Computers, Materials & Continua
DOI: 10.32604/cmc.2022.026464
Article

Quantum Artificial Intelligence Based Node Localization Technique for Wireless Networks

Hanan Abdullah Mengash[1], Radwa Marzouk[1], Siwar Ben Haj Hassine[2], Anwer Mustafa Hilal[3,*], Ishfaq Yaseen[3] and Abdelwahed Motwakel[3]

[1]Department of Information Systems, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, Riyadh 11671, Saudi Arabia
[2]Department of Computer Science, College of Science & Art at Mahayil, King Khalid University, Abha, 62529, Saudi Arabia
[3]Department of Computer and Self Development, Preparatory Year Deanship, Prince Sattam bin Abdulaziz University, AlKharj, Saudi Arabia
*Corresponding Author: Anwer Mustafa Hilal. Email: a.hilal@psau.edu.sa
Received: 27 December 2021; Accepted: 22 February 2022

Abstract: Artificial intelligence (AI) techniques have received significant attention among research communities in the field of networking, image processing, natural language processing, robotics, etc. At the same time, a major problem in wireless sensor networks (WSN) is node localization, which aims to identify the exact position of the sensor nodes (SN) using the known position of several anchor nodes. WSN comprises a massive number of SNs and records the position of the nodes, which becomes a tedious process. Besides, the SNs might be subjected to node mobility and the position alters with time. So, a precise node localization (NL) manner is required for determining the location of the SNs. In this view, this paper presents a new quantum bird migration optimizer-based NL (QBMA-NL) technique for WSN. The goal of the QBMA-NL approach is for determining the position of unknown nodes in the network by the use of anchor nodes. The QBMA-NL technique is mainly based on the mating behavior of bird species at the time of mating season. In addition, an objective function is derived based on the received signal strength indicator (RSSI) and Euclidean distance from the known to unknown SNs. For demonstrating the improved performance of the QBMA-NL technique, a wide range of simulations take place and the results reported the supreme performance over the recent NL techniques.

Keywords: Artificial intelligence; wireless communication; wireless sensor networks; metaheuristics; quantum computing; node localization

1 Introduction

With the recent developments in wireless transmission, designing, manufacturing, and electronics of wireless sensor nodes (SN) using reasonable price, small size, low power consumption, and many other applications have become widespread. These tiny SNs with the capabilities like receiving environmental data on the basis of processing and sensor type transmitting data have affected the development of network types that are known as wireless sensor networks (WSN) [1]. The problem of spatial coordinate/location evaluation of WSN is known as localization. Over the last decades, localization in WSN has become a popular field of research. Knowing the location of nodes in WSN is essential for few protocols and applications, e.g., inquiry and tracking [2]. Because of the randomly distributed nodes and the mobility in few applications a suitable node localization (NL) algorithms are required [3]. Sensors localization is critical in almost all the aforementioned cooperative tasks since the location data play a significant part in the coordinated performances. In general, NL methods could be categorized into distributed approaches and centralized approaches, and the later methods are assumed to be more flexible and efficient in largescale networks. Even though the present approaches could provide solutions to the NL problems, still there is a great possibility to study more on it. Fig. 1 depicts the structure of WSN.

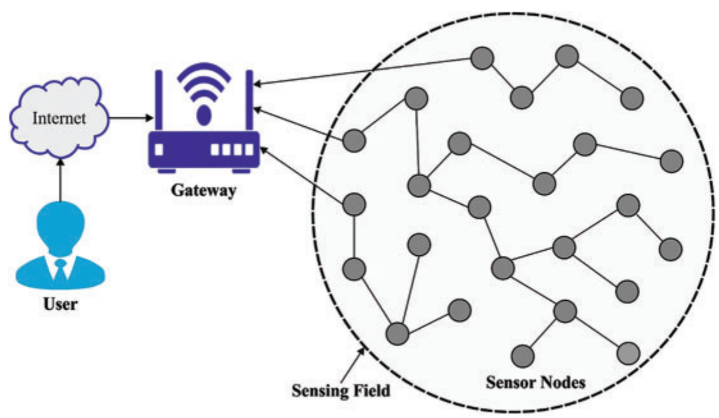

Figure 1: Overview of WSN

Even though GPS could locate accurately, it isn't realistic to equip each microsensor using GPS in WSN because of their limited usage environment and high price. Likewise, the NL performance of GPS in indoor and other complicated environment may not be sufficient. Hence, it is one of the difficult processes for designing effective and intelligent localization algorithms under restricted conditions [4]. Currently, the study goals to exploit the connection and interaction among the sensors for achieving the aim of localization. Based on the requirement to calculate the distance among the original nodes in the NL method, it may split the localization algorithms into range free and range based localization algorithms. The previous need to calculate the accurate azimuth/distance among nearby nodes and make use of the original distance among nodes to measure the NL of the unknown nodes [5]; like angle of arrival (AOA), received signal strength indicator (RSSI), time-difference of arrival (TDOA), and time-of-arrival (TOA). With regard to this last, it can depend on the networks connectivity among the nodes, using the calculated distance among the nodes to measure the NL algorithm without calculating the original distance amongst others; it involves Approximate Point in Triangle Test (APIT), Amorphous, Multi-Dimensional Scaling-programming (MDS-MAP), Centroid, and Distance Vector-Hop (DV-Hop).

Range free approach has the advantage of being simple hardware equipment, lower costs and energy utilization strong anti-measurement noise capability; they could offer satisfactory NL performances and, subsequently, gained more interest over the past few decades [6]. DV-Hop, as the distributed NL method depends on distance vector routing, is a procedure which has received considerable interest because of its low equipment requirements and simplicity. There exist 2 types of sensors in WSN: the anchor nodes along known position, as well as the unknown nodes, to be placed [7]. The NL method's aim is to measure the position of the unknown node in different manners. DV-Hop includes 3 stages: initially, each node in the network receive a hop count value from an anchor node; then it is measured the normal distance for all hops per anchor node; Next, the calculated distance is attained by increasing the normal distance for all hops as well as the minimal hop count values [8]. Lastly, the 3rd stage is for calculating the NL of unknown nodes on the basis of minimum square approach, once the unknown nodes retrieve a calculated distance from more than three anchor nodes. The DV-Hop algorithms are easier to implement, and the NL efficacy attainments are based largely on the calculated performance of normal distance for all hops as well as hop count values among the nodes [9]. We already know that the estimation error of the normal distance for all hops and the calculation error of hop count values are the 2 major causes of the calculation distance error.

Han et al. [10], proposed a DEIDV-Hop, an improved WSNL algorithm on the basis of DE and enhanced DV-Hop algorithm, that enhances the challenge of possible errors regarding the normal distance for all hops. Presented to the arbitrary individual of mutation operations which increases the wide range of the population, arbitrary mutations are infused to improve the premature convergence and search stagnation of the DE method. Depending on the produced individuals, the social learning parts of PSO method are embedding from the crossover operations which accelerate the convergences speed and improve optimization results. In order to decrease the error in the distance calculation phase, an NL approach for WSN depends on VPDC is presented in [11]. In the distance calculation step, initially, the distance per hop on the short transmission paths among the beacon and unknown nodes are estimated by the utilization of VP approach; Next, the length of short transmission paths is attained by adding the distance per hop; lastly, the unknown distance among the nodes is attained based on the DC and optimum path search method.

Kotiyal et al. [12] propose an ECS approach for minimizing the ALE as well as the amount of time required to localize unknown nodes. In this way, they executed ES method that enhances the search procedure considerably by departing the search loop when the optimum solutions are achieved. Furthermore, they have estimated the ECS method and compare it to the adapted CS approach. Yang et al. [13] aim to define NL using higher accuracy by SIA and proposed a novel NL method called LMQPDV-hop. In this presented method an enhanced DV-Hop has been applied as an alternative method for collecting the calculation distance, where the normal hop distance has been adapted with determined weights for reducing the distance errors amongst the nodes. Further, an effective LMQPSO approach has been proposed for finding an optimal coordinate of the unknown node.

Jiang et al. [14], proposed a DVHop method improved with optimized ISSA. First, the maximal hop distance errors are employed for correcting the hop distance from the unknown nodes to every anchor node for reducing the calculated distance errors. Next, Levy flights were presented for enhancing the capability of sparrow search approach for jumping of local optimal and adapting Powell local search method for improved convergences of the approach. Lastly, the experimental result shows that in uneven regions, related to the traditional DV-Hop method, the localization errors of an enhanced method are significantly decreased, and the localization performances are efficiently developed. El Khediri et al. [15] proposed an algorithm to make various node clusters with an enhanced K-means clustering method named OK-means. A single hop transmission mode is used for intracluster transmission where multihop transmission modes are employed with the intercluster transmission. The accuracy can be estimated by Ns-2 simulators.

Wang et al. [16], proposed A new NL method called KELM-HQ. The presented method uses the actual hop counts among unknown and anchor nodes as the training input and the location of anchor as the training target with a trained KELM. Also, the presented method uses actual hop counts among unknown nodes as the test sample for computing the location of unknown nodes for the KELM training. Karunanithy et al. [17] proposed an RDCM that employs 6 direction antennas for achieving an omnidirectional design of radiation. These transceiver model are employed as an omnidirectional or direction radiation pattern mode for NL algorithm and gathers precise data. On the other hand, the proposed method employs RSS, AoA, also x, y coordinate values come from a single anchor node for locating the sensors location.

This paper presents a new quantum bird migration optimizer-based NL (QBMA-NL) technique for WSN with an intention of determining the position of unknown nodes in the network by the use of anchor nodes. The QBMA-NL algorithm is stimulated by the mating behavior of bird species at the time of mating season. Also, the QBMA algorithm involves the incorporation of quantum computing (QC) concepts into the traditional BMA. Moreover, an objective function is derived using RSSI and Euclidean distance from the known to unknown SNs. A wide range of simulations take place on MATLAB tool and the results are inspected interms of different evaluation parameters.

2 Materials and Methods

2.1 System Model

Consider a WSN which has of N SN as well as sink node. The SN was utilized from 2D observing region. Every SN is homogeneous, static, and self-organization. The sink node has been resource rich device and extended broadcast power which allows it for sending its message to some SN from network. It can be considered as every SN identity it places coordinate and their value was constant. During the clustered based WSN framework, it can be considered that every CHs aggregate the sensed information established in their CM and transfer the aggregated data of cluster to sink node with utilizing inter-cluster multi-hop routing.

During this energy approach, energy utilization at all nodes is dependent upon the size of data packet and distance that exists sent in the source nodes [18]. In order to transmit the l-bits of data packet in the SN to their d distance distant receiver node, entire energy utilization of SN was computed as subsequent formula:

$$E_{Tx}(l,d) = \left\{ l \times E_{elec} + l \times \varepsilon_{fs} \times d^2, if\ d < d_0 l \times E_{elec} + l \times \varepsilon_{mp} \times d^4, if\ d < d_0 \right\} \tag{1}$$

But, to receive the l-bits of data packet at SN, energy utilized by receiver nodes are computed as subsequent formula:

$$E_{Rx} = l \times E_{elec} \tag{2}$$

Where value of E_{elec} implies the energy dissipated per bit in implementation of transmitting/receiving circuit. ε_{fs} and ε_{mp} represents the amplification number of broadcast amplifier to free space and multi-path approach correspondingly. d_0 signifies the threshold broadcast distance and their value has been usually $\sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$.

2.2 Algorithmic Design of QBMA Technique

The BMA is a population based stochastic search approach which is presented by [19] for addressing continuously optimized issues. The performance of this technique was dependent upon mimicking the mating approaches of bird species in mating season. During this technique, the mating procedure of birds contains the utilize of 3 important operators for producing a novel generation: 2-parent mating (PM), multi-parent mating (MPM), and mutation. In 2-PM is 2 parents mate together for breeding individual novel brood, but MPM is if PM with minimum of 2 other parents for breeding one novel brood. The mutation is a technique in which female parent takes a novel brood without the use of males by adapting their individual genes.

The parthenogenesis has been mating type where the female bird creates the brood without mating with male. During this technique, all females attempt to generate their brood by adjusting and altering their genes with existing rate. All the female birds from parthenogenetic group produce the brood as projected from Eq. (3):

$$
\begin{aligned}
&\text{for } i = 1 : n \\
&\text{if } r_1 > mcf_p \\
&x_{brood}(i) = x(i) + \mu \times (r_2 - r_3) \times x(i); \\
&\text{else } x_{brood}(i) = x(i) \\
&\text{end} \\
&\text{end}
\end{aligned}
\tag{3}
$$

where $x(i)$ represents the i^{th} bird, x_{brood} implies the output brood, n refers the issue dimensional (gene count), mcf_p signifies the mutation control issue of parthenogenesis, r_1 indicates the arbitrary number amongst [0,1], and μ defines the step size. Eq. (4) demonstrates the procedure of generating a novel brood in 2 elected parents [20]:

$$
\begin{aligned}
&\vec{x} = \vec{x} + w \times \vec{r}. \times (\vec{x}^i - \vec{x}) \\
&c = a\, arbitrary\ integer\ number\ amongst\ 1\ and\ n \\
&if\ r_1 > mcf \\
&x_{brood}(c) = l(c) - r_2 \times (l(c) - u(c)); \\
&\text{end}
\end{aligned}
\tag{4}
$$

where w stands for a time-varying weight for adjusting the elected female, $\vec{r}$ implies the $1 \times d$ vector where all elements are distributed arbitrary number amongst [0,1] and this arbitrary vector controls the equivalent element of $\left(\vec{x}^i - \vec{x}\right)$, n defines the issue dimensional, mfc indicates the mutation control influence that is allocated amongst [0,1] and [u, l] are the upper as well as lower bounds of elements correspondingly. Fig. 2 illustrates the flowchart of BMA technique.

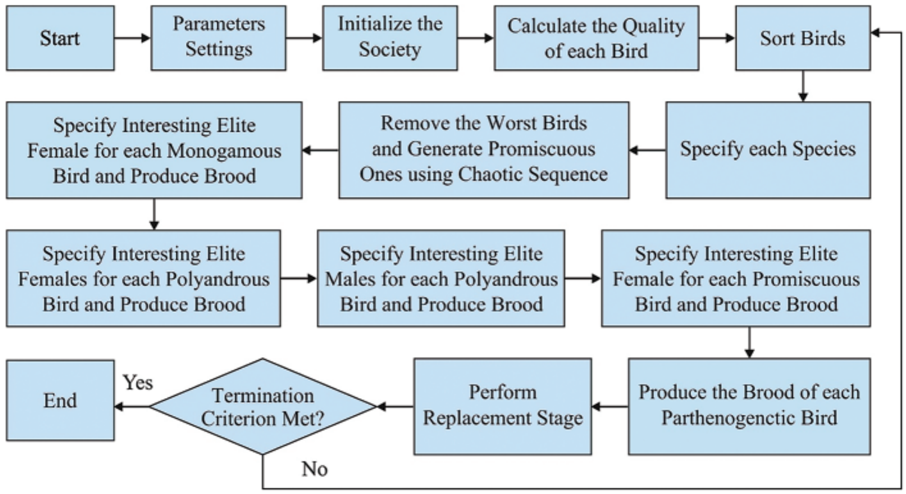

Figure 2: Flowchart of BMA [19]

Then, electing the female by a selective method and all the male birds mate with his elected females. The outcome brood was generated by subsequent procedure:

$$\vec{x}_i = \vec{x} + w \times \sum_{j=1}^{n_1} \vec{r}_j. \times \left(\vec{x}_j^i - \vec{x}\right)$$
$$C = a\,arbitrary\ number\ amongst\ 1\ and\ n$$
$$if\ r_1 > mcf$$
$$x_{brood}(c) = l(c) - r_2 \times (l(c) - u(c));$$
$$\text{end} \tag{5}$$

where n_i implies the amount of elected female birds and x_j^i refers the *jth* elected bird.

The process of BMA is as following:

- Step1 (Parameter Initialize): Initialization the BMA parameters such as society size (SS), percentage of all groups from the society, number of mates (nm), Mutation control factor (mcf), and maximum number of generations (NG).
- Step2 (Society Initialize): arbitrarily initialization the group of possible solutions and increase to the society. All the solutions are assumed as bird and it is identified by vector with length of n.
- Step3 (Society Estimation): compute the quality of all birds utilizing an estimation function.
- Step4 (Ranking): ranking the birds from society depends upon their quality.
- Step5 (Classification): Split the society as to 5 sets of birds: polyandrous, polygynous, monogamous, parthenogenetic and promiscuous.
- Step6 (Breeding): all birds generate a novel brood utilizing their individual design.
- Step7 (Replacement): when the amount of brood was superior to the amount of birds from the society, afterward the brood changes the bird, else, the bird endures from the society, and brood was unrestricted.
- Step8 (End Form): repeating steps 4-7 still a set the NG was implemented.

- Step9 (Report the optimum): choose the optimum feature of bird from the society as optimum solution.

For improving the performance of the BMA technique, the QC concept is integrated into it. QC has a novel kind of computing technique that adopts the approaches connected to quantum theory like quantum entanglement, quantum measurement, and state superposition. A fundamental unit of QC has qubit. The 2 fundamental conditions $|0>$ and $|1>$ method in qubit that is written as linear combination of these 2 basic conditions as undrt.

$$|Q> = \alpha|0> + \beta|1> \tag{6}$$

$|\alpha|^2$ indicates the probabilities of noticing condition $|0>$, $|\beta|^2$ implies the probabilities of detecting condition $|1>$, where $|\alpha|^2 + |\beta|^2 = 1$. The quantum has been established of n qubits. Based on the nature of quantum superposition, each quantum involves 2^n feasible values. An n-qubits quantum is defined as under.

$$\psi = \sum_{x=0}^{2^n-1} C_x|x>, \sum_{x=0}^{2^n-1} |C_x|^2 = 1 \tag{7}$$

The quantum gate is variation the condition of qubits like rotation gate, NOT gate, Hadamard gate, etc. The rotation gate was give details as mutation operator for making quanta schme optimum solution and lastly define the global optimum solutions [21].

The rotation gate was determined as under:

$$\left[\alpha^d(t+1)\beta^d(t+1)\right] = \left[cos(\Delta\theta^d) - sin(\Delta\theta^d)sin(\Delta\theta^d)cos(\Delta\theta^d)\right]\left[\alpha^d(t)\beta^d(t)\right] \, for \; d = 1, 2, \ldots, n \tag{8}$$

$\Delta\theta^d = \Delta \times S(\alpha^d, \beta^d)$, $\Delta\theta^d$ demonstrates the rotation angle of qubit in which Δ and $S(\alpha^d, \beta^d)$ are size and directions of rotation correspondingly.

2.3 Application of QBMA for Node Localization

The presented technique was planned to anchor-based localization utilizing QBMA computational intelligence techniques. This technique to anchor-based localization of SN utilizing the QBMA technique was presented [22]. The $Target_{area}$ has been provided target area in which SN is to utilize arbitrarily, l implies the length and b represents the breath of target area, AN (u, v) refers the anchor nodes coordinates, centroid (a, b, c, d) has been functioning for calculating the centroid of provided region and a, b, c, d are the sides of provided destination region, SN (u, v) implies the present place of SNs, SN_{total} represents the entire amount of SNs, dim stands for the dimension of destination region, i implies the index of SNs, SN_{ref} computes the entire amount of anchor nodes are in its range, $dist_i$ defines the evaluating the distance amongst sensor as well as anchor nodes, the place is for saving an optimum place of optimized technique from all iterations, Max_{iter} demonstrates the maximal of iteration for place modification, *SearchAgent* refers the agent id needed for determining a better place, *lb* represents the lower bound and *ub* indicates the upper bound of the provided destination region.

Algorithm 1: Pseudocode of QBMA-NL Technique

Begin:
  $Target_{area} = l * b$
  $AN\ (u, v) =$ centroid (a, b, c, d)
  $SN\ (u, v) = Taget_{area} *$ rand (SN_{total}, dim)

(Continued)

Algorithm 1: Continued

for $i = 1$ to SN_{total}
do
$$SN_{ref} = RSSI_{recvied}(AN)$$
If (size $\left(SN_{ref}\right)$ <= three))
then
The distance amongst anchor as well as SNs are computed utilizing the under formula:
$$dist_i = \sqrt{\left((u_t - u)^2 + (v_t - v)^2\right)}$$
Evaluate the coordinate value of SN (u, v, w) utilizing under formulas:
Assume that $w = 0$ for 2D area
$(u - u_1)^2 + (v - v_1)^2 + (w - w_1)^2 = dist1^2$
$(u - u_2)^2 + (v - v_2)^2 + (w - w_2)^2 = dist2^2$
$(u - u_3)^2 + (v - v_3)^2 + (w - w_3)^2 = dist3^2$
Call QBMA
Initialization of the arbitrary populations
Positions = initialize (SearchAgents$-no$, dim, ub, lb)
while ($1 < Max_{Iter}$)
do
Upgrade the place of search agents from the exploration stage utilizing escape energy of prey $|E|$.
End while
End if
End For
END
Outputs: Localized node count, mean localization error, and calculation cost

3 Performance Validation

The performance of the QBMA-NL approach is simulated utilizing MATLAB tool. The outcomes are investigated interms of distinct measures under varying anchor node count. Tab. 1 and Fig. 3 examine the MLE analysis of the QBMA-NL technique with recent techniques in distinct anchor node count. The outcomes depicted that the QBMA-NL technique has accomplished effectual outcomes with the minimalized MLE under all anchor nodes. For instance, with 10 anchors, the QBMA-NL technique has resulted in the least MLE of 0.9002 whereas the EO, GWO, SSA, and HHO techniques have obtained a higher MLE of 7.6511, 1.3536, 1.9581, and 1.3032 respectively. Likewise, with 40 anchors, the QBMA-NL technique has caused a minimum MLE of 0.6483 but the EO, GWO, SSA, and HHO methodologies have reached a superior MLE of 5.3336, 1.4040, 1.7566, and 1.1521 respectively. Meanwhile, with 60 anchors, the QBMA-NL manner has resulted in a lesser MLE of 0.5979 while the EO, GWO, SSA, and HHO algorithms have gained an increased MLE of 7.5000, 1.5047, 1.9581, and 1.1521 correspondingly. Eventually, with 80 anchors, the QBMA-NL system has to lead to a minimal MLE of 1.0009 whereas the EO, GWO, SSA, and HHO techniques have obtained a higher MLE of 13.8982, 1.8574, 2.3612, and 1.5551 respectively. At last, with 100 anchors, the QBMA-NL approach has caused a lower MLE of 1.1017 whereas the EO, GWO, SSA, and HHO methodologies have achieved an improved MLE of 18.2536, 1.9756, 2.5719, and 1.9835 correspondingly.

Table 1: Mean localization error (MLE) analysis of QBMA-NL technique

Mean localization error (m)					
No. of anchor nodes	EO	GWO	SSA	HHO	QBMA-NL
10	7.6511	1.3536	1.9581	1.3032	0.9002
20	3.8334	1.1399	2.3612	0.8703	0.4467
30	4.8802	1.3536	1.5882	0.9505	0.6483
40	5.3336	1.4040	1.7566	1.1521	0.6483
50	6.9458	1.3032	1.8574	1.0513	0.7490
60	7.5000	1.5047	1.9581	1.1521	0.5979
70	9.0114	1.6559	2.2101	1.4040	0.7490
80	13.8982	1.8574	2.3612	1.5551	1.0009
90	12.5884	1.9285	2.5123	1.7062	1.0513
100	18.2536	1.9756	2.5719	1.9835	1.1017

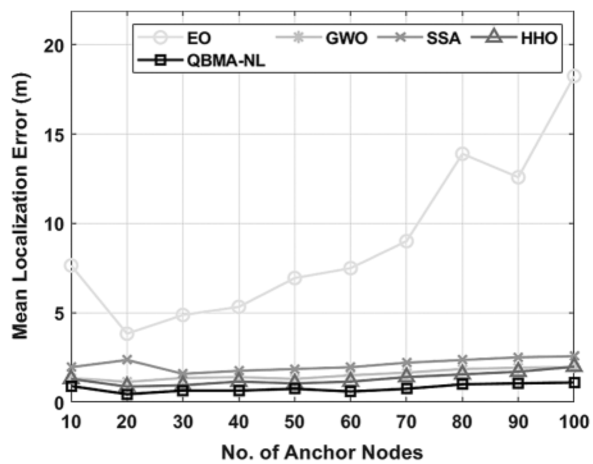

Figure 3: MLE analysis of QBMA-NL model with different anchor nodes

Tab. 2 and Fig. 4 demonstrate the performance of the QBMA-NL technique interms of maximum and minimum MLE values. On examining the minimum MLE values, the QBMA-NL technique has accomplished capable performance with the least MLE of 0.4467 whereas the EO, GWO, SSA, and HHO techniques have obtained an increased MLE of 3.8334, 1.1399, 1.5882, and 0.8703 respectively. At the same time, on investigative the maximum MLE values, the QBMA-NL approach has accomplished proficient performance with the minimum MLE of 1.1017 but the EO, GWO, SSA, and HHO methods have attained a maximum MLE of 18.2536, 1.9756, 2.5719, and 1.9835 correspondingly.

Table 2: Maximum and minimum MLE analysis of QBMA-NL technique

Methods	Minimum value	Maximum value
EO	3.8334	18.2536
GWO	1.1399	1.9756
SSA	1.5882	2.5719
HHO	0.8703	1.9835
QBMA-NL	0.4467	1.1017

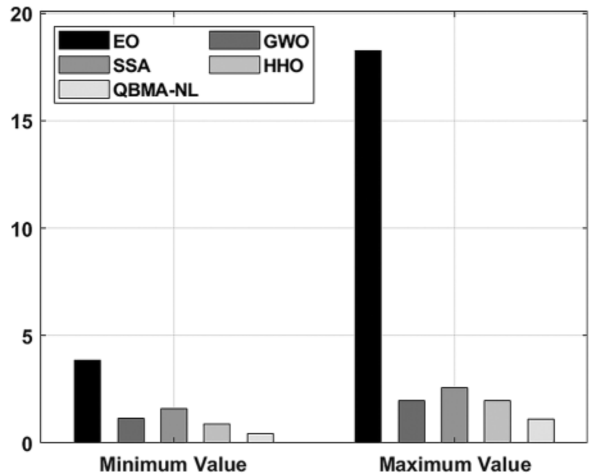

Figure 4: Minimum and maximum analysis of QBMA-NL model interms of MLE

Tab. 3 and Fig. 5 explores the CC analysis of the QBMA-NL approach with state-of-art manners under different anchor node count. The outcomes depicted that the QBMA-NL technique has accomplished effectual outcomes with the minimalized CC under all anchor nodes. For sample, with 10 anchors, the QBMA-NL technique has to lead to the least CC of 90.5512s whereas the EO, GWO, SSA, and HHO techniques have obtained a higher CC of 189.0195s, 206.9228s, 180.0678s, and 162.1645s correspondingly.

Table 3: Computational cost (CC) analysis of QBMA-NL technique

Computational cost (sec)					
No. of anchor nodes	EO	GWO	SSA	HHO	QBMA-NL
10	189.0195	206.9228	180.0678	162.1645	90.5512
20	189.0195	197.9711	189.0195	180.0678	108.4545
30	3408.5060	226.8486	223.5646	162.1645	108.4545
40	197.9711	215.8745	197.9711	184.5646	117.4062
50	171.1162	171.1162	162.1645	144.2612	72.6479
60	153.2128	171.1162	171.1162	135.3095	72.6479

(Continued)

Table 3: Continued

Computational cost (sec)					
No. of anchor nodes	EO	GWO	SSA	HHO	QBMA-NL
70	144.2612	171.1162	123.5735	135.3095	81.5995
80	144.2612	162.1645	162.1645	126.3578	63.6962
90	144.2612	153.2128	162.1645	126.3578	72.6479
100	117.7639	136.2610	153.2128	120.0025	54.7446

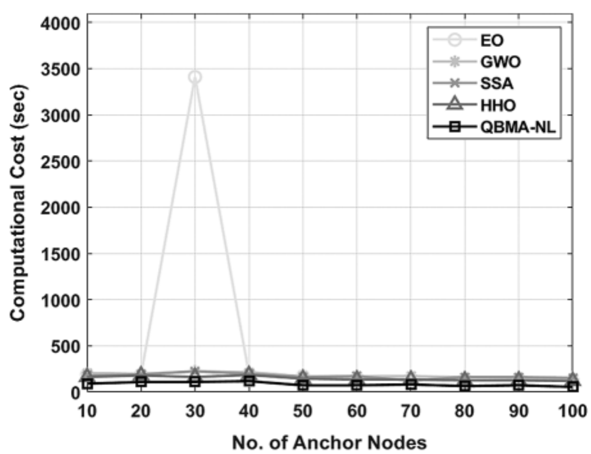

Figure 5: CC analysis of QBMA-NL model with different anchor nodes

Also, with 40 anchors, the QBMA-NL technique has resulted in a minimal CC of 117.4062s whereas the EO, GWO, SSA, and HHO methods have obtained a maximum CC of 197.9711, 215.8745, 197.9711 and 184.5646s respectively. In the meantime, with 60 anchors, the QBMA-NL approach has ensued to a lower CC of 72.6479s whereas the EO, GWO, SSA, and HHO techniques have obtained a higher CC of 153.2128, 171.1162, 171.1162 and 135.3095s respectively. Followed by, with 80 anchors, the QBMA-NL system has resulted in a minimum CC of 63.6962s whereas the EO, GWO, SSA, and HHO techniques have obtained a higher CC of 144.2612, 162.1645, 162.1645 and 126.3578s correspondingly. Finally, with 100 anchors, the QBMA-NL manner has resulted in a lesser CC of 54.7446s whereas the EO, GWO, SSA, and HHO algorithms have gained a superior CC of 117.7639, 136.2610, 153.2128, and 120.0024s correspondingly.

Tab. 4 and Fig. 6 illustrate the performance of the QBMA-NL technique interms of maximum and minimum CC values. On investigative the minimum CC values, the QBMA-NL technique has accomplished proficient performance with the least CC of 54.7446 whereas the EO, GWO, SSA, and HHO techniques have gained an enhanced CC of 117.7639, 136.2610, 123.5735, and 120.0025 correspondingly. At the same time, on examining the maximum CC values, the QBMA-NL technique has accomplished capable performance with the least CC of 117.4062 whereas the EO, GWO, SSA, and HHO methodologies have achieved a superior CC of 3408.5060, 226.8486, 223.5646, and 184.5646 correspondingly.

Table 4: Maximum and minimum CC analysis of QBMA-NL Technique

Methods	Minimum value	Maximum value
EO	117.7639	3408.5060
GWO	136.2610	226.8486
SSA	123.5735	223.5646
HHO	120.0025	184.5646
QBMA-NL	54.7446	117.4062

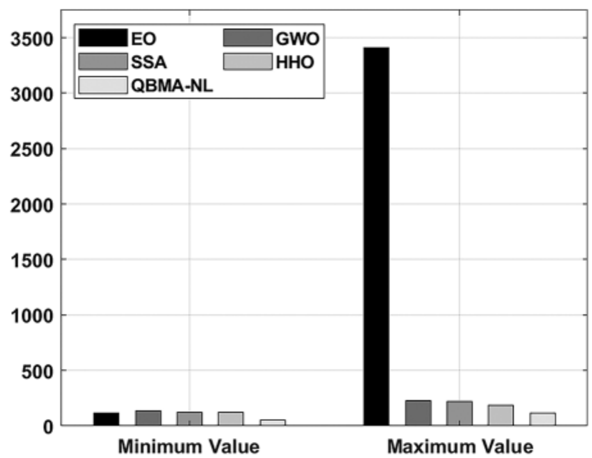

Figure 6: Minimum and maximum analysis of QBMA-NL model interms of CC

Tab. 5 and Fig. 7 consider the NNL analysis of the QBMA-NL technique with existing techniques under diverse NNL. The table values denoted the betterment of the QBMA-NL technique with the higher NNL. For instance, with 10 anchors, the QBMA-NL technique has gained an increased NNL of 134 whereas the EO, GWO, SSA, and HHO techniques have resulted in a reduced NNL of 68, 130, 123, and 110 respectively. Also, with 40 anchors, the QBMA-NL manner has reached a maximum NNL of 166 whereas the EO, GWO, SSA, and HHO methods have resulted in a reduced NNL of 92, 140, 151, and 157 respectively. In line with, 60 anchors, the QBMA-NL technique has gained an increased NNL of 158 whereas the EO, GWO, SSA, and HHO systems have resulted in a reduced NNL of 76, 150, 150, and 150 respectively. Along with that, with 80 anchors, the QBMA-NL approach has obtained a higher NNL of 141 whereas the EO, GWO, SSA, and HHO techniques have resulted in a decreased NNL of 51, 130, 130, and 130 correspondingly. Finally, with 100 anchors, the QBMA-NL method has gained a maximum NNL of 120 whereas the EO, GWO, SSA, and HHO algorithms have resulted in a minimum NNL of 42, 109, 111, and 120 respectively.

Table 5: Number of nodes localized (NNL) analysis of QBMA-NL technique

No. of Nodes Localized (NNL)					
No. of anchor nodes	EO	GWO	SSA	HHO	QBMA-NL
10	68	130	123	110	134
20	107	136	127	159	168
30	95	155	167	173	180
40	92	140	151	157	166
50	79	135	150	152	161
60	76	150	150	150	158
70	71	141	141	141	152
80	51	130	130	130	141
90	55	120	121	121	132
100	42	109	111	113	120

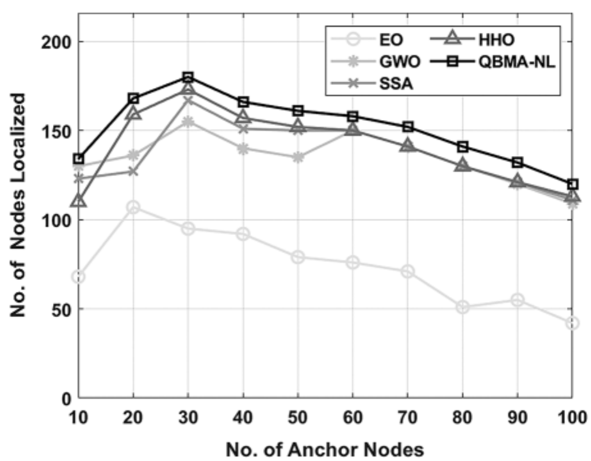

Figure 7: NNL analysis of QBMA-NL model with different anchor nodes

Tab. 6 and Fig. 8 depict the performance of the QBMA-NL manner interms of maximum and minimum NNL values. On investigative the minimum NNL values, the QBMA-NL technique has accomplished proficient performance with the higher NNL of 120 whereas the EO, GWO, SSA, and HHO approaches have gained a lower NNL of 42, 109, 111, and 113 correspondingly. Simultaneously, on inspecting the maximum NNL values, the QBMA-NL technique has accomplished proficient performance with the maximum NNL of 180 whereas the EO, GWO, SSA, and HHO methodologies have achieved a decreased NNL of 107, 155, 167, and 173 respectively.

Table 6: Maximum and minimum NNL analysis of QBMA-NL Technique

Methods	Minimum value	Maximum value
EO	42	107
GWO	109	155
SSA	111	167
HHO	113	173
QBMA-NL	120	180

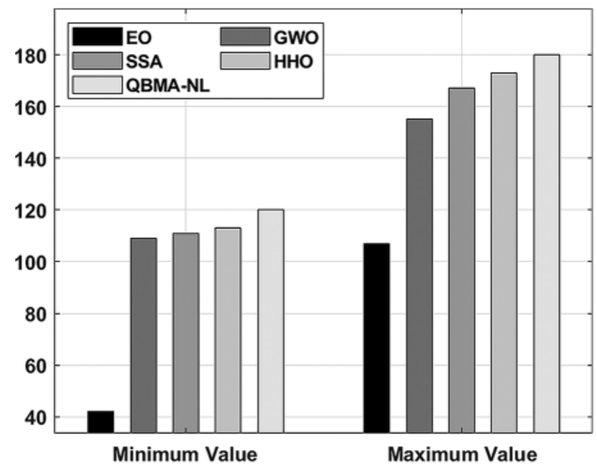

Figure 8: Minimum and maximum analysis of QBMA-NL model interms of NNL

4 Conclusion

This paper has presented a novel QBMA-NL technique for WSN with the aim of determining the position of unknown nodes in the network by the use of anchor nodes. The QBMA-NL algorithm is stimulated by the mating behavior of bird species at the time of mating season. Also, the QBMA algorithm involves the incorporation of QC concepts into the traditional BMA. Furthermore, an objective function is derived using RSSI and Euclidean distance from the known to unknown SNs. A wide range of simulations take place on MATLAB tool and the outcomes are inspected with respect to distinct evaluation parameters. The resultant experimental outcomes reported the supreme performance over the recent NL techniques. In future, the design of QBMA-NL technique can be improved by the inclusion of data aggregation and resource scheduling protocols in WSN.

Funding Statement: The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University for funding this work under grant number (RGP 1/279/42). Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2022R114), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

[1] Z. Wang, X. Wang, L. Liu, M. Huang and Y. Zhang, "Decentralized feedback control for wireless sensor and actuator networks with multiple controllers," *International Journal of Machine Learning and Cybernetics*, vol. 8, no. 5, pp. 1471–1483, 2017.

[2] G. Kadiravan, A. Sariga and P. Sujatha, "A novel energy efficient clustering technique for mobile wireless sensor networks," in *2019 IEEE Int. Conf. on System, Computation, Automation and Networking (ICSCAN)*, Pondicherry, India, pp. 1–6, 2019.

[3] J. Wang, R. K. Ghosh and S. K. Das, "A survey on sensor localization," *Journal of Control Theory and Applications*, vol. 8, no. 1, pp. 2–11, 2010.

[4] S. Arjunan, S. Pothula and D. Ponnurangam, "F5N-based unequal clustering protocol (F5NUCP) for wireless sensor networks," *International Journal of Communication Systems*, vol. 31, no. 17, pp. e3811, 2018.

[5] G. Bhatti, "Machine learning based localization in large-scale wireless sensor networks," *Sensors*, vol. 18, no. 12, pp. 4179, 2018.

[6] S. Arjunan and P. Sujatha, "Lifetime maximization of wireless sensor network using fuzzy based unequal clustering and ACO based routing hybrid protocol," *Applied Intelligence*, vol. 48, no. 8, pp. 2229–2246, 2018.

[7] B. Peng and L. Li, "An improved localization algorithm based on genetic algorithm in wireless sensor networks," *Cognitive Neurodynamics*, vol. 9, no. 2, pp. 249–256, 2015.

[8] K. Romer and F. Mattern, "The design space of wireless sensor networks," *IEEE Wireless Communications*, vol. 11, no. 6, pp. 54–61, 2004.

[9] L. Song, L. Zhao and J. Ye, "DV-Hop node location algorithm based on GSO in wireless sensor networks," *Journal of Sensors*, vol. 2019, no. 7, pp. 1–9, 2019.

[10] D. Han, Y. Yu, K. C. Li and R. F. de Mello, "Enhancing the sensor node localization algorithm based on improved dv-hop and de algorithms in wireless sensor networks," *Sensors*, vol. 20, no. 2, pp. 343, 2020.

[11] Y. Meng, Q. Zhi, M. Dong and W. Zhang, "A node localization algorithm for wireless sensor networks based on virtual partition and distance correction," *Information*, vol. 12, no. 8, pp. 330, 2021.

[12] V. Kotiyal, A. Singh, S. Sharma, J. Nagar and C. C. Lee, "ECS-NL: An enhanced cuckoo search algorithm for node localisation in wireless sensor networks," *Sensors*, vol. 21, no. 11, pp. 3576, 2021.

[13] J. Yang, Y. Cai, D. Tang and Z. Liu, "A novel centralized range-free static node localization algorithm with memetic algorithm and Lévy flight," *Sensors*, vol. 19, no. 14, pp. 3242, 2019.

[14] Z. Jiang, W. Hu and H. Qin, "WSN node localization based on improved sparrow search algorithm optimization," in *Int. Conf. on Sensors and Instruments (ICSI 2021)*, Qingdao, China, pp. 34, 2021.

[15] S. El Khediri, W. Fakhet, T. Moulahi, R. Khan, A. Thaljaoui *et al.,* "Improved node localization using K-means clustering for wireless sensor networks," *Computer Science Review*, vol. 37, no. 3, pp. 100284, 2020.

[16] L. Wang, M. J. Er and S. Zhang, "A kernel extreme learning machines algorithm for node localization in wireless sensor networks," *IEEE Communications Letters*, vol. 24, no. 7, pp. 1433–1436, 2020.

[17] K. Karunanithy and B. Velusamy, "Directional antenna based node localization and reliable data collection mechanism using local sink for wireless sensor networks," *Journal of Industrial Information Integration*, vol. 24, no. 1, pp. 100222, 2021.

[18] G. P. Gupta and S. Jha, "Integrated clustering and routing protocol for wireless sensor networks using Cuckoo and Harmony Search based metaheuristic techniques," *Engineering Applications of Artificial Intelligence*, vol. 68, no. 3, pp. 101–109, 2018.

[19] A. Askarzadeh, "Bird mating optimizer: An optimization algorithm inspired by bird mating strategies," *Communications in Nonlinear Science and Numerical Simulation*, vol. 19, no. 4, pp. 1213–1228, 2014.

[20] A. Arram, M. Ayob, G. Kendall and A. Sulaiman, "Bird mating optimizer for combinatorial optimization problems," *IEEE Access*, vol. 8, pp. 96845–96858, 2020.

[21] H. B. Duan, C. F. Xu and Z. H. Xing, “A hybrid artificial bee colony optimization and quantum evolutionary algorithm for continuous optimization problems,” *International Journal of Neural Systems*, vol. 20, no. 1, pp. 39–50, 2010.
[22] R. Sharma and S. Prakash, “HHO-LPWSN: Harris hawks optimization algorithm for sensor nodes localization problem in wireless sensor networks,” *ICST Transactions on Scalable Information Systems*, vol. 21, no. 31, pp. 168807, 2018.