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ABC-BASED ROUTING AND DATA AGGREGATION IN WIRELESS SENSOR NETWORK USING HFQKLMS

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Abstract: Wireless Sensor Network (WSN) is comprised with substantial quantity of sensor nodes to monitor various environmental conditions and collectively send their data packets to the sink node by means of network. Wireless nodes possess limited amount of energy because of the presence of multiple sensor nodes. To save energy in network, it is necessary to introduce data aggregation. Moreover, conventional routing protocols are prone to various malicious attacks that considerably affect the data security. Hence, the research proposes an efficient strategy for routing protocol and data aggregation mechanism to elevate network efficiency. Besides, it mitigates energy consumption and elongates the lifespan of whole network. Here, the routing mechanism is performed using Fractional Artificial Bee Colony (FABC), which is derived by incorporating idea of Fractional Calculus (FC) with Artificial Bee Colony (ABC) algorithm. Furthermore, the compilation of data is achieved through the utilization of the Hierarchical Fractional Quantized Kernel Least Mean Square Filter (HFQKLMS). The proposed FABC + HFQKLMS achieves a maximum energy of 0.258J, low prediction error of 7.152Kbps, and maximum throughput of 69640.

Keywords: ***Wireless Sensor Network (WSN), Data aggregation, Artificial Bee Colony (ABC) algorithm, Fractional Calcuus (FC).***

1. Introduction

WSN is mainly comprised with huge number of less expensive nodes and numerous of resource constrained nodes that are essential for observing the deployment area, linked with adjacent nodes and transmit the data packets to the destination node through broadcasting. WSNs act a huge role in many applications, such as health care, border surveillance, and smart cities. WSN nodes are named for its essential characteristics, like consumption of minimum energy by the nodes. Moreover, they have the potential to recharge all of its interior units because of the small size battery, low processing time, and small power interaction unit. The constraints in the WSN nodes motivate the researchers to invent new strategy for energy conservation technique due to its high demand among the technologies [1]. Sensor nodes are highly desirable because of its low cost devices and they are comprised with large number of hardware components and self-operating batteries [1]. Sensor nodes collect the information packets from the node known as Base station (BS) or destination node. The BS exists either in multi-hop or in one-hop. Sensor nodes basically suffer from various challenges, like post deployment [6]. The major challenges arise due to the lack of finite energy and absence of availability of safe neighbor. The power source impelled within the sensor nodes are not necessarily to recharge and they lose the recharging capacity based on the deployment environment. Moreover, resource constraints have serious impact on the system network that degrades the performance of energy dissipation, network lifetime, and relaying [2]. Because of the availability of self-resource constraints, the sensor nodes cannot provide direct transmission to BS, which is a promising solution for data aggregation. This saves the energy drain of the node [20] [2].The major limitation exists in WSNs routing algorithms is low assurance level for the delivery of sensed data packets due to the existence of nodes failure and presence of interruptions between the communications. However, data packets consist of group of data information from various sensor nodes. In fact, the failure of node may cause serious impact on the performance of data aggregation in the routing paths. Data aggregation has been considered as a main component of the sensor system in research areas. It is termed as mechanism of grouping data from various sensors in order to avoid the unnecessary transmission and offer fused data to BS [25] [3]. One of the data aggregation techniques is Tree on Dag (ToD), a semi structured technique, which utilizes dynamic forwarding and is mainly comprised with various brief path trees to assist the scalability of network. In [21], approach of two-tier weighted periodic data grouping is utilized to determine and minimize the fake sensor measurements. However, automatic data aggregation in WSN, where every node is comprised with a knowledge automation that knows the knowledge about routing path and the ratio of data aggregation in order to reduce the amount of packets broadcasted throughout system [26] [21]. In addition, sensor nodes possess low computation power, low battery and very small storage capacity. In order to resolve such issues, there is a necessity for preserving such resources by minimizing the data transmission. This can be accomplished using an efficient mechanism known as data aggregation [9].

In fact, very large number of sensors are aggregated in one node is termed as aggregator and thus, interacts the aggregated information with BS [9]. In general, data aggregation mechanisms can be broadly classified into two types: structure-based schemes and structure-free schemes. Within the structure-based scheme, Typically, data aggregation mechanisms are widely categorized into two kinds, namely structure-based scheme, and structure free scheme. In Structure-based scheme, the network area is divided into various regions called clusters or zones. On the other hand, in structure free scheme, the sensor node gathers the sensor data without default structure and follows the data aggregation scheme depending on partial data. Within each area, there consists of local data aggregator node that gathers the information from all of its corresponding members [12] [3]. Iterative Filtering (IF) algorithms are an eminent and promising solution for WSNs, since they resolve the limitations, like data trustworthiness, and data aggregation [24] [11]. Such data trustworthiness determines each sensor depending on distance and readings that obtains in the earlier course of iteration by various means of aggregation. Such type of aggregation is commonly a weighted average, in which the readings are highly varied from such estimations [23]. However, frequency filtering techniques that utilizes the range of measurements based on its frequencies. A frequency is termed as the occurrence of measure in a predefined group at an initial phase of aggregation [22] [7].

Proposed FABC + HFQKLMS:

An effective strategy for efficient routing protocol and data aggregation mechanism is designed and developed using newly developed FABC algorithm and HFQKLMS. However, FABC is modified using Fractional Calculus Concept with Artificial Bee Colony algorithm. Moreover, the developed data aggregation mechanism using HFQKLMS provides better effectiveness of the network as well as enhances the lifespan of network.The remaining section of article is structured as follows: Section 2 elabotaes the literature review of conventional techniques employed for effective routing and data aggregation along with their benefits and limitations that motivate the researchers to develop an efficient strategy. Section 3 deliberates the system model of WSN and developed FABC and HFQKLMS is deliberated in section 4. Section 5 explains the results and discussion of developed system. Finally, section 6 concludes the paper.

2. Motivation

This section deliberates the literature survey of different conventional approaches utilized for routing and data aggregation methods along with their merits and disadvantages, which motivates the researchers to develop an effective approach.

2.1 Literature Survey

Various techniques employed for routing and data aggregation are deliberated as follows: Nihar Ranjan Roy, and Pravin Chandra, [1] developed an effective data aggregation scheme for clustered WSN named EEDAC-WSN. This developed approach effectively reduced the intra-cluster interactions by granting permission to cluster nodes to transfer tiny sized control frames. This method considerably saved the energy and maintained the stability of the network due to less transmission of bits while intra-cluster communications. However, it was not suitable for real time applications. A. Latha, *et al.* [2] designed a Trust Assisted- Energy Efficient Aggregation (TA-EEA) approach, which enhances the entire aggregation process. The developed approach was completely free from resource constraints. The developed method provided high efficiency but, it failed to support for large scale WSNs. Khalid Haseeb, *et al.* [3] introduced light-weight structure depending on Data Aggregation Routing (LSDAR) for enhancement of performance in energy routing process and to provide effective data protection against various attacks. The designed scheme divided the nodes into tiny size clusters depending on distance from sink node and considerably discarded energy hole problem. Moreover, the developed approach increased the network performance. Chetan N. Aher, [4] developed an efficient trust calculation mechanism for solving the issue of energy conservation problem. This method increased the reliability of routing and data aggregation by exploiting a trust value. The trust system worked on the concept of majority of nodes. However, aggregation was performed utilizing tree structure.

2.2 Major Challenges

The limitations confronted by some of the traditional works related to routing and data aggregation are deliberated as follows:

- The frequency filtering approach developed in [7], reduced the unnecessary sensor measures but, it failed to consider reactive periodic sensor networks as it saves more energy.
- In [8], the k-means algorithm was applied on the whole data sets to reduce data latency. By applying the k-means algorithm on prefixes can accelerate the data aggregation phase even better.
- The major limitation in [10], was failure of link transmission and packet loss that deteriorates the performance of data aggregating and still it remains as a challenging issue.

3. System model of WSN

WSN is comprised with numerous of sensor nodes and Base station (BS). Some essential characteristics of sensor networks are explained as follows: All the nodes in WSN are heterogeneous in nature. However, the nodes in WSN are randomly scattered over the sensor network. The BS is situated outside of the sensor network and it consists of a invariant power supply with absence of energy constraints. The communicated placed between the sensor nodes is multi-hop symmetric communication. The WSN consists of one BS, which is denoted as B_s, Cluster head C_h and also n number of nodes. The system model of WSN is represented in Figure 1. The direct communication inside the radio limit is represented using the wireless links. Each node possesses its high communication range that is evenly spread over the network with a dimension of M_t and N_t meters. Every node owns a specific Identity number and such groups are gathered to create clusters. The best location of sink node in system model is specified as $\{0.5\,M_t\,,\,0.5\,N_t\}$. The BS is responsible for receiving the data packets transmitted from all the nodes. Hence, the nodes broadcast the data packets to BS by exploiting the cluster head technique. The cluster head C_h aggregates all data packets from all the nodes in the network and transmits to BS B_s

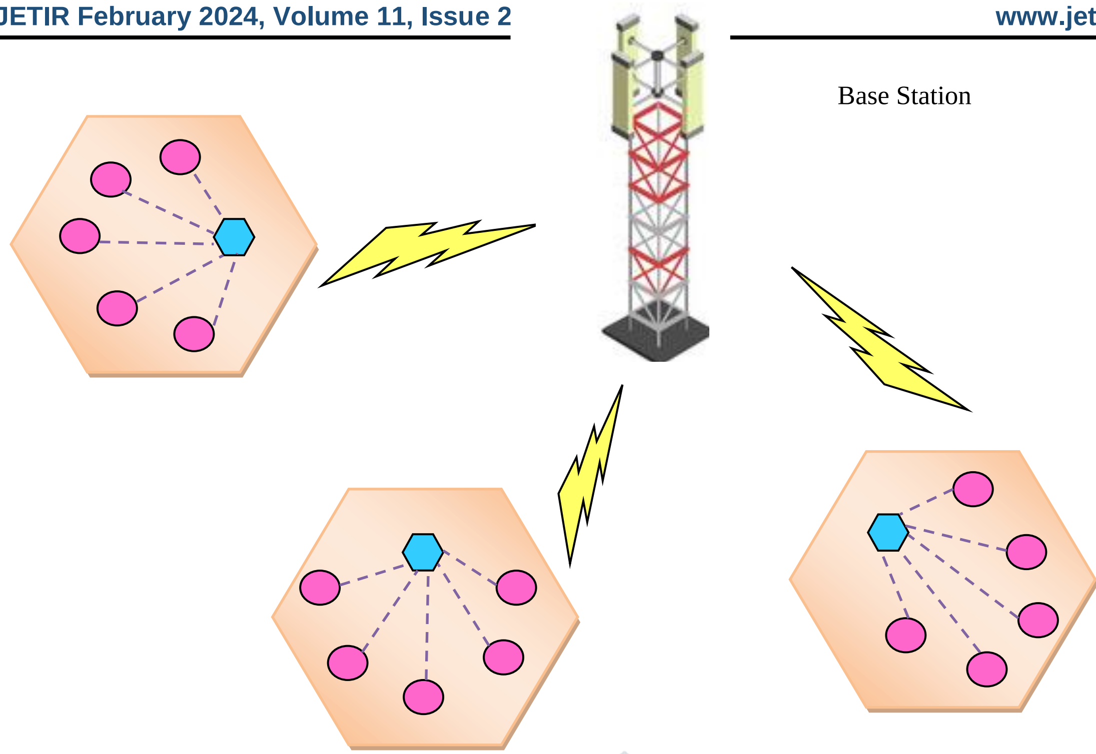


Figure 1. System model of WSN

3.1 Energy model

Each and every nodes consist of initial energy E_0 and the energy in the sensor node cannot be recharged. Typically, the data transfer process is accomplished using Time Division Multiple Access (TDMA) scheme and also each node possesses both receiver and transmitter component. In order to distribute the energy, the transmitter used a power amplifier and radio electronics. Similarly, the receiver also utilized radio signals to disperse energy. Furthermore, energy dissipation for every packet with a dimension P_0 utilizes two types of energy dissipation mechanisms that are solely dependent on the distance of node. However, the dissipation of energy is given as,

$$D_u(H^o) = D_v * P_0 + D_w * P_0 * \left\| J^o - K_g^o \right\|^4, \quad if \ \left\| J^o - K_g^o \right\| \geq A_0 \tag{1}$$

$$D_u(H^o) = D_v * P_0 + D_{gh} * P_0 * \left\| J^o - K^o{}_g \right\|^2, \ if \ \left\| J^o - K_g^o \right\| < A_0 \tag{2}$$

4. Proposed FABC and HFQKLMS

The ultimate intention of this research is to provide an effective strategy for better routing and data aggregation mechanism to the WSN network in order to eliminate the high power consumption and to prolong the lifespan of network. Initially, nodes are simulated in the WSN network. After that, the routing process is carried out using FABC algorithm [5], which is modified using the concept of Fractional Calculus (FC) [13] with Artificial Bee Colony (ABC) [14] to provide efficient routing in WSN that considerably reduces the intra cluster distances among the cluster nodes. Once the routing is successfully completed, data aggregation is performed using Hierarchical Fractional quantized kernel least mean square filter (HFQKLMS) in order to enhance the effectiveness of network. Figure 2 illustrates schematic view of developed FABC-based routing and HFQKLMS-based data aggregation.

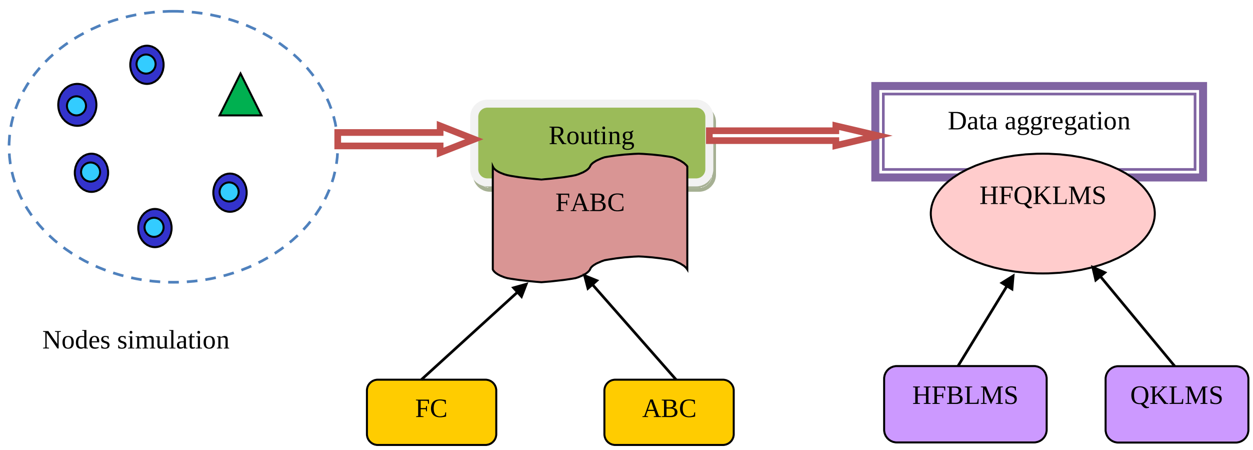


Figure 2. Schematic view of proposed FABC + HFQKLMS

4.1 Nodes simulation

WSN is generally comprised with number of sensor nodes and nodes are initially simulated within network. The cluster heads are determined to aggregate sensor nodes.

4.2 FABC based routing

The main intention for utilizing the FABC algorithm is that it prolongs the lifespan by assigning suitable information packets to a best routing path. FABC algorithm is derived by the integration of FC with ABC algorithm. By employing this FABC algorithm, the intra cluster distances among members of clusters are minimized thereby optimizing the energy distribution.

4.2.1 Algorithmic procedure of FABC algorithm

Fractional Calculus (FC) [13] is called as a normal expansion of traditional calculation. The essential characteristics of FC exploit the property of irreversibility and inherent memory that leads to an evolutionary mechanism. On the other side, ABC algorithm [14] is nature inspired meta-heuristic algorithm that mimics the foraging characteristics of honey bees. In this research, FC is incorporated with ABC to provide an efficient searching solution particularly in a predefined search space. However, in FABC algorithm, the optimal solution is represented using the food ways that are updated in each iteration. The major benefit of FABC is better utilization of global data.

Step 1: Initialization

Let us initialize the food source as F_s that are initialized in a search space. The dimension of the food source is represented as $F_s \times C_h$ and integer values are arranged in the matrices varying from 1 to k.

Step 2: Generation of food source by a bee employee

The employed bee step updates the food sources presented in the partial area of colony. The equation for creating the new food source is expressed as,

$$G_{l,m}^{r+1} = G_{l,m}^{r} + L_{l,m}(G_{l,m}^{r} - G_{j,m}) \tag{3}$$

After applying the differential derivative, the Eq. (3) can be rewritten as,

$$G_{l,m}^{r+1} = \left[\beta G_{l,m}^{r} + \frac{1}{2} \beta G_{l,m}^{r-1} + L_{l,m} (G_{l,m}^{r} - G_{j,m}) \right] \tag{4}$$

where, $G_{l,m}^{r}$ is l^{th} food source of m^{th} value in r^{th} iteration and the random value created between $[-1,1]$ is denoted as $L_{l,m}$ and j represents the index of neighbor solution, $j \in \{1,2,\ldots,F_s\}$

Step 3: Evaluate fitness function

The fitness function is mainly utilized to generate newly created food sources. If the newly generated food source $G_{l,m}^{r+1}$ is low in comparison with the previous food source $G_{l,m}^{r}$. Thus, the solution is updated with new one.

$$fitness_l = \eta * f_l^{loc} + \alpha * f_l^{energy} + \gamma * f_l^{delay} \tag{5}$$

Step 4: Onlooker bee phase

The onlooker bee step updates the food sources in the next half in bee colony and equation of the onlooker bee phase is represented by,

$$b_l = \omega_1 + \frac{fitness_l}{\underset{l=1}{\overset{F_s}{Max}}\ fitness_l} + \omega_2 \tag{6}$$

Step 5: Scout bee

This step is implemented if there is no food origin is varied for last iterations. In this circumstance, the chosen food origin is rejected and then updated using irregularly created latest food source.

Step 6: Termination

The process is repeated until r satisfies the maximum criteria and till the necessary need is satisfied.

4.3 HFQKLMS-based Data aggregation

Once the routing is accomplished successfully, the data aggregation mechanism is performed using HFQKLMS filter. Data aggregation process is recognized as a significant component in improving the efficiency of network. Moreover, it stores packets to mitigate the energy consumption of network and prolongs whole lifespan of network.

4.3.1 Quantized Kernel Least Mean Square (QKLMS)

The QKLMS method is obtained by means of quantizing feature vector. The main principle behind the approach is quantizing, thereby compressing the input space. Typically, this mechanism is designed according to the online vector quantization technique. The QKLMS scheme is computed as below,

$$\begin{cases} q_0 = 0 \\ p(e) = z(e) - q_{e-1}[V(e)] \\ q_e = q_{e-1} + \phi\, p(e) S_k (I[V(e)]) \end{cases} \tag{7}$$

where, $V(e)$ illustrates the input vector, $I(\cdot)$ represents the quantization operation and q is a mapping done between input and output. However, size of step is signified as ϕ, $p(e)$ shows the prediction error, S_k represents the kernel size of the signal and the desired signal is denoted as $z(e)$.

According to the vector quantization, the output $O(e)$ is expressed as,

$$O(e)=\sum_{i=1}^{a} Q_i(e-1)\,S_k\left[Y_i(e-1),V(e)\right]=Q(e-1)\,S_k^{aa}(e) \tag{8}$$

where, $Q(e-1)=\left[Q_1(e-1),Q_2(e-1),...,Q_a(e-1)\right]$ signifies the coefficient vector.

4.3.2 Algorithmic procedure of Hierarchical Fractional Quantized Kernel Least Mean Square Filter (HFQKLMS)

This chapter describes about process of data aggregation using HFQKLMS. However, the HFQKLMS approach is obtained by the integration of Hierarchical Fractional Bidirectional Least-Mean-Square (HFBLMS) [15], and QKLMS [16]. Furthermore, the HFBLMS scheme is established by merging Hierarchical Least Mean Square (HLMS) [19] with concept of FC [13]. The significance of selecting the HLMS scheme is that it provides better convergence solution due to the minimum size of filters and minimized correlation matrix of Eigen values. Hence, HLMS scheme is designed by stacking the different levels of LMS filters. The implementation process of two-level HLMS scheme is explained as follows:

Step 1: Initialize the input and weight at level-1

Let us consider the input at level-1 is computed as,

$$X^1(d)=\left[G_g(d-1),G_g(d-2),....,G_g(d-x)\right] \tag{9}$$

where, $x=4$ denotes the filter length and d signifies the time and coefficient matrix at level-1 is given by,

$$Pc^1(d)=\begin{bmatrix} R_{1,1}^1 & R_{1,2}^1 \ldots\ldots R_{1,x_1}^1 \\ R_{2,1}^1 & R_{2,2}^1 \ldots\ldots R_{2,x_1}^1 \\ \vdots & \\ R_{x_2,1}^1 & R_{x_2,2}^1 \ldots\ldots R_{x_2,x_1}^1 \end{bmatrix} \tag{10}$$

where, $R_{y,c}^1$ indicates the c^{th} weight of th sub filter at level-1.

Step 2: Determination of output and error at level-1

The incorporation of BLMs is a traditional LMS and evaluation is carried out in both forward and backward direction. Hence, accuracy of data prediction is highly increased.

The backward direction error is determined using following equation,

$$B_b W_y^1(d)=\sigma(d)-B_b Z_y^1(d) \tag{11}$$

where, $B_b Z_y^1(d)$ specifies result of y^{th} sub-filter in backward movement.

Hence, the resultant output at level-1 is calculated as,

$$Z_y^1(d)=\sum_{c=1}^{x_1} R_{y,c}^1(d)\,G_g(d-(y-1)x_1-c) \tag{12}$$

Here, $R_{y,c}^1(d)$ denotes the final weight coefficient.

Step 3: Initialize the input and weight at level-2

The weight coefficient matrix of sub-filter at grade-2 is computed as,

$$Pc^2(d) = [R_1^2(d), R_2^2(d), \ldots\ldots, R_{x_2}^2(d)] \tag{13}$$

The input specification of sub filter at level-2 is illustrated as,

$$X^2(d) = [Z_1^2(d), Z_2^2(d), \ldots Z_{x_2}^2(d)] \tag{14}$$

Step 4: Determination of output and error at level-2

The result and error of y^{th} sub filter in forward movement at level-2 is estimated as,

$$F_f\, Z(d) = \sum_{y=1}^{x_2} F_f\, R_y^2(d)\, Z_y^1(d) \tag{15}$$

$$F_f\, W(d) = \sigma(d) - F_f\, Z(d) \tag{16}$$

Therefore, the final result of sub filter at level-2 is given by,

$$Z(d) = \sum_{y=1}^{x_2} R_y^2(d)\, Z_y^1(d) \tag{17}$$

Step 5: Update of weight

The weight update in HFBLMS at level-1 in forward and backward direction at interval $d+1$ is represented by employing step size and it is illustrated as,

$$\begin{aligned} F_f\, R_{y,c}^1(d+1) = \rho_{F_f}\, R_{y,c}^1(d) + \frac{1}{2}\rho_{F_f}\, R_{y,c}^1(d-1) + \frac{1}{6}(1-\rho)_{F_f}\, R_{y,c}^1(d-2) + \\ \frac{1}{24}\rho(1-\rho)(2-\rho)_{F_f}\, R_{y,c}^1(d-3) + \delta_{1,F_f}\, W_y^1(d)\, G_g\,(d-(y-1)x_1-c) \end{aligned} \tag{18}$$

Moreover, the updated weight Eq. in backward direction and it is calculated as,

$$\begin{aligned} B_b\, R_{y,c}^1(d+1) = \rho_{B_b}\, R_{y,c}^1(d) + \frac{1}{2}\rho_{B_b}\, R_{y,c}^1(d-1) + \frac{1}{6}(1-\rho)B_b\, R_{y,c}^1(d-2) + \\ \frac{1}{24}\rho(1-\rho)(2-\rho)_{B_b}\, R_{y,c}^1(d-3) + \delta_{1,B_b}\, W_y^1(d)\, G_g\,(d-(y-1)x_1-c) \end{aligned} \tag{19}$$

Likewise, the updated weight at level-2 in HFBLMS for forward movement at time $d+1$ is formulated as,

$$\begin{aligned} F_f\, R_{y,c}^2(d+1) = \rho_{F_f}\, R_{y,c}^2(d) + \frac{1}{2}\rho_{F_f}\, R_{y,c}^2(d-1) + \frac{1}{6}(1-\rho)_{F_f}\, R_{y,c}^2(d-2) + \\ \frac{1}{24}\rho(1-\rho)(2-\rho)_{F_f}\, R_{y,c}^2(d-3) + \delta_{2,F_f}\, W_y^2(d)\, G_g\,(d-(y-1)x_1-c) \end{aligned} \tag{20}$$

The updated weight Eq. in backward direction is represented as,

$$\begin{aligned} B_b\, R_{y,c}^2(d+1) = \rho_{B_b}\, R_{y,c}^2(d) + \frac{1}{2}\rho_{B_b}\, R_{y,c}^2(d-1) + \frac{1}{6}(1-\rho)B_b\, R_{y,c}^2(d-2) + \\ \frac{1}{24}\rho(1-\rho)(2-\rho)_{B_b}\, R_{y,c}^2(d-3) + \delta_{2,B_b}\, W_y^2(d)\, G_g\,(d-(y-1)x_1-c) \end{aligned} \tag{21}$$

By incorporating the update weight Eq. in QKLMS approach. After that, the updated weight Eq. of HFQKLMS at level-1 in forward movement is formulated as,

$$B_b\, R^1_{y,c}(d) = B_b\, R^1_{y,c}(d-1) + \rho_{1,B_b} W^1_y(d)\, S_k\,(I\,[G_g\,(d-(y-1)x_1-1)]) \tag{22}$$

Substituting Eq. (22) in Eq. (18),

$$\begin{aligned} F_f\, R^1_{y,c}(d+1) = {} & \frac{3}{2}\rho_{F_f}\; R^1_{y,c}(d-1) + \delta_{1,F_f}\; W^1_y(d)[\beta\, S_k\,(I\,[G_g\,(d-(y-1)x_1-c)] + \frac{1}{6}(1-\beta)\;{}_{F_f} R^1_{y,c}(d-2) + \\ & \frac{1}{24}\rho(1-\rho)(2-\rho)_{F_f}\; R^1_{y,c}(d-3) \end{aligned} \tag{23}$$

5. Results and discussion

This part explains result and discussion of developed FABC + HFQKLMS with respect to the evaluation metrics.

5.1 Experimental setup

The implementation of developed FABC + HFQKLMS is experimented in MATLAB tool with 8 GB RAM and Intel core-i3 processor.

5.2 Dataset description

The dataset utilized in this proposed scheme is Air quality database and localization database.

(i) Air quality dataset: Air quality dataset [18] is implemented based on the result created according to the chemical multi-sensor situated in Italy. Here, replies are gathered utilizing an analyzer at regular duration from March 2004 to February 2005.

(ii) Localization dataset: Localization dataset [17] consists of five different people responses preserved on implementing different performances. In order to record data, ankle left, ankle right and belt, and four tags or sensors are utilized. This dataset consists of 8 attributes and 164860 instances.

5.3 Performance metrics

The performance of designed FABC + HFQKLMS approach is analyzed with respect to evaluation metrics, like energy, throughput, and prediction error.

(i) Energy: Energy is a measure employed for evaluating the quantity of energy used while implementation process.

(ii) Throughput: Throughput is a measure of total quantity of data packets transmitted in a certain interval of time.

(iii) Prediction error: Prediction error is defined as the occurrence of breakdown of estimated event and it is computed as follows,

$$\chi = P_v - M_v \tag{24}$$

where, P_v denotes the predicted value and the measured value is signified as M_v.

5.4 Comparative techniques

The performance of developed FABC + HFQKLMS is evaluated with conventional techniques, like Routing + HLMS, Routing [19] + HFBLMS [15], and Routing + M-QKLMS [16].

5.5 Comparative analysis

This section elaborates the comparative analysis of FABC + HFQKLMS using Air quality dataset and Localization dataset.

(i) Analysis using Air quality dataset

Figure 3 represents the analysis of developed FABC + HFQKLMS using Air quality dataset. Figure 3a) illustrates the comparative analysis of developed FABC + HFQKLMS with respect to energy by varying rounds. If number of rounds is 500, energy attained by proposed FABC + HFQKLMS is 0.254J, whereas the existing methods attained the energy of 0.1460J for routing + HLMS, 0.0562J for routing + HFBLMS, and routing + M-QKLMS is 0.1137J.

The analysis of proposed FABC + HFQKLMS with respect to the prediction error by changing the step size is portrayed in figure 3b). If the step size=0.2, the prediction error obtained by the conventional approaches, like routing + HLMS is 9.668, routing + HFBLMS is 9.071, and routing + M-QKLMS is 10.498, whereas the proposed scheme achieved the prediction error of 8.003. By varying the step size to 0.4, proposed FABC + HFQKLMS achieved the prediction error, and traditional methods, such as routing + HLMS, routing + HFBLMS, and routing + M-QKLMS are 8.070, 10.003, 9.082, and 10.448, respectively.

Figure 3c) illustrates the analysis of proposed FABC + HFQKLMS with respect to throughput. At round=500, the throughput attained by the proposed approach is 33472Kbps. However, the existing techniques, such as routing + HLMS, routing +HFBLMS, and routing + M-QKLMS achieved the throughput of 40423Kbps, 43924Kbps, and 35029Kbps, respectively.

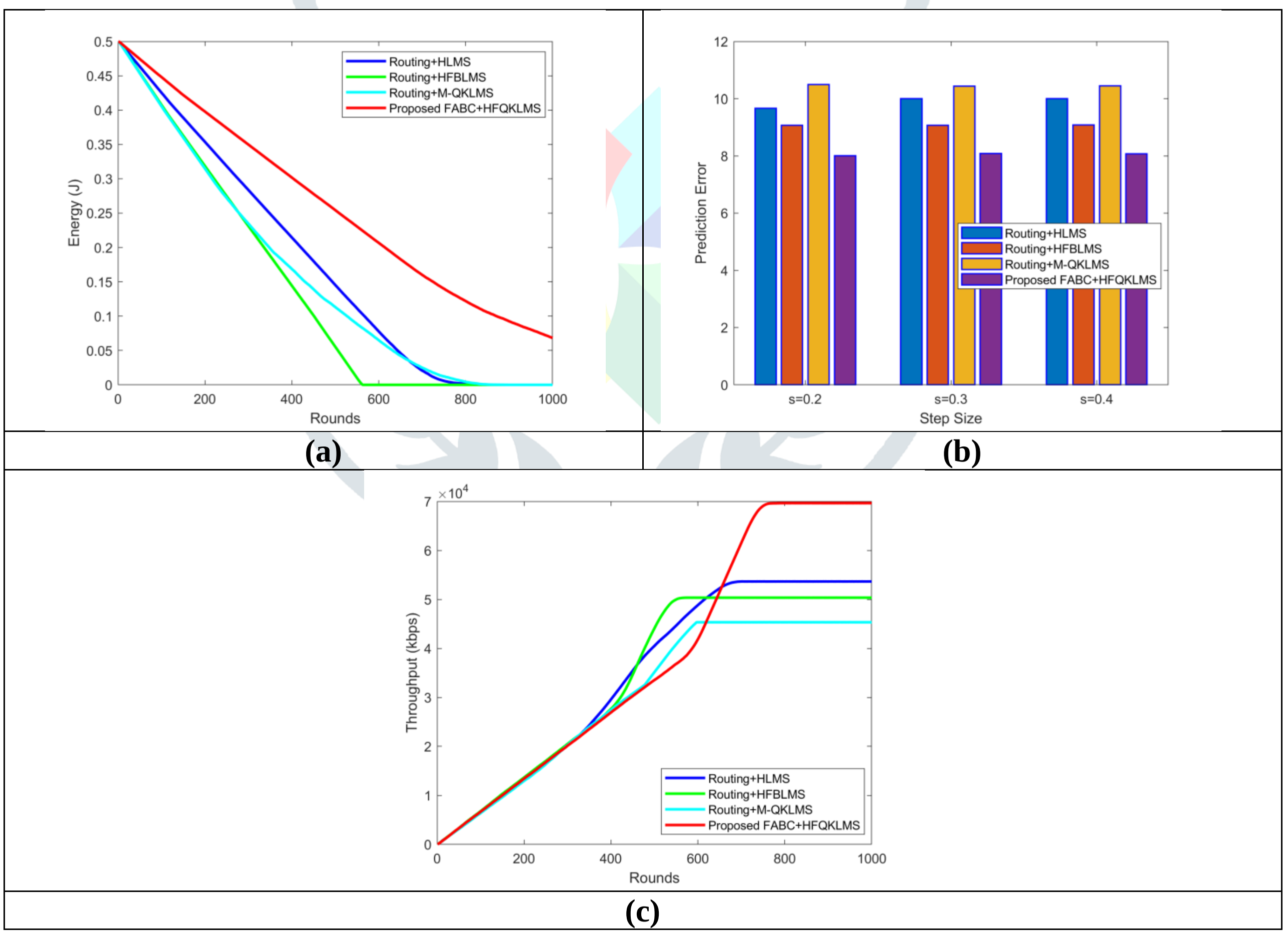


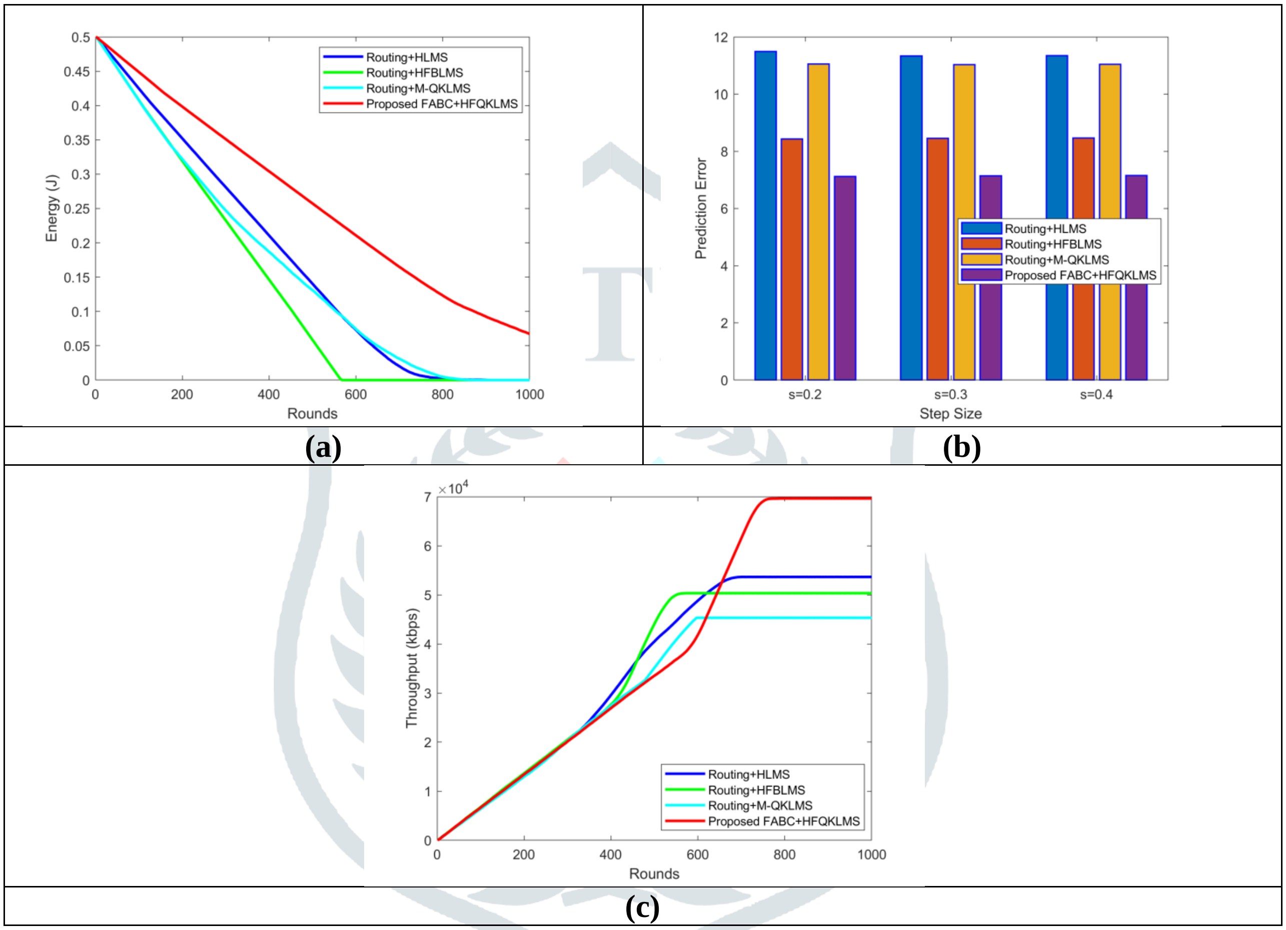
Figure 3. Analysis using Air quality dataset a) Energy b) Prediction error c) Throughput

(ii) Analysis using Localization database

Figure 4 portrays the analysis of proposed FABC + HFQKLMS in terms of performance metrics. Figure 4a) illustrates analysis of proposed scheme with respect to energy. The energy achieved by the proposed FABC + HFQKLMS at round=500 is 0.258J. However, the existing schemes attained the energy for routing + HLMS is 0.141J, for routing + HFBLMS is 0.059J, and routing + M-QKLMS is 0.131J.

The analysis of proposed FABC + HFQKLMS with respect to prediction error is signified in figure 4b). If the step size is 0.4, the existing methods obtained the prediction error for routing + HLMS is 11.348, routing + HFBLMS is 8.467, and routing + routing + M-QKLMS is 11.040.

Figure 4c) portrays the analysis of proposed scheme with respect to throughput. When the round is at 1000, the proposed FABC + HFQKLMS attained the throughput of 69640Kbps, whereas the conventional techniques achieved the throughput of 53650Kbps, 50339Kbps, and 45326Kbps for routing + HLMS, routing + HFBLMS, and routing + M-QKLMS, respectively.



(a) (b)

(c)

Figure 4. Analysis based on Localization dataset a) Energy b) Prediction error c) Throughput

5.6 Comparative discussion

Table 1 portrays comparative discussion of proposed FABC + HFQKLMS. The energy achieved by routing + HLMS is 0.1460J, routing + HFBLMS is 0.0562, and routing + M-QKLMS is 0.1137 for air quality dataset. For localization dataset, the throughput attained by traditional approaches, like routing + HLMS is 53650, routing + HFBLMS is 50339, and routing + M=QKLMS is 45326. It is clear that the proposed FABC + HFQKLMS achieved a maximum energy of 0.258J, low prediction error of 7.152Kbps, and high throughput of 69640.

Table 1. Comparative discussion

Dataset	Metrics	Routing + HLMS	Routing + HFBLMS	Routing + M-QKLMS	Proposed FABC + HFQKLMS
Air quality	*Energy (J)*	0.1460	0.0562	0.1137	**0.254**
	Prediction error	10.003	9.082	10.448	**8.070**
	Throughput (Kbps)	53650	50344	45330	**69642**
Localization	*Energy (J)*	0.141	0.059	0.131	**0.258**
	Prediction error	11.348	8.467	11.040	**7.152**
	Throughput (Kbps)	53650	50339	45326	**69640**

6. Conclusion

Typically, WSN is comprised with numerous of sensor nodes that are utilized to monitor various physical and environmental conditions and also transmits data packets to the BS that are collected from network. Wireless nodes have small amount of energy and since energy conservation is the major issue in WSN. In order to conserve energy efficiency in network, it is essential to done data aggregation. Furthermore, data aggregation is the mechanism of avoiding redundancy and also reduces the amount of transmission packets. Hence, this article proposes an energy effective protocol using FABC algorithm and data aggregation mechanism using HFQKLMS. Moreover, the proposed method provides efficient routing protocol and groups data in an effective way such that the lifetime of system is prolonged. Initially, the nodes are simulated in WSN and then routing is performed using FABC algorithm, which is derived by merging the concept of FC with ABC algorithm. Furthermore, the data aggregation is performed using HFQKLMS, which is obtained by integrating HFBLMS and QKLMS. Moreover, the proposed FABC + HFQKLMS achieved a maximum energy of achieved a maximum energy of 0.258J, minimum prediction error of 7.152Kbps, and maximum throughput of 69640.

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