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 of 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 multiobjective 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 nondominated sorting genetic algorithm (NSGA-II) to obtain the Pareto-optimal front. In particular, NSGA-II is applied to solve the formulated multiobjective optimization problem, and the 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 the QoS provisioning by sacrificing about 10% network lifetime but improving about 15% outage performance.**

***Index Terms*—Cluster, cooperative communication, industrial Internet of Things (IoT) system, network lifetime, nondominated sorting genetic algorithm (NSGA-II), quality of service (QoS), quantum particle swarm optimization (QPSO).**

I. Introduction

Internet of Things (IoT) system is viewed to have the 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.

A capillary network was introduced to improve reliable and energy-efficient communications for the IoT systems. The capillary network is a specific local network that 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. The 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 networks. One form of cooperative communications, which is also 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 multiple-input–single-output (MISO) system in the long-haul transmission by decode-and-forward technique, with the objective of even energy distribution among the networks. Despite the advantages of CMISO scheme, it reduces the transmit power and thus degrades the quality of service (QoS) performance of long-haul communication in the capillary network. However, QoS provisioning [7], [8] 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 works 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 [9]. 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 this paper are summarized as follows.

1) First, considering that most recent literature works (see Section II for further detail) have aimed 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 multiobjective optimization problem of the tradeoff between QoS provisioning and energy efficiency. In this

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paper, we use outage performance and network lifetime as the metric for QoS provisioning and energy efficiency, respectively.

2) 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 stronger searching capability, rapid convergence, short computing time, and small population size [10]. 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-D search space by updating the fitness values of network lifetime and outage performance until reaching the predefined generation.
3) Third, to solve the multiobjective optimization of QoS provisioning and energy efficiency, the improved nondominated 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 nondominated 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 nondominated front compared with evolutionary algorithms (EAs), such as Pareto-archived evolution strategy and strength-Pareto EA [11].
4) 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 follows: In Section II, we present the related work. Section III introduces the network model, the system model, and the 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 communication for cluster-based networks has also been introduced to achieve different objectives, including energy efficiency and QoS, with the consideration of channel interference, node location, and residual energy.

In [12], authors proposed a cluster formation scheme based on low-energy adaptive clustering hierarchy (LEACH) algorithm in CMISO network that considers residual energy and the distance between every node to the sink node, to minimize energy consumption and 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 the most residual energy within the cluster. In [13], 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 the signal-to-noise ratio (SNR) of the received signal of the Coop is larger than a predefined SNR threshold level, and the second condition is that the Coop is within the transmission domain of the destination cluster. In [14], 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 a certain PER threshold. However, the authors in [12]–[14] only considered several Coop selection constraints instead of the cooperation benefit with CH.

In [15] and [16], the authors proposed a cluster-based CMISO communication with LEACH protocol [17]. However, LEACH only selects CHs with a certain probability and does not consider residual energy and location of nodes. In [18], the authors designed a cooperative communication scheme to achieve the optimal solution of a random tradeoff between the QoS provisioning and the energy efficiency by the Lambert W function and the coalition formation game theory. In [15], the authors assume that both CH and Coops are selected randomly, while in [16] and [18], the authors assume that 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 2-D space with the following assumptions:

1) All wireless devices perform the data collection task periodically and always have data to send to the sink node.
2) All wireless devices are homogeneous and energy constrained.
3) All wireless devices are capable of adjusting their transmit powers dynamically to reach the intended recipients with the minimum required energy.
4) All wireless devices are aware of their geographical locations and residual energies.
5) All wireless devices are equipped with short-range local area wireless radio, e.g., IEEE 802.15.4.
6) All devices are classified into three kinds of nodes: CH, CNs, and Coops.

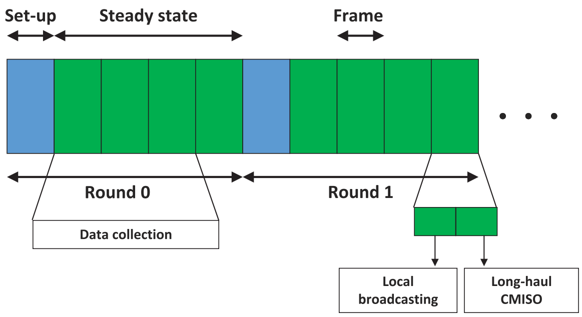

Fig. 1. Transmission structure in cluster-based IoT system.

7) All devices are capable of operating in data collection and aggregation mode as well as cooperative transmission mode.
8) 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 Coop 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:

1) Data collection phase (DC): CH collects and aggregates data from all the other devices, including both CNs and Coops.
2) Local broadcasting phase (LB): CH broadcasts the aggregated data to all Coops.
3) Long-haul cooperative transmission phase (LH): CH and Coops jointly transmit the aggregated data to the sink node based on the distributed space–time code (DSTC), which is a cooperative technique investigated in [19], 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

The system model considers 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 $\eta = \{\text{CH}, \text{CN}_1, \ldots, \text{CN}_i, \text{Coop}_1, \ldots, \text{Coop}_j\}$. The channels of CN_i and Coop_j to CH, denoted by $h_{\text{CH},\text{CN}_i}$ and $h_{\text{CH},\text{Coop}_j}$, respectively, and the channels between all transmitting nodes within the cluster (CH and Coop) 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.

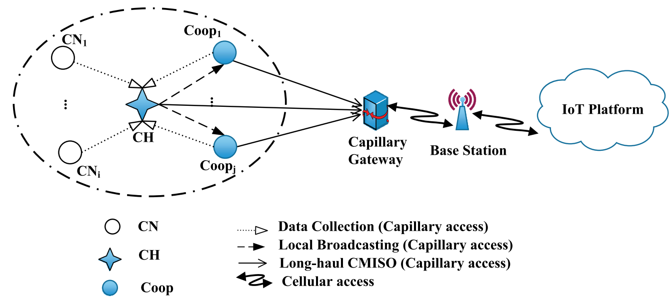

Fig. 2. System model.

C. Power Consumption Model

In this paper, we use the following power consumption model, as defined in [20]:

$$p = p_a + p_c \tag{1}$$

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 radio-frequency power amplifier and modulation scheme. In addition, p_c is composed of transmitter circuit block power consumption denoted by p_{ct} and receiver circuit block power consumption denoted by p_{cr}.

1) Data Collection Phase Power Consumption: In the Data Collection (DC) phase, the 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 and of transmitter circuit blocks. Therefore, the power consumption for CH, CNs, and Coops in this phase respectively are

$$p_{\text{CH}}^{\text{DC}} = p_{cr,\text{CH}}^{\text{DC}} \tag{2}$$
$$p_{\text{CN}_i}^{\text{DC}} = p_{a,\text{CN}_i}^{\text{DC}} + p_{ct,\text{CN}_i}^{\text{DC}} = (1+\alpha)p_{t,\text{CN}_i}^{\text{DC}} + p_{ct,\text{CN}_i}^{\text{DC}} \tag{3}$$
$$p_{\text{Coop}_j}^{\text{DC}} = p_{a,\text{Coop}_j}^{\text{DC}} + p_{ct,\text{Coop}_j}^{\text{DC}} = (1+\alpha)p_{t,\text{Coop}_j}^{\text{DC}} + p_{ct,\text{Coop}_j}^{\text{DC}}. \tag{4}$$

2) 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 and 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

$$p_{\text{CH}}^{\text{LB}} = p_{a,\text{CH}}^{\text{LB}} + p_{ct,\text{CH}}^{\text{LB}} = (1+\alpha)p_{t,\text{CH}}^{\text{LB}} + p_{ct,\text{CH}}^{\text{LB}} \tag{5}$$
$$p_{\text{CN}_i}^{\text{LB}} = 0 \tag{6}$$
$$p_{\text{Coop}_j}^{\text{LB}} = p_{cr,\text{Coop}_j}^{\text{LB}}. \tag{7}$$

3) 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 and power of transmitter circuit blocks, while CNs do not participate in this phase.

Assuming that 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

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

$$p_{\mathrm{CN}_i}^{\mathrm{LB}} = 0 \tag{9}$$

$$p_{\mathrm{Coop}_j}^{\mathrm{LH}} = p_{a,\mathrm{Coop}_j}^{\mathrm{LH}} + p_{ct,\mathrm{Coop}_j}^{\mathrm{LH}} = (1+\alpha)p_{t,\mathrm{Coop}_j}^{\mathrm{LH}} + p_{ct,\mathrm{Coop}_j}^{\mathrm{LH}}. \tag{10}$$

D. Transmit Power

1) Transmit Power of the Data Collection Phase: As referred to in [21], the transmit power of CN_i and Coop_j denoted by $p_{t,\mathrm{CN}_i/\mathrm{Coop}_j}^{\mathrm{DC}}$ can be derived from

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

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 $h \sim \mathrm{CN}(0,1)$ is unitary power and Rayleigh fading coefficients for all intracluster connections. In order to improve energy efficiency, we set (11) to be the lower bound, i.e.,

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

2) Transmit Power of the Local Broadcasting Phase: In terms of the CMISO transmission, as referred to in [22], the outage probability $\mathcal{P}_{\mathrm{out}}$, under a predetermined transmission rate R, can be expressed as

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

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

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

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

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

Denote the number of transmit devices to be n_t. Since $|h_{s,d}|^2 \sim X_{2n_t}^2$ (i.e., chi-square distributed random variable with $2n_t$ degrees of freedom) and the cumulative distribution function of $X_{2n_t}^2$ is the regularized incomplete Gamma function [23], i.e., $F_{X_{2n_t}^2}(b) = \gamma(1,b)$, where $\gamma(n_t,b) = (1/(n_t-1)!)\int_0^b x^{n_t-1}e^{(-x)}dx$, we have

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

Due to the broadcasting nature of wireless channel, once the Coop Coop_j with the worst channel receives data from CH, other Coops can receive the data simultaneously. As referred to in [24], the data received by all Coops need to be decoded correctly, and the transmit power $p_{t,\mathrm{CH}}^{\mathrm{LB}}$ can be derived from

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

As referred to in [25], R_{LB} cannot be lower than the long-haul transmission rate C_{out}; hence, we have

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

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 $p_{t,\mathrm{CH}}^{\mathrm{LB}}$ can be derived from

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

In order to reduce energy consumption, we set (19) to be the lower bound, i.e.,

$$p_{t,\mathrm{CH}}^{\mathrm{LB}} = \frac{(2^{2C_{\mathrm{out}}}-1)\sigma^2\kappa^{-1}d_{\mathrm{CH},\mathrm{Coop}_j}^{\delta}}{\left|h_{\mathrm{CH},\mathrm{Coop}_w}\right|^2}. \tag{20}$$

3) Transmit Power of the Long-Haul Cooperative Transmission Phase: Based on DSTC, each transmitting device has the same transmit power. Thus $p_{t,\mathrm{CH}}^{\mathrm{LH}} = p_{t,\mathrm{Coop}_j}^{\mathrm{LH}} = (p_t^{\mathrm{MISO}}/(J+1))$. That is

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

IV. Problem Formulation

The objective is to strike a balance between energy efficiency and QoS provisioning. As illustrated in [18], the design of CMISO communication scheme falls into two categories:

1) optimization of QoS provisioning subject to an energy constraint;
2) 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. Network Lifetime

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

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

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

$$T_{\mathrm{net}} = \min\left\{T_{\mathrm{CH}}, T_{\mathrm{CN}_1}, \ldots, T_{\mathrm{CN}_i}, T_{\mathrm{Coop}_1}, \ldots, T_{\mathrm{Coop}_j}\right\}. \tag{24}$$

B. QoS Provisioning

The outage performance can be formulated by

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

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

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

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

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

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

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

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

C. Multiobjective Optimization Problem Formulation

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

$$\{\mathrm{CH}, 1, \ldots, \mathrm{Coop}_j\} = \arg\max\{T_{\mathrm{net}}, J\}. \tag{29}$$

V. QPSO-Based NSGA-II Algorithm

A. QPSO

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 [26], 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 mth particle at generation t is defined as

$$v_m^t = \begin{bmatrix} \alpha_{m1}^t & \alpha_{m2}^t & \cdots & \alpha_{mR}^t \\ \beta_{m1}^t & \beta_{m2}^t & \cdots & \beta_{mR}^t \end{bmatrix} \tag{30}$$

where $m \in [1, 2, \ldots, h]$, 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 (30) as

$$\boldsymbol{v}_m^t = \begin{bmatrix} \boldsymbol{\alpha}_{m1}^t & \boldsymbol{\alpha}_{m2}^t & \cdots & \boldsymbol{\alpha}_{mR}^t \end{bmatrix}. \tag{31}$$

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

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

where $\delta_{mn} \in [0, 1]$ is a 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 (23) and (25).

Denoting 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 $\boldsymbol{p}_m$ are defined as follows:

$$\boldsymbol{f}_m = \min\left\{f_m^1, f_m^2, \ldots, f_m^t\right\} \tag{33}$$
$$\boldsymbol{p}_m = [p_{m1}, \ldots, p_{mn}, \ldots, p_{mR}]. \tag{34}$$

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

$$\boldsymbol{f}_g = \min\{\boldsymbol{f}_1, \ldots, \boldsymbol{f}_m, \ldots, \boldsymbol{f}_h\} \tag{35}$$
$$\boldsymbol{p}_g = [p_{g1}, \ldots, p_{gn}, \ldots, p_{gR}]. \tag{36}$$

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

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

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 the mth quantum particle at $t+1$ generation is

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

If $\theta_{mn}^{t+1} = 0$ and $r = c_1$, the updated velocity of the mth 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 in [27], in a maximization problem, a vector $\boldsymbol{x} = [x_1, x_2, \ldots, x_p]^T$ is said to dominate $\boldsymbol{y} = [y_1, y_2, \ldots, y_p]^T$, 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 multiobjective 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 [11], each solution has two entities:

1) domination count n_p, which is defined as the number of solutions that dominate individual p;
2) S_p, which is the set containing all the individuals that are being dominated by p.

The nondominated sorting focuses on identifying all fronts, which is described as follows:

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 ith solution, and $F^{(1)}$ is the first nondominated front.
iii) For each solution i in $F^{(1)}$, visit each member q of its domination set S_i. For every member q, where $q \in S_i$, $n_q = 0$, $n_q^{\text{new}} = n_q - 1$. Put q in a separate list Q if $n_q^{\text{new}} = 0$. The members in Q belong to the second nondominated front $F^{(2)}$.
iii) Visit each member in $F^{(2)}$ and repeat Step ii) until all fronts are identified.

The authors in [11] 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 nondominated 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-D 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 Coop 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. In addition, 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:

1) Step 1: Assume every device to be CH in turn and operate the following steps to select the optimum Coops for the assumed CH.
2) 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 are randomly generated. The local optimum position of the particle is equal to the current position of the particle.
3) 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 nondominated sorting scheme in NSGA-II. Choose nondominated solutions from the first Pareto front to the last Pareto front and add them into $\boldsymbol{P}$, which is an external memory to store nondominated solutions with the maximum predefined size N_0. The global optimum position $\boldsymbol{p_g}$ is chosen from the top part of $\boldsymbol{P}$ (i.e., top 5%) randomly.
4) Step 4: Generate a new population $\boldsymbol{S_{\text{new}}}$ through the QPSO algorithm from $\boldsymbol{S}$. Renew the quantum rotation angle of each quantum particle by (37). Update $\boldsymbol{p}_m$ and $\boldsymbol{p}_g$ correspondingly from (33) to (36). Update the quantum position of each particle by (32). Update $\boldsymbol{p}_m$ and $\boldsymbol{p}_g$ correspondingly from (33) to (36).
5) Step 5: Evaluate each quantum particle of the new population $\boldsymbol{S_{\text{new}}}$ by the fitness value of both objectives: network lifetime and long-haul transmit power. Combine the current population and the parent population and form a new population, i.e., $\boldsymbol{S^*_{\text{new}}} = \boldsymbol{S_{\text{new}}} \cup \boldsymbol{S}$. Sort the new population $\boldsymbol{S^*_{\text{new}}}$ according to nondominated sorting scheme in NSGA-II. Select nondominated solutions and add them to $\boldsymbol{Q}$, which is an external memory similar to $\boldsymbol{P}$.

6) Step 6: Combine $\boldsymbol{Q}$ and $\boldsymbol{P}$ to form a new Pareto solution memory set $\bar{\boldsymbol{S}}$, i.e., $\bar{\boldsymbol{S}} = \boldsymbol{P} \cup \boldsymbol{Q}$. Sort $\bar{\boldsymbol{S}}$ according to nondominated 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.
7) Step 7: Replace $\boldsymbol{S}$ by $\boldsymbol{S}_{\mathbf{new}}$ to participate in the next generation.
8) Step 8: If it has reached the maximum generation, then stop the process. The solutions in $\bar{\boldsymbol{S}}$ are nondominated solutions. Otherwise, go to Step 4 until it has reached the maximum generation denoted by $T_{\max}$. The solutions in $\bar{\boldsymbol{S}}$ are Pareto front solutions.
9) Step 9: Repeat Steps 1–8 until finding the optimum cooperative coalition for every CH. Add all Pareto front solutions obtained in Step 8 for each CH in external memory $\boldsymbol{S}_{\text{final}}$ with the maximum predefined size N_0. Sort $\boldsymbol{S}_{\text{final}}$ according to nondominated 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 $\boldsymbol{S}_{\text{final}}$ are the optimum ones.

VI. Simulation

The simulation tool used in this paper is MATLAB. There are ten wireless devices randomly distributed within a circle of 100-m radius. We adopt the circuit power consumption model in [20]. 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 1 and 1.5 J, randomly. In addition, we adopt the circuit power consumption model in [20]. 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) and the single-input–single-output (SISO) transmission scheme between the cluster and the gateway, i.e., LEACH [17]. The fitness values are implemented by (23) and (25). In QPSO algorithm, we simulate particles by the following attributes: the particle position in (32), the rotation angle in (37), and the velocity in (38) and (39). For each generation, the particle velocity and position are updated according to the rotation angle. The particle position can suggest the Coop selection in each generation, and fitness values can then be updated correspondingly based on different Coop selection. In NSGA-II, we implement the nondominated 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 Pareto-optimal front, which are the two variables to update the rotation angle in (37).

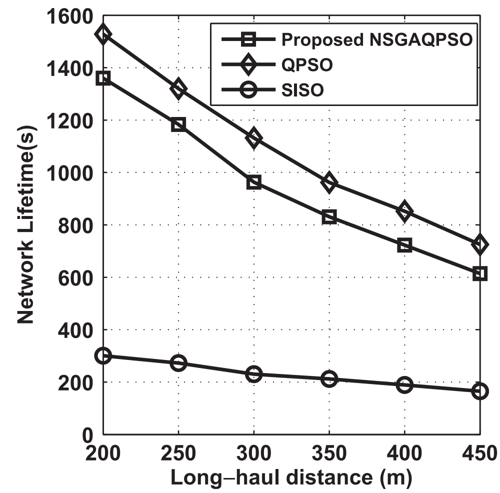

Fig. 3. Network lifetime versus long-haul distance.

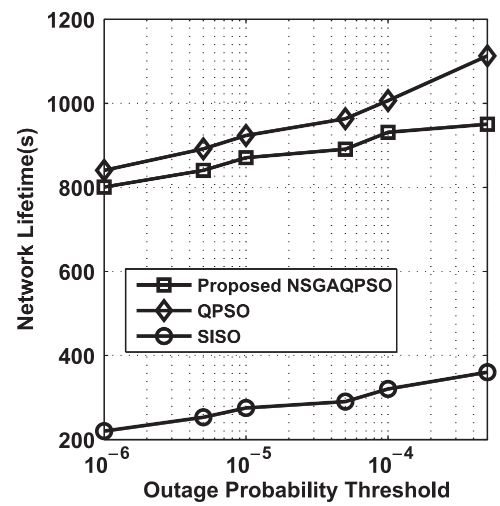

Fig. 4. Network lifetime versus outage probability threshold.

First, we observe that the network lifetime with different long-haul distances in Fig. 3. The outage probability threshold is $P_{\text{out}}^{\text{thr}} = 10^{-3}$. 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. In addition, the network lifetime of QPSO network lifetime optimization algorithm is better than that of the proposed NSGA-QOSP algorithm, due to higher long-haul transmit power of the proposed NSGA-QPSO algorithm. Note that both CMISO schemes outperform the SISO scheme significantly.

Second, Fig. 4 shows the network lifetime with different outage probability thresholds. The long-haul distance is 300 m. 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 QoS, in terms of minimum transmit power to avoid outage, i.e., the lower the outage probability, the more transmit power and the better received signal quality. It is shown in Fig. 4 that the network lifetime goes up with the increase of

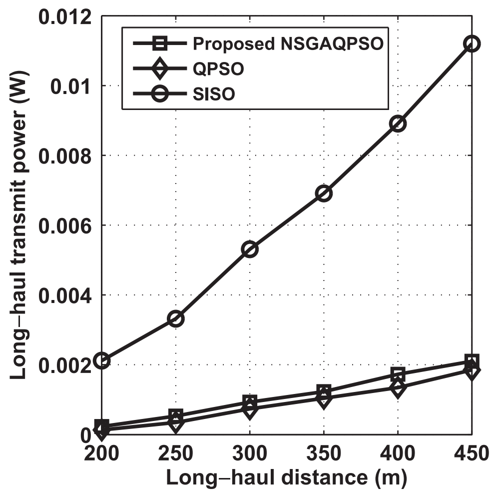

Fig. 5. Transmit power versus long-haul distance.

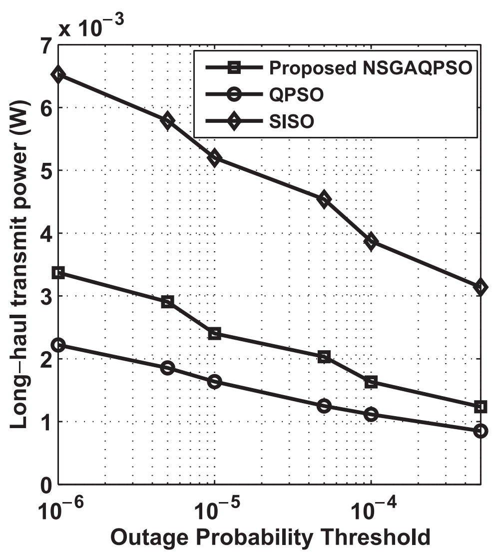

Fig. 6. Transmit power versus outage probability threshold.

outage probability threshold. The QPSO network lifetime optimization algorithm outperforms the proposed NSGA-QPSO algorithm in network lifetime due to higher long-haul transmit power of the proposed NSGA-QPSO algorithm. In addition, both the QPSO network lifetime optimization algorithm and the proposed NSGA-QPSO algorithm outperform the SISO scheme.

However, in terms of the long-haul transmit power, we can observe in Figs. 5 and 6 that the proposed NSGA-QPSO algorithm outperforms the QPSO long-haul transmit power optimization, which indicates that the proposed NSGA-QPSO 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 the 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 nondominated 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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