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An Energy Efficient Internet of Things Network Using Restart Artificial Bee Colony and Wireless Power Transfer

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ABSTRACT The Internet of Things (IoT) provides a beautiful and intelligent landscape for humanity's future. The connections of various sensors and devices in the IoT result in a large consumption of energy. Therefore, research on energy saving and energy efficient methods is imperative. For wireless sensors in an IoT network, sustainable operation in an energy efficient manner is essential due to the limited battery capacity of sensors. This paper attempts to study an IoT network containing wireless sensors and base stations. Wireless power transfer techniques for supplying battery charging are becoming increasingly mature. For wireless sensors, a charging vehicle is responsible for the electrical power supply. To save electrical energy, data transfer of the discussed IoT network scenario is expressed as a minimization problem. A three-stage method is proposed to handle the optimization problem. A restart artificial bee colony (RABC) method is proposed to solve the subproblems of the data transfer model. It is proved that the RABC method asymptotically converges to the optimal solution of the problem. Numerical simulations show that energy consumption in the studied network scenario can be minimized using the proposed method with a good, robust property.

INDEX TERMS Artificial bee colony, global optimization, Internet of Things, wireless power transfer, wireless sensor.

I. INTRODUCTION

The Internet of things (IoT) is a network that extends through the Internet. In the Internet of things, "things" and the internet are connected through radio frequency identification equipment, sensors and positioning equipment in accordance with a certain agreement to exchange and communicate information, so that the recognition, location and supervision of the object will become more intelligent. Its greatest feature is communication and dialog between things that can also interact and communicate with the environment [1], [2].

In 2003, Technical Comments of the United States proposed that sensor network technology will be the first technology to change people's lives in the future. In 2004, the Ministry of Internal Affairs and Communications (MIC) of Japan proposed the u-Japan project, which strived to realize the connection between people, things, and people and things, and hoped to build Japan into a network society anytime, anywhere, between any things and any people [3]. In 2005, the International Telecommunication Union (ITU) published "ITU Internet Report 2005: Things" at the World Summit on the Information Society (WSIS) held in Tunisia. In this report, the concept of the "Internet of Things" is defined. The scope of the IoT had been expanded greatly, and no longer referred to the Internet of things based on RFID technology [4]. In 2008, Innovation 2.0 was proposed in China to develop the mobile and IoT technologies, which represented the formation of a new generation of information technology, and promoted the transformation of economic and social forms to innovative forms. In 2009, the IoT became one of the key points for revitalizing the economy in America. IoT technology has attracted attention worldwide and has developed rapidly. The number of interconnected devices increased from 7 billion to 9 billion worldwide in three years from 2010 to 2013. It is expected to reach 24 billion devices by 2020. According to the Global System for the Mobile Communications Alliance (GSMA), this amounts to $1.3 trillion in revenue opportunities for mobile network operators involving health care, automotive transportation, utilities and consumer electronics [1].

The development of the IoT requires the connection of all types of wired or wireless sensors and other devices. Wireless sensors are usually equipped with batteries of limited capacity. The limited power constrains the data transfer in the IoT. Hence, finding an energy efficient method for promoting the development of the IoT is inevitable. This paper attempts to study an IoT scenario with wireless sensors and base stations (BSs). Wireless sensors generate data and transmit to the BSs. There are two levels of BSs: the micro base station and the macro base station (BS). The micro BS receives data from wireless sensors and sends it to the macro BS. The macro BS then sends data to the database or cloud computing platform. Regarding the limited battery capacity, the wireless power transfer (WPT) technique is suitable for charging the battery. It is assumed that a vehicle equipped with a large capacity battery is responsible for charging the batteries of the sensors. A novel method is proposed to solve the data transfer problem. The contributions of this paper are as follows:

(1) The IoT scenario is modeled as an optimization problem. In the model, the total energy cost of the wireless sensors and vehicle are minimized. Hence, the energy consumption of the network is also minimized.

(2) A three-stage method is proposed for the problem. The stages are finding the shortest travel path, mutual interference reduction and determining the optimal uplink route. The travel path is the route of the vehicle to visit all wireless sensors. Mutual interference is the signal interference among sensors and micro BSs. The uplink route is the data transfer route from the sensors to the macro BS.

(3) A restart artificial bee colony (RABC) method is proposed to solve for the travel path and uplink route. The asymptotic convergence of the RABC method is also proved. The RABC method can provide a set of promising solutions to the problem.

Section II introduces the recent studies of the IoT, wireless sensor network and WPT. Section III describes the IoT scenario and its mathematical model discussed in this paper. Section IV presents the three-stage method. Section V presents the RABC method. The simulation results are provided in Section VI to verify the usefulness of the proposed method. The conclusion is drawn in Section VII.

II. RELATED WORKS

There are five technologies in the IoT: radio frequency identification (RFID), wireless sensor networks (WSNs), middleware, cloud computing and IoT application software [1], [2]. Among these, the WSN is the important technology for obtaining the data and information from the environment.

A wireless sensor network is a computer network system that uses space distributed autonomous devices to monitor the physical or environmental status of different positions such as the temperature, sound, vibrations, pressure, etc. Recently, the technology of WSNs has been widely applied in industrial control, smart homes, security, military safety, intelligent agriculture, environmental awareness and health monitoring [5]. Synchronization and/or localization of a WSN can be modeled as optimization problems, which can then be tackled using nonlinear programming methods [6]–[10]. Because of the small volume of the sensor nodes, the battery energy that they carry is limited, which restricts the application of a WSN. To address this problem, Han *et al.* [11], [13], [14], Liang *et al.* [12], Ma and Wang [15], and Wu *et al.* [16] designed energy saving routing protocols to solve the energy problem. However, these studies could only reduce the energy consumption, and did not replenish energy to the sensor nodes that lack energy. Thus, the technology of wireless power transfer (WPT) [17]–[21] provides the opportunity for replenishing a sensor with energy at any time.

In 2007 [17], a research team from MIT proposed the technology of wireless power transfer based on the coupled magnetic resonances. In this system, the power can transfer from the transmitter coil to the receiver coil wirelessly, which have identical resonant frequencies. In contrast to the inductive wireless power transfer system, the wireless power transfer system based on coupled magnetic resonance can transfer power over a mid-range distance with high efficiency [19], [20]. Zhang and Zhang [21] studied the charging problem in the WPT system using a near field plate structure. Zhao *et al.* [22] studied the assignment of time for a three-node WPT communication system. Rana and Xiang [23] studied the estimate of the state and stabilization of the IoT network for the WPT system.

Combining the technology of the WSN and WPT, in this case, the wireless rechargeable sensor network (WRSN) is designed and studied [24]–[26]. Xie *et al.* [24] studied the operation of charging each sensor's battery wirelessly using a mobile charging vehicle. The researchers obtained the maximum vacation time of the mobile charging vehicle over the cycle time. Fu *et al.* [25] proposed a charging scheme for WRSNs to minimize charging delays. The authors did not consider the data transmission between the sensors and the base stations. Han *et al.* [26] proposed a grid-based joint routing and charging algorithm in which the sensor nodes were not charged one by one.

III. PROBLEM MODELING

The scenario considered in this paper is comprised of wireless sensors, micro base stations (BSs) and a macro base station as in Figure 1. Connections of wired devices (e.g., a wired sensor or computer) are more reliable than those of wireless sensors. Hence, wired devices are not considered in this study. Wireless sensors contain batteries with a limited capacity. They are assumed to have the same type of battery and are fully charged in the beginning. There are two types of base stations: macro BS and micro BS. It is assumed that wired connections are present between the micro BSs and a macro BS. As wireless connections are less reliable and consume more energy than wired connections, it is reasonable to put more effort on wireless sensors.

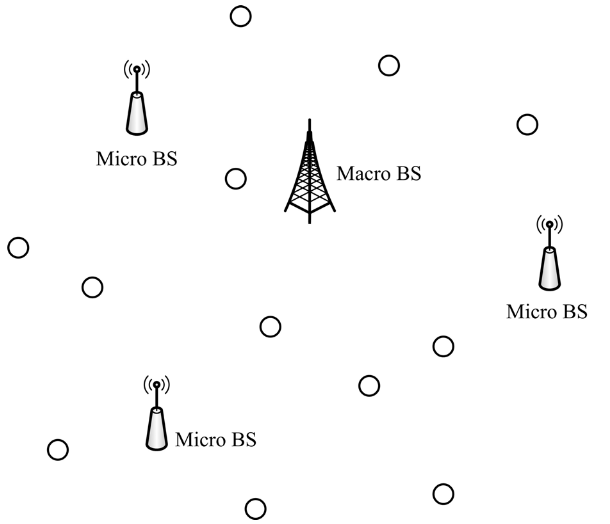


FIGURE 1. An example of a problem scenario.

Denote *Nws* and N_{MI} as the number of wireless sensors and the number of micro BSs, respectively. Suppose the sensing data rate of sensor i is R_i. The sensors send the collected data to the micro BSs, which send data to the macro BS. In case a sensor is not covered by a micro BS, its nearest sensor becomes a relay to transmit data. Multi-hop data transmission may be required in such a case. Hence, the data transmitted, received and sent by sensor i should be balanced:

$$\sum_{k \neq i} f_{ki} + R_i \geq \sum_{i \neq j} f_{ij} \tag{1}$$

where f_{ki} is the data from sensor k to sensor i, and f_{ij} is the data from sensor i to sensor j; the first term is the data received by sensor i, and the last term is the data sent by sensor i, either to another sensor or to a micro BS. Let the sensing data rate of the micro BS be $R_i = 0$, then formula (1) is also correct for the micro BS. Note that a sensor may hold its data transmission when Signal to Interference plus Noise Ratio (SINR) or Signal to Noise Ratio (SNR) is too low. Thus, the left hand side of (1) should be greater than or equal to the right hand side.

Based on data transmission, the energy consumption per unit time can be computed as:

$$e_i = \rho_i \sum_{k \neq i} f_{ki} + \sum_{j \neq i} C_{ij} f_{ij}, \tag{2}$$

where e_i is the energy cost for node i, the second term is the energy cost for receiving data and ρ_i is the basic consumption per unit data rate. In (2), C_{ij} is the energy cost for sending one data unit. It is usually related with the distance between two nodes and computed as:

$$C_{ij} = \beta_1 + \beta_2 D_{ij}^{\alpha}, \tag{3}$$

where D_{ij} is the distance between node i and node j and α, β_1 and β_2 are constants depending on D_{ij}. Formula (3) was used in [24].

For simplicity, N_{ws} wireless sensors and N_{MI} micro BSs are considered nodes in the IoT network. Spectrum resources are very precious in wireless communication networks, and proper spectrum allocation is necessary for data transfer in IoT networks such as cellular networks and cognitive relay networks [27], [28]. Mutual interference among wireless sensors and micro BSs must be considered. It is also necessary to reduce consumption power so that their interferences are below a predefined threshold IT_i. Denote $g(m, i, j)$ as the channel gain between node i and node j operating on the same channel m. Denote $P(m, i)$ as the transmission power of sensor i. Thus, the following formula is established:

$$\sum_{j \neq i} P(m, j) * g(m, j, i) \leq IT_i. \tag{4}$$

For the scenario, a sustainable network uses a charging vehicle to supply electric power for the wireless sensors. Clearly, the charging vehicle should work periodically to construct a sustainable cycle. During one cycle, each sensor collects and transmits data according to some route, and the interference caused by data transmission must be less than an interference threshold. The macro base station is responsible for transmitting data to the data center or destination. Given that wireless sensors can be charged periodically, the IoT network can run in a cycle.

Suppose there is a place for charging the vehicle, which is the starting place. Clearly, the vehicle should visit all wireless sensors to recharge the batteries. Denote v as the velocity of the vehicle, and suppose the vehicle maintains a constant velocity to traverse all sensors. Thus, the travel time of the vehicle is:

$$\tau_v = \frac{l}{v}, \tag{5}$$

where l is the path length of the vehicle trip. The vehicle should return to the starting place after its travel to recharge its battery or substitute another battery.

Denote τ as the time for the vehicle to traverse all sensors and recharge all nodes. The amount of electric power used by sensor i must equal the amount of power recharged by the vehicle. Hence, the recharging time of sensor i is:

$$\tau_i = \frac{e_i \tau}{U}, \tag{6}$$

where U is the electric power transfer rate. Thus, the cycle time of the network τ is:

$$\tau = \sum_{i=1}^{N_{ws}} \tau_i + \tau_v. \tag{7}$$

Because v and U are considered constants, minimizing the cycle time (6) is equivalent to minimizing the energy consumption of the network.

Finally, the problem is expressed as in (8). In problem model (8), the data transmission rate f_{ij}, energy consumption e_i, and travel length l are independent variables. The objective is to minimize the travel time and charging time of all nodes.

IV. PROBLEM SOLVING

Formula (8) is a non-differentiable optimization problem. A three-stage method is proposed to solve this problem. The first stage is to determine the variable l. This variable is the shortest path for traveling to all wireless sensors. The second stage is to reduce the mutual interference of wireless sensors and micro BSs. This stage assigns different channels to satisfy the third inequality constraints in (8). The third stage is to determine f_{ij} and e_i so that an optimal uplink route is found for the problem.

$$\begin{aligned} &\min \tau = \tau_v + \sum_{i=1}^{N_{ws}} \tau_i \\ &s.t. \sum_{k\neq i} f_{ki} + R_i - \sum_{i\neq j} f_{ij} \geq 0, \\ &\quad e_i - \rho_i \sum_{k\neq i} f_{ki} + \sum_{j\neq i} C_{ij} f_{ij} = 0, \\ &\quad \sum_{j\neq i} P(m,j) * g(m,j,i) \leq IT_i \\ &\quad i = 1, \cdots, N_{ws}, \quad \text{or } i = 1, \cdots, N_{MI}, \\ &\quad f_{ij}, e_i, l \geq 0,. \end{aligned} \tag{8}$$

In model (8), the variables are the data from sensor i to sensor j f_{ij}, energy consumption of sensor ie_i and travel length l. By optimizing the travel length l, all sensors are able to keep working. By optimizing sensor energy consumption e_i and data transfer route f_{ij}, energy cost of sensors can then be minimized.

A. SHORTEST TRAVEL PATH

The charging vehicle must traverse all wireless sensors. Based on graph theory [29]–[31], all sensors are represented as nodes, so they are the starting points of the vehicle. If the vehicle is restricted, then it passes each node only once. The shortest travel path belongs to the traveling salesman problem (TSP). The TSP was proved to be a non-deterministic (NP) complete problem. In our case, the vehicle returns to the starting place, hence, its trip is a cycle. Finding the shortest path becomes finding the shortest Hamilton circuit for the trip.

Theorem 1: For an optimal solution of model (8), the vehicle travel path must follow one of the shortest Hamilton circuits (the shortest Hamilton circuit might not be unique).

Proof by Contradiction: Suppose $\mathbf{x} = (f_{ij}, e_i, l)$ is an optimal solution of model (8), but the travel path of this solution does not follow one of the shortest Hamilton circuits.

Denote l' as one of the shortest Hamilton circuits. Based on solution $\mathbf{x}$, another solution $\mathbf{x}'$ could be constructed $\mathbf{x}' = (f'_{ij}, e'_i, l')$ with $f'_{ij} = f_{ij}$, and $e'_i = e_i$. Because $\mathbf{x}$ is a solution of model (8), it satisfies the first three constraints. Thus, based on the construction of $\mathbf{x}'$, solution $\mathbf{x}'$ also satisfies the first three constraints. This means that $\mathbf{x}'$ is a feasible solution of model (8).

Based on (5), $\mathbf{x}'$ follows one of the shortest Hamilton circuits, whereas $\mathbf{x}$ does not. Hence, $\tau_v(\mathbf{x}') < \tau_v(\mathbf{x})$. Moreover, $\tau_i(\mathbf{x}') = \tau_i(\mathbf{x})$ due to $e'_i = e_i$. Then, we have $\tau(\mathbf{x}') < \tau(\mathbf{x})$. On the other hand, based on the assumption that $\mathbf{x}$ is an optimal solution, we have $\tau(\mathbf{x}) \leq \tau(\mathbf{x}')$. The conclusions contradict each other. Therefore, the theorem holds.

Although there are many methods for finding the shortest Hamilton circuit, a new method will be designed in the next section for such a problem. This method is not only effective but also more robust than other methods.

B. REDUCING THE MUTUAL INTERFERENCE

Due to the dense deployment of sensors and/or BSs, wireless data transmission causes mutual interference. The following method is useful for reducing or removing such mutual interferences.

First, it is practicable to determine the interference region for each node. Because the transmission power of the sensors and micro BS are limited, the radius of their interference region can be computed. For simplicity, it is assumed that the wireless sensors have the same radius R_{ws}, and the micro BSs have the same radius R_{MI}. If two nodes are distant from the interference radius, then both nodes can use the same channel; otherwise, both nodes interfere with each other if using the same channel, which can be solved in the second step.

Second, the graph coloring principle is used to remove the mutual interference of nodes. For nodes located in the interference region, the graph coloring principle is very useful for removing the mutual interference. The nodes having potential interference constitute an undirected graph. The covering region of each micro BS is considered an undirected graph. It is assumed that the mutual interference does not occur between two micro BSs. According to the Headwood theorem, the number of colors is not greater than 5. Thus, if the mutual interference can be reduced to an undirected planar graph, five channels are sufficient for removing it.

C. OPTIMAL UPLINK ROUTE

After the mutual interference is reduced to the required level, there are many possible uplink transmission routes, especially when the number of nodes becomes large. For energy-saving purposes, it is necessary to find the optimal or suboptimal route.

As observed from model (8), parameters f_{ij} and e_i must be determined. Parameter e_i can be computed using the second equality constraint of (8). Thus, determining f_{ij} is crucial. There are $(N_{ws}+N_{MI})^2$ parameters to be determined, which is very difficult. The following method is used to find an optimal solution for the uplink route.

First, find a set of good and feasible solutions to model (8). Let the sensors and micro BSs be graph nodes. Then, construct an undirected graph of all nodes, in which two nodes are connected by an edge if data can be transmitted based on the allowed interference. After a graph is constructed, its minimum spanning tree (MST) can be found [30]. It is assumed that micro BSs can connect to the macro BS, so it is better to decide the MST for each micro BS and its corresponding covering region. This makes each micro BS the center of its covering region. The method proposed in the next section can be used to find the MST. Next, we will show that data transfer based on the MST is a feasible solution to model (8).

Theorem 2: For a data transfer route based on a minimum spanning tree, the route is a feasible solution to model (8).

Proof: Suppose $\mathbf{x} = (f_{ij}, e_i, l)$, where l is determined in Section III-A, and f_{ij} (the data transmitted from node i to node j) follows an MST. It is easy to verify that $\mathbf{x}$ is a feasible solution.

Mutual interference was discussed in Section III-B. Based on the construction of the graph, an edge exists only if two nodes can transmit data without violating the interference threshold. Hence, the third constraint of (8) is satisfied.

For the MST, all wireless sensors can be connected directly or indirectly to the nearest micro BS. Micro BSs then connect with the macro BS. Hence, the data received and generated by a sensor or micro BS equals the data sent to other sensors, micro BSs or the macro BS. Thus, the first equality constraint of (8) holds. The energy consumption e_i is computed using the second constraint of (8). This constraint also holds with respect to $\mathbf{x}$. Then, $\mathbf{x}$ is a feasible solution of (8).

Having found a feasible solution based on the MST, the proposed method is initialized in the next section. Then, the proposed optimization method is responsible for finding better solutions. The proposed optimization method is provided in the next section.

V. RESTART ARTIFICIAL BEE COLONY METHOD

To evaluate global optimization problems, the restart artificial bee colony (RABC) method is proposed in this section. Note that in this section index i and j refers to solutions and variables of optimization problems, which differs from the meaning of Section III and Section IV. First, the RABC method is provided, followed by the convergence analysis.

The work flow of the RABC method is shown in Figure 2. It begins with a set of food sources (potential solutions for a problem). In general, the initial food source set is created based on a uniform distribution. The bee colony consists of employed bees and onlooker bees. Denote N_b as the number of bees in the colony. Half of the N_b bees are employed bees and half are onlooker bees. Accordingly, the pseudocode of the RABC method is shown in Algorithm 1.

A. PROCEDURES OF THE RABC METHOD

The employed bees perform a search in a large region and are responsible for reaching the neighborhood of the global optimum. For continuous optimization problems, the following formula is used to produce a candidate solution $\mathbf{v}_i$:

$$v_{ij} = x_{ij} + r_{ij}\left(x_{ij} - x_{kj}\right), \tag{9}$$

where $\mathbf{x}_i$ and $\mathbf{x}_k$ $(i \neq k)$ are two solutions, index j refers to the j-th parameter of a solution, and r_{ij} is a random number between -1 and 1. For discrete optimization problems, such as the shortest Hamilton cycle problem, all nodes are encoded by integers to constitute a solution, and then the candidate solution $\mathbf{v}_i$ is produced either by a reverse operation or by an exchange operation:

$$\mathbf{v}_i = \begin{cases} \textit{reverse opeartion} & \textit{if } r_i < p_{rev} \\ \textit{exchange operation} & \textit{otherwise}, \end{cases} \tag{10}$$

where p_{rev} is the probability of doing the reverse operation. The reverse operation refers to reversing the order of

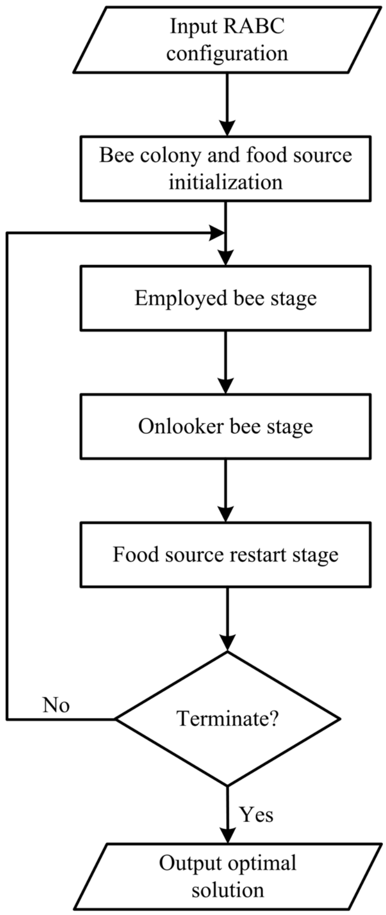


FIGURE 2. Flow chart of the RABC method.

Algorithm 1 Pseudocode of the RABC Algorithm

Input Model (8), N_b, range of variables
Output The best solution found by the algorithm
Randomly create a set of N_b solutions;
Evaluate the solutions by model (8);
Repeat
    Send out employed bees by (9) and (10);
    Evaluate the solutions by model (8);
    Do greedy selection to attain good solutions;
    Send out onlooker bees by (11);
    Evaluate the solutions by model (8);
    Do greedy selection to attain good solutions;
    Send out restart scout bees by (12);
    Evaluate the solutions by model (8);
    Do greedy selection to attain good solutions;
Until termination criteria are met.

a fraction of a solution. This operation may result in a candidate solution much different from the older one. The probability p_{rev} is set to 0.1 in this paper. The exchange operation refers to exchanging the positions of two parameters of a solution.

The onlooker bees perform their search in a small region and are responsible for refining high fitness solutions. For continuous optimization problems, a food source $\mathbf{x}_t$ is chosen based on its fitness, and then the following formula is used to produce the candidate solution $\mathbf{v}_i$:

$$v_{tj} = x_{tj} + r_{tj}\left(x_{tj} - x_{kj}\right), \tag{11}$$

where $\mathbf{x}_t$ and $\mathbf{x}_k$ $(t \neq k)$ are two solutions. For the shortest Hamilton cycle problem, the exchange operation is used to produce $\mathbf{v}_i$.

In the RABC method, the restart stage substitutes the scout bee stage of the standard artificial bee colony (ABC) method. The advantage of the restart technique is that it assures asymptotic convergence of the method to the global optimum. The restart technique refers to a proportion of low fitness food sources that are replaced by new food sources as follows:

$$\mathbf{x}_i^{new} = \mathbf{x}^{\min} + \mathbf{r}_i\left(\mathbf{x}^{\max} - \mathbf{x}^{\min}\right), \tag{12}$$

where $\mathbf{x}^{\min}$ and $\mathbf{x}^{\max}$ are the lower and upper bounds of a solution, and $\mathbf{r}_i$ is a vector of random numbers between 0 and 1. Denote p_{ro} as the proportion of food sources to be replaced. It is set to 5% in this paper.

B. CONVERGENCE ANALYSIS OF THE RABC METHOD

For a continuous or discrete optimization problem $f(\mathbf{x})$, there may be several global optima. Denote S^* as the global optima set of $f(\mathbf{x})$. In real world applications such as the wireless communication field, optimal solutions are generally not isolated. Therefore, given a threshold ε of the global optimal function value $f(\mathbf{x}^*)$, that is:

$$\left|f(\mathbf{x}) - f\left(\mathbf{x}^*\right)\right| < \varepsilon, \tag{13}$$

it is reasonable to assume that the size of S^* under some metric is a positive number, that is:

$$\mu\left(S^*\right) = \delta > 0, \tag{14}$$

where μ stands for some measure of set S^*. Given threshold ε of the optimal function value, the associated solutions satisfying the threshold constitutes an optimal solution set S_ε^*. Hence, we can define the convergence of a method in probability to the optimal solutions.

Definition 1: Suppose $\{\mathbf{X}^t, \mathrm{t} = 1, 2, \ldots\}$ is the population sequence produced by a stochastic method when solving problem $f(\mathbf{x})$. If

$$\lim_{t\to\infty} p\left\{\mathbf{X}^t \cap S_\varepsilon^* \neq \emptyset\right\} = 1, \tag{15}$$

then we say that the stochastic method can converge to S_ε^* in probability.

Theorem 3: Denote $\{\mathbf{X}^t, \mathrm{t} = 1, 2, \ldots\}$ as the sequence produced using the RABC method. Denote $\frac{\mu(S_\varepsilon^*)}{\mu(S)} = \delta > 0$ as the ratio of the optimal solution set to the feasible solution set. If $0 < p_{ro} < 1$, then the RABC method converges to S_ε^* with a probability of 1.

Proof: Let $p\left\{\mathbf{x} \in S_\varepsilon^*\right\}$ be the probability of solution $\mathbf{x}$ being an optimal one. In the restart stage of the RABC method, there are $p_{ro} \times N_b$ random restart solutions. The probability that such solutions lie in S_ε^* is no less than δ. As the restart stage works at each generation of the RABC method, the probability that solutions in population $\mathbf{X}^t$ lie outside of S_ε^* is:

$$p\left\{\mathbf{x}^t \notin S_\varepsilon^*\right\} \leq 1 - \delta, \quad where\ \mathbf{x}^t \in \mathbf{X}^t, \tag{16}$$

Based on (16), the probability that the first t generations do not produce an optimal solution is:

$$\prod_{i=1}^{t} p\left\{\mathbf{X}^i \cap S_\varepsilon^* = \emptyset\right\} \leq (1-\delta)^t, \tag{17}$$

On the other hand, considering the evolution process of the RABC method, the best-so-far solution survives and stays in the population if $p_{ro} < 1$. Thus, the best solution in the t-th generation is identical to the best solution in the first t generations. The following formula holds:

$$\begin{aligned}\lim_{t\to\infty} p\left\{\mathbf{X}^t \cap S_\varepsilon^* = \emptyset\right\} &= \lim_{t\to\infty} \prod_{i=1}^{t} p\left\{\mathbf{X}^i \cap S_\varepsilon^* = \emptyset\right\} \\ &\leq \lim_{t\to\infty} (1-\delta)^t = 0,\end{aligned} \tag{18}$$

Therefore,

$$\lim_{t\to\infty} p\left\{\mathbf{X}^t \cap S_\varepsilon^* \neq \emptyset\right\} = 1. \tag{19}$$

This completes the proof.

The above analysis shows that the proposed RABC method converges asymptotically to the global optimum. The RABC method belongs to the swarm intelligence category. Such approaches have been used to evaluate optimization problems in the communication and energy optimization fields [32]–[37].

VI. EXPERIMENTAL RESULTS

This section presents the results for designing a sustaining IoT network with wireless power transfer using the proposed RABC method.

A. VEHICLE ROUTING BY THE RABC METHOD

Given a network, an optimal route must be found so that the vehicle takes the shortest time to pass all nodes once. Considering the sensor and/or base station as graph nodes, the vehicle routing is equivalent to finding the shortest Hamilton cycle of the network. There are many powerful solvers for the Hamilton path problem such as the Concorde solver. It is necessary to show the advantages of the RABC method over other methods.

Suppose the network with 15 nodes is distributed in a 1000×1000 m^2 square area as shown in Figure 3. The nodes

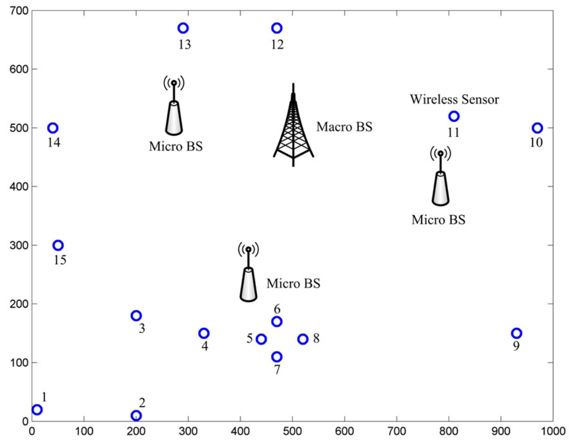


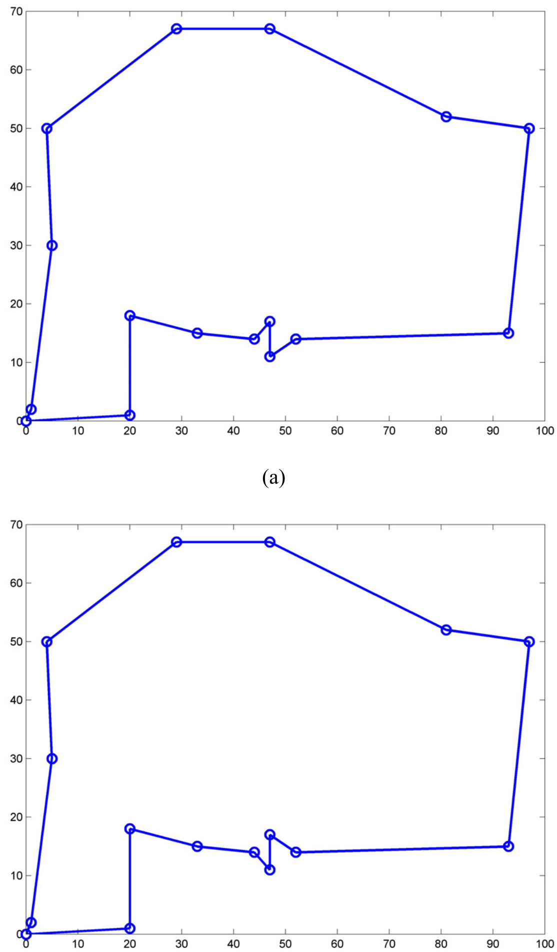
FIGURE 3. An IoT network, instance 1.

may be sensors, relays or base stations. The Euclidean distance is used to measure the distance between two nodes. The distance is set as the edge of the network. Suppose a vehicle locates at the origin and goes through each node only once to traverse all nodes of the network. Its forward velocity is 5 m/s. Constant speed is assumed for simplicity.

Using the RABC method, two optimal Hamilton paths are found as shown in Figures 4 (a) and (b). As shown in Figure 3, the distance between node 5 and node 6 is equal to the distance between node 5 and node 7. The distance between node 6 and node 8 is equal to the distance between node 7 and node 8. Hence, the shortest Hamilton path of the network is not unique. The proposed RABC method can find both optimal paths. On the other hand, the Concorde solver only provides one solution, which is the one in Figure 4 (a). Compared with standard ABC method, it could find optimal paths as in Figure 4, however, it is not as stable as the RABC method. Standard ABC method sometimes was trapped in local optima and could not find optimal paths. Furthermore, the RABC method returns a population of feasible solutions including optimal and suboptimal ones. As computer memory becomes less expensive, it is reasonable to memorize several paths to make the network more robust. For example, if the road between node 5 and node 6 is suddenly blocked, the vehicle can instantly find another optimal solution as in Figure 4 (b). The travel time of the vehicle following the paths in Figure 4 is 0.17 h.

B. UPLINK ROUTE USING THE RABC METHOD

Based on the vehicle travel path, the data transfer route problem can be solved using the RABC method. Suppose there are 3 micro BSs, 1 macro BS and 15 wireless sensors, and the locations are provided in Table 1. The data rates generated by the wireless sensors are between 1 kb/s and 200 kb/s. The transfer rates for the micro BSs and the macro BS are set to infinity, which means that they can handle all data received from the sensors. The node locations and data rates are randomly created in the simulation. In the simulation,



(a)

(b)

FIGURE 4. Two shortest Hamilton paths of network instance 1 found using the RABC method.

severe channel fading or interference is ignored, hence a sensor could send out its data without holding operation.

The constants of (2) and (3) are set as $\alpha = 4$, $\rho_i = \beta_1 = 5 \times 10^{-8}$ J/b, and $\beta_2 = 1.3 \times 10^{-15}$ J/b [24]. For the vehicle, it is assumed that its power transfer rate is $U = 5$ W. The interference radii R_{ws} and R_{MI} are set to 300 m and 350 m, respectively.

The optimal data transfer route found via the RABC method is provided in Figure 5. Compared with standard ABC method, it finds the same data transfer route as RABC for the instance. The recharging time of all sensors is 0.4583 h. Moreover, the RABC method found a colony of suboptimal solutions. The second, third and fourth data transfer routes cost 0.4588 h, 0.4588 h and 0.4748 h, respectively. Recording these routes could make the network more robust against emergent events.

C. AN IoT NETWORK, INSTANCE 2

In instance 1, there are 19 nodes in the IoT network. Another instance is discussed with 60 wireless sensors, 4 micro BSs

TABLE 1. **Node information of an IoT network with 1 macro BS, 3 micro BSs and 15 wireless sensors.**

Type	Location (m)	R_i (kb/s)
Sensor 1	(10,20)	40
Sensor 2	(200,10)	160
Sensor 3	(200,180)	140
Sensor 4	(330,150)	20
Sensor 5	(440,140)	60
Sensor 6	(470,170)	80
Sensor 7	(470,110)	20
Sensor 8	(520,140)	80
Sensor 9	(930,150)	100
Sensor 10	(970,500)	160
Sensor 11	(810,520)	140
Sensor 12	(470,670)	120
Sensor 13	(290,670)	120
Sensor 14	(40,500)	60
Sensor 15	(50,300)	200
Micro BS1	(450,220)	N/A
Micro BS2	(780,400)	N/A
Micro BS3	(210,540)	N/A
Macro BS	(500,500)	N/A

N/A means not available as the base station does not generate data.

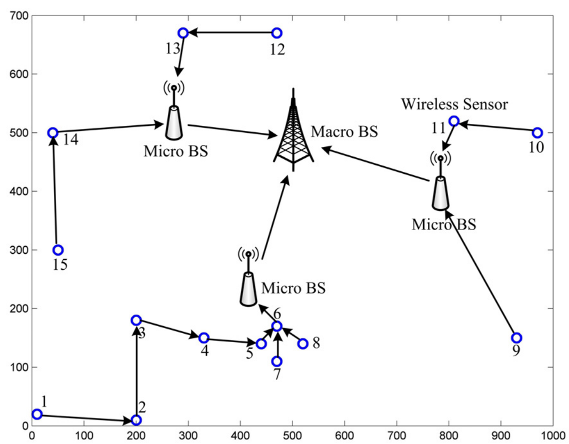


FIGURE 5. **Uplink route of instance 1 found using the proposed method.**

and a macro BS as shown Figure 6. Suppose all nodes are distributed in a 1000×1000 m^2 square area. The node locations and data rates are randomly created and the details are provided in Table 2. As in instance 1, the data rates of all sensors are between 1 kb/s and 200 kb/s. The data transfer rates for the micro BSs and the macro BS are set to infinity, which means that they can handle all data received from sensors.

In the simulation of instance 2, the constants of (2) and (3) are the same as in instance 1. The interference radii R_{ws} and R_{MI} are set to 160 m and 300 m, respectively.

The shortest Hamilton path of the IoT network for instance 2 is shown in Figure 7. Following the path in Figure 7, the travel time of the vehicle is 0.3922 h. The vehicle can travel on the path in either a clockwise or counterclockwise direction as the cost in time is identical. Note that the starting location of the vehicle in Figure 7 is the origin (0, 0). The starting location could be any other place in the region.

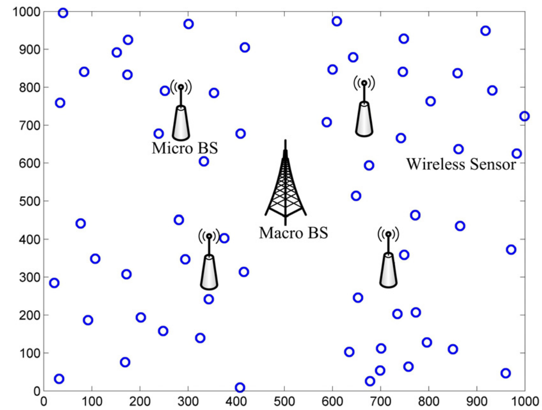


FIGURE 6. **An IoT network, instance 2.**

TABLE 2. **Node information of an IoT network with 1 macro BS, 4 micro BSs and 60 wireless sensors.**

Type	Location (m)	R_i (kb/s)	Type	Location (m)	R_i (kb/s)
Sensor 1	(609,974)	160	Sensor 31	(252,791)	200
Sensor 2	(169,76)	180	Sensor 32	(676,594)	160
Sensor 3	(107,349)	60	Sensor 33	(175,925)	180
Sensor 4	(418,905)	40	Sensor 34	(918,949)	120
Sensor 5	(862,637)	60	Sensor 35	(34,759)	160
Sensor 6	(772,463)	80	Sensor 36	(758,64)	80
Sensor 7	(77,442)	60	Sensor 37	(773,207)	60
Sensor 8	(746,841)	200	Sensor 38	(701,112)	80
Sensor 9	(174,833)	20	Sensor 39	(152,892)	120
Sensor 10	(333,605)	120	Sensor 40	(796,128)	180
Sensor 11	(635,103)	40	Sensor 41	(678,128)	60
Sensor 12	(588,708)	180	Sensor 42	(343,242)	100
Sensor 13	(971,373)	40	Sensor 43	(735,203)	180
Sensor 14	(375,403)	120	Sensor 44	(92,187)	140
Sensor 15	(932,792)	200	Sensor 45	(742,666)	200
Sensor 16	(699,54)	80	Sensor 46	(600,847)	60
Sensor 17	(294,347)	20	Sensor 47	(748,928)	180
Sensor 18	(202,194)	60	Sensor 48	(865,435)	140
Sensor 19	(281,451)	80	Sensor 49	(301,967)	60
Sensor 20	(653,246)	80	Sensor 50	(84,841)	100
Sensor 21	(32,32)	60	Sensor 51	(999,724)	80
Sensor 22	(643,879)	200	Sensor 52	(325,140)	120
Sensor 23	(354,785)	140	Sensor 53	(850,110)	180
Sensor 24	(408,9)	200	Sensor 54	(749,359)	40
Sensor 25	(40,996)	100	Sensor 55	(649,514)	180
Sensor 26	(22,285)	200	Sensor 56	(804,763)	180
Sensor 27	(172,308)	20	Sensor 57	(983,625)	80
Sensor 28	(960,47)	140	Sensor 58	(416,314)	100
Sensor 29	(860,837)	180	Sensor 59	(409,678)	120
Sensor 30	(248,158)	60	Sensor 60	(239,678)	160
Micro BS1	(345,280)	N/A	Micro BS3	(670,715)	N/A
Micro BS2	(720,330)	N/A	Micro BS3	(290,700)	N/A
Macro BS	(500,500)	N/A			

N/A means not available as base station does not generate data.

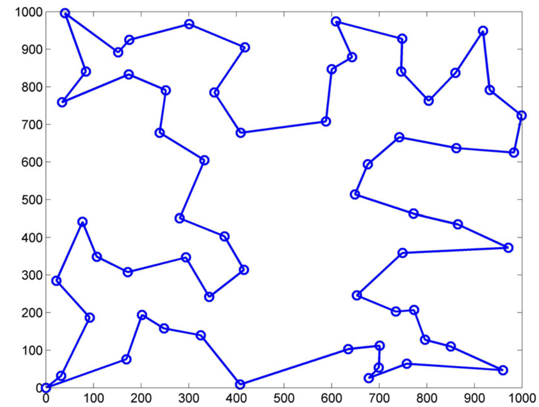


FIGURE 7. Shortest Hamilton path of network instance 2 found via the RABC method.

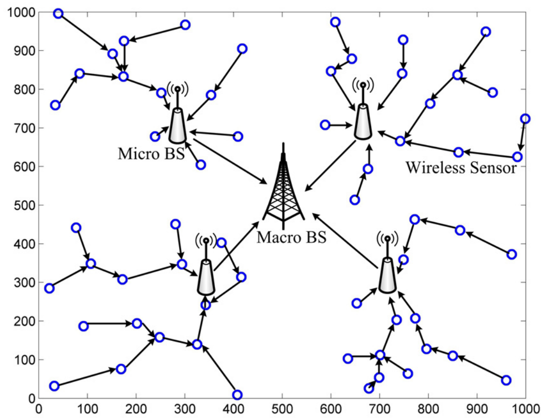


FIGURE 8. Uplink route of instance 2 found using the proposed method.

The optimal data transfer route found using the proposed method is shown in Figure 8. Compared with standard ABC method, it fails to find the same data transfer route as RABC for the instance 2. This is because instance 2 contains more sensor nodes than the last instance. Standard ABC method was trapped in local optima. Thus, the recharging time of standard ABC method is greater than the time of the RABC method. For the RABC method, the recharging time of all sensors is 4.0385 h. The recharging time for standard ABC method is 4.3476 h. Moreover, the RABC method found a colony of suboptimal solutions with a similar recharging time. It is observed from Figure 8 that some sensors work as relays and are in charge of transmitting data from other sensors such as sensor 9. There are six sensors relying on sensor 9 to transmit data. Hence, sensor 9 becomes a critical sensor. It requires more electrical energy than the leaf nodes such as sensors 25, 35, and 49.

Through the above simulation, it is observed that the proposed method can optimize the data transfer of the given IoT scenario.

VII. CONCLUSION

This paper studies an IoT scenario with wireless sensors and base stations (BSs). A micro BS receives data from wireless sensors and sends it to a macro BS. The macro BS then sends data to a database or cloud computing platform. Regarding the limited battery capacity, the WPT technique is suitable for charging the battery. The IoT scenario is modeled as an optimization problem. In the model, the energy consumption of the network is minimized. A three-stage method is proposed for the problem. The stages are finding the shortest travel path, mutual interference reduction and determining the optimal uplink route. A restart artificial bee colony method is proposed to solve for the travel path and uplink route. The asymptotic convergence of the RABC method is also proved.

Simulations are conducted to verify the usefulness of the proposed method. It is shown that the method can solve the data transfer problem of the IoT network. The RABC method can provide a set of optimal and suboptimal solutions. This capability improves the robustness of the network against emergent events. Wireless sensors working as relays become critical nodes of the network. This requires designing a reliable and robust data transfer network. The power transfer efficiency of the WPT system becomes increasingly practical [38]. Physical experiments will be conducted in the future to test the performance of the method.

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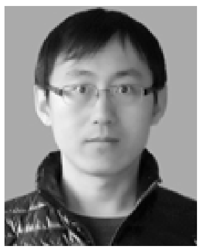

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