Fuzzy Extended Krill Herd Optimization with Quantum Bat Algorithm for Cluster Based Routing in Mobile Adhoc Networks

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MANET integrates a set of autonomous mobile nodes which move independently and send data through wireless links. Clustering and routing are the commonly employed energy efficient techniques, which can be treated as an NP hard problem and is resolved by computational intelligence algorithms. The mobility of the nodes leads to repeated link failures and low energy efficiency. In order to achieve high energy efficiency and network connectivity, this paper presents a new Fuzzy Extended Krill Herd Optimization with Quantum Bat algorithm (FEKHO-QBA) for Cluster Based Routing in MANET.

The presented model uses FEKHO algorithm by integrating the concepts of fuzzy logic and KHO algorithm for clustering process and effective selection of cluster heads (CHs). Besides, the QBA is applied as a routing technique to determine the optimal paths to the destination nodes. The QBA involves the features of faster convergence rate, easier to implement, and improved accurateness. The application of FEKHO-QBA algorithm offers maximum energy efficiency and network longevity. For determining the effectual performance of the FEKHO-QBA algorithm, a set of different experiments were carried out and highlighted the supremacy over the compared methods interms of different performance measures.

Keywords: MANET, Clustering, Routing, Krill herd algorithm, Bat algorithm

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1. Introduction

In general, Mobility sensor networks were developed progressively in various domains like weather forecasting and modern mechanics [1]. The wireless system and mobile devices transmitted for exceptional intention are called Mobile Ad Hoc Network (MANET). Self-organization and inexistence of national management tend to make incorporate MANET and prevent several challenging issues [2]. Followed by, flexibility is one of the fundamental objectives considered by means of various complexities in MANET. Numerous nodes pursue limited data communication in the remote system [3].

In MANET, it is impossible to develop remote networks due to the absence of fundamental infrastructure and it requires limited stability and many other assets [4]. At some point, mobility of sensor nodes impacts the routing to compute sampling and complex, that obstructs the power efficacy of routing protocols [5]. Initially, routing protocols that have low power finds power effective routing path from source to destination [6] whereas maximum system duration tries to manage the node energy and find energy-preserving router [7].

In addition, Ant Colony model outperforms the traditional outcomes with respect to energy preservation and is widely applied in several applications. Followed by, a bionic model resembles the behavior of existing creatures. The main aim of this model is to achieve best simulation results with low energy resources. Basically, it is applied to encircle heuristic frameworks inside the dispersed process [8]. Initially, Ant Colony Optimization (ACO) model is comprised of numerous merits and properties. Then, ACO is defined as a novel heuristic scheme applied for solving combined optimizing issues. Some of the features of ACO are positive feedback, shared computation as well as dynamic modifications [9].

A Probabilistic Emergent Routing Algorithm (PERA) is presented in [10]. The expanded version of ACO for MANET is named PACONET as depicted in [11] uses forward and backward ants for enhancing the pheromone level which differs from AntNet method. A Rank-Based mechanism of Ant System (ASrank) is designed in [12]. It is presented by creating an approach for sorting in Genetic Algorithm (GA). An ant-swarm based energy-effective ad hoc on-demand routing protocol (ACO-EEAODR) is designed in [13] with respect to RE and router length of a node.

In [14], ACO is applied in mesh routing system for identifying optimal routes while organizing the distributed coordination between the nodes with Low-Power and Lossy network (LNNs) with reduced power consumption.

In [15], AC based Energy Control Routing Protocol (ACECR) has been proposed. It assumes that high and low RE for each path. In case of route identification, backward ant update is activated and pheromone table depends upon the low power and hops count. Thus, ACECR is not applicable for ensuring the complete transmission energy can be limited with defined router. Mohsen [16] utilized Simulated Annealing (SA) concept for discovering global optimal path, where the unification of SA and ACO.

In order to achieve high energy efficiency and network connectivity, this paper presents a new Fuzzy Extended Krill Herd Optimization with Quantum Bat algorithm (FEKHO-QBA) for Cluster Based Routing in MANET. The presented model uses FEKHO algorithm by integrating the concepts of fuzzy logic and KHO algorithm for clustering process and effective selection of cluster heads (CHs). Also, the QBA is applied as a routing technique to fix the optimal paths to the destination nodes.

The QBA contains the features of faster convergence rate, easier to implement, and improved accurateness. The utilization of FEKHO-QBA algorithm reached improved energy efficiency and network longevity. A detailed experimental results analysis was performed to highlight the effectiveness of the proposed method.

2. The Proposed FEKHO-QBA Algorithm

The process involved in the FEKHO-QBA technique is shown in Fig. 1. Assume a MANET with 'n' nodes deployed in a random way upon requirement. The nodes are deployed and then started to gather details about the atmosphere. Followed by, the FEKHO algorithm is employed by the BS for the election of CHs. Next to that, the QBA is applied for the optimum selection of routes to BS. At last, the data transmission process will begin from CMs to BS via CHs.

2.1. FEKHO based Clustering Process

In this approach, the uncertainties in CH election can be resolved using fuzzy inference system (FIS) model with KHO to generate the chance score for all nodes. In set-up phase, CH election is processed by sink node or BS with the help of FIS relied upon KHO from active SNs with Residual Energy (RE) when compared with threshold energy level. KHO manages the population of various individual solutions and the response is depicted by an individual. The full-fledged solution is illustrated by depicting the individual solution that represents complete allocation of sensor nodes (SNs).

It estimates the CHs and CM placed in WSN. Hence, this phase is initialized by generating basic population. Assume $X_i = \left(X_{i1,}, X_{i2}, ..., X_{iN}\right)$ refers the ith population vector of wireless sensor network (WSN) in conjunction with $d_p = N$ sensors, in which $X_i\ X_i\left(J\right) \in \{0, 1\}$.

Active SNs and CH nodes are reflected by 0 and 1. Binary factors are involved in the SN selection. For example, consider a solution $X = (0, 0, 1, 0, 0, 0, 1, 0, 0, 0)$. Moreover, 10 sensors have been applied in region and nodes are elected as CH [17]. The encoding process is sufficient and effective as it is comprised of complete searching region. The basic populations of krills are illustrated by,

$$X_i(j) = \begin{cases} 1, \text{ if } \left(\text{rand } \le \text{pand } E\left(\text{node }_j\right) \ge E_{\text{avg}}\left(r\right)\right) \\ 0, \text{ otherwise} \end{cases} \tag{1}$$

Where ρ indicates the required CHs, and rand means uniform random value.$E_{avg}\left(r\right)$ refers the average power of complete system in recent iterationr, and $E\left(node_j\right)$ defines the present energy of sensor j. Consequently, the fittest vector is applied for inducing next phase in which non-CH nodes are related to CHs in cluster formation.

First, BS broadcasts a small communication to stimulate and demand identifications, position and power density

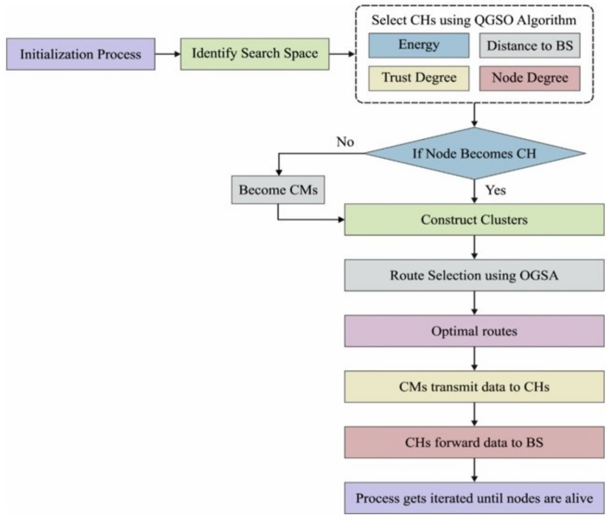

Fig. 1. Block diagram of FEKHO-QBA algorithm

as well as node type either advanced or normal for a sensor in sensor organization. A node processes the chance value by applying FIS. Based on the acknowledgment data from sensors, BS applies KHO for CH election according to the chance value of a node. The complete process for CH election is depicted in Fig. 2.

Besides, BS assigns the related sensors of CH according to the low Euclidean distance. RE, node centrality *(NC)*, and distance to BS (D) is 3 input parameters for FIS and CH election probability of a node called chance. The universal discourse of variables *RE,NC,D,* and fit are $[0...1]$, $[0...1]$, $[0...1]$, and $[0...1]$, correspondingly.

The FIS input set of values are RE,NC, andD. Hence, linguistic parameters of input values are assumed to be very low, low, medium, high, and very high for *RE*, close, rather close, reachable, rather distant and distant for *NC*, and close, nearby, average, far and farthest for distance to sink node. Under the application of these properties in Fuzzy Logic (FL) and resulting FIS have following set of input fuzzy parameters (i) Residual energy *RE* (ii) Node centrality *NC*(iii) Distance to BS D (iv) chance.

A node with maximum RE, closer node centrality, and closer to BS has maximum probability of CH election. Subsequently, KHO algorithm is applied for finalizing the CH election process.

In general, KHA [18] is defined as a novel metaheuristic optimization approach used for resolving the optimization process which depends upon the herding behavior of krill swarms by responding to the specific biological as well as ecological process. The time-based location of an individual krill in 2D space is selected by 3 major functions namely, movement influenced by alternate krill individuals, foraging movement, as well as random diffusion. Also, KHO model has applied Lagrangian method in d-dimensional decision space as given below (2):

$$\frac{dX_i}{dt} = N_i + F_i + D_i \tag{2}$$

Where N_i, F_i and F_i implies the motion of adjacent krill individuals, foraging action, and physical diffusion of ith krill individual, correspondingly. Initially, the direction of motion, α_i is processed by the target effect (target swarm density), local impact (local swarm density) as well as a repulsive effect (repulsive swarm density). Thus, the movement of krill individual is measured by,

$$N_i^{\text{new}} = N^{\text{max}}\alpha_i + \omega_n N_i^{\text{old}} \tag{3}$$

And N^max means the speed induced, ω_n refers the inertia weight of motion projected from $[0,1]$, and N_i^{old} defines the final motion. Followed by, foraging action is evaluated by 2 major elements. The initial one is food location and alternate module is advanced knowledge regarding the food location. For ith krill individual, this action is approximately derived as given below:

$$F_i = V_f\beta_i + \omega_f F_i^{old} \tag{4}$$

Where

$$\beta_i = \beta_i^{\text{food}} + \beta_i^{\text{best}} \tag{5}$$

and V_f indicates the foraging speed, ω_f defines the inertia weight of foraging action from 0 and 1, F_i^{old} implies the final foraging action. Also, random diffusion of krill individuals is processed randomly. It is defined by means of high diffusion speed as well as random directional vectors. Then, it is represented by:

$$D_i = D^{max}\delta \tag{6}$$

Where D^{max} means the high diffusion speed, and δ illustrates the random directional vector and random values are ranged from $[-1,1]$. According to the 3 pre-defined movements, diverse attributes of action in time and position vector of a krill individual from the interval t to $t + \Delta t$ be depicted by the given expression:

$$X_i(t + \Delta t) = X_i(t) + \Delta t\frac{dX_i}{dt} \tag{7}$$

2.2. QBA based Route Selection Process

Echolocation is one of the significant behaviors of bats; Yang [19] projected Bat Algorithm (BA) which is initialized from bats' foraging behavior. Bats fly randomly in searching for prey under the application of echolocation to find food sources and remove the hurdles.

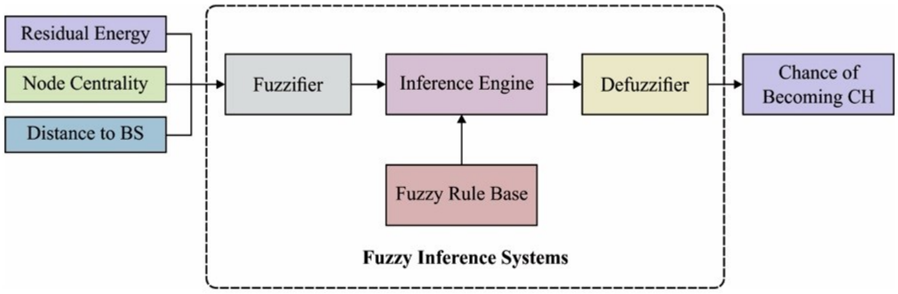

Fig. 2. Process involved in fuzzy logic based CH election

In BA, for ith bats of swarm with position x_i (solution), velocity k_i, and frequency f_i, every bat moves to the recent optimal position (solution), and corresponding location, velocity, and frequency are maximized by using the given function:

$$\begin{gathered} f_i + f_{\min} + (f_{\max} - f_{\min})\,\beta \\ v_i^t = v_i^{t-1} + \left(x_i^{t-1} - x_g^{t-1}\right) f_i \\ x_i^t = x_i^{t-1} + v_i^t \end{gathered} \tag{8}$$

where β mplies a random value of uniform distribution from $[0,1]$ and x_g^{t-1} depicts the present global best solution after comparing the attained solutions over the n bats. The above-mentioned function enhances the exploring capability of BA. For a local search, if a solution is decided from optimal solutions, a new candidate solution is regarded as,

$$x_{new} = x_{old} + \varepsilon \bar{A}^t \tag{9}$$

Where ε indicates a random value from $[-1,1]$. In this mechanism, A^{-t} denotes the mean value of bat's loudness. While searching the prey, bats gradually reduce the loudness and enhance the rate of pulse mission to monitor the prey and capture it. Hence, loudness and pulse emission rates are upgraded in iterations as given below:

$$\begin{gathered} A_i^t = \alpha A_i^{t-1} \\ r_i^t = r_i^0(1 - \exp(-\gamma t)) \end{gathered} \tag{10}$$

Where α and γ denote the constants. BA model is a well-known algorithm with robust convergence and simply executed; hence, it is applied extensively in real-time engineering. But BA gets trapped within the local optimal point while optimizing multimodal process.

The newly developed QBA depends upon the fundamentals of actual BA scheme [20]. The variables r and A balances the exploitation and exploration, correspondingly, by improvising 2 factors for guiding BA within local search or global search; butthe novel candidate solutions are emulated by given expressions varied from traditional BA:

$$x_{i,j}^t = \begin{cases} x_{i,j}^{t-1} + \left(x_j^* - x_{i,j}^{t-1}\right) \text{rand}, & \delta_j > TH \\ x_{i,j}^{t-1} + \varepsilon, & \delta_j \leq TH \end{cases} \tag{11}$$

Where,

$$\delta_j = \left| x_j^* - x_{i,j}^{t-1} \right| \tag{12}$$

It refers the distance among position of jth of ith bat and jth dimension of recent best position over the bats, and rand implies a random value from $[0,1]$. When δ_j is maximum than a threshold TH, it refers the distance from ith bat and recent optimal position; thus, the new bat moves to optimal position by random step.

Therefore, when δ_j is minimum than threshold TH, it recommends that recent bat is closer to best position; hence, the bat moves in random fashion. Also, diversity of bat population as well as exploration potential is enhanced by self-organization by means of distance. In searching process, according to probability of mutation ρ_m, few bats are mutated with quantum nature and bats are upgraded using the given expression:

$$x_i^t = \begin{cases} x_{\text{best}}^t + \alpha \left| M_{\text{best}}^t - x_i^{t-1} \right| \ln\left(\frac{1}{\text{rand}}\right), & \text{rand} > 0.5 \\ x_{\text{best}}^t + \alpha \left| M_{\text{best}}^t - x_i^{t-1} \right| \ln\left(\frac{1}{\text{rand}}\right), & \text{rand} \leq 0.5 \end{cases} \tag{13}$$

Where α denotes the contraction-expansion coefficient as,

$$\alpha = \alpha_0 - \frac{\alpha_0 - \alpha_1}{T} t \tag{14}$$

α_0 and α_1 indicates the first and last values of α, and T denotes numerous iterations. Actually, it is allocated that $\alpha_0 = 1$ and $\alpha_1 = 0.5$ for accomplishing best performance. M_{best}^t defines the mean optimal position as average of P_i^t positions which are expressed by,

$$M_{best}^t = \frac{1}{M}\left(\sum_{i=1}^{M} P_{i,1}^t, \sum_{i=1}^{M} P_{i,2}^t, \sum_{i=1}^{M} P_{i,3}^t, \ldots, \sum_{i=1}^{M} P_{i,D}^t\right) \tag{15}$$

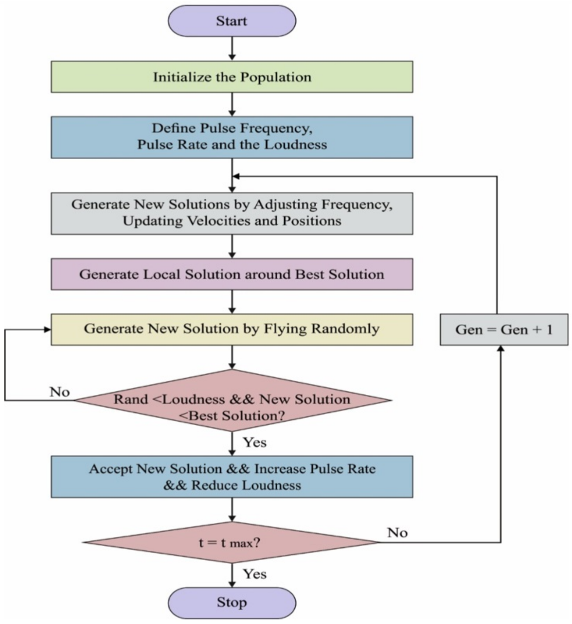

Fig. 3. Flowchart of QBA based Route Selection Process

where P_i^t refers the optimal position of ith bat, M denotes the population size, and D implies the dimension of problem. Bat along with quantum behavior enhances the diversity of population and involves in jumping from local optima. Finally, exploration, location of bats is upgraded using the applied function:

$$x_i^t = x_i^{t-1} + \left(M_{\text{best}} - x_i^{t-1}\right) * \text{rand} \tag{16}$$

The mean best position is applied for guiding bats flying in searching scale and the accuracy of solutions are increased and maximizes the convergence of a model as it applies statistical data of bat's position. Fig. 3 illustrate the flowchart of QBA model.

Here, the routing problem is defined as multi-objective minimization issue and is solved by QBA There are 2 objectives applied to increase the scalability of data delivery. The main aim of this method is to reduce the cost of intra-cluster as well as inter-cluster communication. Hence, immune-based optimization mechanism is applied for acquiring data reliability. These intra-cluster and inter-cluster communication costs are optimized under the application of given function.

$$\sum_{k=1}^{|V|} \sum_{m=1}^{|C_k|} w_{cm_{m,k} \to CH_k} \tag{17}$$

$$\sum_{k=1}^{|V|} w_{CH_k \to NextHop_{CH_k}} \tag{18}$$

where, CH_K denotes the CH value k;k refers the overall number of elected CHs; $NextHop_{CH_k}$ defines Next hop for CH_k; $cm_{m,k}$ implies Cluster member (CM) value m of cluster k; V depicts vector with elected CHs; C_k signifies vector with CM in a cluster that corresponds CH_k.

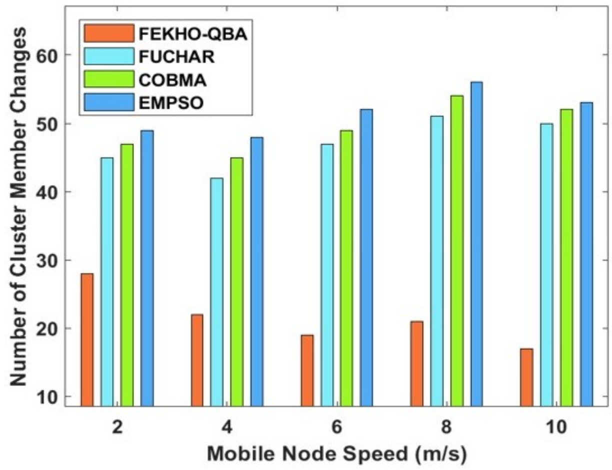

Fig. 4. Result analysis of FEKHO-QBA model on CM

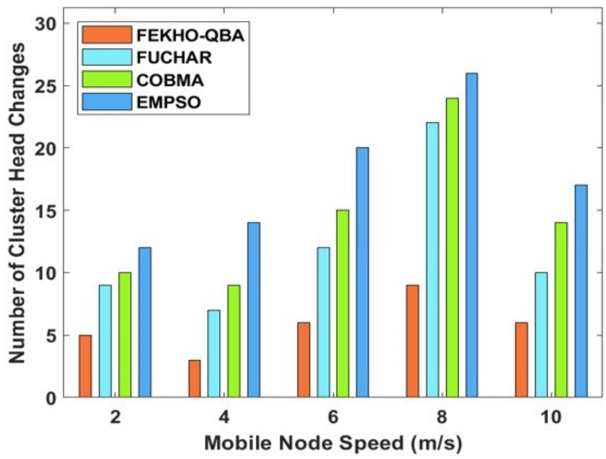

Fig. 5. Result analysis of FEKHO-QBA model on CH

3. Performance Validation

The proposed model is simulated using MATLAB tool. This section validates the results of the FEKHO-QBA technique under diverse dimensions. An analysis of variation in CH and CM changes under different mobile node speed is provided in Table 1 and Figs. 4 and 5.

Fig. 5 revealed that the EMPSO algorithm has depicted inferior results by enabling maximum number of CH changes whereas the proposed FEKHO-QBA technique has reported effective outcome by allowing only least number of CH changes.

Fig. 4 depicted that the EMPSO method has demon-

Table 1. Results analysis of FEKHO-QBA Technique under varying speed of mobile nodes

Number of Cluster Head Changes					Number of Cluster Member Changes			
Mobile Node Speed (m/s)	FEKHO-QBA	FUCHAR	COBMA	EMPSO	FEKHO-QBA	FUCHAR	COBMA	EMPSO
2	05.00	09.00	10.00	12.00	28.00	45.00	47.00	49.00
4	03.00	07.00	09.00	14.00	22.00	42.00	45.00	48.00
6	06.00	12.00	15.00	20.00	19.00	47.00	49.00	52.00
8	09.00	22.00	24.00	26.00	21.00	51.00	54.00	56.00
10	06.00	10.00	14.00	17.00	17.00	50.00	52.00	53.00

strated poor results by enabling maximum number of CM changes whereas the proposed FEKHO-QBA approach has reported effective outcomes by allowing only least number of CM changes.

A detailed comparative study of the results offered by the FEKHO-QBA technique with three existing techniques took place in Table 2. Fig. 6(a) illustrates the results offered by the FEKHO-QBA technique in terms of EC under varying mobile node count. The energy consumption analysis of FEKHO-QBA results revealed that the FEKHO-QBA technique has shown better performance with lower EC.

Fig. 6(b) examines the outcome of the FEKHO-QBA technique in terms of NL under varying mobile node count. Fig. 6(b) stated that the EMPSO algorithm has resulted in a lower NL over the other methods. Though the FUCHAR and COBMA techniques have tried to display reasonable NL, the FEKHO-QBA technique has resulted in a maximum NL over the other methods.

Fig. 7(a) defines the results provided by the FEKHO-QBA technique by means of ETE delay under varying mobile node count. Fig. 7(a) revealed that the FEKHO-QBA technique has shown better function with lower ETE delay. Simultaneously, the EMPSO has depicted poor outcomes with higher ETE delay whereas the FUCHAR and COBMA models have demonstrated considerable results.

Fig. 7(b) inspects the result of the FEKHO-QBA approach by means of throughput under varying mobile node count. Fig. 7(b) stated that the EMPSO method has resulted in minimal lower throughput over the other methods. Though the FUCHAR and COBMA techniques have managed to showcase considerable throughput, the FEKHO-QBA technique has resulted in a high throughput over the other methods.

4. Conclusion

This paper has presented a novel FEKHO-QBA technique for MANET to achieve energy efficiency and network lifetime. The FEKHO-QBA technique encompasses the idea of Cluster Based Routing in MANET. The nodes are deployed and then started to gather details about the atmosphere. Followed by, the FEKHO algorithm is employed by the BS for the election of CHs. Next to that, the QBA is applied for the optimum selection of routes to BS. At last, the data transmission process will begin from CMs to BS via CHs.

The application of FEKHO-QBA algorithm offers maximum energy efficiency and network longevity. In order to evaluate the outcome of the presented FEKHO-QBA technique, a series of simulations were performed and the experimental results verified the effectiveness over the compared techniques. As a part of future work, the proposed model can be extended to the design of real-time routing techniques for improved network performance.

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Table 2. Result Analysis of Existing with Proposed FEKHO-QBA Method in terms of Various Parameters

No. of Mobile Nodes	EC(mJ)				NL (Rounds)			
	FEKHO-QBA	FUCHAR	COBMA	EMPSO	FEKHO-QBA	FUCHAR	COBMA	EMPSO
100	27	45	49	59	5950	5300	5100	4890
200	52	68	73	88	5720	5260	5070	4600
300	64	89	101	116	5560	5100	4900	4560
400	81	109	118	148	5490	5060	4790	4200
500	106	141	156	172	5580	4800	4500	4140
No. of Mobile Nodes	**ETE Delay (sec)**				**Throughput (Mbps))**			
	FEKHO-QBA	FUCHAR	COBMA	EMPSO	FEKHO-QBA	FUCHAR	COBMA	EMPSO
100	3.09	4.93	5.96	6.67	0.98	0.91	0.89	0.84
200	3.23	5.68	7.46	8.77	0.96	0.80	0.76	0.71
300	4.02	6.38	8.56	9.97	0.94	0.71	0.66	0.62
400	5.01	7.58	9.36	11.67	0.92	0.65	0.59	0.51
500	5.19	8.78	9.96	12.77	0.89	0.60	0.55	0.46

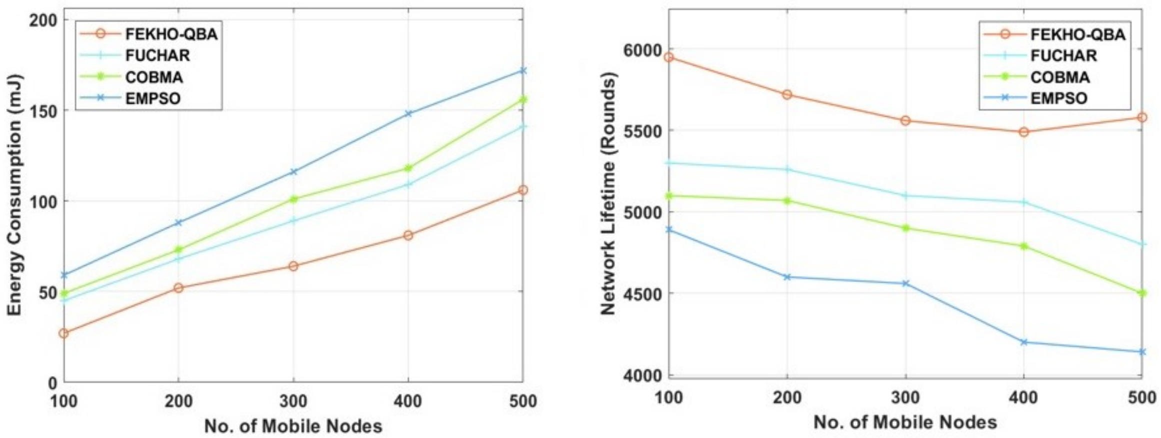

Fig. 6. (a) Energy consumption analysis of FEKHO-QBA model, (b)Network Lifetime analysis of FEKHO-QBA model

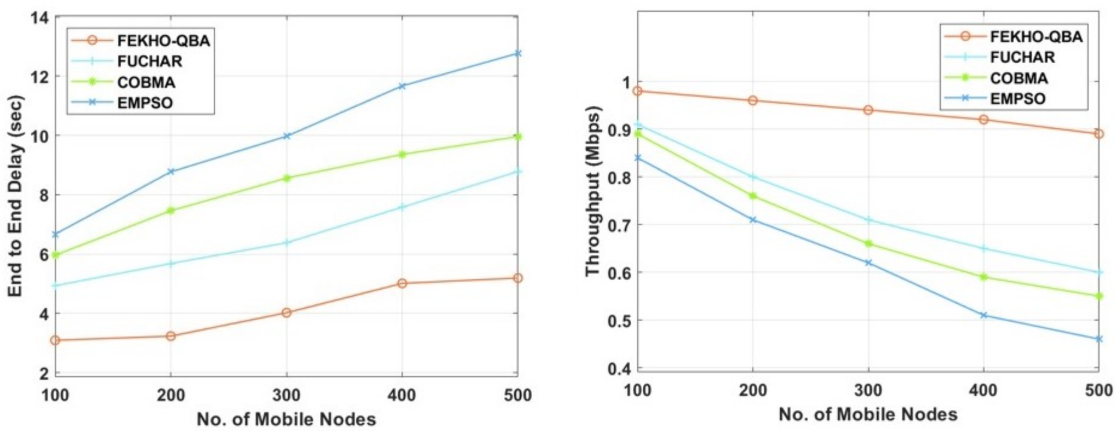

Fig. 7. (a) ETE delay analysis of FEKHO-QBA model, (b). Throughput analysis of FEKHO-QBA model

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