the end to end delay of CMIMO is longer than SISO and MISO modes for about 0.024 s and 0.015 s, respectively. CMIMO is superior to Fuzzy-BT for sparse and dense network due to the decision making in the CMIMO is faster than the Fuzzy-BT.

Both SISO and MISO are weak in terms of end to end delay in a dense network due to the high traffic load. In turn, one or two CHs nodes require longer waiting time before sending data to the sink or next CH nodes. Meanwhile, the mQHBM and Fuzzy-BT have CN nodes that cooperate, in turn, it requires short waiting time for data gathering. Thus, mQHBM and Fuzzy-BT are better than SISO and MISO in dense networks in term of an end to end delay. For example, at the points marked by a dashed-circle, the end to end delay of data gathering in a network with PSO is 0.007 s shorter than Fuzzy-BT and Neuro-Fuzzy, 0.002 s shorter than mQHBM.

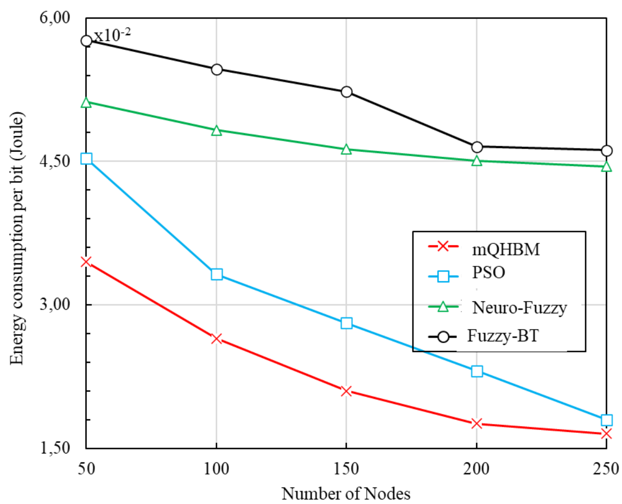

FIGURE 13. Energy consumption in IoT network (n varied).

C. ENERGY CONSUMPTION

The energy usage per bit of several node densities in 100 m × 100 m area is depicted in FIGURE 13. The mQHBM has successfully reduced the energy consumed by nodes. For any number of nodes, the total energy consumption in IoT is decreased significantly by mQHBM. Compared to the former schemes, the proposed CMIMO using mQHBM makes the nodes consuming a lower portion of energy. The main reason is that the average distance of data communication in mQHBM is shortened. In specific, the Fuzzy-BT and Neuro-Fuzzy performed higher energy consumption due to the distance among the CH to sink, including the intra-cluster communication among CN and CH nodes that requires more energy above 4.5 × 10^{-5} Joule/bit for any case of node' densities.

To test the scalability of the proposed CMIMO using mQHBM, the network size is varied from 100 × 100 m^2 to 300 × 300 m^2 and 100 nodes deployed in that area. The energy consumption increases as the area of interest are enlarged. This is evidenced by FIGURE 14, which shows the comparative results of energy consumption performances of mQHBM and its rivals. Again, the energy consumption of mQHBM is the lowest in the graph. The highest energy consumption is performed by Fuzzy-BT. The gap between them is about 46.21% on average. In the largest deployment area, the mQHBM is about 2.81% higher than PSO, whereas, in the smallest area, the gap between them is about 20.18%. In conclusion, the energy consumption for data gathering in IoT is decreased significantly by CMIMO, which is 46% more efficient than Neuro-Fuzzy.

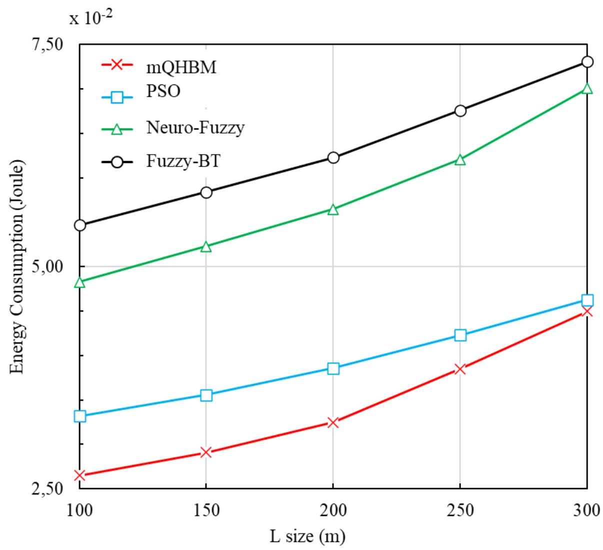

FIGURE 14. Energy consumption in IoT network (n = 100 nodes, L varied).

D. OPEN CHALLANGES

A fair comparison between mQHBM and other hybrid methods have been discussed both in terms of lifetime, energy consumption, and throughput. Although mQHBM is superior to previous works in all three aspects, mQHBM also has a drawback. The selection of cooperative nodes with the mQHBM execution period is longer than the conventional methods because algorithms are more complex. The mQHBM has drifted for 0.02 s from PSO and around 0.01 s from hybrid Fuzzy, wherein this case, we employed Neuro-Fuzzy [17] and Fuzzy-BT [48].

In general, it can be concluded that mQHBM is a little slower than PSO and Fuzzy, and conventional routing of existing hierarchical topology. But, the difference is not very significant when compared with other computing on a computer processor and adequate memory. Thus, mQHBM can be aligned with other methods that have already received recognition [1], [17], [48], which makes us optimistic that mQHBM has good prospects for future applications. The mQHBM may be combined with Fuzzy [51], sleep-wake up [52], or other LEACH extension for performing more precise distance calculation, energy used reduction, and lifetime extension in the future. On the other hand, the original QHBM could be well-performing for IoT or WSN with mobile nodes [5], but the mQHBM is not suggested for the same results, so this could be an open issue for future research.

V. CONCLUSION

Our study concluded that the new mQHBM has been successfully developed, and its performance was excellent. In terms of lifetime, the mQHBM-CMIMO can extend the IoT network lifetime longer than mQHBM-SISO, mQHBM-MISO, and previous CMIMO(s). For example, in $100 \times 100\ m^2$ networks with the varying number of nodes, mQHBM is proven to be able to extend network lifetime for about 1.22 and 1.17 times compared to Fuzzy-BT and current PSO, respectively.

The mQHBM-CMIMO is better than other competitors for any kind of network since mQHBM selects the optimal link. The appropriate link was selected by mQHBM and could optimize the energy saving because the cost function considered the portion of residual energy on the selection process. Compared to any PSO, both Fuzzy-BT and Neuro-Fuzzy have a longer delay in networks with heavy traffic, so both require long waiting times. Meanwhile, mQHBM algorithms can save more energy than Fuzzy-BT and Neuro-Fuzzy do, except in the wider area PSO, which is slightly superior to mQHBM. Interestingly, on other network variations, overall, mQHBM can save energy for data collection in IoT, up to 1.46 times better than Fuzzy-BT.

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