QoS-aware Energy Efficient Cooperative Scheme for Cluster-based IoT Systems

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Abstract—The Internet of Things (IoT) technology with huge number power-constrained devices has been heralded to improve the operational efficiency of many industrial applications. It is vital to reduce the energy consumption of each device, however, this could also degrade the Quality of Service (QoS) provisioning. In this paper, we study the problem of how to achieve the tradeoff between the QoS provisioning and the energy efficiency for the industrial IoT systems. We first formulate the multi-objective optimization problem to achieve the objective of balancing the outage performance and the network lifetime. Then we propose to combine the Quantum Particle Swarm Optimization (QPSO) with the improved Non-dominated Sorting Genetic algorithm (NSGA-II) to obtain the Pareto optimal front. In particular, NSGA-II is applied to solve the formulated multi-objective optimization problem and QPSO algorithm is used to obtain the optimum cooperative coalition. The simulation results suggest that the proposed algorithm can achieve the tradeoff between the energy efficiency and QoS provisioning by sacrificing about 10% network lifetime but improving about 15% outage performance.

Index Terms—Industrial IoT system, cluster, cooperative communication, network lifetime, QoS, QPSO, NSGA-II.

I. INTRODUCTION

INTERNET of Things (IoT) system is viewed to have potential to improve the operational efficiency of many industrial applications. There is an increasing need of huge number of reliable devices equipped with short-range radio interfaces, such as IEEE 802.15.4 and IEEE 802.11ah. to provide connectivity to other devices in IoT systems in order to maintain the operational efficiency.

Capillary network was introduced to improve reliable and energy efficient communications for the IoT systems. Capillary network is a specific local network consists of a group of wireless devices to be connected to the other communication infrastructure such as mobile networks [1]. It uses clustering mechanism to reduce the transmission distance between the sink node and devices, as typically the cluster head (CH) is close to all the nodes in each cluster. Clustering mechanism organizes the devices into different clusters and selects CHs, and consequently transmits the aggregated data from the CHs to the sink node via communication infrastructure networks. However, the CHs consume more energy as compared to other devices in the networks as they take more responsibility and dissipate additional energy to transmit aggregated data to the sink node.

In principle, cooperative communications aim at improving effective energy efficiency [2], overall throughput [3], power control [4] and resource allocation [5] in wireless network-s. One form of cooperative communications known as cooperative multiple-input-single-output (CMISO) transmission scheme is used for the long-haul transmission between the cluster and the sink node [6] to help release the transmission burden of CH. CMISO increases the spatial diversity of wireless channels by introducing additional cooperative nodes (Coops) to help CH in long-haul transmission which is the most energy consuming phase of the communication between the cluster and the sink node. The Coops and CH form a virtual MISO system in the long-haul transmission by decode-and-forward technique, with the objective of evenly energy distribution among the networks. Despite the advantages of CMISO scheme, it reduces the transmit power and thus degrades the QoS performance of long-haul communication in the capillary network. However, QoS provisioning could be further improved but requires higher energy consumption.

The aforementioned challenges raise the concerns of the tradeoff between energy consumption and QoS provisioning in the cluster-based IoT systems. In addition, most literature measure the energy efficiency with energy consumption under several constraints such as bit error rate and power control, instead of network lifetime. The capillary network lifetime is defined as the duration from the deployment of the capillary network to the time that the battery of the first device is fully drained [7]. It reflects not only the energy consumption of the whole network but also the fairness of energy consumption among individual devices.

The main contributions of the paper are summarized as following:

- First, considering most recent literature (see Section II for further detail) aim at energy efficiency or QoS provisioning optimization only and the fact that the QoS provisioning could be further improved at the cost of the energy consumption , we formulate a multi-objective optimization problem of the tradeoff between QoS provisioning and energy efficiency. In this paper, we use outage performance and network lifetime as the metric for QoS provisioning and energy efficiency respectively.

- Second, we introduce a new method to select optimum cooperative coalition for CH and Coops by using exhaustive search combined with Quantum-inspired Particle Swarm Optimization (QPSO). The exhaustive search is used to determine a potential CH candidate. The QPSO, which combines the quantum computing theory and the evolutionary algorithm, would have a stronger searching capability, rapid convergence, short-computing time, and small-population size [8]. By taking advantage of the fast

convergence and low complexity of QPSO, we formulate the possible cooperative coalitions by the quantum-coded particles. In order to select the optimum Coops for the potential CH candidate, the quantum-coded particles are flown through the 2-dimensional search space by updating the fitness values of network lifetime and outage performance until reaching the pre-defined generation.

- Third, to solve the multi-objective optimization of QoS provisioning and energy efficiency, the improved Non-dominated Sorting Genetic Algorithm (NSGA-II) is used in this paper. Unlike the scalarization method where multiple objectives are combined to form one objective by user-determined weight factors, NSGA-II applies non-dominated sorting and crowding distance mechanism to obtain a good quality and uniform spread nondominated solution set. The NSGA-II algorithm has been proven to be able to maintain a better spread of solutions and converge better in the obtained non-dominated front compared with evolutionary algorithm such as Pareto-archived evolution strategy (PAES) and strength-Pareto EA (SPEA) [9].

- Fourth, we combine QPSO algorithm with NSGA-II to obtain the Pareto optimal front. To the best of our knowledge, the use of QPSO-based NSGA-II theory and how it is applied to select the cooperative coalition in the capillary networks has not been investigated. In particular, the fitness values are computed and updated through the QPSO algorithm by selecting different devices as Coops. On the other hand, the Pareto optimal front is generated and sorted according to the obtained fitness values by NSGA-II.

The rest of this paper is organized as follow. In Section II, we present the related work. Section III introduces network model, system model and power consumption model. In Section IV, the problem formulation is given in detail. Then in Section V, we explain the procedure of QPSO algorithm and how to apply QPSO to obtain the optimum Coops for specific CH. Simulation results are provided in Section VI, and conclusions are drawn in Section VII.

II. RELATED WORK

The cooperative communications for cluster based networks has also been introduced to achieve different objectives including energy efficiency and Quality of Service (QoS) with the consideration of channel interference, node location and residual energy.

In [10], authors proposed a cluster formation scheme based on Low Energy Adaptive Clustering Hierarchy (LEACH) algorithm in CMISO network that considering residual energy and the distance between every node to the sink node to minimize energy consumption as well as to balance energy consumption across the whole network. The number of Coops is determined by the distance between the CH and the sink node, and Coops are selected from the cluster nodes (CNs) with most residual energy within the cluster. In [11], authors proposed a fair cooperative communication scheme which encourages nodes to participate in cooperative communication by giving an extra reward. The Coops are selected if two conditions are satisfied: the first is that signal-to-noise ratio (SNR) of the received signal of Coop is larger than a predefined SNR threshold level, and the second condition is that Coop is within the transmission domain of the destination cluster. In [12], the authors analyzed the overall system performance in terms of packet error rate (PER) in the cluster-based cooperative communication system and proposed a novel node sleep strategy to minimize the overall energy consumption under certain PER threshold. However, [10–12] only considered several Coops selection constraints instead of the cooperation benefit with CH.

In [13] [14], the authors proposed a cluster-based CMISO communication with LEACH protocol [15]. However, LEACH only selects CHs with a certain probability and does not consider residual energy and location of nodes. In [16], the authors designed a cooperative communication scheme to achieve the optimal solution of a random tradeoff between QoS provisioning and the energy efficiency by the Lambert W function and coalition formation game theory. In [13], the authors assume both CH and Coops are selected randomly, while in [14] and [16], the authors assume all the CHs are always located in the center of the network.

III. SYSTEM MODEL

A. Network Model

The power-constrained wireless devices in the capillary networks of the IoT system are randomly distributed in a two-dimensional space with following assumptions:

- All wireless devices perform data collection task periodically and always have data to send to the sink node.
- All wireless devices are homogeneous and energy constrained.
- All wireless devices are capable of adjusting their transmit powers dynamically to reach the intended recipients with the minimum required energy.
- All wireless devices are aware of their geographical locations and residual energies.
- All wireless devices are equipped with short-range local area wireless radio, e.g. IEEE 802.15.4.
- All devices are classified into three kinds of nodes: CH, CNs and Coops.
- All devices are capable of operating in data collection and aggregation mode as well as cooperative transmission mode.
- A static capillary gateway is equipped with two radio interfaces: the local area capillary radio to communicate with the capillary network and the cellular radio to communicate with the industrial IoT systems.

The transmission is operated in two phases as shown in Fig.1: setup phase and steady state phase. During the setup phase, the gateway executes the clustering algorithm as well as the CH and Coops selection algorithm, and informs every device with its role. During the steady-state phase, all nodes collect and transmit data in TDMA scheduling. The communication protocol in steady state consists of the following phases:
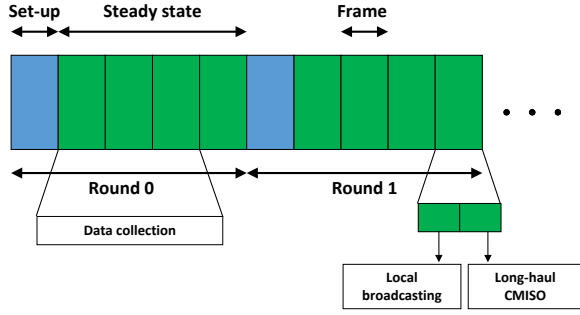
Fig. 1: Transmission structure in cluster-based IoT system

- Data collection phase (DC): CH collects and aggregates data from all the other devices, including both CNs and Coops.
- Local broadcasting phase (LB): CH broadcasts the aggregated data to all Coops.
- Long-haul cooperative transmission phase (LH): CH and Coops jointly transmit the aggregated data to the sink node based on the distributed space time codes (DSTC) which is a cooperative technique investigated in [17] such that CH and Coops share their antennas to create a virtual array through distributed transmission and signal processing.

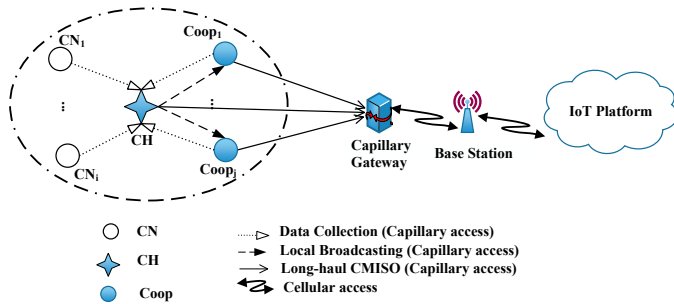Phase LB and LH form the CMISO transmission.

B. System Model

Fig. 2: System model

The system model considers a capillary networks for IoT system with $\mathcal{N}$ devices: one CH, i CNs and j Coops as shown in Fig.2, where $\mathcal{N} = 1 + i + j$. All devices are randomly distributed over the same cluster and the set of all devices are denoted by $\eta = \{CH, CN_1, \cdots, CN_i, Coop_1, \cdots, Coop_j\}$. The channels of CN_i and $Coop_j$ to CH, denoted by h_{CH,CN_i} and $h_{CH,Coop_j}$ respectively and the channels between all transmitting nodes within the cluster (CH and $Coops$) to the sink node, denoted by $h_{\sin k}$, are all modeled by Rayleigh-fading with square-law path loss. We assume that CH, CNs and Coops in the same cluster know their channel conditions and the distances between each transmitting node in the cluster and the sink node, which is also known as long-haul distance denoted by d, are the same.

C. Power Consumption Model

In this paper, we use the power consumption model as defined in [18]:

$$p = p_a + p_c, \quad (1)$$

where p is the power consumption of an individual device, p_a is the power consumption of the power amplifiers and p_c is the power consumption of all the other circuit blocks. Specifically, p_a is dependent on the transmit power p_t. Without loss of generality, $p_a = (1 + \alpha)p_t$, where α is a constant depending on RF power amplifier and modulation scheme. And p_c is composed of transmitter circuit blocks power consumption denoted by p_{ct}, and receiver circuit blocks power consumption denoted by p_{cr}.

1) The Data Collection Phase Power Consumption: In the Data Collection (DC) phase, CH acts as receiver dissipating power of receiver circuit blocks, while all other devices (CNs and Coops) transmit data to CH, dissipating power of power amplifiers as well as power of transmitter circuit blocks. Therefore, the power consumption for CH, CNs and Coops in this phase respectively, are

$$p_{CH}^{DC} = p_{cr,CH}^{DC}, \quad (2)$$

$$p_{CN_i}^{DC} = p_{a,CN_i}^{DC} + p_{ct,CN_i}^{DC} = (1+\alpha)p_{t,CN_i}^{DC} + p_{ct,CN_i}^{DC}, \quad (3)$$

$$p_{Coop_j}^{DC} = p_{a,Coop_j}^{DC} + p_{ct,Coop_j}^{DC} = (1+\alpha)p_{t,Coop_j}^{DC} + p_{ct,Coop_j}^{DC}. \quad (4)$$

2) The Local Broadcasting Phase Power Consumption: In the Local Broadcasting (LB) phase, CH acts as transmitter to broadcast the aggregated data to Coops, dissipating power of power amplifiers as well as power of transmitter circuit blocks, and Coops receive data information from CH, dissipating power of receiver circuit blocks, while CNs do not participate in this phase. Therefore, the power consumption for CH, CNs and Coops in this phase respectively, are

$$p_{CH}^{LB} = p_{a,CH}^{LB} + p_{ct,CH}^{LB} = (1+\alpha)p_{t,CH}^{LB} + p_{ct,CH}^{LB}, \quad (5)$$

$$p_{CN_i}^{LB} = 0, \quad (6)$$

$$p_{Coop_j}^{LB} = p_{cr,Coop_j}^{LB}. \quad (7)$$

3) The Long-haul Cooperative Transmission Phase Power Consumption: In the Long-haul Cooperative Transmission (LH) phase, CH and Coops jointly transmit data to the sink node, dissipating power of power amplifiers as well as power of transmitter circuit blocks, while CNs do not participate in this phase. Assuming energy of the gateway is infinite, the energy consumption by the gateway can be omitted. Therefore, the power consumption for CH, CNs and Coops in this phase respectively, are

$$p_{CH}^{LH} = p_{a,CH}^{LH} + p_{ct,CH}^{LH} = (1+\alpha)p_{t,CH}^{LH} + p_{ct,CH}^{LH}, \quad (8)$$

$$p_{CN_i}^{LB} = 0, \quad (9)$$

$$p_{Coop_j}^{LH} = p_{a,Coop_j}^{LH} + p_{ct,Coop_j}^{LH} = (1+\alpha)p_{t,Coop_j}^{LH} + p_{ct,Coop_j}^{LH}. \quad (10)$$

D. Transmit Power

1) Transmit Power of the Data Collection Phase: As referred to [19], the transmit power of CN_i and $Coop_j$ denoted by $p_{t,CN_i/Coop_j}^{DC}$ can be derived from

$$\log_2\left(1 + |h_{CH,CN_i/Coop_j}|^2 \frac{p_{t,CN_i/Coop_j}^{DC}\kappa}{\sigma^2\left(d_{CH,CN_i/Coop_j}\right)^\delta}\right) \geq R_{DC}, \tag{11}$$

where R_{DC} is the channel capacity, σ^2 is the Gaussian noise variance, d is the distance between the source device and destination device, κ is a constant which depends on the propagation environment, δ is the path loss parameter and $h \sim CN(0,1)$ is unitary power, Rayleigh fading coefficients for all intra-cluster connections. In order to improve energy efficiency, we set Eq.(11) to be the lower bound, that is,

$$p_{t,CN_i/Coop_j}^{DC} = \frac{(2^{R_{DC}}-1)\sigma^2\kappa^{-1}\left(d_{CH,CN_i/Coop_j}\right)^\delta}{|h_{CH,CN_i/Coop_j}|^2}. \tag{12}$$

2) Transmit Power of the Local Broadcasting Phase: In terms of the CMISO transmission, as referred to [20], the outage probability $\mathcal{P}_{out}$ under a predetermined transmission rate R, can be expressed as

$$\begin{aligned}\mathcal{P}_{out} &= \Pr\{\log_2(1 + |h_{s,d}|^2 \frac{p_t\kappa}{\sigma^2 d^\delta}) < R\}, \\ &= \Pr\{|h_{s,d}|^2 < \frac{(2^R-1)\sigma^2 d^\delta \kappa^{-1}}{p_t}\}.\end{aligned} \tag{13}$$

In order to guarantee the QoS requirement, the outage probability $\mathcal{P}_{out}$ should not be larger than the threshold value $\mathcal{P}_{out}^{thr}$, the corresponding outage capacity is defined as

$$C_{\text{out}} = \sup\{R : \mathcal{P}_{out} \leq \mathcal{P}_{out}^{thr}\}. \tag{14}$$

Eq.(14) represents the largest rate C_{out} that can be sustained over all the channel states except over a subset with probability $\mathcal{P}_{out}^{thr}$. Thus, we can rewrite Eq.(13) by

$$\mathcal{P}_{out} = \Pr\{|h_{s,d}|^2 < \frac{(2^{C_{out}}-1)\sigma^2 d^\delta \kappa^{-1}}{p_t}\}. \tag{15}$$

Denote the number of transmit devices to be n_t. Since $|h_{s,d}|^2 \sim X_{2n_t}^2$ (i.e., chisquare distributed R.V. with $2n_t$ degrees of freedom) and the cumulative distribution function (cdf) of $X_{2n_t}^2$ is the regularized incomplete Gamma function [21], i.e. $F_{X_{2n_t}^2}(b) = \gamma(1,b)$, where $\gamma(n_t,b) = \frac{1}{(n_t-1)!}\int_0^b x^{n_t-1}e^{(-x)}dx$, we have

$$\mathcal{P}_{out} = \gamma(n_t, \frac{(2^{C_{out}}-1)\sigma^2\kappa^{-1}d^\delta}{p_t}). \tag{16}$$

Due to the broadcasting nature of wireless channel, once the cooperative node $Coop_j$ with the worst channel receives data from CH, other Coops can receive the data simultaneously. As referred to [22], the data received by all Coops needs to be decoded correctly, and the transmit power $p_{t,CH}^{LB}$ can be derived from

$$R_{LB} \leq \frac{1}{2}\log_2(1 + |h_{CH,Coop_j}|^2 \frac{p_{t,CH}^{LB}\kappa}{\sigma^2 d_{CH,Coop_j}^\delta}). \tag{17}$$

As referred in [23], R_{LB} cannot be lower than the long-haul transmission rate C_{out}, hence we have,

$$C_{out} \leq R_{LB}. \tag{18}$$

In addition, due to the broadcast nature of wireless channel, if the Coop with the worst channel condition (denoted by $Coop_w$) can receive the data, other Coops can also receive it simultaneously. Therefore the transmit power $p_{t,CH}^{LB}$ can be derived from

$$\frac{1}{2}\log_2(1 + |h_{CH,Coop_w}|^2 \frac{p_{t,CH}^{LB}\kappa}{\sigma^2 d_{CH,Coop_w}^\delta}) \geq C_{out}. \tag{19}$$

In order to reduce energy consumption, we set Eq.(19) to be the lower bound, that is,

$$p_{t,CH}^{LB} = \frac{(2^{2C_{out}}-1)\sigma^2\kappa^{-1}d_{CH,Coop_j}^\delta}{|h_{CH,Coop_w}|^2}. \tag{20}$$

3) Transmit Power of the Long-haul Cooperative Transmission Phase: Based on DSTC, each transmitting device has the same transmit power, thus, $p_{t,CH}^{LH} = p_{t,Coop_j}^{LH} = p_t^{MISO}/(J+1)$, that is

$$\mathcal{P}_{out,miso} = \gamma(j+1, \frac{(2^{2C_{out}}-1)\sigma^2\kappa^{-1}d_{miso}^\delta}{p_t^{MISO}/(j+1)}). \tag{21}$$

IV. PROBLEM FORMULATION

The objective is to strike a balance between energy efficiency and QoS provisioning. As illustrate in [16], the design of CMISO communication scheme falls into two categories:

- The optimization of QoS provisioning subject to a energy constraint.
- The minimization of energy consumption (or the network lifetime prolonging) subject to a QoS provisioning constraint.

However, the QoS provisioning could be further improved at the cost of the energy consumption, and vice versa. Hence, there exists a tradeoff between the energy efficiency and the QoS provisioning. In this paper, we adopt network lifetime to represent energy efficiency and the outage performance to represent the QoS provisioning in long-haul transmission.

A. The Network Lifetime

Denote the energy consumption of a device during the communication process in unit time by e, we have,

$$e = \frac{1}{\mathcal{N}} \times p^{DC} + \frac{1}{2\mathcal{N}} \times p^{LB} + \frac{1}{2\mathcal{N}} \times p^{LH}. \tag{22}$$

The lifetime of an individual device is,

$$T = \frac{E}{e}, \tag{23}$$

where E is residual energy of the device when setting up a scenario. Denote T_{CH}, T_{CN_i} and T_{Coop_j} to be the lifetime of CH, CN_i and $Coop_j$ respectively.

The network lifetime denoted by T_{net} is

$$T_{net} = \min\{T_{CH}, T_{CN_1}, \cdots, T_{CN_i}, T_{Coop_1}, \cdots, T_{Coop_j}\}. \tag{24}$$

B. QoS Provisioning

The outage performance can be formulated by Eq.(25).

$$J = \mathcal{P}_{out}^{thr} - P_{out,CH/Coop_j},$$
$$= \mathcal{P}_{out}^{thr} - \gamma(j+1, \frac{(2^{2C_{out}}-1)\sigma^2\kappa^{-1}d_{miso}^{\delta}}{p_t^{MISO}/(j+1)}),$$
$$\text{s.t.} \quad J \geq 0,$$
$$E_t \geq \frac{1}{\mathcal{N}}\sum_{i=1}^{\mathcal{N}}p_i^{DC} + \frac{1}{2\mathcal{N}}\sum_{i=1}^{\mathcal{N}}p_i^{LB} + \frac{1}{2\mathcal{N}}\sum_{i=1}^{\mathcal{N}}p_i^{LH}, \quad (25)$$

where $\mathcal{P}_{out}^{thr}$ is the maximum outage probability threshold and E_t is the maximum energy constraints of network communication. Let $B = (2^{2C_{out}}-1)\sigma^2\kappa^{-1}d_{miso}^{\delta}$, which should be a constant after scenario setting up. Therefore, we have,

$$J = \mathcal{P}_{out}^{thr} - \gamma(j+1, \frac{B(j+1)}{p_t^{MISO}}). \quad (26)$$

By making the derivative of J with respect to p_t^{MISO}, we obtain,

$$\frac{\partial J}{\partial p_t^{MISO}} = \frac{B^{j+1}e^{-\frac{B}{p_t^{MISO}}}}{j!(p_t^{MISO})^{j+2}}. \quad (27)$$

By making the second derivative of J with respect to p_t^{MISO}, we obtain,

$$\frac{\partial^2 J}{(\partial p_t^{MISO})^2} = -\frac{B^{j+1}e^{-\frac{B}{p_t^{MISO}}}}{j!(p_t^{MISO})^{j+4}}(j+2-\frac{B}{p_t^{MISO}}). \quad (28)$$

Since $j+2-\frac{B}{p_t^{MISO}}$ is positive, Eq.(25) is a concave optimization problem, that is, the optimum outage performance can be obtained using numerical methods.

C. The Multi-Objective Optimization Problem Formulation

The tradeoff between energy efficiency and QoS provisioning research problem can be expressed as

$$\{ CH, 1, \ldots, Coop_j \} = \text{argmax}\{ T_{net}, J\}. \quad (29)$$

V. QPSO-BASED NSGA-II ALGORITHM

A. Quantum Particle Swarm Optimization

PSO is an evolutionary computing technique based on bird flocking principle. QPSO uses quantum coding mechanism to encode each particle by a quantum bit. In [24], a quantum bit is defined as a pair of composite numbers (α, β), where $|\alpha|^2 + |\beta|^2 = 1$ and $\alpha > 0$, $\beta > 0$. $|\alpha|^2$ gives the probability that the quantum bit is found in $'0'$ state and $|\beta|^2$ gives the probability that the quantum bit is found in $'1'$ state. Then the quantum velocity of the $m-th$ particle at generation t is defined as

$$v_m^t = \begin{bmatrix} \alpha_{m1}^t & \alpha_{m2}^t & \cdots & \alpha_{mR}^t \\ \beta_{m1}^t & \beta_{m2}^t & \cdots & \beta_{mR}^t \end{bmatrix}, \quad (30)$$

where $m \in [1, 2, \cdots, h]$, h is the number of particles and $R = 1 + i + j$ which represents number of devices in the

network. Since $\beta_{mn} = \sqrt{1-\alpha_{mn}^2}$, we can simplify Eq.(30) as

$$v_m^t = [\ \alpha_{m1}^t \quad \alpha_{m2}^t \quad \cdots \quad \alpha_{mR}^t\ ]. \quad (31)$$

The quantum particle position according to Eq.(31) can be expressed as

$$x_{mn}^t = \begin{cases} 1 & \text{if} \quad \delta_{mn} > (\alpha_{mn}^t)^2 \\ 0 & \text{if} \quad \delta_{mn} \leq (\alpha_{mn}^t)^2 \end{cases}, \quad (32)$$

where $\delta_{mn} \in [0, 1]$ is uniform random number. In this paper, the quantum position indicates whether the device n is a member of the cooperative coalition in particle m: $x_{mn}^t = 1$ represents that device n in particle m is a Coop at generation t; otherwise, device n in particle m is a CN at generation t. Therefore each particle in this paper represents a candidate solution of a particular cooperative coalition and a group of CNs, and the fitness value of each particle can then be obtained by Eq.(23) and (25).

Denote the fitness value of particle m at generation t to be f_m^t, then the local individual optimum fitness value $\boldsymbol{f}_m$ and the corresponding local individual optimum position $\boldsymbol{p}_m$ is defined as below,

$$\boldsymbol{f}_m = \min\{f_m^1, f_m^2, \cdots, f_m^t\}, \quad (33)$$

$$\boldsymbol{p}_m = [p_{m1}, \cdots, p_{mn}, \cdots, p_{mR}]. \quad (34)$$

Similarly, the global optimum fitness value $\boldsymbol{f}_g$ and the corresponding global optimum position $\boldsymbol{p}_g$ is defined as below,

$$\boldsymbol{f}_g = \min\{\boldsymbol{f}_1, \cdots, \boldsymbol{f}_m, \cdots, \boldsymbol{f}_h\}, \quad (35)$$

$$\boldsymbol{p}_g = [p_{g1}, \cdots, p_{gn}, \cdots, p_{gR}]. \quad (36)$$

At generation $t+1$, the quantum rotation angle θ_{mn}^{t+1} is updated by

$$\theta_{mn}^{t+1} = e_1(p_{mn} - x_{mn}^t) + e_2(p_{gn} - x_{mn}^t), \quad (37)$$

where e_1 and e_2 are two positive learning factors of cognitive and social acceleration factors respectively.

If $\theta_{mn}^{t+1} \neq 0$, the updated velocity of $m-th$ quantum particle at $t+1$ generation is,

$$v_{mn}^{t+1} = |\alpha_{mn}^t \times \cos\theta_{mn}^{t+1} - \sqrt{1-(\alpha_{mn}^t)^2} \times \sin\theta_{mn}^{t+1}|. \quad (38)$$

If $\theta_{mn}^{t+1} = 0$ and $r = c_1$, the updated velocity of $m-th$ quantum particle at $t+1$ generation is,

$$v_{mn}^{t+1} = \sqrt{1-(\alpha_{mn}^t)^2}. \quad (39)$$

where r is a uniform random number between 0 and 1, and c_1 is a constant which refers to the mutation probability, $c_1 \in [0, 1/R]$.

B. NSGA-II algorithm

As referred to [25], in a maximization problem, a vector $\boldsymbol{x} = [x_1, x_2, \cdots, x_p]^T$ is said to dominate $\boldsymbol{y} = [y_1, y_2, \cdots, y_p]^T$, denoted by $\boldsymbol{x} \succ \boldsymbol{y}$, if $\forall i \in \{1, 2, \ldots, p\}$: $x_i \geq y_i$ and $\exists i \in \{1, 2, \ldots, p\} : x_i > y_i$. That is, no value in $\boldsymbol{y}$ is more than $\boldsymbol{x}$ and at least one value of $\boldsymbol{x}$ is strictly greater than $\boldsymbol{y}$. Similarly, in a multi-objective maximization problem, a solution $\boldsymbol{x}^*$ is said to dominate $\boldsymbol{x}$, if $\forall i \in \{1, 2, \ldots, M\}$: $f_i(\boldsymbol{x}^*) \geq f_i(\boldsymbol{x})$ and $\exists i \in \{1, 2, \ldots, M\} : f_i(\boldsymbol{x}^*) > f_i(\boldsymbol{x})$. That is, a solution $\boldsymbol{x}^*$ is Pareto optimal if there exists no feasible solution $\boldsymbol{x}$ which would increase some criteria without causing a simultaneous decrease in at least other criterion. The NAGA-II is proposed to be an effective algorithm to find the Pareto optimal solutions.

In NSGA-II [9], each solution has two entities:

- Domination count n_p, which is defined as the number of solutions which dominate individual p.
- S_p, which is the set containing all the individuals that are being dominated by p.

The non-dominated sorting focus on identifying all fronts, which is described as below:

i) Evaluate the population according to fitness value.

ii) Identify the first nondominated front denoted by $F^{(1)}$. That is, $\forall i, n_i = 0, i \in F^{(1)}$, where i is the $i-th$ solution and $F^{(1)}$ is the first non-dominated front.

iii) For each solution i in $F^{(1)}$, visit each member q of its domination set S_i. For every member q, where $q \in S_i$, $n_q = 0$, $n_q^{new} = n_q - 1$. Put q in a separate list Q if $n_q^{new} = 0$. The members in Q belong to the second non-dominated front $F^{(2)}$.

iv) Visit each member in $F^{(2)}$ and repeat Step ii) until all fronts are identified.

[9] also proposed crowding distance to maintain the diversity among population members. The crowding-distance is the average distance of two points along each of the objectives. The crowding-distance computation requires sorting the population according to each objective value in ascending order of magnitude for every front. Therefore, for each objective function, the boundary solutions (solutions with smallest and largest function values) are assigned an infinite distance value. All other intermediate solutions are assigned a distance value equal to the absolute normalized difference in the function values of two adjacent solutions. The calculation is continued with other objective functions. The overall crowding distance value is calculated as the sum of individual distance values corresponding to each objective. From the description of non-dominated sorting and crowding distance, we can see that the solutions with better front and larger crowding distance are better than others.

C. QPSO-based NSGA-II algorithm

In this paper, we formulate the possible cooperative coalitions to be quantum-coded particles which are flown through the 2-dimensional search space. Each particle has several attributes: the rotation angle, the current velocity, the current position, the local optimum position and the global optimum position. The current position of the particle suggests the Coops selection. In order to joint optimize the network lifetime and QoS provisioning, we apply NSGA-II to search the Pareto-optimal particle solutions by setting the fitness values to be network lifetime and the outage performance. Besides, exhaustive search is used to find the optimal CH by assuming every device in the cluster to be CH. The QPSO-based NSGA-II algorithm can be summarized in the following steps:

- Step 1: Assume every device to be CH in turn and operate the following steps to select the optimum Coops for the assumed CH.
- Step 2: Initialize a population $\boldsymbol{S}$ with h quantum particles based on quantum coding mechanism. Specifically, The current position and velocity of every particle is randomly generated. The local optimum position of the particle is equal to the current position of the particle.
- Step 3: Evaluate each quantum particle by the fitness value of both objectives: network lifetime and the long-haul transmit power. Sort population $\boldsymbol{S}$ according to non-dominated sorting scheme in NSGA-II. Choose non-dominated solutions from the first Pareto front to the last Pareto front and add them into $\boldsymbol{P}$ which is an external memory to store non-dominated solutions with the maximum pre-defined size N_0. The global optimum position $\boldsymbol{p_g}$ is chosen from the top part of $\boldsymbol{P}$ (i.e. top 5%) randomly.
- Step 4: Generate a new population $\boldsymbol{S_{new}}$ through QPSO algorithm from $\boldsymbol{S}$. Renew the quantum rotation angle of each quantum particle by Eq.(37). Update $\boldsymbol{p_m}$ and $\boldsymbol{p_g}$ correspondingly from Eq.(33) to Eq.(36). Update the quantum position of each particle by Eq.(32). Update $\boldsymbol{p_m}$ and $\boldsymbol{p_g}$ correspondingly from Eq.(33) to Eq.(36).
- Step 5: Evaluate each quantum particle of the new population $\boldsymbol{S_{new}}$ by the fitness value of both objectives: network lifetime and the long-haul transmit power. Combine the current population and the parent population and form a new population, that is, $\boldsymbol{S_{new}^*} = \boldsymbol{S_{new}} \cup \boldsymbol{S}$. Sort the new population $\boldsymbol{S_{new}^*}$ according to non-dominated sorting scheme in NSGA-II. Select non-dominated solutions and add them to $\boldsymbol{Q}$ which is an external memory similar to $\boldsymbol{P}$.
- Step 6: Combine $\boldsymbol{Q}$ and $\boldsymbol{P}$ to form a new Pareto solution memory set $\bar{\boldsymbol{S}}$, that is, $\bar{\boldsymbol{S}} = \boldsymbol{P} \cup \boldsymbol{Q}$. Sort $\bar{\boldsymbol{S}}$ according to non-dominated sorting scheme in NSGA-II. Calculate the crowding distance and sort the solutions according to the crowding distance in each front in a descending order. Limit the size of $\bar{\boldsymbol{S}}$ to be N_0 by selecting the former N_0 Pareto solutions and rejecting the others. The global optimum is chosen from the top part of $\bar{\boldsymbol{S}}$ (e.g. top 5%) randomly and the local optimum of each particle is chosen from $\bar{\boldsymbol{S}}$ randomly.
- Step 7: Replace $\boldsymbol{S}$ by $\boldsymbol{S_{new}}$ to participate in the next generation.
- Step 8: If it has reached the maximum generation, then stop the process. The solutions in $\bar{\boldsymbol{S}}$ are non-dominated solutions. Otherwise, go to Step 4 until it has reached the maximum generation denoted by T_{max}. The solutions in
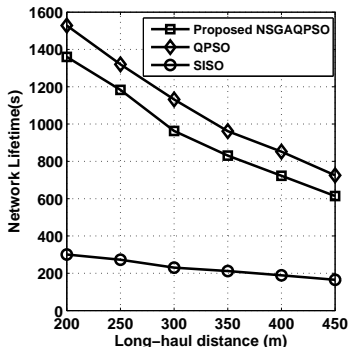
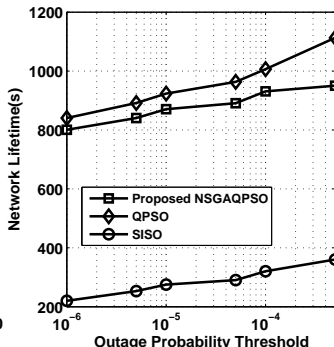Fig. 3: Network lifetime vs. long-haul distance

Fig. 4: Network lifetime vs. outage probability threshold
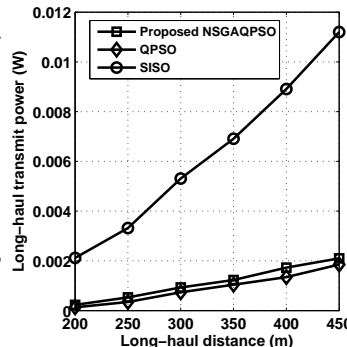

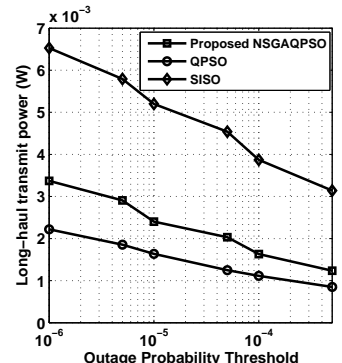
Fig. 5: Transmit power vs. long-haul distance

Fig. 6: Transmit power vs. outage probability threshold

$\bar{S}$ are Pareto front solutions.

- Step 9 Repeat *Step1* to *Step8* until finding the optimum cooperative coalition for every CH. Add all Pareto front solutions obtained in Step 8 for each CH in external memory S_{final} with the maximum pre-defined size N_0. Sort S_{final} according to non-dominated sorting scheme in NSGA-II. Calculate the crowding distance and sort the solutions according to the crowding distance in each front in a descending order. The former N_0 Pareto front solutions in sorted S_{final} are the optimum ones.

VI. Simulation

The simulation tool used in this paper is Matlab. There are 10 wireless devices randomly distributed within a circle of 100 meter radius. We adopt circuit power consumption model in paper [18]. The constant κ is set to 1, the path loss parameter δ is set to 3, the Gaussian noise variance σ^2 is 10^{-12} W, the capacity C_{out} and R_{DC} is 1.4 b/s/Hz. The initial residual energy of each device is between $1J$ to $1.5J$ randomly. Besides, we adopt circuit power consumption model in paper [18]. For QPSO, the maximum generation is set to 100, the number of particle h is 20, learning factors e_1 and e_2 are 0.06 and 0.03 respectively, and the mutation probability c_1 is 1/300. For NSGA-II, the buffer size N_0 is 20.

To verify the proposed joint optimization algorithm, we simulate and compare the results with the QPSO single objective optimization scheme (QPSO network lifetime optimization and QPSO long-haul transmit power optimization) as well as the single-input-single-output transmission scheme between the cluster and the gateway, i.e. LEACH [15]. The fitness values are implemented by Eq.(23) and Eq.(25). In QPSO algorithm, we simulate particles by following attributes: particle position in Eq.(32), the rotation angle in Eq.(37), and the velocity in Eq.(38) and Eq.(39). For each generation, the particle velocity and position are updated according to the rotation angle. The particles position can suggest the Coops selection in each generation, and fitness value can then be updated correspondingly based on different Coops selection. In NSGA-II, we implement the non-dominated sorting and crowding distance calculation to obtain the Pareto optimal front by the updated fitness values obtained in QPSO. Then, the global optimum and local optimum are updated by the the

Pareto optimal front, which are the two variables to update the rotation angle in Eq.(37).

First, we observe that the network lifetime with different long-haul distance in Fig.3. The outage probability threshold is $P_{out}^{thr} = 10^{-3}$. In Fig.3, the network lifetime of both algorithms decreases significantly with respect to long-haul distance, as more long-haul transmit power is required. Besides, the network lifetime of QPSO network lifetime optimization algorithm is better than that of the proposed NSGAQOSP algorithm, due to higher long-haul transmit power of the proposed NSGAQOSP algorithm. Note that both CMISO schemes outperform the SISO scheme significantly.

Secondly, Fig.4 shows the network lifetime with different outage probability threshold. The long-haul distance is 300m. The outage probability gives the probability of unsuccessful transmission when the received SNR falls below a certain specific SNR threshold. Correspondingly, outage probability threshold represents quality of service in terms of minimum transmit power to avoid outage, that is, the lower the outage probability, the more transmit power and the better received signal quality. It can be seen in Fig.4 that the network lifetime goes up with the increase of outage probability threshold. The QPSO network lifetime optimization algorithm outperforms the proposed NSGAQOSP algorithm in network lifetime due to higher long-haul transmit power of the proposed NSGAQOSP algorithm. And both the QPSO network lifetime optimization algorithm and the proposed NSGAQOSP algorithm outperform the SISO scheme.

However, in terms of the long-haul transmit power, we can observe from Fig.5 and Fig.6, the proposed NSGAQOSP algorithm outperforms the QPSO long-haul transmit power optimization, which indicates that the proposed NSGAQOSP algorithm achieve better QoS compared with the QPSO network lifetime optimization. In particular, as the outage probability threshold increases, the minimum transmit power is also decreased. Compared with two CMISO scheme, the SISO scheme requires highest long-haul transmit power.

VII. Conclusion

In this paper, we have investigated investigate QPSO-based NSGA-II algorithm with the aim to optimize both energy efficiency and QoS in cluster-based IoT systems. We show

the joint optimization problem can be formulated into non-dominated sorting research problem. In addition, the proposed algorithm applies the QPSO algorithm to select the optimum cooperative coalition. Simulation results show that the proposed QPSO-based NSGA-II joint optimization algorithm can achieve a balance between network lifetime and outage performance.

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