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A Novel Enhanced Quantum PSO for Optimal Network Configuration in Heterogeneous Industrial IoT

Sheetal N. Ghorpade¹, Marco Zennaro², Sr. Member, IEEE, Bharat S. Chaudhari³, Sr. Member, IEEE, Rashid A. Saeed⁴, Sr. Member, IEEE, Hesham Alhumyani⁴, and S. Abdel-Khaled⁴

¹RMD Sinhgad School of Engineering, Savitribai Phule Pune University, Pune 411058, India

²Science, Technology and Innovation Unit, Abdus Salam International Centre for Theoretical Physics 34151 Trieste, Italy

³School of Electronics and Communication Engineering, MIT World Peace University, Pune 411037, India

⁴Department of Computer Engineering, College of Computers and Information Technology, Taif University, Taif, 21944, Saudi Arabia

Corresponding author: Sheetal N. Ghorpade (e-mail: sn_ghorpade@yahoo.com).

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ABSTRACT A novel enhanced quantum particle swarm optimization algorithm for IIoT deployments is proposed. It provides enhanced connectivity, reduced energy consumption, and optimized delay. We consider heterogeneous scenarios of network topologies for optimal path configuration by exploring and exploiting the hunts. It uses multiple inputs from heterogeneous IIoT into quantum and bio-inspired optimization techniques. The differential evolution operator and crossover operations are used for information interchange among the nodes to avoid trapping into local minima. The different topology scenarios are simulated to study the impact of p -degrees of connectivity concerning objective functions' evaluation and compared with existing techniques. The results demonstrate that our algorithm consumes a minimum of 30.3% lesser energy. Furthermore, it offers improved searching precision and convergence swiftness in the possible search space for p -disjoint paths and reduces the delay by a minimum of 26.7%. Our algorithm also improves the throughput by a minimum of 29.87% since the quantum swarm inclines to generate additional diverse paths from multiple source nodes to the gateway.

INDEX TERMS Connectivity, energy consumption, Industrial Internet of Things, optimization, PSO, QPSO, route configuration, throughput.

I. INTRODUCTION

With the advent of technologies for the Internet of Things (IoT), machine-to-machine communication, and the related ecosystem, a new paradigm of Industrial IoT (IIoT) has recently emerged. As per Forbes [1], it is forecasted that by 2025, more than 75 billion IoT devices will be connected to the Internet, catering to the large number of applications, including industrial, environmental, medical, and others. The IIoT contains intelligent machines, robots, equipment, and tools with multiple IoT sensors to monitor and control the required parameters. The data received at the centralized controller or server is analyzed to enhance the efficiency of industrial systems [2]. The IIoT may also comprise anything related to industrial sectors such as factories, factory floors, warehouses, shipyards, locomotives, trailers, cargo planes, and similar. It can be deployed in diverse applications of

manufacturing, production, supply chain, quality assurance, predictive maintenance and control, optimization of resources, and others. The emerging fields of artificial intelligence, Big data, and Blockchain, there are huge prospects for IIoT deployments to achieve the emerging paradigms of Factory as a Service (FaaS), Machine as a Service (MaaS), Equipment as a Service (EaaS), and others. Cloud-based data processing, analytics, and storage may not have the scalability required for IIoT as a huge amount of sensor data can incorporate the latency and pose storing challenges. IIoT solutions also require energy efficient and resilient operations, enhanced connectivity, co-existence, interoperability, and data security. Hence in the recent past, the researchers have started working on hybridized data processing at local and cloud levels to reduce the network load. Edge and fog computing are used for

distributing the required information and intelligence to the different layers in the network.

Most of the sensing applications require wireless access to the Internet and connectivity to the cloud. IoT is dependent on diverse communication technologies, viz. Wi-Fi, ZigBee, Bluetooth, RFID, Cellular, LPWANs, 5G, and others. It is employed in distinct networks and layered structures where connectivity is the key issue. When these technologies are used in an integrated manner in industrial scenarios, connectivity between sensing devices and Internet servers, service reliability, and productivity improves. These multi-technology hybrid networks are particularly relevant for complex applications which require different IoT protocols [2].

The coordinator or gateway communicates the received data to the cloud via the core network. The network servers and related entities perform device management roles related to the registration, security, allocating the resources, traffic management [2]. Most of the existing approaches are considered for homogeneous network scenarios. However, some approaches based on heterogeneity have the challenges of energy efficiency, connectivity among the networks, and time criticality. One of the main objectives for heterogeneous sensor node distribution in the multilevel IIoT framework is to guarantee sensor nodes' connectivity in the supervised region over multiple hops with minimum delay and optimized energy consumption. Sensor nodes are considered at the lowest layer, whereas fog nodes and gateway are employed at the higher layer. Though the sensor nodes have the capabilities to communicate with their neighbors directly, they have to be furnished with more complex processors that are costly and uneconomical. Therefore, it is crucial to examine accessibility and connectivity for low complex sensor nodes for optimized and energy efficient network topology for IIoT applications.

In this work, a unique enhanced quantum particle swarm optimization (EQPSO) algorithm is designed for IIoT applications with enhanced connectivity, lesser delay, and energy consumption. The main objectives of our research are to combine the network topologies for exploitation and converge in the direction of optimal route configuration and maintain diversity during the collaboration of sensor nodes. We considered a multi-layered heterogeneous network structure for the IIoT environment. The framework includes low complex sensor nodes and fog nodes with comparatively robust computing and storage abilities. The novelty of our work is in employing multiple inputs from heterogeneous IIoT using a hybrid approach based on quantum and bio-inspired optimization techniques for optimal routing. It achieves energy efficiency, reliability, and scalability for wide-range IIoT systems. We used robust optimization techniques to interchanges the information efficiently for maintaining multi-network topologies and attains the best objective function for the chosen connecting paths. The differential evolution operator is used to avoid the group moving in small ranges and dropping into local optima, which improves global

searchability. We have also incorporated crossover operator with quantum particle swarm optimization. It promotes knowledge sharing among the individual particles of a group.

The structure of the papers is organized as: Section II covers the related work to the node deployment. Section III focuses on the QPSO, whereas Section IV presents the development of enhanced QPSO. Section V presents the framework for the proposed optimized IIoT deployment considering Quality of Service (QoS) parameters such as energy consumption, delay constraints, and throughput. Finally, section VI discusses results and performance evaluation, whereas the paper is concluded in Section VII.

II. RELATED WORK

The industrial IoT (IIoT) applications in different industries aim to enhance the functioning of processes by optimizing coverage, connectivity, energy efficiency, fault tolerance, and reliability issues in IIoT [3 - 7]. Chouikhi *et al.* [6] have analyzed fault tolerance approaches for the coverage and connectivity improvement based on the sleep schedule, relay node deployment, and node repositioning [7]. Meng *et al.* [8] have emphasized the key drawbacks of homogeneous communication between the nodes for IIoT and proposed a relationship technique to improve auto-configuration by concentrating on connectivity. Zero message quality-based communication into the industrial systems is proposed in [9] for different sensing applications. The approach improves the reliability, but it is not suitable for a wide range IIoT framework as the sensor nodes lying close to the gateway generally consume more energy and drains earlier or may face temporal death as they are involved in forwarding packets received from the large number of end nodes, and ultimately affect the network's lifetime. The temporal death model for energy harvesting of resources proposed in [10, 11] is based on a 3D stochastic method that uses the buffer queue and packet blocking probability to define the dynamic strategy of energy harvesting. Topology control is considered as a technique to progress and maintain connectivity [12]. Several topology control techniques are based on accessibility, accuracy [13, 14], number of devices [15], the influence of transmission range [16], duty cycle management [17], and clustering for data aggregation [18]. Ghorpade *et al.* [19] have proposed a topology control algorithm based on binary grey wolf optimization to produce the reduced topology by preserving network connectivity. It uses the active and inactive sensor nodes' schedule in binary format. In addition, it introduces a fitness function to minimize the number of active nodes for achieving the target of lifetime expansion of the nodes and network [19].

Fang *et al.* [20] presented an Integrated Information System (IIS) based IoT framework for environmental monitoring, categorized in the four layers: perception, network, middleware, and application. Yang *et al.* [21] proposed a direct and greedy search algorithm for deploying the minimum number of sensor nodes while ensuring

energy-efficient coverage and connectivity. A single-phase manifold initiator technique [22] has been offered for determining the link cover set to fulfill the coverage and connectivity necessities by calculating a connected set. However, both of the above approaches fall into local maxima due to their inherited greedy behavior. To avoid local maxima in greedy algorithms, a nature-inspired genetic algorithm [23] decreases the number of sensor nodes in a network sensor area with obstacles [24].

Various metaheuristic techniques have been proposed to find the optimal solution for coverage and connectivity issues in the IIoT framework [25]. To avoid early convergence of swarm, a concept of diversity is proposed in [26, 27]. Lower and upper bounds of the achievable region are set for ensuring the better search ability to get optimum solutions for real-time applications. The duty cycle approach is used for scheduling the smallest set of sensor nodes into active mode [28]. In addition to these, other approaches are based on localization [29], geometry [30], and hybridization of direct information methods [31] to solve k-connectivity issues in wireless sensor networks.

Rebai et al. [32] have proposed a combination of local search genetic algorithm to decrease the number of positioned sensor nodes that attain maximum coverage for a 2D sensing area and forms a connected network [33]. Li et al. [34] have developed quantum ant colony multiobjective routing for monitoring complex manufacturing environments by considering the nodes' energy consumption, transmission delay, and network load-balancing degree. A range-free localization algorithm based on quantum particle swarm optimization (QPSO) is proposed to estimate the distance among the nodes for the random and uniform deployment of nodes in heterogeneous wireless sensor networks [35].

However, most of the existing node deployment approaches are based on a basic disk coverage model, which is unrealistic for implementing in actual industrial environments. Moreover, in these approaches' spatial relationship of the supervised physical characteristics, sensor nodes' association, and network fault tolerance are ignored. As a result, they fail to attain the global requirements of optimization. Hence, there is a scope to improve the performance of the metaheuristic algorithms because of the slower convergence rate for optimal solutions. It can be achieved by altering and enhancing the exploration and exploitation abilities of the algorithms [36]. To address these issues, we propose an enhanced PSO (EQPSO) algorithm for IIoT based on quantum PSO, differential evolution operator and crossover operator.

III. QUANTUM PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) proposed by Kennedy et al. [37] is based on the concept of swarm social behavior, which results in a set of particles that spread into the search space. PSO starts with the initial swarm population called

particles which explore arbitrary position p_{lm} and velocity v_{lm} in m-dimensional hyperspace for the particle. Every particle is determined using an objective function $f(p_1, p_2, p_3, \dots, p_m)$ where $f: R^m \rightarrow R$, represents the number of sensors/particles exposed by other nearby sensors/particles. For position update, each sensor node will consider a certain number of other sensor nodes in its vicinity. PSO attempts to attain maximal coverage determined by the network connectivity [29]. PSO guides each particle for the position updates in the search space by considering some aspects of the global solution and best fitness locations with one of the whole members of the swarm. The position update process is continued until the desirable global best solution is attained or performed the fixed number of iterations [36].

To determine the next position in each iteration, velocity and positions are updated using (1) and (2), respectively.

$$V_{lm}^{t+1} = V_{lm}^t + a_1 b_1 (Pbest_{lm}^t - P_{lm}^t) + a_2 b_2 (gbest_{lm}^t - P_{lm}^t) \quad (1)$$

$$P_{lm}^{t+1} = P_{lm}^t + V_{lm}^{t+1} \quad (2)$$

$l = 1, 2, 3, \dots, N$; $m = 1, 2, 3, \dots, M$. l, m represents an index of the sensor. P_{lm}^t and V_{lm}^t are the m^{th} component of the position and velocity of the l^{th} sensor in t^{th} iteration. b_1 and b_2 are the random numbers such that $0 \leq b_1, b_2 \leq 1$. $Pbest_{lm}^t$ and $gbest_{lm}^t$ are the best and global best positions experienced by the l^{th} sensor and whole swarm topology [29]. a_1 and a_2 are confidence particles as in perception and community behavior. In the process of estimation sensor/particle will take the weighted average position, which is determined [36] as

$$W_{lm}^t = \frac{a_1(b_1)_{lm}^t Pbest_{lm}^t + a_2(b_2)_{lm}^t gbest_{lm}^t}{a_1(b_1)_{lm}^t + a_2(b_2)_{lm}^t}, 1 \leq m \leq M \quad (3)$$

PSO tends to be trapped into local optimization while solving complex multimodal problems. We have applied a swarm behavior into IIoT with the help of pervasive intelligence, smart devices, and other new approaches of merging computational improvements into swarm behavior. Subsequently, we will be benefited from establishing a complex setup on the IIoT. Nevertheless, there will be many questions that are to be answered. Will these steps be common for all the devices in multimodal data communication or regulate specific devices? Which form of swarm behavior turns out to be feasible on the extensive networks that are spread over a vast region? Will it activate an innovative phase of progression in an industrial area? Generally, there are numerous PSO techniques that go through the alterations in the velocity updating equations for getting a robust optimal solution. We have studied these alterations methods reported in the literature to identify the variation among the QPSO algorithms over the extensive connection between the swarm behavior and the technique of positioning sensor and fog nodes. Consequently, a network

progression can produce a technique of directing and handling the connectivity of devices during the iterative process.

To improve PSO, Sun *et al.* [38] have proposed quantum PSO (QPSO). It is assumed that the particle swarm system satisfies quantum mechanics' elementary proposition. Particle l moves in the δ probable well centered at the point W in m^{th} dimension with quantum basic actions characteristic [35], and its state can be described [36] as

$$\psi(P_{lm}^{t+1}) = \frac{1}{\sqrt{C_{lm}^t}} \exp\left(\frac{-|P_{lm}^{t+1} - W_{lm}^t|}{C_{lm}^t}\right) \quad (4)$$

where C is the characteristic length of the probable well δ , and its value is directly related to an algorithm's convergence speed and searching ability [40]. The probability density function of particle l is as given as

$$Q(P_{lm}^{t+1}) = \frac{1}{\sqrt{C_{lm}^t}} \exp\left(\frac{-2|P_{lm}^{t+1} - W_{lm}^t|}{C_{lm}^t}\right) \quad (5)$$

To obtain the particle's position, it has to be collapsed from the quantum to the classical state. The position of the particle is determined by

$$P_{lm}^{t+1} = W_{lm}^t \pm \frac{C_{lm}^t}{2} \ln \frac{1}{r_{lm}^t} \quad (6)$$

where W is the particle motion center and is called the attractor of the particle. r is a random number with a uniform distribution function ranging between 0 and 1. Parameter C is determined as

$$C_{lm}^t = 2\gamma \|L_m^t - P_{lm}^t\| \quad (7)$$

$$L_m^t = \frac{\sum_{l=1}^N P_{lm}^t}{N} \quad (8)$$

γ is the contraction and expansion factor, which is to be reduced while running an algorithm. $L^t = \{L_1^t, L_2^t, \dots, L_m^t\}$ is the mean optimal position, representing the mean value of the optimal position in the individual of all particles and the expression.

IV. ENHANCED QUANTUM PARTICLE SWARM OPTIMIZATION

In QPSO, every particle holds the weighted mean position obtained by considering the individual earlier optimal position and the optimal position of group history as its desirability point. This computation method has the advantage of simple calculations but holds the weighted mean position and has two drawbacks. Apart from its own learning experience, each particle's position depends on the group's optimal historical position. In addition to this, the possible dispersal space of each particle's attraction point progressively declines during an algorithm's development process [36]. It leads to swift decay in the diversity of huge groups, which reduces the algorithm's ability to solve

complex multiobjective optimization problems, ultimately leading to its ability to jump out of local optimization. Since the algorithm falls into the local optimum in its final stage, it indicates that the particle's individual and global optimum positions are almost adjacent to each other or maybe coincident [39].

Hence for improving the QPSO algorithm's performance, sufficient information about the individual and optimal global positions of the particles should be utilized by choosing an appropriate technique. To overcome this drawback, a differential evolution operator is incorporated into QPSO. A differential evolutionary algorithm proposed by Storn *et al.* [41] is based on population differences. It uses competition and cooperation among individuals to solve optimization problems. The proposed differential evolution operator improves the population diversity and jumps out of the local optimum. Enhanced QPSO algorithm aims to improve control of exploring and exploiting hunts by considering adjacent relationships between the particles by a linear increase in the connectivity of the swarm's topology and carrying out regulating mechanisms [36].

Position update in QPSO is performed by using

$$W_{lm}^t = \chi P_{best_{lm}}^t + (1 - \chi) g_{best_{lm}}^t \quad (9)$$

$$AV_{best_{lm}} = \frac{1}{N} \sum_{l=1}^N P_{best_{lm}}^t \quad (10)$$

$$P_{lm}^{t+1} = W_{lm}^t \pm \gamma |AV_{best_{lm}} - P_{lm}^t| \ln\left(\frac{1}{r_{lm}^t}\right) \quad (11)$$

χ is a random number lying between (0, 1), W_{lm}^t is the random position between P_{best} and g_{best} . By combining (3) and (5), the position evolution equation changes to

$$P_{lm}^{t+1} = \chi(P_{best_{lm}}^t - g_{best_{lm}}^t) + g_{best_{lm}}^t \pm \gamma |AV_{best_{lm}} - P_{lm}^t| \ln\left(\frac{1}{r_{lm}^t}\right) \quad (12)$$

Let a and b be the particles in the existing swarm distinct from l , then the differential evolution operator (position difference between them) is

$$\emptyset = P_b - P_a \quad (13)$$

Substitute \emptyset to replace $P_{best_{lm}}^t - g_{best_{lm}}^t$ of (12) and randomness can be increased by adding a random number $(1 - \chi)$ to the second term $g_{best_{lm}}^t$ of (12). The new evolution equation [36] is

$$P_{lm}^{t+1} = \chi\phi_m + (1 - \chi)g_{best_{lm}}^t \pm \gamma |AV_{best_{lm}} - P_{lm}^t| \ln\left(\frac{1}{r_{lm}^t}\right) \quad (14)$$

Differential evolution operator introduced in (14) helps avoid the group moves in a small range and fall into local optima, which is favorable in improving the ability of global search. In the next phase, we have introduced a crossover

operator with QPSO. These cross operations will promote the information interchange among individuals in a group, and those exceptional genes can be continued moderately, accompanying the continuance of the evolutionary process. Ultimately groups can progress in the desired route. The position estimate P_l^{t+1} of particle l is generated by using (3), (7), (8), and (14). Later, the estimated position P_l^{t+1} and individual optimal position $Pbest_l^t$ are separated for the generation of the test position $Y_l^m = \{y_{l1}^t, y_{l2}^t, \dots, y_{lm}^t\}$, the cross equation is written as

$$Y_{lm}^{t+1} = \begin{cases} P_{lm}^{t+1}, & (rand)_m < c, m = m_{rand} \\ Pbest_{lm}^t, & Otherwise \end{cases} \quad (15)$$

where $(rand)_m$ is a random number satisfying uniform distribution such that $(rand)_m \in [0,1]$ and c is the crossover probability. m_{rand} is randomly and uniformly generated integer on $[1, M]$. Lastly, the optimal position of the particle's individual history is updated as

$$Pbest_{lm}^{t+1} = \begin{cases} Y_{lm}^{t+1}, & f(Y_{lm}^{t+1}) < f(Pbest_{lm}^t) \\ Pbest_{lm}^t, & Otherwise \end{cases} \quad (16)$$

where $f(*)$ is a compatible cost function. The value of crossover probability plays an important role in an algorithm's searchability and convergence speed. Smaller probability values enable individuals in a group to hold further their individual information and preserve a higher diversity of the group, which is suitable for the global exploration of an algorithm. On the contrary, the larger value of the probability impules individuals to acquire additional experimental information in the group, consequently accelerating an algorithm's convergence speed [36].

By considering the crucial role of crossover probability c , it is directly encoded into each particle to achieve adaptive control. After extended encoding, particle l in the population is defined

$$P_l^t = \{p_{l1}^t, p_{l2}^t, \dots, p_{lm}^t, c_l^t\} \quad (17)$$

Crossover probability for every particle in the population is updated as

$$c_l^{t+1} = \begin{cases} rand_m(0, 1), & rand_m(0, 1) < \alpha \\ c_l^t, & Otherwise \end{cases} \quad (18)$$

α is the update probability of parameter c . For ease of operations, we have introduced an additional binary vector B_l^{t+1} for every particle l .

$$B_l^{t+1} = \{b_{l1}^{t+1}, b_{l2}^{t+1}, \dots, b_{lm}^{t+1}\} \quad (19)$$

$$b_{lm}^{t+1} = \begin{cases} 1, & rand_m(0, 1) < c_l^{t+1}, m = m_{rand} \\ 0, & Otherwise \end{cases} \quad (20)$$

$$Z_l^{t+1} = \frac{1}{M} \sum_{l=1}^M b_{lm}^{t+1} \quad (21)$$

FIGURE 1. Process flow of Enhanced QPSO

By ignoring the influence of m_{rand} , Z_l^{t+1} follows the binomial distribution with M parameters and probability c_l^{t+1} . The probability c_l^{t+1} is calculated by

$$c_l^{t+1} = \begin{cases} B_l^t Z_l^{t+1} + (1 - B_l^t) c_l^t, & f(Z_l^{t+1}) < f(c_l^t) \\ c_l^t, & Otherwise \end{cases} \quad (22)$$

B_l^t is a random number satisfying uniform distribution with $0.9 \leq B_l^t \leq 1$. In addition to this, reduction-extension coefficient γ is structured so that; with the increase in the number of iterations, γ decreases linearly.

$$\gamma = \gamma_{max} - \frac{t}{T} * (\gamma_{max} - \gamma_{min}) \quad (23)$$

T is the maximum number of iterations to be attained [36]. The systematic moves are defined to guarantee connectivity with interparticle communication for the satisfying data exchange among the sensor nodes for distinct topologies. Velocity update means the best sensor node location of the restricted neighborhood to determine the adjacency with another sensor node neighborhood rather than the whole swarm topology [29]. Hence, swarm network topology in PSO can exceptionally regulate the performance of the algorithm. Moreover, the proposed enhanced quantum PSO (EQPSO) utilizes the entirely linked topology in which all the sensor nodes are neighbors. It helps the sensor node to link directly to a global best sensor node and influences it concurrently.

Consequently, the swarm topology in EQPSO avoids exploring additional regions of the search space and trap into local optimum solutions. In the meantime, a sensor node of QPSO utilizes the information received from all other sensor nodes adjacent to it rather than that of the best one only. This alteration improves the performance of QPSO bilaterally, i.e., by assisting the sensor node to obtain information about promising areas of search space and prohibiting the error in sensors participating in the swarm's movement so that algorithm's exploration abilities are enhanced. The novel EQPSO algorithm improves the control of exploring and exploiting hunts in the completely connected network topology to get an optimal solution for IIoT. The process flow and pseudocode of the proposed algorithm is as shown in Fig. 1 and Fig. 2, respectively.

V. FRAMEWORK FOR IIOT DEPLOYMENT

Generally, an IIoT contains a network of several wireless devices and technologies positioned in a wide area, making it heterogeneous. We have considered a scenario in which sensor nodes and fog nodes are deployed in IIoT with fault-tolerant network topology in a heterogeneous layer framework [42]. This framework comprises three layers; the

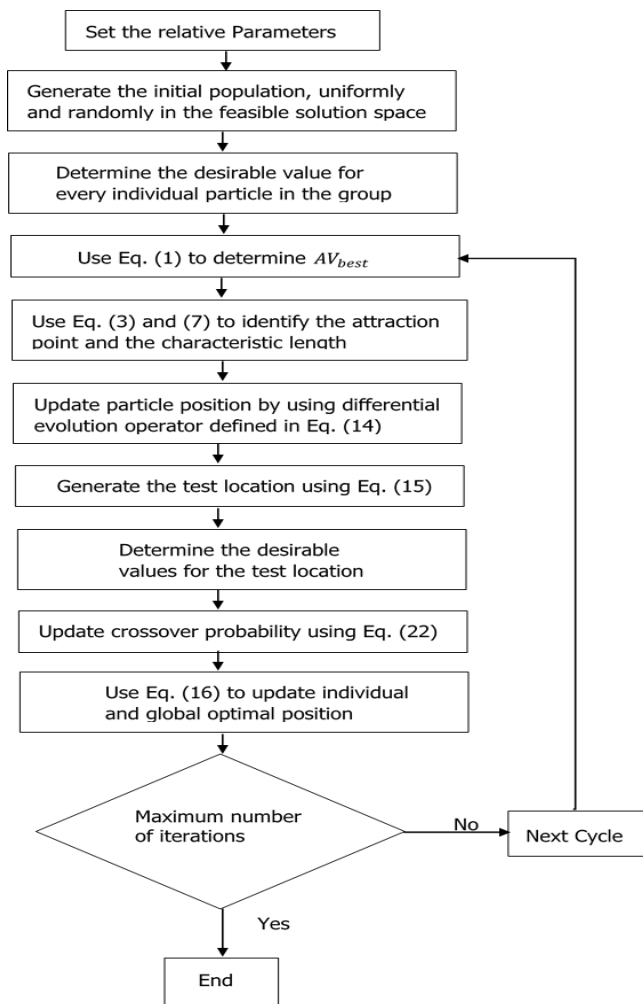


FIGURE 1. Process Flow of EDQPSO

cloud back-end, the middle layer for fog nodes, and the last layer for sensor nodes, as shown in Fig. 3.

The middle layer contains few resource-rich fog nodes. The sensor nodes are inhibited by limited battery capacity and ceaseless QoS constraints. Every sensor node can change its transmission range by varying its power level inside the network topology regulated by conclusive or non-conclusive workload to communicate or receive a message [29]. We try to find a solution that curtails power consumption while preserving network connectivity and delay requirements. Actually, the transmission cost of a message between sensor nodes depends on the distance among them but is independent of the number of receiving sensor nodes. In a multi-hop network, connectivity can be maintained without every sensor transmitting at its maximum power. Most of the approaches reported in the literature have performed worse in some cases. We have identified the challenges in different IIoT setups and tried to address them while ensuring network coverage consistency by adopting the network topology control. It has also been observed that the appropriate

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Set  $t = 0$ , initialize current position  $P_i^0$  of every node in the swarm, and assemble  $c_i^0 = P_i^0$ . Also, set other relevant parameters.
do
 $\gamma$  decreases linearly from 1.5 to 0.5
for  $m = 1$  to  $M$ 
    if  $\chi < rand(0, 1)$ , then
        then determine  $AV_{best_m}$  using (10)
    end if
Generate the characteristic length and attraction point using (3) and (7) resp.
for  $l \neq a, l \neq b$ 
     $\phi = P_b - P_a$ 
end for
for  $l = 1$  to  $N$ 
Generate test location  $Y_{lm}^{t+1}$  using (15)
Update crossover probability  $c$  using (22)
    If  $f(Y_{lm}^{t+1}) < f(P_{best_{lm}}^t)$ , then
         $P_{best_{lm}}^{t+1} = Y_{lm}^{t+1}$ 
    else
         $P_{best_{lm}}^{t+1} = P_{best_{lm}}^t$ 
    end if
end for
Update individual global and optimal positions using (10)
end for
until the maximum number of iterations attained
    
```

positioning of sensor nodes is critical in most IIoT systems and influences network coverage. The existing techniques

FIGURE 2. Pseudocode for Enhanced QPSO

assume that the specified sensor node's sensing range and transmission range are the same. However, it is not applicable in wide range IIoT setups because some of the sensor nodes have extended routing capabilities, but they communicate through a short distance. Therefore, adopting static routing for IIoT is more feasible to achieve an energy-efficient, reliable and scalable network.

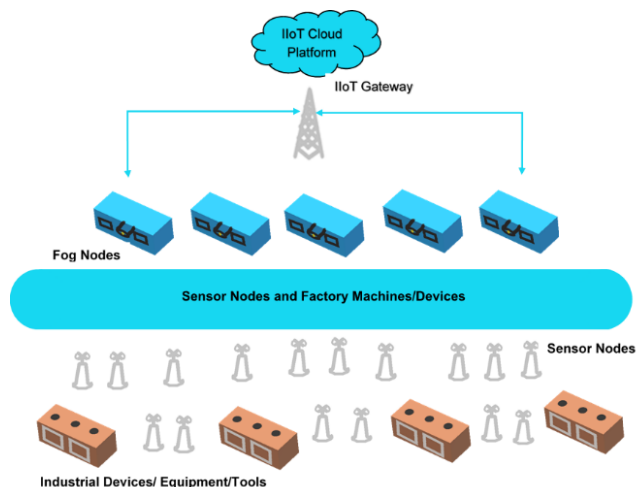


FIGURE 3. Industrial Internet of Things architecture

We propose EQPSO to solve the IIoT deployment problem with distinct considerations for the framework [42] by centralized and distributed routing for the different network topologies. Centralized routing is appropriate for the networks in which the processing control trusts mostly on a single device, which is accountable for the processing, coordinating, and managing the identified activities. It

allows roaming inside the network, deals with energy management and context information availability. Furthermore, it permits an improved application design in terms of nodes placement, application awareness, etc. In distributed routing, the information is managed by every node, and decisions are locally taken. The main features of distributed routing are: autonomous devices can be included, every node shares information to its adjacent node, and it is fit for distributed applications such as multiagent systems and self-organized systems.

The establishment of p -disjoint paths for attaining connectivity degrees greater than three and complete coverage for sensor deployment is a crucial challenge due to smaller battery capacities. Furthermore, we have considered a default wireless network in which fog nodes and sensor nodes can guarantee the desired connectivity degree through many to one traffic patterns. Moreover, there is a need for frequent information interchange about the route to avoid a sudden rise in traffic and excessive energy consumption.

Our model is the directed graph that uses the concept of disjoint node paths and p -connected networks. Paths are said to be node disjoint if they do not have any common node, and the sensor network is said to be p -connected if every interior node of its graphical structure is connected with at least p -node disjoint paths. Node disjoint paths are modeled in graph $G(P, Q)$ in two-dimensional space. P is the set of sensor nodes and fog nodes, whereas links between them are included in set Q . $V \subseteq A$ represents a set of sensor nodes, and $W \subseteq B$ represents fog nodes. Every link in Q is assigned with a non-negative number which QoS parameters among the sensor nodes. a_u and a_v are two sensor nodes connected with Euclidian distance $d_{u,v}^p$. All the sensor nodes are supposed to be alike with power transmission range τ_R and sensing range τ_S ($\tau_R \geq \tau_S$). Every sensor node identifies neighbors by sending messages periodically and gathering information about its adjacent nodes' energy consumption, distance, total latency, and throughput. $Hop(a_u, a_v)$ describes distance among sensor nodes a_u and a_v . $Q = \{(a_u, a_v) | Hop(a_u, a_v) \leq \tau_R\}$, represents the set of all edges among the nodes a_u and a_v with distance between them less than or equal to the transmission range. $p_a(a_u, a_v)$ is path from node a_u to a_v , which is an alternating sequence of nodes and links between them. Set of alternative paths is $P(a_u, a_v) = \{p_a(a_u, a_v) \in P | \forall p_a(a_u, a_v) \in P, Hop(a_u, a_v) \leq \tau_R, u \neq v = 1, 2, \dots, V + W\}$. $Q(a_u, a_v \in p_a(a_u, a_v))$ represents node disjoint paths among $(p_a(a_u, a_v), (a_v, a_{v+W}))$ and $(e \in p_a(a_u, a_v), (a_v, a_{v+W}))$ represents direct link among two nodes. The communication rule for such direct links among the nodes is described as below:

- i. For any $a_u, a_v \in V \subseteq A$, even if $d_{u,v}^p < \tau_R$, then a_u and a_v cannot communicate with each other.
- ii. For any $a_u \in W \subseteq B$ and $a_v \in V \subseteq A$, even if $d_{u,v}^p \geq \tau_R$, then a_u and a_v can communicate with each other.

In this way, p -disjoint paths in graph G and the objective function can be determined by considering QoS parameters. The p -disjoint paths are used to communicate the information collected by sensor nodes to the fog nodes.

Network connectivity directly influences energy efficiency. Hence, defining the relationship between the number of sensor nodes that remain dynamic and linked while maintaining desirable QoS is essential. As a result, we emphasize p -vertex fog node connectivity for obtaining fault-tolerant network topologies as a transmission range assignment in which every sensor node is connected with at least one fog node by p -disjoint paths. In these situations, an objective function's main aim is to save energy attained by curtailing transmission power and delay. To get an optimum communication path, an objective function is applied to the distributed sensor nodes having p -disjoint paths among them and fog nodes.

A. MODELING QUALITY OF SERVICE FOR IIOT

The QoS optimization for IIoT in terms of energy, delay, and throughput is planned. To get an optimal distribution scenario with the minimal number of sensor and fog nodes, it needs to define the distribution pattern. The neighboring correlation between sensor and fog nodes is considered a constraint. The set of disjoint sensors and another neighborhood of the p -disjoint path is $D_{u,v}$.

$$D_{u,v} = \{u, v \neq u | \|a_u - a_v\| \leq T_{P_{a(u,v)}}\} \quad (24)$$

$T_{P_{a(u,v)}}$ is the sensor transmit power for one hop. Conditional adjacency matrix M of graph $G(P, Q)$ guarantees connections among two nodes,

$$M = \begin{bmatrix} m_{11} & m_{12} & \dots & m_{1|P|} \\ m_{21} & m_{22} & \dots & m_{2|P|} \\ \vdots & \vdots & & \vdots \\ m_{|P|1} & m_{|P|1} & \dots & m_{|P||P|} \end{bmatrix} \quad (25)$$

$$m_{uv} = \begin{cases} 1, & \text{if } a(u, v) \in D_{u,v} \\ 0, & \text{Otherwise} \end{cases} \quad (26)$$

The connectivity feature, the intermediary distance among two sensor nodes along the chosen path, and the number of hops is the constraints considered for addressing the topology specifications. If $d_{u,v}^p \leq T_{P_{a(u,v)}}$, then the binary connectivity constraint defined in (26) identifies whether the sensor lies within its transmission range or not. For a new association to be included in directed graph $G(P, Q)$, (26) can be rewritten as,

$$m_{uv} = \begin{cases} 1, & \text{if } \{u, v \neq u | \|a_u - a_v\| \leq T_{P_{a(u,v)}}\} \in D_{u,v} \subseteq A \cup B \\ 0, & \text{Otherwise} \end{cases} \quad (27)$$

a) Energy Consumption:

The IIoT energy consumption model is dependent on dissipation and gain during communication. During the processing and sensing, power dissipation should be less

than data transmission or reception. Every sensor will have a transmission range for communicating with adjacent nodes. By exploiting the closest neighborhood, the subsequent hop will be chosen by each sensor node. Energy consumption per bit is calculated as

$$E_{a_{sd}} = \sum_{u,v \in V \cup W}^{B \cup A} \left(E_{P_{aV \cup W}}^t + \beta_0 T_{P_{a(u,v)}}^\phi + E_{P_{aV \cup W}}^r \right) S_p \quad (28)$$

where $E_{P_{aV \cup W}}^t$ is the energy used by the transmitter, $E_{P_{aV \cup W}}^r$ is the energy utilized by the receiver, $T_{P_{a(u,v)}}$ is the transmission range, β_0 is the multipath model of transmit amplifier of the sensor, and S_p is the set of paths. ϕ is the energy drop due to the loss in the path, assuming that the network link is obstacle-free.

The rate of data transfer in unit time from the sensor node a_u to a_v is the same as that of a_v to a_u , which is represented by G_{uv} . Hence, the overall consumption of energy in transmitting and receiving per time unit is calculated by

$$E_{a_u} = \sum_{v \in A} m_{uv} G_{uv} \left(E_{P_{aV \cup W \subset B \cup A}}^t + \beta_0 T_{P_{a(u,v)}}^\phi \right) \quad (29)$$

$$E_{a_v} = \sum_{u \in B \cup A} m_{uv} G_{uv} \left(E_{P_{aV \cup W \subset B \cup A}}^r \right) \quad (30)$$

Hence the total energy consumption from source to destination is

$$E_{a_{sd}} = \sum_{u,v \in B \cup A} m_{uv} G_{uv} \left(2 \left[E_{P_{aV \cup W}} + \beta_r T_{P_{(u,v)}}^\phi \right] \right) \quad (31)$$

where β_r is the multipath model of the response amplifier of the sensor node. We have considered communication of the sensed data between the set of sensors belonging to the p -disjoint path, which can fluctuate through communication. If the constraints are not fulfilled, it may disconnect adjacent nodes and separate paths.

To guarantee the optimal number of hops between the p -disjoint paths, we have considered one more parameter called as intervening gap among two sensors along the chosen path. It plays a crucial role in the design and performance of the IIoT network. The intervening gap among two sensors along the chosen path is given by

$$Hop = \sqrt{\phi d_{a(u,v)} \left[\frac{3\beta_r}{2E_{P_{a(u,v)}}} \right]} \leq T_{P_{u,v}} \quad (32)$$

The constraint defined in (32) is a crucial configuration and performance parameter in IIoT, which makes sure that the optimum number of hops between the chosen p -disjoint paths can be attained. The intervening gap among two sensor nodes and hop count are directly associated with each other.

Theoretical hop count for the chosen p -disjoint paths is,

$$No. \text{ of Hops} = \frac{\text{Total distance}}{\psi^{opt}} \quad (33)$$

$$\psi^{opt} = \sqrt{\phi d_{a(u,v)} \left[\frac{3\beta_r}{2E_{P_{a(u,v)}}} \right]} \quad (34)$$

In the dynamic environment, the degree of network connectivity varies subject to changes in the topology. The parameter designed in (33) and (34) describes dynamic objective functions with reference to lower and upper limits for preferred solution space to decide the optimal pattern of sensor positioning in the target region. With the evolution in the optimization process, the established topology's connectivity degree is varied for reducing energy consumption.

b) Delay Constraint

Delay can be classified into distinct types, viz. queuing, prorogation, processing, transmission, retransmission, and idle. The delay in delivery among two sensor nodes is represented as $\nabla(a_u, a_v)$. The average value of delay is calculated as

$$\nabla = \nabla_{que} + \nabla_{prop} + \nabla_{proc} + \nabla_{trans} + \nabla_{retrans} + \nabla_{idle} \quad (35)$$

The optimal number of forwarding hops is determined using (33) and (34) targets to decrease the desired transmission delay. This means that the sensor nodes may receive the data through the many hops, but it collects and transmits the data only once. Then the number of hops and delays are optimized cooperatively. Every sensor node in the network periodically computes the delay from one-hop neighbors. When the overall QoS necessities are fulfilled at each hop, the entire QoS controlled by the devices are attained [40]. The proposed technique uniformly splits the bounded delay ∇_{bd} at every hop as defined in (36).

$$\nabla(a_u, a_v) = \nabla_{sd}(S_p) \{a_u, a_v | \forall a = D_{u,v} = a_u, a_v \in V \cup W \subseteq B \cup A\} \quad (36)$$

Overall delay due to data transfer from the source to a destination over the set of path S_p is defined as

$$\nabla_{sd}(S_p) = \sum_{a_u, a_v \in V \cup W \subseteq B \cup A} \nabla(a_u, a_v) \quad (37)$$

Since the delay $\nabla(a_u, a_v)$ is the time needed to effectively communicate data once the initial sensor gets it, accordingly,

$$\sum_{a_u=1, a_v=1}^{V \cup W} \nabla(a_u, a_v) \leq \nabla_{bd} \quad (38)$$

The bounded delay ∇_{bd} depends on the number of hops taken and delay of sensor node, which are additive and denoted by ψ and ∇^a , respectively. Hence,

$$\nabla_{bd} = \nabla_0^s + \nabla_{\psi_1}^{a+1} + \nabla_{\psi_2}^{a+2} + \dots + \nabla_{\psi_{V+W}}^d \quad (39)$$

Per hop delay from source to destination is

$$S_a^\nabla = \frac{\nabla_{bd} - \nabla^a}{\psi_u} \quad (40)$$

Then the constraint in (39) is defined as

$$\sum_{a_u=1, a_v=1}^{V \cup W} \nabla(a_u, a_v) \leq S_a^\nabla \quad (41)$$

c) Throughput

Throughput is the whole quantity of successfully communicated data packets along with the optimum number of hops.

$$\text{Throughput} = \left[\frac{V_{trans}}{a} \right] G_{\forall u, v \in V \cup W} \quad (42)$$

B. Enhanced QPSO for IIoT Deployment:

The population of swarm topology in positioning sensor nodes and fog nodes is represented by employing complex network connectivity to have better performance. The routing technique is propelled to interchange complex computations on each sensor node and report the objective function that minimizes the energy consumption and delay. Accordingly, making an appropriate choice, the sensor node's relativity degree increases or decreases with identical sensor node help.

Optimized IIoT connectivity deployment model aims at minimization in energy consumption \vec{F} and delay $\nabla(S_p)$ while transmitting a data packet of length G_{uv} bits with the objective function defined as

$$\min \left[\sum_{a_u, v \in V \cup W} \vec{F} \right] \quad (43)$$

$$\min \left[\sum_{a_u, v \in V \cup W} \nabla(S_p) \right] \quad (44)$$

$$\text{Subject to, } E_{asd}, \quad \forall u, v \in B \cup A \quad (45)$$

$$\phi \sqrt{d_{a(u,v)} \left[\frac{3\beta_r}{2E_{P_{a(u,v)}}} \right]} \leq T_{P_{u,v}} \quad (46)$$

$$\sum_{a_u=1, a_v=1}^{V \cup W} \nabla(a_u, a_v) \leq S_a^\nabla \quad (47)$$

$$d_{a(u,v)} \leq T_{P_{u,v}} \leq m_{uv} E_{auv} \leq E_{asdmax} \quad \forall u, v \in V \cup W \quad (48)$$

E_{auv} represents energy utilized by sensor node a_u to link with its adjacent sensor node a_v . It is assumed that the p -distance path algorithm allocates the transmission range to every sensor node by considering the hop distance calculated by (32) for every neighbor; it helps to take advantage of the diversity of swarm topology.

Due to the differential evolution operator used, every swarm contributes to the process of optimization. It can improve the convergence rate of hunt space by producing and grouping new subswarms to help in escaping from local optima and aiming for the global solution.

In addition, every sensor can enhance collective learning behavior by interchanging the information to the neighbors. After requesting the information interchange, every sensor calculates the disjoint paths and updates local path data. As a result, new promising paths are created corresponding to objective functions defined in (43) and (44).

The process for generation of subswarm from the complete set of sensor nodes by perceiving the objective function with respect to the communication cost is also discussed. If the sensor node is linked with the neighboring node, it is merged into a new subswarm. Later, every subswarm individualistically upgrades its velocity.

After initializing each swarm of the sensor nodes, it is identified by the next adjacent sensor node. Every sensor gets linked with the other sensor created in the new subswarm. These operations are continued until the network topology is created. It leads to the initialization of velocity and position for every sensor node, and then every sensor estimates the objective function. While estimating the objective function, the sensors have connectivity during each iteration.

Individual information interchange influences these sensors. The personal and global evaluated position allows the sensors to choose the next hop towards the ultimate evaluated position within the search domain's scope in every iteration.

As a result, the sensor diverts from the constraint field and rarely converges to the constraint field's ultimate evaluated position. The influence of objective function \vec{F} on the personal best and global best positions is represented by the particle-wise multiobjective matrix-vector multiplication by using the symbol $*$. The position update is defined as

$$P_{lm}^{t+1} = \chi \vec{F} * \phi_m + \vec{F} * (1 - \chi) gbest_m^t \pm \gamma \vec{F} * |AVbest_m - P_{lm}^t| \ln \left(\frac{1}{r_{lm}^t} \right) \quad (49)$$

Each sensor node benefits from cross operations introduced into EQPSO, and it takes advantage of information interchange to avoid trapping into local minima.

The efficiency of EQPSO is determined by the number of steps required to an optimal region $O(R)$. The process assesses the distribution of the number of steps required to attain $O(R)$ by correlating the expected value and the moments of the distribution. The total number of steps required to reach the optimal region is calculated as $S(R) = \inf\{x/g_x \in O(R)\}$. The variance $V[S(R)]$ and expected value $E[S(R)]$ are determined by using

$$E[S(R)] = \sum_{x=0}^{\infty} x k_x \quad (50)$$

$$V[S(R)] = \sum_{x=0}^{\infty} x^2 k_x - \left(\sum_{x=0}^{\infty} x k_x \right)^2 \quad (51)$$

Actually, $E[S(R)]$ is dependent on the convergence of $\sum_{x=0}^{\infty} xk_x$. EQPSO converges globally if $\sum_{l=0}^{\infty} xk_x = 1$. The time is measured by using the number of evaluations of the objective function. The key advantage of this technique is that it demonstrates correspondence among the processor and computation time with the increase in complexity of the objective function. Time complexity is computed by combining Range function $R_f(x) = x^t x$ and a linear parameter $L(x) = \sum_{m=0}^M x_m \geq 0$ for N particles.

VI. RESULTS AND PERFORMANCE EVALUATION

We have carried out simulations to generate network topology and design the objective functions to test and analyze the proposed algorithm's performance. The performance of the proposed algorithm is evaluated and compared with other quantum-based algorithms such as Quantum Ant Colony Optimization (QACO) [34] and Quantum Particle Swarm Optimization (QPSO) [35]. We implemented these algorithms in MATLAB to obtain their results with the same settings for comparison as we used for our results. The parameter settings are given in Table I.

TABLE I
PARAMETER SETTINGS

Algorithm	Other Parameters
QACO [33]	$\delta \neq 0, \omega = 0.01, \beta = [0.001, 0.01, 0.1]$
QPSO [34]	$\gamma \in [0.7, 0.8], r \in [0, 1]$
EQPSO	$B_l^i \in [0, 1], \chi \in (0, 1)$

Several sensor nodes and fog nodes are uniformly distributed over a 2D area of $2000\text{ m} \times 2000\text{ m}$ and produced homogeneous and heterogeneous connectivity among the sensor nodes. Furthermore, sensors are placed at a distance $\sqrt{2}\tau_s$ without overlapping and with or without holes by using deterministic deployment, as shown in Fig. 4.

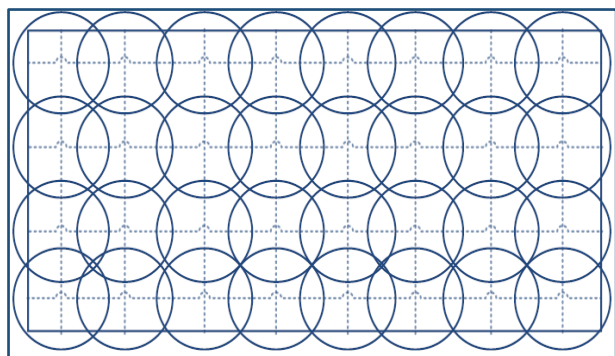


FIGURE 4. IIoT node deployment scenario

Diverse scenarios of topologies are simulated to study the impact of p -degrees of connectivity concerning the number of evaluations of objective functions with reference to energy consumption, delay, and throughput. It is assumed that energy consumed by every sensor node for transmitting

or receiving data packets is 40 nJ/bit , in the meantime transmitter utilizes an additional 90 pJ/bit . The transmission range fluctuates between 10 m to 40 m , the proportion of transmission range and sensing range fluctuates between $0:4$ to $1:9$ to assure the connectivity between the sensor nodes and fog nodes while satisfying the constraints of the algorithm. The details of the simulation metrics are as given in Table II.

The impact of applying swarm techniques on heterogeneous multi-tiered layered IIoT topology is illustrated in Fig. 4. A particle's connectivity increases since the quantum swarm allow a sensor node to choose a new neighborhood. It occurs throughout the exploration procedure to retain the trace of every particle's searching ability, and then suitable alterations are made on the connectivity of particle. Adding new sensor nodes to the network leads to increased hops that are essential to describe an event. EQPSO algorithm tries to find the optimal number of hops to minimize energy consumption and delay. EQPSO updates position twice per iteration.

TABLE II
SIMULATION METRIC

Metric	Notation	Specification
Number of nodes	N	100
Rectangular area		$2000\text{ m} \times 2000\text{ m}$
Initial Transmission Range	τ_R	12 m
Energy consumed	$E_{a,s,d}$	40 nJ/bit
Transmission amplifier energy	β_{fs}	8 pJ/bit/m^2
Amplifier energy	β_r	0.0011 pJ/bit/m^2
Message payload		64 bytes
Data length	p	2000 bits
Transmitted data rate	T_x	275 kbps

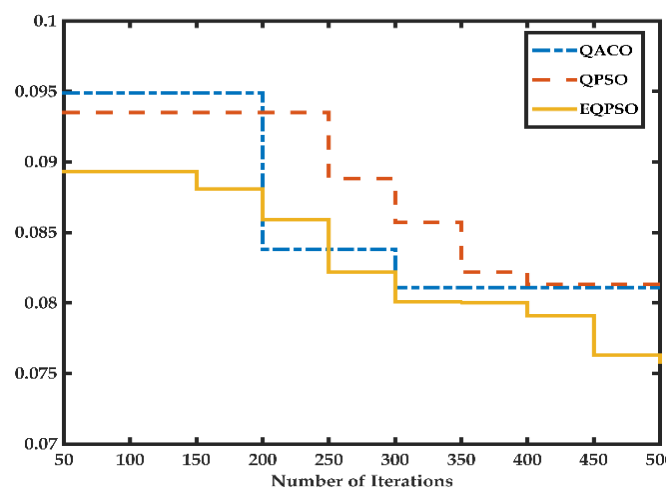


FIGURE 5 (a). Energy consumption for 100 sensor node

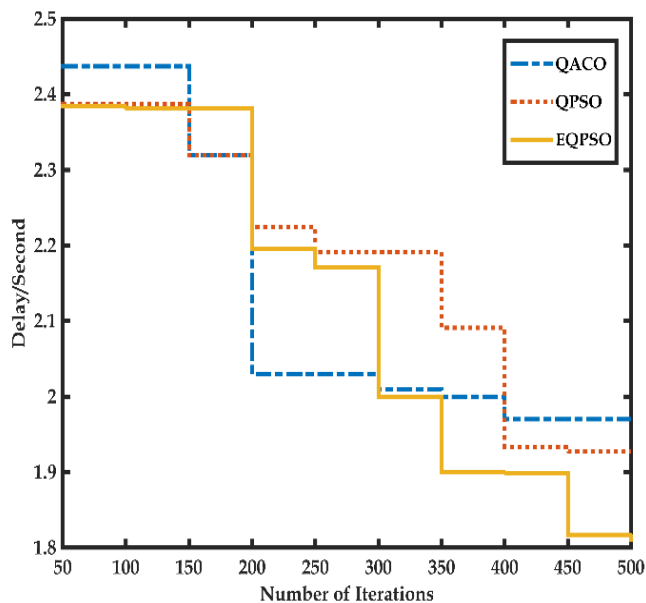


FIGURE 5(b). Average delay for 100 sensor nodes

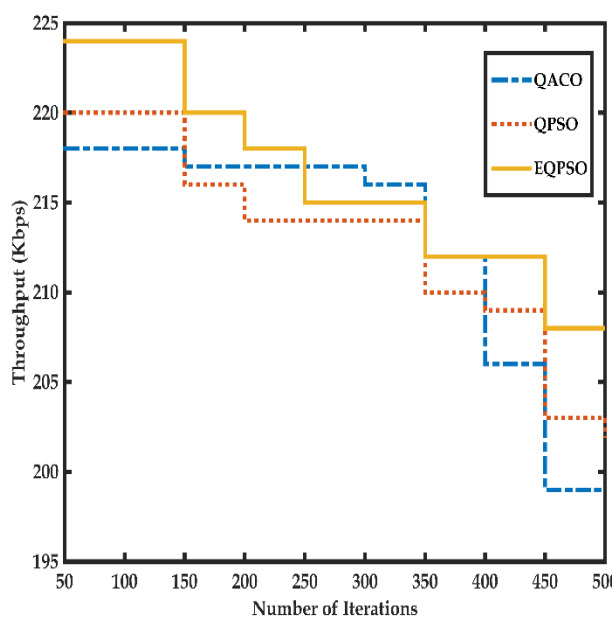


FIGURE 5(c). Throughput with 100 sensor nodes

It can be noticed that with the increase in the number of iterations, energy consumption decreases. Figure 5 (a) shows that the proposed algorithm consumes less energy than QPSO and QACO, as its objective function is to locate p -disjoint paths while recovering from the fault-tolerance error messages due to the big size of the search space. We have also analyzed the influence of the number of hops and the interchange of messages for fault tolerance among sensor

nodes and fog nodes. QPSO searches for p -disjoint paths within its accessible neighborhoods based on communication history. On the contrary, QACO and EQPSO searches paths directly within its accessible neighborhoods.

This new swarm reinforces the optimal number of p -disjoint paths to achieve lesser energy consumption. The results show that the proposed algorithm consumes around 47.1% and 30.3% lesser energy than QPSO and QACO, respectively. From Fig. 5 (b), it can be noticed that the average delay of packet transmission along the chosen p -disjoint paths by the proposed algorithm is lesser than QACO and QPSO. However, QACO performs better for fewer iterations and degrades performance with an increasing number of iterations.

Although the number of sensor nodes and fog nodes are constant, the number of hops decreases with the increase in the transmission range. The number of nodes chosen by EQPSO inside the subswarm is lesser than the total number of sensor nodes and variables. It qualifies sensor node in terms of further choice of p -disjoint path that satisfies the hop availability condition. This helps the sensor node to improve the connectivity, which ultimately helps EQPSO to interchange fewer control messages for topology maintenance than QACO and QPSO. Hence, EQPSO offers improved searching precision and convergence swiftness in the possible search space for p -disjoint paths than QACO and QPSO.

The impact of a number of hops on the objective functions defined in (43) and (44) is presented in Fig. 5(c) in terms of throughput. For QACO and QPSO, minimizing delay at the cost of increased hops leads to a proportionate increase in the number of sensor nodes and fog nodes, resulting in reduced throughput.

EQPSO can solve network connectivity issues to attain optimal solutions with fewer fitness function estimations due to its feature of creating new subswarms and utilizing them to form a group with the new particle in the search space. As a result, new paths are created to improve the proposed algorithm's ability to escape from local optima to improved network connectivity.

We have also investigated another scenario that needs instruction from multiple resources after particular intervals. Our algorithm generates results for all links among the sensor nodes and fog nodes positioned while executing QACO, QPSO, and EQPSO. Metric considered for generating the IIoT framework's topologies is an information exchange for fault tolerance among sensor nodes and fog nodes. The simulations for optimizing energy usage, delay, and throughput for p -connectivity values equal to 3, 4 and 5 with respect to the number of evaluations are carried out. Results for all three algorithms are shown in Figs. 6, 7, and 8.

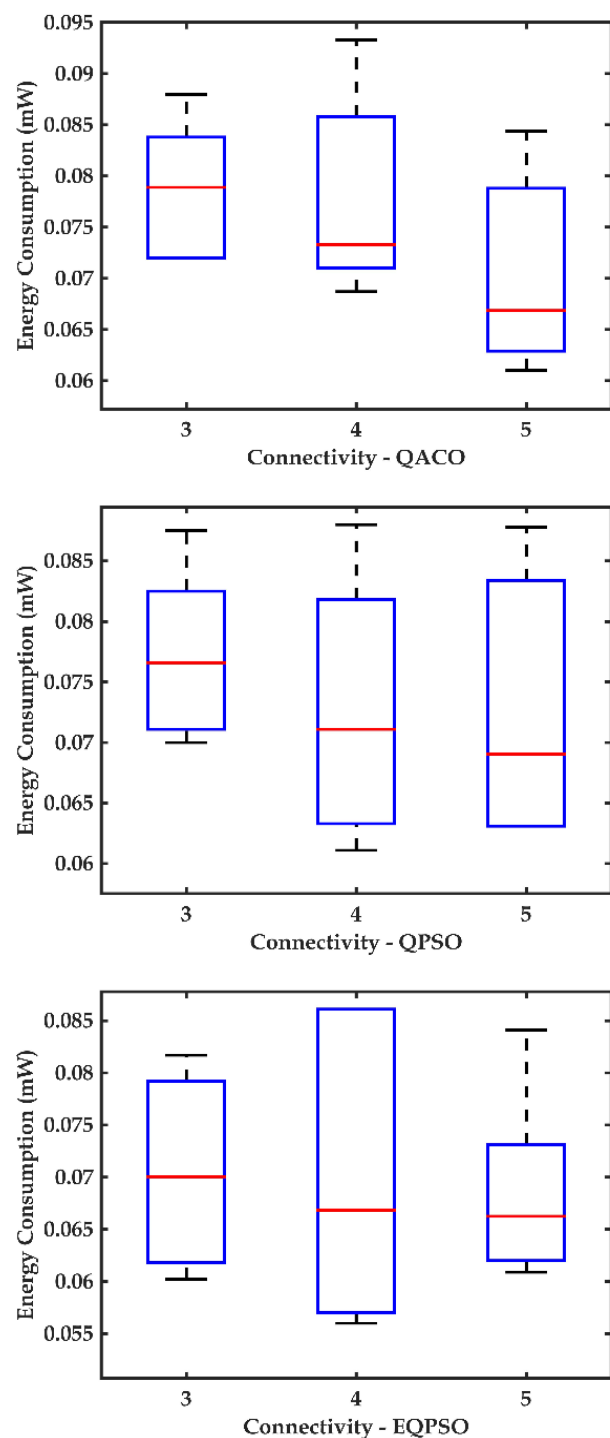
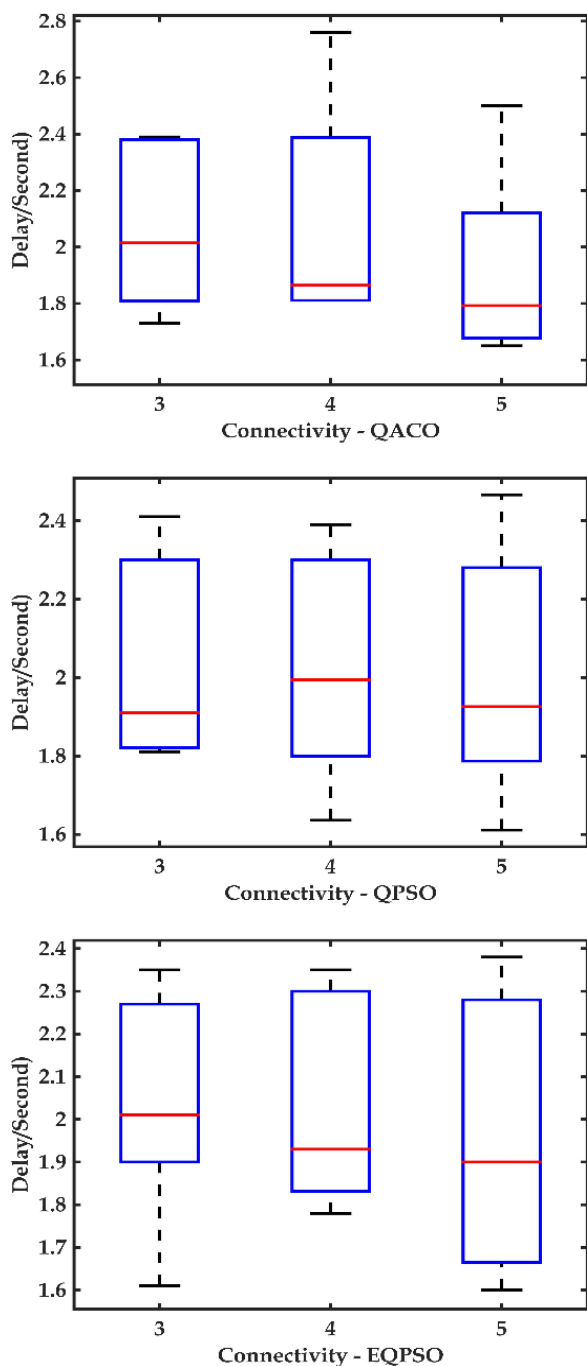


FIGURE 6. Energy consumption with distinct connectivity

FIGURE 7. Delay with distinct connectivity

The performance of the proposed algorithm improves with the increase in connectivity between sensor nodes and fog nodes. If the connectivity is two or less, then information sharing happens only among adjacent sensor nodes. Consequently, topology has less availability of information for the predefined connectivity. As a result, it explores and creates fewer diverse paths while evaluating the objective functions. Whereas topologies generated through higher connectivity $p = 3, 4, 5$ have complete sharing of the

information among the sensor and fog nodes, which helps generate additional diverse paths. It has been observed that the EQPSO performs better than QACO and QPSO since quantum swarm inclines to generate additional diverse paths from multiple source nodes to the gateway. Due to the

accessibility to entire information among the sensor nodes and fog nodes, EQPSO needs lesser communication among the nodes to get the desired connectivity.

ring and mesh topology using QACO, QPSO, and EQPSO is shown in Fig. 9(a) and Fig. 9(b).

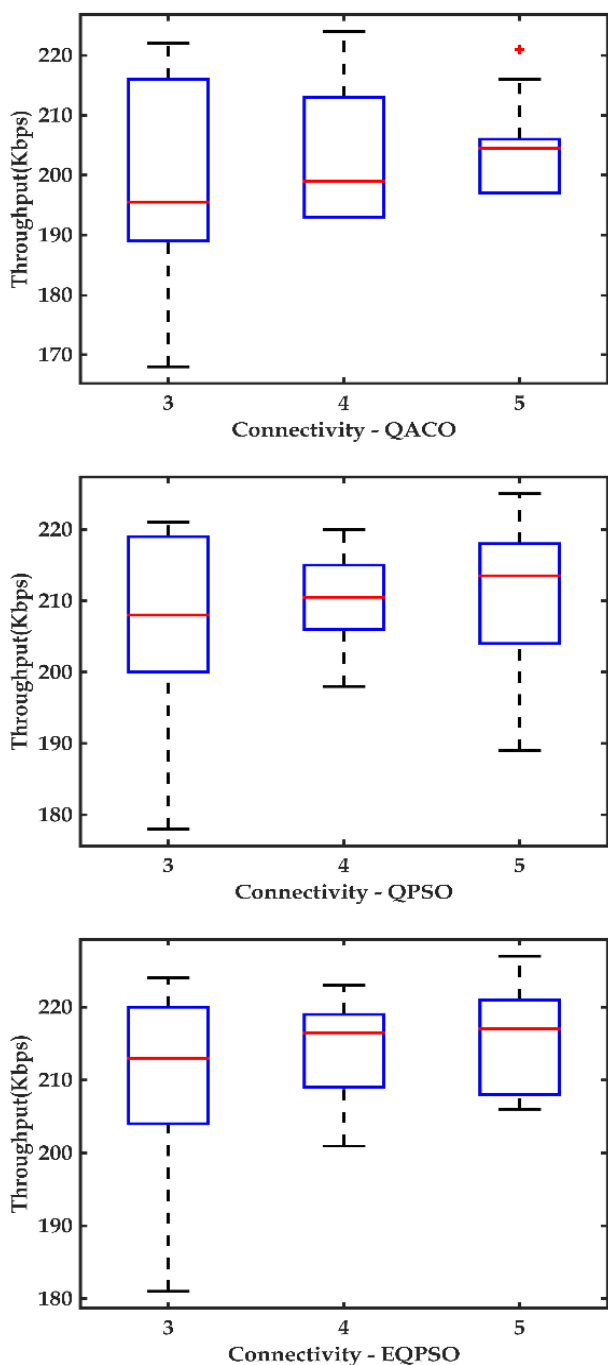


FIGURE 8. Throughput with distinct connectivity

We have investigated the performance of EQPSO for ring and mesh patterns by deploying optimal topologies with increased connectivity for achieving coverage and connectivity. Connectivity is increased steadily from 5 to 10. The results of energy consumption, delay, and throughput for

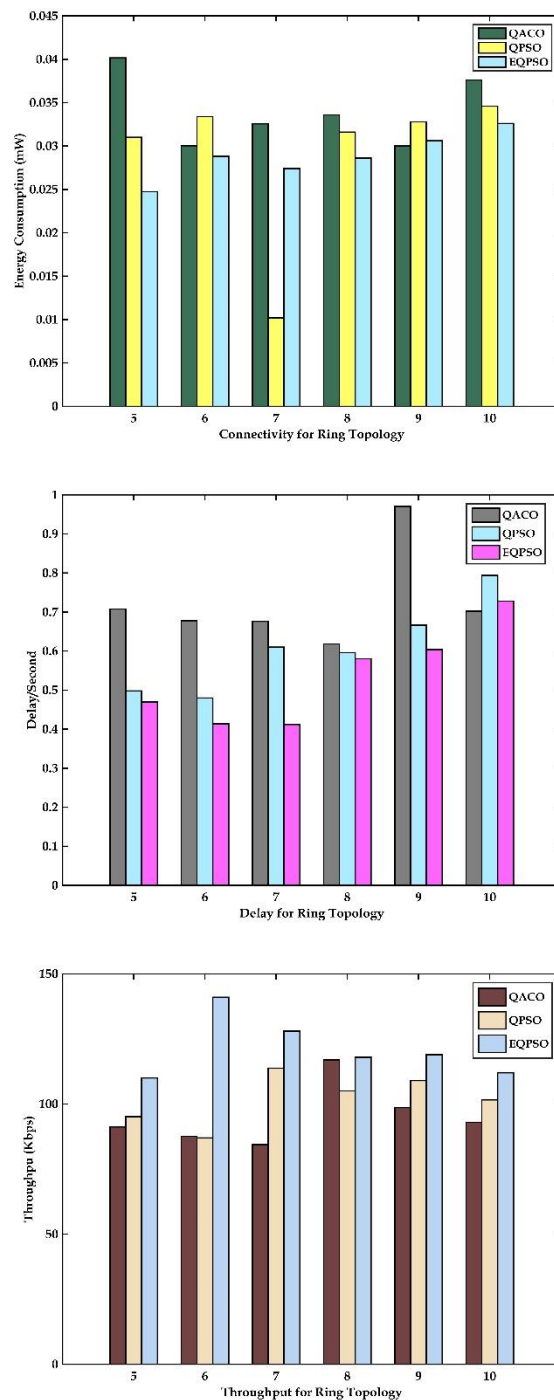


FIGURE 9(a). Energy Consumption, Delay and Throughput for Ring Topology with distinct connectivity

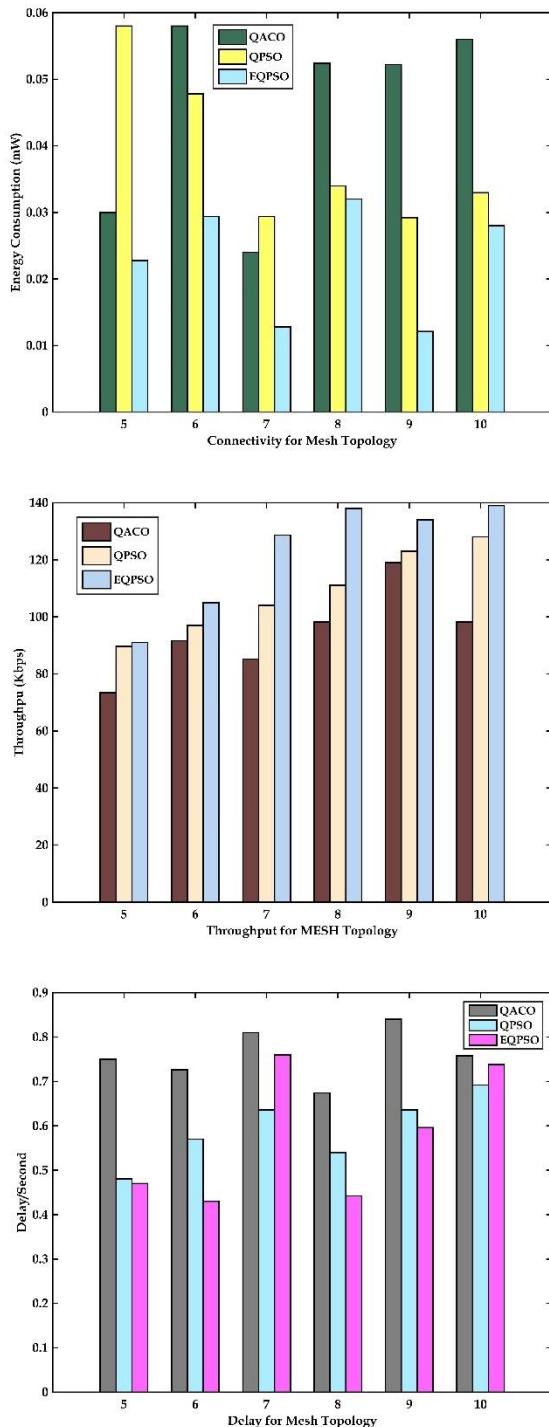


FIGURE 9(b). Energy Consumption, Throughput and Delay for Mesh Topology with distinct connectivity

Energy consumption for the proposed algorithm is minimized by 18.78% and 14.08% compared to QACO and QPSO. Average delay is also curtailed by 25.29% and 14.02% in comparison with QACO and QPSO. It also improves the throughput by approximately 30.70% and 13.66%,

representing better performance in finding an optimal solution than QACO and QPSO, respectively.

It is observed that for ring and mesh deployments, the optimal energy consumption, delay, and throughput of the proposed algorithm are improved when the degree of connectivity is increased. The information to be shared among the nodes for fault tolerance is available with the nodes. For ring topology, the information sharing occurs between the neighboring nodes only whereas in mesh, it is shared to a group. Hence, mesh performance is comparatively better as they have information of additional disjoint paths for communication.

To determine the complexity, we considered the variance $V[S(R)]$, standard deviation, and average error by setting $O(R) = O(10^{-5})$, $\gamma = 0.75$, and $\chi = 0.66$. It has been observed that EQPSO shows a robust correlation among $S(R)$ and N with the constant coefficient value 0.9998 for all the evaluations.

VII. CONCLUSION

Most Industrial Internet of Things applications require strict reliability and extremely low delay in real-time communications between different devices, focusing on improving energy efficiency. To achieve it, we propose a novel enhanced quantum particle swarm optimization algorithm based on quantum and bio-inspired techniques for IIoT networks. Our algorithm combines the heterogeneous network topologies for exploitation and converges in the optimal route direction, and maintains diversity during the collaboration of nodes. The results show that the proposed algorithm has better energy efficiency, reliability, and scalability than the existing approaches. This was achieved by using efficient information exchange, differential evolution and crossover operators to configure the optimal path. The proposed algorithm is useful for optimized deployments of sensor and fog nodes in IIoT environments.

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SHEETAL N. GHORPADE received her M.Sc. degree in Mathematics from University of Pune, Pune, India, and Ph.D. degree in Mathematics from Gyanvihar University, Jaipur, India. With more than 20 years of teaching experience, she is currently an Associate Professor in Applied Mathematics with RMD Sinhgad School of Engineering, Pune, India. Her research interests are graph theory, optimization techniques, wireless sensor networks and Internet of Things.

She has undertaken research visits at the International Centre for Theoretical Physics (ICTP), Italy as Simon's Visitor in 2018 and 2019.



MARCO ZENNARO received his M.Sc. degree in electronic engineering from the University of Trieste, Italy and Ph.D. from the KTH-Royal Institute of Technology, Stockholm, Sweden. He is a research scientist at the Abdus Salam International Centre for Theoretical Physics in Trieste, Italy, where he is unit coordinator of Science, Technology and Innovation department. He is a visiting professor at the KIC-Kobe Institute of Computing, Japan. His research interest is in ICT4D, the use of

ICT for development, and in particular he investigates the use of IoT in

developing countries. He has given lectures on wireless technologies in more than 30 countries.



BHARAT S. CHAUDHARI received his ME in Telecom Engineering and Ph.D. from Jadavpur University, Kolkata, India in 1993 and 2000, respectively. After being a full professor in electronics and telecommunication engineering with the Pune Institute of Computer Technology and Dean at the International Institute of Information Technology Pune, Dr. Chaudhari joined MIT World Peace University, (then MIT Pune) Pune, India as a Professor in 2014. Dr. Chaudhari has authored more than 75 research papers

in the field of wireless, telecom, and optical networks. His research interests include low power wide area networks, Internet of Things, wireless sensors networks, and optical networks. He is a Simon's Associate of the International Centre for Theoretical Physics (ICTP), Italy since 2015. He received a young scientist research grant from Department of Science and Technology, Government of India. He is founder chair of IEEE Pune Section and a senior member of IEEE, a fellow of IETE and IE (I).



RASHID A. SAEED received his PhD in Communications and Network Engineering, Universiti Putra Malaysia (UPM). Currently he is a professor in Computer Engineering Department, Taif University. He is also working in Electronics Department, Sudan University of Science and Technology (SUST). He was senior researcher in Telekom Malaysia™ Research and Development (TMRND) and MIMOS. Rashid published more than 150 research papers, books and book chapters on

wireless communications and networking in peer-reviewed academic journals and conferences. His areas of research interest include computer network, cognitive computing, computer engineering, wireless broadband, WiMAX Femtocell. He is successfully awarded 3 US patents in these areas. He supervised more 50 MSc/PhD students. Rashid is a Senior member IEEE, Member in IEM (I.E.M), SigmaXi, and SEC.



HESHAM ALHUMYANI is working in Department of Computer Engineering in College of Computers and Information Technology, Taif University at Taif Saudi Arabia. He has appointed as a faculty Dean in 2019. He has obtained his Ph.D. Degree from University of Connecticut Storrs, USA. His research interests are Wireless Sensor Networks, Underwater Sensing, IoT (Internet of Things), and Cloud Computing. Dr. Hesham Alhumyani has

published many research papers in distinctive journals and conferences.



S. ABDEL-KHALEK received PhD degree in Computer Science in 2016 from Azhar University. His research interests include different directions in quantum information and computer sciences. He is the author of several articles published in different international scientific journals and is a member of different working groups. He is a Full Professor, of Applied Mathematics, Mathematics Department, Faculty of Science, Sohag University, Egypt. Also,

he is an Associate Professor, of Applied Mathematics, Mathematics Department, Faculty of Science, Taif University, Taif, Saudi Arabia.