Towards Energy Oriented Optimization for Green Communication in Sensor Enabled IoT Environments

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***Abstract*—One of the major bottlenecks towards realizing IoT systems is the energy constraint of sensors. Prolonging network lifetime is a fundamental issue for implementing IoT systems. The energy optimization problem, being NP-hard in nature for scalable networks, has been addressed in literature using traditional meta-heuristic techniques. Quantum inspired meta-heuristics have shown better performance than their traditional counterparts in solving such optimization problems in different domains. Towards this end, this paper proposes a Quantum inspired green communication framework for Energy Balancing in sensor enabled IoT systems (Q-EBIoT). Firstly, an energy optimization model for sensor enabled IoT environments is presented, where energy consumption is derived as cost of the energy-oriented paths. Secondly, a quantum computing oriented solution is developed for the optimization problem focusing on energy centric solution representation, measurement, and rotation angle. The proposed solution is implemented to evaluate the comparative performance with the state-of-the-art techniques. The evaluation demonstrates the benefit of the proposed framework in terms of various energy related metrics for sensor enabled IoT environments.**

***Index Terms*— Internet of things, Green computing, Energy balancing, Wireless sensor networks.**

I. INTRODUCTION

SENSOR enabled technologies have been successfully leveraged for military, industry, healthcare and agriculture purposes [1]. Recently, it has become the center of attraction for smart application in emerging research and development fields, such as, smart cities, body area networks, Internet of Things (IoT), Internet of Vehicles (IoV), and smart grid [2, 3]. The sensor enabled IoT environment has potential to integrate the cyber and physical world [4]. However, there is an inherent issue of network lifetime in sensor enabled IoT environments. The battery-operated tiny sensors are power constrained, due to the growing computation demand in smart applications and smaller battery size. The judicious use of energy is quite significant for tiny sensor enabled IoT environments [5].

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Several energy conservation techniques for sensor enabled IoT environments exist in literature [6-7], which have been aimed at minimizing the energy consumption. Early energy depletion in sensors near to sink leads towards IoT network collapse, while the distant sensors still retain sufficient energy for operations [8]. The retained energy of distant sensors cannot be utilized due to the network breakdown in IoT environments. This has shifted the focus of energy related research from energy consumption to energy balancing in sensor enabled IoT environments [9]. Energy balancing is a hard-combinatorial optimization problem considering a large number of sensors in realistic IoT implementations [10]. Evolutionary and swarm-based techniques have been applied for handling optimization problem with larger solution space [11-13].

Recently, quantum inspired meta-heuristic techniques have been developed for addressing hard-combinatorial optimization problems better than their traditional evolutionary counterparts [14-16]. However, the applicability of the quantum-inspired implementations in literature is very limited for energy balancing in sensor enabled IoT environments. The Q-bit[1] oriented binary solutions have been generated, and subsequently converted into numeric solutions in a quantum-based implementation [16]. The binary solutions of Q-bit individual[2] is repaired repeatedly leading higher operation complexity. The generation of binary solutions should be avoided due to the processing constraint in sensor enabled IoT environments. The consideration of constant rotation angle[3] also reduces solution convergence. In another quantum-oriented network optimization, sensors have been represented as Q-bits [14]. The presentation restricts pheromone updating to individual sensors. It increases time complexity for updating operation as compared to the common pheromone updating for all sensors. Similarly, network security-oriented quantum implementation has been suggested without detailing Q-bit representational and pheromone updating operational steps [15]. In these quantum-oriented implementations, the distance between sensors has been considered as heuristic parameter, without relating it to energy balancing aspects of the network.

In this context, this paper proposes a Quantum inspired green computing framework for Energy Balancing in sensor enabled IoT environments (Q-EBIoT). The framework optimizes network lifetime relying on energy-oriented Q-bit representation, measurement and rotation angle step size calculation. It also improves optimization efficiency by directly generating numeric solution and single energy updating for all Q-bit individuals. Specifically, the key contributions of the paper are as follows:

[1]Q-bit refers to the smallest unit of information in quantum computing. In green computing, it generally refers to energy-oriented communication links
[2]Q-bit individual refers to a set of Q-bits representing a possible solution of a problem in quantum computing. Here, it is an energy-oriented forwarding path
[3]Rotation angle refers to the magnitude of solution convergence towards optimal solution in quantum computing. Here, it is the energy difference between paths

1) Firstly, the energy optimization model is presented for sensor enabled IoT environments deriving energy consumption as cost of the energy-oriented paths.
2) Secondly, a quantum computing oriented solution is proposed for the optimization problem focusing on quantum representation, measurement, and rotation angle.
3) The quantum solution is implemented to evaluate the performance comparatively with the state-of-the-art techniques considering energy related metrics.

The rest of the paper is organized in following sections. Section II qualitatively reviews related literature on energy optimization in IoT. Section III presents the derivation of energy optimization problem. Section IV presents the proposed quantum computing solution Q-EBIoT of the optimization problem. Section V discusses simulation setting and analysis of results, followed by conclusion in Section VI.

II. Related Work

Recently, energy balanced position-based routing has been suggested using forward search space (FSS) for maximizing network lifetime in sensor enabled network environments [19]. Energy level-based switching technique has been suggested using Markov decision process for rechargeable sensor enabled environments [20]. The nodes switch from one parent to another parent in the tree based on the energy level defined by the harvested-energy and utilized-energy.

Energy efficient hierarchical routing has been explored based on dynamic cluster head rotation and re-clustering in sensor enabled network environments [21]. Multiple mobile sink-based routing has been investigated to reduce higher energy consumption of the nodes closer to the sink [22]. However, the network configuration with mobile sink is not suitable for indoor IoT environment, where mobility of sink could not be guaranteed. The Forward Aware Factor (FAF) based energy balanced routing has been suggested to utilize the neighborhood awareness [23]. The consideration of energy in terms of density reduces practical implementation as the density of nodes could be misunderstood as density of energy. Some similar non-metaheuristic-based approaches are explored [24, 25].

Recently, Harmony Search (HS) algorithm-based energy efficient routing for sensor enabled network environments has been suggested for maximizing network lifetime [10]. Energy efficient routing path has been represented as harmony in Harmony Memory (HM). However, energy balancing is compromised in HS based routing, due to the energy consumption and hop count-based path selection and avoidance of residual energy parameter in the decision. Bee swarm intelligence based hierarchical routing has been explored for energy constrained sensor enabled IoT environments [18]. The conversion of routing problem into bee swarm-based optimization problem is omitted which reduces the practical applicability of the suggested solution. A cross-layer routing protocol has been suggested based on fuzzy and ant colony optimization [17]. In particular, the cross-layer protocol is a hierarchical protocol which also coordinates with MAC layer.

Energy efficient multi-path routing has been suggested using ant colony optimization [26]. Interference among multiple paths is critical for multi-path routing, which has been completely omitted from the consideration during multiple path establishment. A transmission scheme based on ant colony optimization has been investigated to unite energy balancing and energy balancing for maximizing network lifespan of sensor network [27]. The sensors belonging to the strips near the sink have been designated smaller transmission range as compared to the outer strip sensors. Disseminating the knowledge of the sectors and strips would be another computation and communication overhead.

Quantum computing based evolutionary algorithm (QEA) was introduced by Han & Kim for solving combinatorial optimization problems [28]. The implementation of QEA for solving routing problem in sensor enabled IoT environments is quite limited except some initial effort [14-16]. Recently, a quantum inspired genetic algorithm has been suggested for addressing quality of service (QoS) routing in IoT network environments [15]. The population initialization, update operator, crossover and mutation have been formulated. Quantum inspired evolutionary algorithm-based clustering technique has been suggested for hierarchical routing in sensor network [14]. Similarly, quantum inspired ant-based routing algorithm for sensor enabled IoT environments has been suggested considering hop count or distance-based energy consumption [16]. Pheromone representation using Q-bits, updating using Q-gate operator, and five steps of the algorithm are major components of the ant-based routing technique.

III. Energy Optimization Model in Sensor Enabled IoT-Quantum Optimization Aspect

A. Energy Consumption Model for Green Computing

The sensor energy is consumed in performing sensing, processing, and communication activities. The data communication consumes most of the energy of sensors. it is mainly considered during the energy oriented data relaying in sensor enabled IoT environments. Considering the radio model for sensor enabled IoT environments [29], energy consumption to transmit E_T and receive E_R a message at distance d can be expressed as given by Eq. (1) and (2).

$$E_T(l,d) = \begin{cases} l\times E_{elec} + l\times \varepsilon_{fs}\times d^2 & if \;\; d < d_0 \\ l\times E_{elec} + l\times \varepsilon_{mp}\times d^4 & if \;\; d \geq d_0 \end{cases} \tag{1}$$

$$E_R(l) = l \times E_{elec} \tag{2}$$

where E_{elec} is the energy requirement for transmitter and receiver circuit, l is the message length, ε_{fs} and ε_{mp} are the energy consumption for amplifying transmission using free space and multipath model, respectively, in order to attain a satisfactory signal to noise ratio (*SNR*). The threshold distance $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$ is used to determine the power loss model.

B. Energy Oriented Cost Model for Sensors

The energy oriented cost model is directly proportional to the energy consumption model. The energy model is utilized to derive energy cost (*EC*) for next hop communication. An energy transfer from a sender node v_i to neighbor v_j can be expressed as given by Eq. (3).

$$EC_{ij} = \frac{E_T(l, d_{i,j})}{E_i^r} \quad (3)$$

where $d_{i,j}$ is the distance between node v_i and node v_j, and E_i^r is the residual energy of node v_i. The total energy cost (TEC) of data relaying through a neighbor node v_k from sender v_i can be expressed as given by Eq. (4).

$$TEC_{i,k} = EC_{i,k} + EC_{k,S} \quad k \in N(v_i) \quad (4)$$

where $EC_{i,k}$ is the cost of transmission from sensor v_i to v_k, and $EC_{k,S}$ is the cost of transmission from sensor k up to the sink node S. The set of neighbors of node v_i is represented by $N(v_i)$. The sender node also calculates $EC_{i,S}$ for the comparison purpose. If $TEC_{i,k} < EC_{i,S}$ then neighbor based multi-hop communication path is utilized, otherwise direct communication link is considered.

C. *Energy Optimization in Sensor enabled IoT*

An undirected graph based IoT network modelling is considered. Specifically, a graph $G = (V, E)$, where V is the set of vertices, i.e., sensor nodes and E is the set of edges, i.e., wireless connection between sensors. For all v_i and $v_j \in V$, $v_i \neq v_j$, there exists an edge between v_i and v_j if and only if v_i is the neighbor of v_j. The set of nodes in the transmission range constitute the neighborhood. The graph based network with N nodes is represented using an $N \times N$ adjacency matrix $A = (a_{ij})$. The matrix elements are defined as expressed by Eq. (5)

$$a_{ij} = \begin{cases} 1 & if \ v_j \in N(v_i) \\ 0 & otherwise \end{cases} \quad (5)$$

A relaying path χ in the graph based network is defined as a sequence of distinct sensors initiating from a source node and ending at the sink. It can be represented as given by Eq. (6).

$$\chi = (v_1, v_2, \ldots\ldots, v_n) \quad (6)$$

where v_i and v_{i+1} are adjacent vertices for $1 \leq i < n$ and v_1 is a source node, and v_n is the sink node. A path χ with n sensor nodes has $(n-1)$ links. The total energy cost of a path TEC_χ can be expressed as given by Eq. (7).

$$TEC_\chi = \sum_{i=1}^{n-1} TEC_{v_i, v_{i+1}}, v_i, v_{i+1} \in \chi \quad (7)$$

The objective of proposed energy-oriented framework for sensor enabled IoT environments is to minimize the total energy cost over all relaying paths originating from a source node. It can be expressed as given by Eq. (8).

$$\underset{\chi \in \varphi}{\operatorname{argmin}} \, TEC_\chi \quad (8)$$

where φ is the set of all possible relaying paths in the network starting from a source node and ending at the sink node.

D. *Quantum Optimization Aspect of Energy*

Quantum computing employs the principles including quantum bits (Q-bits) and superposition [30]. The smallest unit of information that can be handled by a two-state quantum computer referred as Q-bit. A quantum inspired algorithm uses Q-bits for representing solutions instead of numeric, binary or symbolic representation as used in evolutionary or swarm-based algorithms. The Q-bit state Ψ representation is expedient as it allows linear superposition of the solutions which can be expressed as given by Eq. (9).

$$|\Psi> = c_1|0> + c_2|1> \quad (9)$$

where $|\Psi>$ is a quantum superposition of the basic states $|0>$ and $|1>$. Here, hat $|0>$ is Dirac notation of the basic quantum state and will always give the result 0, when it is converted to classical logic by a measurement. Similarly, $|1>$ will give the result 1. Different from a classical bit that can only be in the state corresponding to either 0 or 1, a qubit may be in a superposition of both the states. It means that the probabilities of measuring 0 or 1 for a qubit are in general neither 0.0 nor 1.0, and multiple measurements made on qubits in identical states will not always give the same result. The pair (c_1, c_2) denotes the probability of Q-bit being found in state 0 and state 1, respectively, with the constraint $|c_1|^2 + |c_2|^2 = 1$. If the probability of one state increases, the probability of other state decreases. A system of m Q-bits can represent 2^m states simultaneously. This induces parallelism in quantum computing. A quantum gate (Q-gate) operator is applied for modifying the Q-bits in a solution. It is defined based on the characteristics of the problem to be solved. The Q-gate is also termed as rotation gate, and it can be expressed as given by Eq. (10).

$$U(\Delta\theta i) = \begin{bmatrix} Cos(\Delta\theta_i) & -Sin(\Delta\theta_i) \\ Sin(\Delta\theta_i) & Cos(\Delta\theta_i) \end{bmatrix} \quad (10)$$

where θ_i is the rotation angle for i^{th} Q-bit in a Q-bit string. The sign of θ determines Q-bits to move towards 0 or 1. In quantum systems, size of the system affects the computational space. Linear increase in size results in exponential increase in computational space. It provides the opportunities for exponential parallelism in quantum algorithm implementations. Thus, it is capable of providing better solutions even with very small population size. The efficient implementation of quantum computing algorithms demands quantum computers, which are not commercially available yet. There has been an increasing propensity of blending the concepts of quantum computing with evolutionary and swarm techniques. A quantum inspired evolutionary or swarm algorithm uses the concepts of quantum computing, in order to harness the potential of quantum system but runs on a classical computer.

E. *Quantum based Ant Colony Optimization of Energy*

Q-ACO conflates the principals of quantum computing with the concepts of ant based optimization, which is a swarm based meta-heuristic technique and mimics the foraging behaviour of real life ants [12]. The real ants deposit a chemical called pheromone on the path travelled from food source to their colony, based on the amount or quality of food and distance of the food source. The path to the nearest food source having quality food is laden with more pheromone. A higher pheromone level on a path pulls in more ants on that path which ultimately results in shortest path from colony to food source. Thus, pheromone is the main element of ant colony's collective learning behaviour. The artificial ants in

ACO technique also take into account the heuristic information η_{ij} in addition to pheromone information τ_{ij}. The pheromone matrix is continuously updated during the search procedure and it represents the past search experience. The four major steps in ACO based energy oriented relaying in sensor enabled IoT environments are as follows.

1) A source node sends a set of forwarder ants towards the sink node.
2) In order to construct a path from sender to the sink, each forward ant selects a next hop based on the probability p_{ij} to move from a node v_i to node v_j as given by Eq. (11).

$$p_{ij} = \begin{cases} \frac{[\tau_{ij}]^{\delta}[\eta_{ij}]^{\beta}}{\sum_{k \in N(i)}[\tau_{ik}]^{\delta}[\eta_{ik}]^{\beta}}, & if\ v_j \in N(v_i), \\ 0, & otherwise \end{cases} \quad (11)$$

   where τ_{ij} and η_{ij} are the pheromone intensity and heuristic information on a link connecting node v_i and node v_j. The environmental parameters δ and β are used to control the weight of pheromone and heuristic information, and $N(v_i)$ represents the set of neighbors for v_i.
3) Each forward ant v_i updates the identity set of the visited nodes.
4) A backward ant is created corresponding to each forward ant arriving at sink. It deposits pheromone on the path established by forward ant. The pheromone is calculated as given by Eq. (12) and (13).

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \quad (12)$$

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{H_k} & \text{the ant } k \text{ traverses link } (i,j) \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

where ρ is the evaporation factor incorporating decrement in pheromone intensity with network time, Q is a constant coefficient, H_k is the number of hops in k^{th} forward ant's path and m is the total number of ants.

In Q-ACO, strings of Q-bit individual are used to represent as ants and Q-gate operator is considered for updating the pheromone trail on the paths established by forward ants [28]. The five major steps in Q-ACO based data relaying are as follows.

1) For combinatorial problems with N variables and m ants, Q-bit representation of ant population in j^{th} generation, $Q(j)$ is expressed as given by Eq. (14).

$$Q(j) = \{q_1^j, q_2^j, q_3^j, \dots., q_m^j\} \quad (14)$$

where

$$q_i^j = \begin{bmatrix} q_i^j(1,1) & q_i^j(1,2)\cdots & q_i^j(1,N) \\ q_i^j(2,1) & q_i^j(2,2)\cdots & q_i^j(2,N) \\ \vdots & \vdots & \vdots \\ q_i^j(N,1) & q_i^j(N,2)\cdots & q_i^j(N,N) \end{bmatrix} \text{for } i = 1,2,3,\dots,\text{m}$$

$$q_i^j(x,y) = \begin{bmatrix} {c_1}_i^j(x,y) \\ {c_2}_i^j(x,y) \end{bmatrix} \text{ for } x, y = 1,2,3,\dots,N$$

where, q_i^j represents i[th] element of the quantum Q-bit in the j[th] iteration. It is a two-dimension matrix for each ant, and each element of the matrix $q_i^j(x,y)$ is a column matrix for variables. The initial value for all c_1 and c_2 is taken as $1/\sqrt{2}$. Thus, at the start of algorithmic all the links have equal probability for traversal.

2) The population of binary solutions $B(j) = (b_1^j, b_2^j, \dots, b_m^j)$ is generated by measuring the Q-bit population. The measuring operator for quantum inspired algorithm measures a Q-bit based on a random number r in the interval [0, 1). It can be expressed as given by Eq. (15).

$$q_i^j(x,y) = \begin{cases} 1, r < \left| c2_i^j(x,y) \right|^2 \\ 0, \quad \text{otherwise} \end{cases} \quad (15)$$

3) A repair procedure is applied on each binary solution violating the constraint.
4) The binary solutions are then evaluated for their fitness with objective function, and the best solution is identified.
5) The pheromone is updated using Q-gate operator as expressed by Eq. (16).

$$\begin{bmatrix} c_1'(x,y) \\ c_2'(x,y) \end{bmatrix} = \begin{bmatrix} \text{Cos}(\Delta\theta_i) & -\text{Sin}(\Delta\theta_i) \\ \text{Sin}(\Delta\theta_i) & \text{Cos}(\Delta\theta_i) \end{bmatrix} \times \begin{bmatrix} c_1(x,y) \\ c_2(x,y) \end{bmatrix} \quad (16)$$

IV. Quantum Inspired Green Computing - Energy Balancing in Sensor Enabled IoT

A. *Energy oriented Quantum Solution Representation*

The Q-bits are utilized for representing pheromone, instead of representing the ants using Q-bits. The pheromone is directly related to the quality of communication link in terms of energy balancing, and thus, the representation is closer to the solution space. In sensor enabled IoT environments with N sensors, the pheromone matrix τ^j in j^{th} generation is expressed as given by Eq. (17).

$$\tau^j = \begin{bmatrix} \tau^j(1,1) & \tau^j(1,2)\cdots & \tau^j(1,N) \\ \tau^j(2,1) & \tau^j(2,2)\cdots & \tau^j(2,N) \\ \vdots & \vdots & \vdots \\ \tau^j(N,1) & \tau^j(N,2)\cdots & \tau^j(N,N) \end{bmatrix} \quad (17)$$

where

$$\tau^j(x,y) = \begin{bmatrix} c_1^j(x,y) \\ c_2^j(x,y) \end{bmatrix} \ for\ x, y = 1,2,\dots,N$$

Here, the pheromone matrix is common for all ants.

B. *Energy Measurement in Quantum Solution*

Conventionally, the ants in the network use quantum measuring operator for constructing a set of binary solutions, by observing the state of Q-bit pheromone. For energy oriented data relaying problem in IoT environments, the set of binary solutions in j^{th} generation $B(j)$ is expressed as given by Eq. (18).

$$B(j) = (b_1^j, b_2^j, \dots, b_m^j) \quad (18)$$

where

$$b_i^j = \begin{bmatrix} b_i^j(1,1) & b_i^j(1,2)\cdots & b_i^j(1,N) \\ b_i^j(2,1) & b_i^j(2,2)\cdots & b_i^j(2,N) \\ \vdots & \vdots & \vdots \\ b_i^j(N,1) & b_i^j(N,2)\cdots & b_i^j(N,N) \end{bmatrix} \text{for } i = 1,2,\dots,m$$

Such that the below constraints given by Eq. (19)-(22) satisfy.

$$\forall x \; \forall y \; b_i^j(x,y) = 0 \,|\, 1 \tag{19}$$

$$\forall x \; \forall y \; if \; x = y, b_i^j(x,y) = 0 \tag{20}$$

$$\forall x \; \sum_{y=1}^{N} b_i^j(x,y) = 1, \; \forall y \; \sum_{x=1}^{N} b_i^j(x,y) = 1 \tag{21}$$

$$\sum_{x=1}^{N} \sum_{y=1}^{N} b_i^j(x,y) = N \tag{22}$$

where $b_i^j(x,y) = 1$ is interpreted as, node y at x^{th} position in the ordering of N nodes in i^{th} solution of j^{th} generation.

Algorithm 1: Measurement of Energy of Q-bit

Input: Q-bit Pheromone τ^j, **Output:** Numeric routing path

Begin

1. **For each** ant $a = 1 : m$
2. $P = \emptyset$, $S = source, P = P \cup S$, NB_s = {neighbor of S}
3. **While** (not empty (NB) & Sink $\notin P$)
4. **if** $rand(1) < |c_2(source, S)|^2$
5. select a node nb such that $nb \in NB_s, \; nb \notin P, \; TEC_{S,nb} = arg \min_{k \in NB_s + \{S\}} TEC_{S,k}$
6. **else**
7. select a node nb randomly such that $nb \in NB_s, nb \notin P$
8. **endif**
8. $P = P \cup nb, \; S = nb, NB_s$ = {neighbor of S}
   Until Sink node is included in P
9. **Endwhile**
9. **Return** P for ant a
10. **Endfor**

End

Conventionally, the binary solutions are generated and then converted into numeric solutions for evaluating their fitness. The construction and then conversion is of $O(N^2)$ operation for this energy oriented relaying combinatorial problem in IoT environments. In Q-EBIoT, the ants directly generate numeric solutions by measuring the Q-bit pheromone, and thus, avoid considerable number of operations needed for constructing binary solutions. The order number in the solution represents the identity of node included in the relaying path. In sensor enabled IoT network with N sensors, natural numbers from 1 to N are assigned as identifier to the sensors. The sink node is assigned an identifier value $(N + 1)$. The proposed method for measuring the Q-bit pheromone to construct the numeric solutions directly is presented in Algorithm 1. The complexity of the measuring algorithm is lower than $O(N^2)$ complexity of its literature counterparts. This is due to the consideration of only the set of neighbors rather than all sensor in the network during generation progress, and no repairing requirement for quantum solutions because of no binary solution generation.

Explanation of Algorithm 1: In step-2, S denotes the source node, NB_s denotes the set of next hop neighbors of S, path P contains identifiers of nodes on the routing path from source to the sink. Initially, the routing path for each ant at S contains only the source node S. In step-4, each ant selects one of the nodes from NB_s based on the state of Q-bit pheromone. If the probability of being in state 1 is greater than a randomly generated number, the node with minimum TEC among NB is selected as the next forwarder node (step-5). Otherwise, the next hop is selected randomly from NB_s by each ant (step-7).

C. Energy oriented Quantum Gate Operator

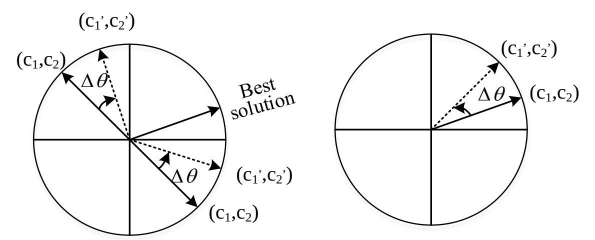
Once a forward ant completes the path from source to sink, a backward ant is generated. Backward ant updates the pheromone trails on links of the path based on the quality of the links in terms of energy balancing capability. A quantum gate operator also termed as reversible operator, is used to update pheromone information. The rotation gate operator is the most commonly used as reversible operator. The updating of Q-bit pheromone information by rotation gate operator can be expressed as given by Eq. (23).

$$\begin{bmatrix} c_1'(x,y) \\ c_2'(x,y) \end{bmatrix} = U(\Delta\Theta) \begin{bmatrix} c_1(x,y) \\ c_2(x,y) \end{bmatrix} \tag{23}$$

where $U(\Delta\theta)$ is the rotation operator, θ is the angle of rotation and $\Delta\theta$ is the step size or the change in angle of rotation. The amount and direction of change in the rotation angle guide the search process, as it modifies the value of c_1 and c_2. The exploration and exploitation are performed based on the value of c_1 and c_2 as these values are used while measuring the Q-bit pheromone.

TABLE I. LOOK UP TABLE FOR θ

s_i	b_i	$f(s) \geq f(b)$	$\Delta\theta_i$	$S(c_1c_2)$			
				$c_1c_2 > 0$	$c_1c_2 < 0$	$c_1 = 0$	$c_2 = 0$
0	0	False	0.01∏	0	0	0	0
0	0	True	0.01∏	0	0	0	0
0	1	False	0.01∏	1	-1	0	1
0	1	True	0.01∏	1	-1	±1	0
1	0	False	0.01∏	-1	+1	±1	0
1	0	True	0.01∏	+1	-1	0	±1
1	1	False	0.01∏	+1	-1	0	±1
1	1	True	0.01∏	+1	1-	0	±1



(a) (b)

Fig. 1. The progress of updating procedure (a) Q-EBIoT, (b) Q-ACO

Algorithm 2: Updating of Pheromone: Energy Efficiency

Input: Q-bit Pheromone (τ^j), **Output:** Updated Pheromone (τ^{j+1})

Begin

1. **For each** routing path *Path* constructed by the ants
2. $S = Path(1)$
3. **For** $i = 2$: length(*Path*)
4. $Next = Path(i)$
5. Calculate value of $\Delta\theta_i$
6. **Update** pheromone using $\begin{bmatrix} c_1^{j+1}(S, Next) \\ c_2^{j+1}(S, Next) \end{bmatrix} = U(\Delta\Theta) \times \begin{bmatrix} c_1^{j}(S, Next) \\ c_2^{j}(S, Next) \end{bmatrix}$
7. $S = Next$
8. **Endfor**
9. **Return** updated Q-bit pheromone
10. **End for**

End

D. Energy Oriented Step Size for Quantum Rotation

The value of $\Delta\theta$ has been decided based on a lookup table for energy oriented problem in IoT (see TABLE I). In the table, s_i represents the i^{th} bit of current solution, b_i is the i^{th} bit of the best solution, $f(s)$ denotes the fitness value of current solution, and $f(b)$ is the fitness value of the best solution, $\Delta\theta_i$ is the step size for i^{th} Q-bit and $S(c_1c_2)$ denotes the rotation direction. The step size for rotation angle change can be expressed as given by Eq. (24).

$$\Delta\theta_i = S(c_1c_2) \times (E_b^r - E_S^r) \times \left(\frac{H_b - H_S}{H_{max}}\right)\pi \tag{24}$$

where E_b^r is the remaining energy of the best path till current iteration, E_S^r is the remaining energy of current path, H_b is the number of hops in the best path, H_S is the number of hops in current path, and H_{max} is the maximum number of hops in a path from all the discovered paths till current generation. The direction of rotation can be determined as expressed by Eq. (25).

$$S(c_1c_2) = \big(TEC(b) - TEC(s)\big) \tag{25}$$

where $TEC(b)$ is the total energy cost of best path till current generation, and $TEC(s)$ is the total energy cost of the path in current generation. The remaining energy of any path p can be expressed as given by Eq. (26).

$$E_p^r = \frac{\sum_{k=1}^{H_p-1} RE_n}{H_p - 1},\ n \in p \text{ such that } n = p[k] \tag{26}$$

where RE_n is the residual energy of a node n belonging to path p and H_p is the number of hops of path p. If $(S(c_1c_2) \leq 0)$ then current Q-bit solution is rotated toward the best solution, otherwise it is rotated in the opposite direction. It is better than the update procedure of traditional counterparts moving in single direction (see Fig. 1(a) and (b)). A complete set of steps for updating Q-bit pheromone measurement using rotation gate operator is presented in Algorithm 2. The proposed updating procedure considers only the sensor nodes of the relaying path, and therefore, time complexity is quite lower that its literature counter. It is also worth noting that calculation of step size $\Delta\theta$ according to the energy balancing characteristics of the solution enhances the efficiency of Q-EBIoT. A complete set of steps for the proposed energy balancing framework Q-EBIoT is presented in Algorithm 3 with operational flow (see Fig 2).

Complexity Analysis of Algorithm-3: The computational complexity or cost of the proposal majorly depends on population of ants m, quantum variable size N and the quantum gate operator. There are unit initialization operation in step 1 and 2. The quantum gate operation in step 3 and 4 is of order $m \times N$, as it repeated for all ant population along with each quantum variables. There are again unit operations in steps 5-7. There is order $m \times m \times N$ operation in step 8 to 14 as it is calling algorithm 1 and 2 inside a while loop operation. Therefore, the complexity or cost of the overall proposal is of $O(m^2 \times N)$.

Algorithm 3: Q-EBIoT

Input: m, j, N, **Output:** Energy balanced network

Begin

1. **Initialize** number of ants *m*, number of iterations $j = 0$
2. **Initialize** Q-bit pheromone τ^j at *j*=0 such that
3. $\tau^0(x,y) = \begin{bmatrix} c_1^0(x,y) \\ c_2^0(x,y) \end{bmatrix}\ for\ x, y = 1,2,\ldots,N$
4. $c_1^0(x,y) = c_2^0(x,y) = \frac{1}{\sqrt{2}}$
5. **Generate** *P(j)* by measuring state of τ^j using Algorithm 1
6. **Evaluate** *P(j)*
7. **Store** the best path among *P(j)*
8. **While** ($m > j$) do
9. $j = j+1$
10. **Update** τ^j using Algorithm 2
11. **Generate** *P(j)* using Algorithm 1
12. **Evaluate** *P(j)*
13. **Store** the optimal routing path among *P(j)* and the best path
14. **Endwhile**

End

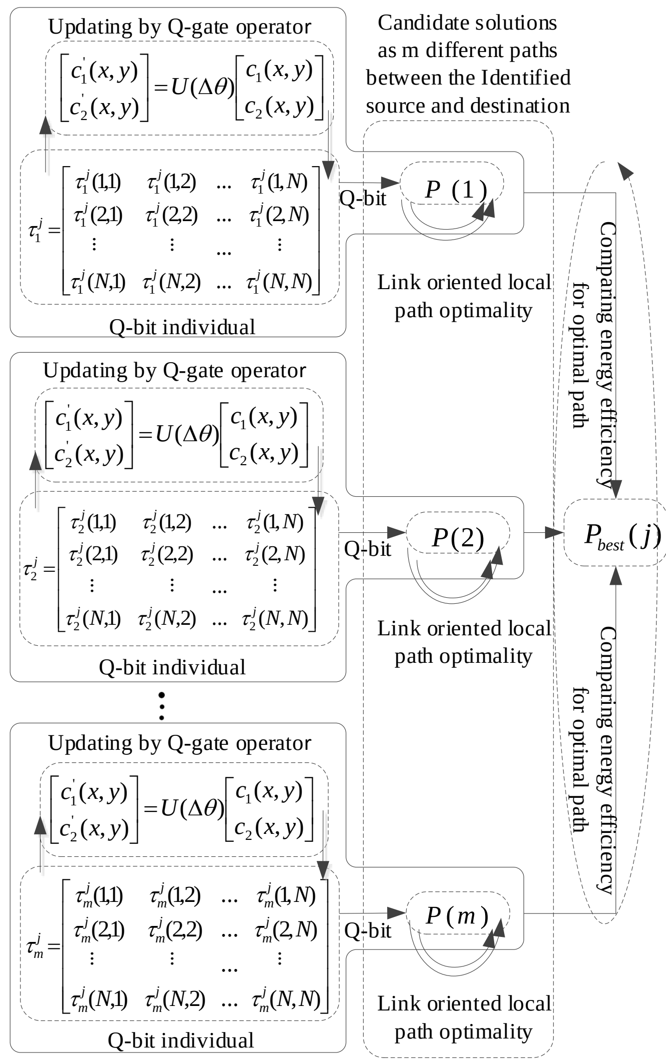


Fig. 2. Operation flow of the proposed Q-EBIoT framework

V. Simulation Results and Analysis

In this section, for network performance analysis (Fig. 4-7), network simulator (ns-2) was used considering the wide range of node level network setting available in the simulator. However, for analyzing performance result via ANOVA test, MATLAB was used considering library availability for the test in the simulator. In the prototype implementation, real sensor testbed was used for experiments which is accessible via a web-link.

A. Simulation Setting

Simulations are carried out in a $500m \times 500m$ square area with uniform random distribution of sensor enabled nodes.

Experiments are performed by varying the number of sensor nodes and position of the sink. An event based environment is considered for simulating the considered energy oriented framework for IoT. The network operation is considered in terms of rounds. Events occur randomly throughout the simulation area. The sensor enabled node with the highest energy in the vicinity of the event reports the event data to the sink. The sensing range of a node has been taken as double of its communication range. Obviously, if there is no node in the neighborhood of an event, which can communicate the event's data to sink, then the event is not reported to the sink.

The maximum number of events that can take place in each round is considered to ten. Experiments are conducted using 30 different network topologies for each scenario due to the random deployment of sensors, random nature of event occurrence and stochastic nature of the frameworks. Average of each 30 experiments is considered in results. ANOVA test is performed for evaluating the performance of all the three frameworks considering average and standard deviation. The radio model and network environment settings used in simulations are given in TABLE II and TABLE III. The ant related parameters are shown in TABLE IV. Other general simulation setting is similar to what it is considered in another IoT use case [31]. The two network configurations with 150 nodes and sink at $(250, 250)$ and $(250, 600)$ are considered. The configuration with two sink positions enable the evaluation under minimum average traffic load, and higher varying traffic load for all the sensor enabled nodes in the IoT network.

TABLE II. RADIO MODEL PARAMETERS

Parameter	Value
ε_{fs}	10 pJ/bit/m^2
ε_{mp}	0.0013 pJ/bit/m^4
E_{elec}	50 nJ/bit
$E_{initial}$	5J
Packet length	2000 bit

TABLE IV. ANT PARAMETERS

Parameter	Value
Ant	10
Generations	50
β	2.5
α	1
ρ	0.1

TABLE III. NETWORK PARAMETERS

Parameter	Value	Parameter	Value
Area	500 × 500 m^2	Transmission Radius	30 m
Sink Location	(250,250) (250,600)	Initial Energy	5 J
Nodes	[100~200]	Network Lifetime	1st event not reported

B. *Analysis of Results*

In literature, the network lifetime has been considered in a number of ways such as, the time when first node exhausts its energy, or some percentage of nodes becomes inactive. Since we considered an event based scenario in experiments, where an event is not reported to the sink only if all the sensors in the neighborhood of the event are dead. Therefore, network lifetime is defined as the number of communication rounds until first event is not reported to the sink node. The results of ANOVA test for comparing network lifetime with $\alpha = 0.05$ is presented in Table V-VI. In all these results, $P - value < \alpha$ and $F > F\ critical$, so we reject the null hypothesis and conclude that mean of at least two of the three techniques are different.

TABLE V. ANOVA WITH 100 NODES

Summary

Groups	Average	Variance
Q-EBIoT	668.4333	11065.4
ACO	583.8667	12377.8
Q-ACO	641.2667	11069.9

ANOVA

Variation Source	SS	DF	MS	F	P-value	F critical
Between group	111843	2	55921.54	4.86089	0.00997	3.101
Within group	1E+06	87	11504.38			
Total	1E+06	89				

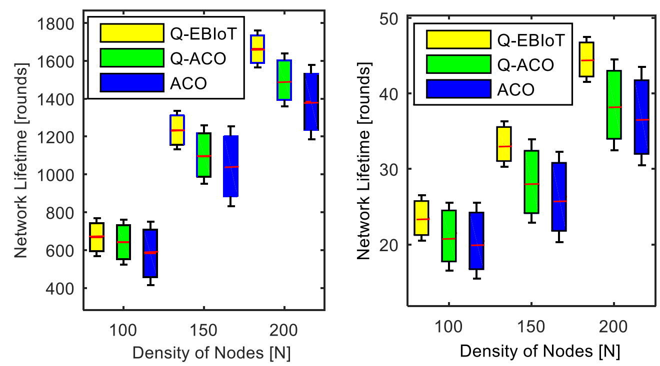
TABLE VI. ANOVA WITH 200 NODES

Summary

Groups	Average	Variance
Q-EBIoT	1662.8	104295.9
ACO	1384.63	44056.03
Q-ACO	1495.4	48301.35

ANOVA

Variation Source	SS	DF	MS	F	P-value	F critical
Between group	1176687.08	2	588343.54	8.975	0.00028	3.101
Within group	5702946.96	87	65551.11			
Total	6879634.05	89				

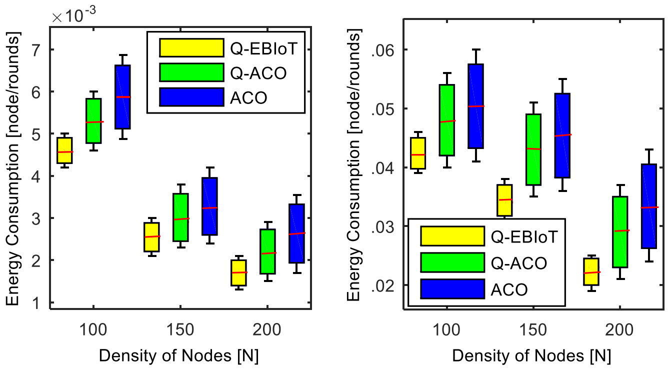


(a) (b)

Fig. 3. Network lifetime with sink at, (a) (250,250), (b) (250, 600)

Analysis of Network lifetime-Communication Rounds:

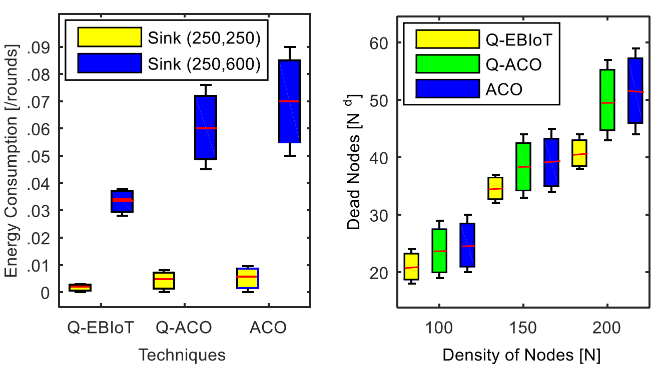
The comparison of impact of network density on network lifetime between Q-EBIoT and the state-of-the-art techniques: ACO and Q-ACO is presented for the two positions of the sink in Fig. 3(a) and (b). It can be clearly observed that the network lifetime of Q-EBIoT is higher than that of ACO and Q-ACO. Specifically, with sink at the center of network, i.e., (250, 250), the network lifetime of Q-EBIoT is 4.23% higher than that of Q-ACO, and 14.48% higher than that of ACO for 100 nodes network. For higher network density, e.g., 200 nodes, the lifetime of Q-EBIoT is 11.19% higher than that of Q-ACO and 20.08% that of ACO. In the second network configuration, i.e., sink is away from the network area at the position (250, 600), the performance of Q-EBIoT further improves as compared to the network configuration with sink at the center of the simulation area considering each network density. In particular, the network lifetime of Q-EBIoT is 9.64% higher than that of Q-ACO, and 15.34% that of ACO for 100 nodes in the network. The performance difference between Q-EBIoT, Q-ACO and ACO further enhances with higher network density, e.g., 150 and 200 nodes in the network area.



(a) (b)

Fig. 4. Energy consumption/node/round, sink at (a) (250,250), (b) (250,600)

Analysis of Energy Consumption- per Node and Dead Nodes: The comparison of impact of network density on average energy consumption between Q-EBIoT and the state-of-the-art techniques is presented for the two positions of the sink in Fig. 4(a) and (b). It can be concluded that energy consumption of a node is lesser in Q-EBIoT as compared to that of Q-ACO and ACO. With higher network density, energy consumption per node decreases for the all the considered protocols due to the availability of more neighbors, which enhances the capable of sustaining the communication through its neighbors for a longer period. It saves energy in comparison to direct communication with sink node. With the sink position away from the center of network is, the energy consumption of a node increases as compared to the scenario when sink is located at the center of the network.

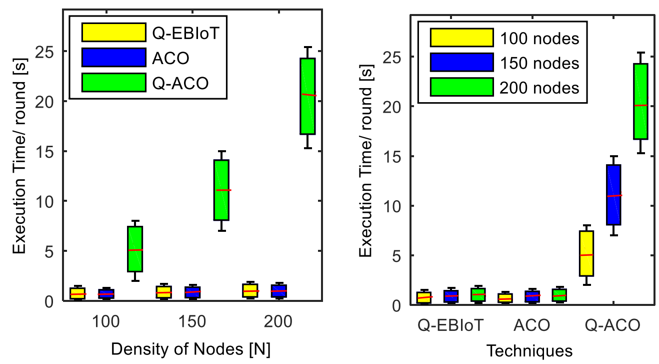


(a) (b)

Fig. 5. Comparison of (a) Energy Consumption, (b) no of dead nodes

The comparison of average energy consumption per communication round is shown in Fig. 5(a). It clearly states that Q-EBIoT has lower energy consumption than that of Q-ACO and ACO for both the cases, e.g., sink at the center and away from the center. The number of dead nodes, until the first event is not reported to the sink, is compared in Fig. 4(b) with sink at center of the network area. Q-EBIoT has lesser number of dead nodes as compared to QACO and ACO for each network density considered.

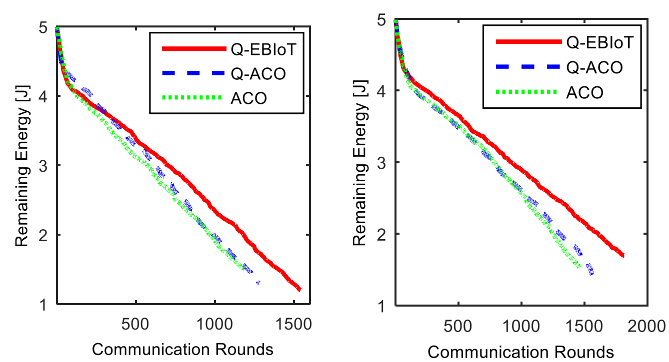
Analysis of Execution Time- per Communication Round: This metric has been used to show the average time taken by each algorithm for one communication round, and the results are presented in Fig. 6(a) and (b). The execution time analysis is significant due to the limited computing capability of sensor nodes and the even-based WSNs environment considered. As seen from the results, ACO has the least execution time per round. The execution time of Q-EBIoT is slightly more than ACO, but the execution time of Q-ACO is much higher than that of Q-EBIoT and ACO. This is due to the consideration of all the nodes in the network during repairing procedure in Q-ACO.



(a) (b)

Fig. 6. (a) Execution time/communication round (a) density, (b) technique

Analysis of Remaining Energy-Communication Rounds: This metric is used for comparing the average remaining energy of the sensors of the network after each round. The comparison of average remaining energy of sensors after each communication rounds, between Q-EBIoT and the state-of-the-art techniques is shown in Fig. 7(a) and (b), for 150 and 200 nodes in the network area, respectively. It can be clearly observed that the average remaining energy of Q-EBIoT is higher as compared to the state-of-the-art techniques. Due to this, Q-EBIoT is capable of providing longer network lifetime which affirms the results shown in Fig. 2.



(a) (b)

Fig. 7. Average remaining energy (a) 150 nodes, (b) 200 nodes.

C. *The Prototype Implementation*

In this section, the prototype implementation of the proposed quantum inspired energy balancing technique is performed in ‘INDRIYA’ testbed for wireless sensor network of the School of Computing, National University of Singapore (NUS) [32]. The testbed nodes or motes N_m were configured for experiment via both offline and online interfaces. The sensors used in these 139 motes of the testbed include WiEye, SBT30, SBT80 and TelosB. These motes are specialized in monitoring different activities on the three floors of the school building, where these motes are physically deployed. The monitored data was accumulated at the interface system of the testbed. It is considered at the 2nd floor for the sink deployment at the center of monitoring area, whereas it considered at the 3rd floor in case of sink deployment at the edge of monitoring area. The connectivity probability among motes was considered approximately 1.0, due to the calculated predefined deployment location for motes on the three floors. An approximate view of the mote deployment on the three floors of the school. In Table VII, the physical characteristics of the components of motes are summarized. A precise set of steps followed in this prototype implementation is shown as workflow in Fig. 8.

Table VII. Major physical components of the motes

Components	**Value**	**Components**	**Value**
Processor	16 bit and 8 MHz	Internal Flash	48 KB
ADC	12 bit	Sensitivity	-95dBm
RAM	10 KB	Transceiver	250 Kbps
RF chip	TI-2420	Microcontroller	TI-MSP430

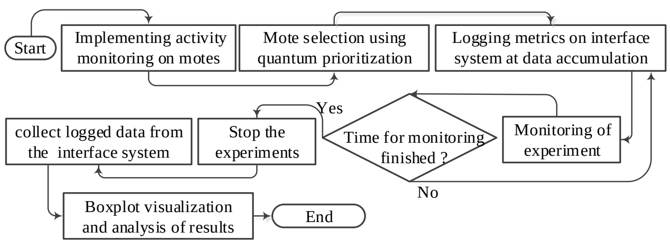


Fig.8. The prototype implementation as workflow

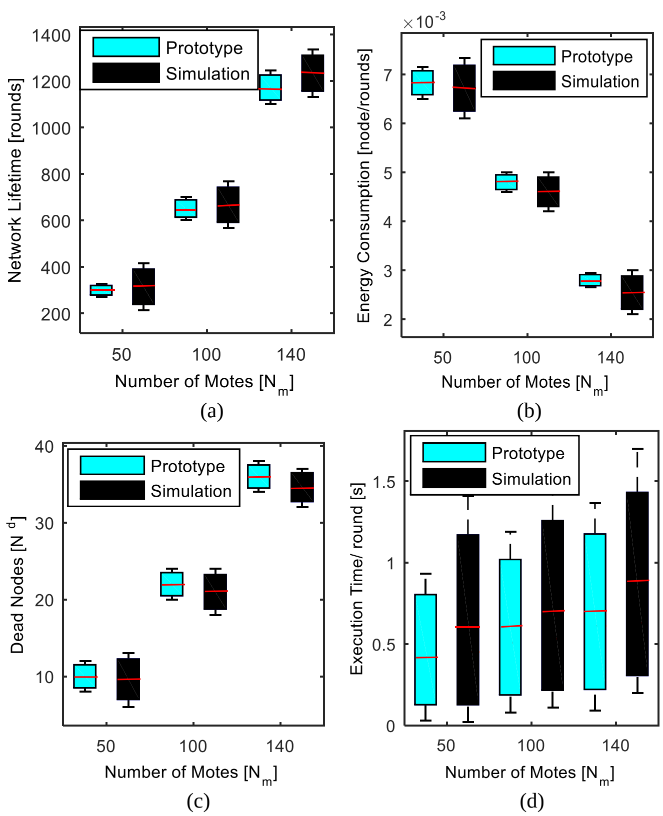
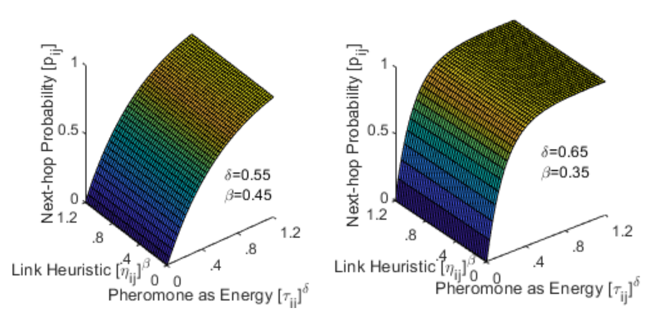


Fig. 9. The prototype results, (a) network lifetime, (b) energy consumption, (c) dead nodes, (d) execution time

The comparison between the prototype results and results obtained through simulation for the proposed quantum computing based energy balancing technique is presented in Fig. 9(a)-(d). It considers four metrics including network lifetime, energy consumption, dead nodes, and execution time. It can be clearly observed that the prototype results attest simulation results, as the average value of metrics measured in prototype experiment are close to those noted in simulations. Specifically, it is worth noting two major points including smaller variance in prototype results, and the difference in average value for the network considering 140 motes in all the four considered metrics. The smaller variance in metric's observation can be attributed to the single user execution environment in motes in case of quantum based prioritization in mote selection. However, simulations are affected by the system environments resulting in terms of larger variance in metric calculation. The difference in average value of metrics is due to the limited number of motes in INDRIYA testbed. The total number of motes available in the testbed is 140 including an interface system as sink node. However, 150 nodes are considered in simulation as larger network environments.

D. Analytical Analysis

In this section, analytical results are discussed for evaluating the characteristics of mathematical derivations. The next-hop selection probability has been measured with jointly increasing value of pheromone as energy and link heuristic information. A critical analysis has been carried out to measure the impact of weighting parameters on next-hop section probability. Fig. 10(a) shows that next-hop probability linearly increases with increasing pheromone as energy in case of approximately equal weighting parameters. Specifically, next-hop probability linearly increases with parameters $\delta = 0.55$ and $\beta = 0.45$ for pheromone as energy and link heuristic, respectively. The rate of increment of next-hop selection probability becomes higher with the increase of parameter δ of pheromone as energy in comparison with the parameter β of link heuristic. In particularly, with weighting parameters $= 0.65$ and $\beta = 0.35$shown in Fig. 4(c), It can be clearly observed that the rate of increment in next-hop probability is leading towards exponential increment until it reaches to 1. Moreover, it is also highlighted that with given weighting parameters δ and β and pheromone as energy, the increase in link heuristic has negligible impact on next-hop probability. Thus, it can be concluded that next-hop probability is majorly depended on weighting parameters and pheromone as energy.



(a) (b)

Fig. 10. The impact of weighting parameters δ and β on next-hop probability

VI. Conclusion

In this paper, a novel quantum based green communication framework (Q-EBIoT) has been presented for solving the energy optimization problem in IoT. The quantum measuring operator has been modified for energy oriented the problem in IoT. A method for computing the value of $\Delta\theta$ has been developed for energy balanced routing. The experimental evaluation shows that Q-EBIoT performs better than both ACO and Q-ACO. The inherent parallelism of quantum computing provides better quality solutions, even with a smaller population size. Due to the modified measuring procedure, Q-EBIoT provides better solution in efficient time as compared to Q-ACO. The proposal significantly increases the network lifetime. In future research, authors will explore Q-EBIoT with other metaheuristic implementation of quantum computing for green communication in IoT environments.

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