Many-objective Sensor Selection in IoT Systems

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ABSTRACT

The Internet of things (IoT) connects physical objects through sensor devices with multiple functionalities. At the planning stage of deploying an IoT system, we are concerned about sensor selection in the IoT system, which allocates predefined IoT services to multiple sensor devices so as to optimize one or more objectives associated with these allocations, under energy and distance constraints. The sensor selection problem that optimizes a utility function in other applications has been shown to be NP-hard, and the number of IoT services to be concerned is enormous in practice. Hence, it is suitable to apply evolutionary algorithms (EA) for solving the large-scale problem with multiple objectives. Recently, the paradigm of multiple-objective EAs (which often addresses only two or three objectives) has advanced to many-objective EAs (which intends to address four or more objectives that may be in conflict with each other in many cases). Therefore, this article considers many objectives of the sensor selection problem in the IoT system, including optimization of communication energy consumption, energy balancing on all devices, energy harvesting, green concerns, and QoS. The problem is resolved by a tailored many-objective EA based on decomposition to increase computational efficiency and solution quality. By simulation, the proposed EA is shown to be promising through scatter charts and parallel coordinates.

Keywords: Internet of things, sensor selection, many-objective optimization, energy efficiency, energy balancing.

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INTRODUCTION

With development of wireless communications technologies and prevalence of smart devices, the concept of the Internet of things (IoT) has risen rapidly [1]. The devices attached with RFIDs, infrared sensors, and various-purpose sensors are connected tightly through the IoT, so that they can easily be identified and managed. In the IoT, objects are connected together through deployment of sensor devices; and data transmissions and controls are achieved by the sensor networks. Sensors have the features of small size and low cost. Hence, they have been widely applied to detecting, tracking, and monitoring tasks in various fields. In planning an IoT system in an environment initially, we consider deploying a number of sensors to provide multiple IoT services in this environment, e.g., in a smart home, once a sensor detects passage of some user, a sequence of multiple IoT services associated with this sensor are actuated automatically. This article is concerned about the sensor selection problem in an IoT system [2], [3], which allocates multiple IoT service components to sensor devices so that one or more objectives associated with the allocations are optimized, under energy and distance constraints.

For instance, consider a smart home environment with three sensor devices, two lights, one air conditioner, one fan, a window, a bed, and a stereo (Fig. 1(a)). Now we are planning to include six services to be switched by IoT devices in this environment (Fig. 1(b)): turning on Light 1 (C_1), closing the window (C_2), turning on the air conditioner (C_3), turning on the fan (C_4), turning on Light 2 (C_5), and turning on the stereo (C_6). According to the user requirements for IoT services, the data and control flow of these service components is represented as a high-level flow-based programming (FBP) (Fig. 1(c)), including five sequences of IoT services: $C_1 \rightarrow C_2 \rightarrow C_3$; $C_1 \rightarrow C_4 \rightarrow C_3$; $C_1 \rightarrow C_4 \rightarrow C_6$; $C_5 \rightarrow C_2 \rightarrow C_3$; and $C_5 \rightarrow C_6$. In addition, the instance includes three physical sensor devices D_1, D_2, D_3 (Figs. 1(a) and 1(d)) and two landmarks L_1 and L_2 (bed and window in Figs. 1(a) and 1(e)). Based on geographical location constraints of the three sensor devices and the six IoT service components on the floorplan (Fig. 1(a)), and the user-predefined constraints of communications between service components and the two landmarks, all the feasible allocations of the six IoT service components to the three devices are represented as a bipartite graph with dotted-line edges (Fig. 1(f)). The sensor selection problem for this smart home instance is to find a many-to-one mapping from service components to sensor devices (shown as solid-line edges in Fig. 1(f)) to achieve one or many objectives, and the allocation corresponding to this mapping is illustrated in Fig. 1(g).

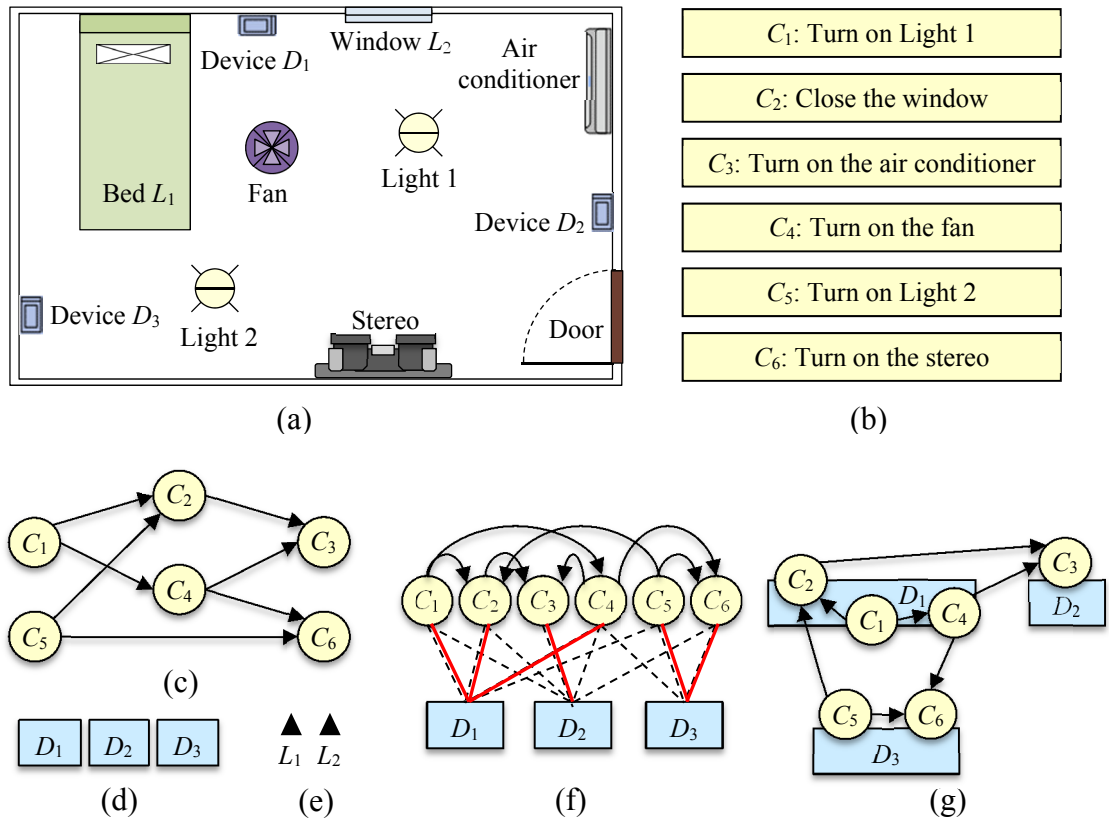

Fig. 1. An example of the sensor selection problem for a smart home environment in (a), consisting of (b) 6 service components with flow relations represented as (c) an FBP with 7 links, (d) 3 sensor devices, and (e) 2 landmarks. (f) Feasible mappings from service components to sensor devices are represented as a bipartite graph with dotted-line edges. (g) A sensor selection result.

However, the sensor selection problem optimizing a utility function in other applications has been shown to be NP-hard [4]. Hence, the problem is suitable to be solved by evolutionary algorithms (EA). Although the problem can be addressed by global search approaches such as the branch-and-bound method [5], global search approaches may not be executed efficiently because the problem size may be huge. Hence, a number of heuristics have been proposed for this problem with various optimization objectives. For instance, the work in [6] considered a sensor selection problem that satisfies the assigned QoS requirements, and modeled it as a maximum weighted bipartite matching problem. Then, they proposed an integer linear program (ILP) and a QoS-oriented mapping algorithm for the problem.

Most of the sensor selection problems concerned in previous works considered only a single or two objectives to be optimized. In practice, however, sensor selection often involves many objectives some of which may be in conflict with each other in many cases, and is required to satisfy a lot of constraints. Recently, a lot of research has

successfully extended multi-objective optimization problems (MOPs) to many-objective optimization problems (MaOPs), in which the former often focuses on only two or three objectives; whereas the latter generally considers optimization of more than four or more objectives. For the MaOP, with increase of number of objectives and the solution search space, a large number of non-dominated solutions lead to a selection pressure of the EA, and it is hard to achieve convergence and diversity of the EA. In addition, it is hard to estimate the amount of computing resources to be required in solving MaOPs.

In light of the above, this article first reviews the previous works on sensor selection problems with different objectives in various IoT applications, and then models a many-objective sensor selection problem in the IoT system, including optimization of communication energy consumption, energy balancing on all devices, energy harvesting, green concerns (i.e., pollution level in this work), and QoS. For instance, in Fig. 1, three IoT service components C_1, C_2, and C_4 are allocated to sensor device D_1, so that the communication energy consumption between C_1 and C_2 and between C_1 and C_4 can be saved, because only the communication between two devices is supposed to consume energy [2]. In addition, the other objectives could also influence the final sensor selection result.

Furthermore, we propose a many-objective EA based on decomposition for efficiently resolving this MaOP. This EA first decomposes the concerned problem into multiple subproblems, and then optimizes the solutions of each subproblem by only applying the information of its neighboring subproblems and its best value so far, so that CPU time can be reduced, and larger-scale problems can be solved. Finally, a simulation environment for evaluating performance of the proposed EA is constructed, and simulation results are analyzed in detail by scatter charts of objective pairs and parallel coordinates of all objectives.

RELATED WORK

SENSOR SELECTION PROBLEM IN THE IOT SYSTEM

The sensor selection problem that optimizes a utility function in other applications has been shown to be NP-hard [4]. Therefore, most of the previous works on sensor selection~~s~~ problems focused on heuristic approaches for various versions of this problem. For sensor selection in the IoT system, the work in [2] considered that heterogeneity of the devices for IoT applications increases complexity of communications among these devices. Especially, when an object in the target environment is changed, the sensor configuration in the IoT system requires a dynamical readjustment immediately. Hence, their team developed a middleware for

translating IoT service requirements to a high-level FBP, based on which the most effective configuration of the corresponding physical devices can be adjusted efficiently and details of low-level heterogeneous processes are shielded from users. Under this middleware, they proposed a two-phase approach for the sensor selection problem when planning the IoT system initially, i.e., a simplified problem in which the allocation of services to sensor devices is determined only once. In this two-phase approach [2], a greedy strategy is first applied to allocate the larger-communication-energy links between services in the predefined FBP to feasible sensor devices so as to minimize the communication energy; and then an ILP for mapping those unallocated services to the sensor devices with the objective of balancing the energies of all devices is constructed. They further considered the communication distance between devices to improve the energy formula [3].

The work in [6] developed a quality score system to shield complexity and diversity of QoS of IoT applications, and proposed a QoS-oriented mapping algorithm for a sensor selection problem in the IoT system. They modeled the problem as a maximum weighted bipartite problem, and solved it by an ILP-based algorithm that finds the sensor selection for an FBP with the optimal QoS score, to provide users a good user experience. However, ILP-based algorithms generally cannot cope with scalability.

In addition to sensor selection in IoT systems, sensor selection in other applications or systems also received much attention. The work in [7] investigated the problem of energy-efficient sensor selection in a medical shoe, which aims to reduce the number of sensors to be deployed on the shoe so as to save the energy and cost, while the diagnosis result is not influenced. The work in [8] investigated the problem of energy-balanced sensor selection for social context detection, and showed it to be NP-complete. Then, they proposed a brute force and a heuristic approach to maximize quality of information to prolong the lifetime of the system. The work in [9] investigated energy-efficient sensor selection in wireless sensor networks (WSN), and proposed a two-hop cooperating transmission algorithm based on exploring spatial correlations between sensors. The work in [10] proposed an energy harvesting (EH)-aware approach for the sensor selection problem in EH WSNs that minimizes the distortion when reconstructing the underlying source.

Based on the above, previous works on different versions of sensor selection in IoT systems or other IoT applications considered optimization of various objectives. Hence, these works are classified according to their objectives in Table 1, including communication energy consumption, energy balance on all devices, EH, green concerns, and QoS. From Table 1, some of these works considered only one or two objectives, but none of them ever considered many objectives.

Table 1. Classification of the sensor selection problems in different applications.

Reference	Energy consumption	Energy balancing	Energy harvesting	Green	QoS
[2]	V	V			
[3]	V	V			
[6]					V
[7]	V				
[8]		V			
[9]	V				
[10]			V		

MANY-OBJECTIVE OPTIMIZATION

Multi-objective EA (MEA) has been one of the main approaches for multiple-objective optimization problems (MOPs). The basic idea of the MEA is to simulate the evolutionary process of a population of individuals to find a non-dominated solution set of the MOP. Each individual represents a candidate solution of the concerned problem. Different from the EA that only considers a fitness function representing the performance of an individual, the MEA applies multiple fitness functions to evaluate the performance of multiple objectives of the individual, respectively. An individual (solution) is said to *dominate* the other individuals if one of the fitness of the former is absolutely higher than the corresponding fitness of the latter, while each of the other fitnesses of the former is not lower than the corresponding fitness of the latter. Then, the MEA iteratively improves all individuals by some evolutionary operators such as natural selection, crossover, and mutation. After some stop criteria of the MEA are achieved, the final non-dominated solution sets are the final outputs of the MEA.

Recently, the paradigm of MEAs for MOPs has shifted to many-objective EAs (MaEA) for many-objective optimization problems (MaOP). Most of the MaEAs improves conventional MEAs by some advanced techniques in evolutionary computation. Among major MOEAs for MOPs [11], the MOEA based on decomposition (MOEA/D) [12] is one of the most popular MOEAs. The MOEA/D is often extended to solve MaOPs. For instance, the work in [13] based on a normal boundary intersection method to decompose an MaOP into multiple subproblems, and then proposed an improved MOEA/D for the problem, which applies a systematic sampling scheme to produce uniformly distributed reference points, and applies two independent distance measures to maintain the balance between convergence and diversity.

The work in [14] proposed an MOEA/D with sorting-and-selection for MaOPs, which associates various solutions with the same subproblems, and flexibly allows some subproblems with no associated solutions. The work in [15] proposed an MOEA/D with localized weighted sum for MaOPs, which selects each optimal solution search direction only from the neighboring solutions of the current solution.

SYSTEM DESCRIPTION

The work is concerned about planning deployment of an IoT system initially in a target environment. That is, once deployment of the IoT system is determined, no further reallocation will be made after. According to the user requirements for IoT services, the sensor selection problem in the IoT system is to allocate n service components to m sensor devices to achieve some objectives, under some constraints. Because of heterogeneity of IoT services and sensor devices, detailed deployment for the IoT applications is much complex. Hence, a middleware was proposed in [2], [3] for translating IoT service requirements to a high-level FBP. Under the middleware, when the IoT planner determines an FBP for n service components, the sensor selection problem concerned in this work is to efficiently find the corresponding mappings from n services to m sensor devices, while many objectives are optimized, under some constraints.

An instance of the problem is represented as (G, D, L, R), detailed as follows. Initially, the IoT system planner determines an FBP for n service components, which is represented as a directed acyclic graph $G = (C, E)$, in which $C = \{C_1, C_2, \ldots, C_n\}$ is the set of service components, where C_i denotes the ith service component; and E is the set of links between service components determined by the planner (e.g., $n = 6$ in Fig. 1(c)). In this FBP, each directed edge determines a sequence of two IoT services: first, the IoT service associated with the source node of this edge; and then, the IoT service associated with the sink node. The sensor selection problem is to allocate (map) the FBP to m sensor devices. Let $D = \{D_1, D_2, \ldots, D_m\}$ denote the set of sensor devices, in which D_j is the jth sensor device (e.g., $m = 3$ in Fig. 1(d)). Note that some of these sensor devices can harvest energy from the nature, but the others cannot.

Furthermore, some IoT services have constraints for distances between services/sensors and some landmarks in the environment. For instance, some sensor is restricted to control of some landmark. Hence, the problem instance includes ν landmarks in the target environment. Let $L = \{L_1, L_2, \ldots, L_\nu\}$ in which L_k is the kth landmark (e.g., $\nu = 2$ in Fig. 1(e)). In addition to the distance constraint described above, this problem has an energy constraint in which a service may require an energy

that a device may not afford, so that the mapping between this service and this device is infeasible. Finally, the planner may have some rules R for preferences or constraints for mappings between services and sensors.

Given a problem instance, feasible mappings from service components to sensor devices in the sensor selection problem can be represented as a bipartite graph $C \times D$ with dotted-line edges (Fig. 1(f)), in which each dotted-line edge represents a feasible mapping from a service component to a sensor device. Note that the rules R from the IoT system planner and the problem constraints for distances and energy filter infeasible edges in this bipartite graph.

According to the problem instance (G, D, L, R) and the corresponding bipartite graph $C \times D$, it suffices to find a many-to-one mapping from service components to devices in this bipartite graph, so that the concerned objectives are optimized. This work considers many objectives of the sensor selection problem in the IoT system as detailed as follows:

- Minimizing the total communication energy consumption: The energy consumption here occurs in communications between two devices, including the energy for data transmitting and receiving [2]. Different sensor selections affect the total communication energy consumption. If two service components of the same link in the FBP G are mapped to the same device, no communication between the two services is required for finishing the corresponding sequential IoT applications, so no communication energy is consumed; otherwise (i.e., two service components are mapped to different devices), the energy consumed by communication between two devices is required.
- Balancing the energy among sensor devices: Energy balancing among different sensor devices could reduce overloading on some devices. This objective can be measured by minimizing the maximal communication energy consumption among all sensor devices [3].
- Maximizing the QoS: The QoS performance of sensor selection is affected by various environmental factors and conditions, and remarkably influences user satisfaction. Lots of QoS attributes for IoT services have exited, and a detail introduction can be found in [11]. This work considers three quantitative QoS attributes: cost, reliability, and availability. Firstly, because implementation of a service component on different sensor devices costs differently, users may require minimizing the cost. Hence, we aim to find the mappings with the minimal cost. Secondly, because heterogeneous sensors have different temporary failure probabilities, users may prefer a lower failure rate for IoT services, i.e., a higher reliability. Hence, we aim to maximize the number of services mapped to

the devices with low failure rates. Thirdly, because each sensor may not always be available, users may prefer a higher availability for IoT services. With the three QoS attributes, we simply use the average of the three QoS values as a single QoS optimization objective.

- Maximizing the total harvested energy: EH sensors can prolong own battery energy by absorbing the energy from the nature like sun and wind. However, their locations are restricted to the natural environment. Hence, this work supposes that not all sensor devices in the environment are EH, i.e., some are common sensors, and the others are EH sensors. With such a setting, because EH sensors may survive longer than common sensors, we prefer to map IoT service component to EH sensors. Therefore, the objective here is to maximize the number of services components to be mapped to EH sensor devices.
- Optimizing the green index / minimizing the total pollution level: Heterogeneous sensors have different pollution levels, e.g., the sensor with a different coverage size may damage creatures to a different degree. We prefer that more service components are mapped to lower-pollution sensor devices. Hence, the objective here is to minimize the total pollution level.

METHODOLOGY

This work focuses on analyzing many objectives of the sensor selection problem in the IoT system. Hence, by analogy from the classical MOEA/D [12], we propose a MOEA/D for the following many-objective sensor selection problem: Maximize $F(x) = (f_1(x), f_2(x), \ldots, f_\mu(x))^T$ for $x = (x_1, x_2, \ldots, x_n) \in \Omega$ subject to constraints and user-predefined rules, where f_k is the kth objective function to be optimized, for $k \in \{1, .., \mu\}$; μ is the number of objectives (e.g., $\mu = 5$ in this work); Ω is the space for decision variables; x_i is the ID of the sensor device mapped by service component C_i, for $i \in \{1, .., n\}$.

The MOEA/D decomposes the concerned problem into multiple subproblems. Among various decomposition approaches, this work follows [12] to apply the Tchebycheff approach, which decomposes the concerned problem of maximizing $F(x) = (f_1(x), \ldots, f_\mu(x))$ into N optimization subproblems respectively corresponding to N weight vectors $\lambda^1, \lambda^2, \ldots, \lambda^N$ where $\lambda^i = (\lambda_1^i, \lambda_2^i, ..., \lambda_\mu^i)$. The subproblem for a neighborhood of weight vector λ^i is to optimize the following objective function:

$$\text{Minimize} \quad g(x|\lambda^i, z) = \max_{1 \le k \le \mu} \left\{ \lambda_k^i \left| f_k(x) - z_k \right| \right\}$$

where $z = (z_1, z_2, \ldots, z_\mu)^T$ in which z_k is the best value found so far for f_k, used as the reference point. That is, the objective is to minimize the maximal difference between

the current value and the best value found so far.

The flowchart of the MOEA/D is given in Fig. 2. Let *EP* denote an external population used for storing non-dominated solutions found so far. Initially, *EP* is set to be empty. Because the MOEA/D applies N weight vectors λ^1, λ^2, …, λ^N to decompose the concerned problem into N subproblems, the N weight vectors are initialized randomly according to a uniform distribution. Next, the idea of the MOEA/D is to optimize the solution of each subproblem by only applying the information of its neighboring subproblems and its best value so far to increase computational efficiency. Hence, let $B(i)$ be the set of indices of the T closest weight vectors to λ^i among N weight vectors for each $i \in \{1, 2, \ldots, N\}$, by comparing the Euclidean distance between every two weight vectors. The remaining steps of the MOEA/D are referred to Fig. 2.

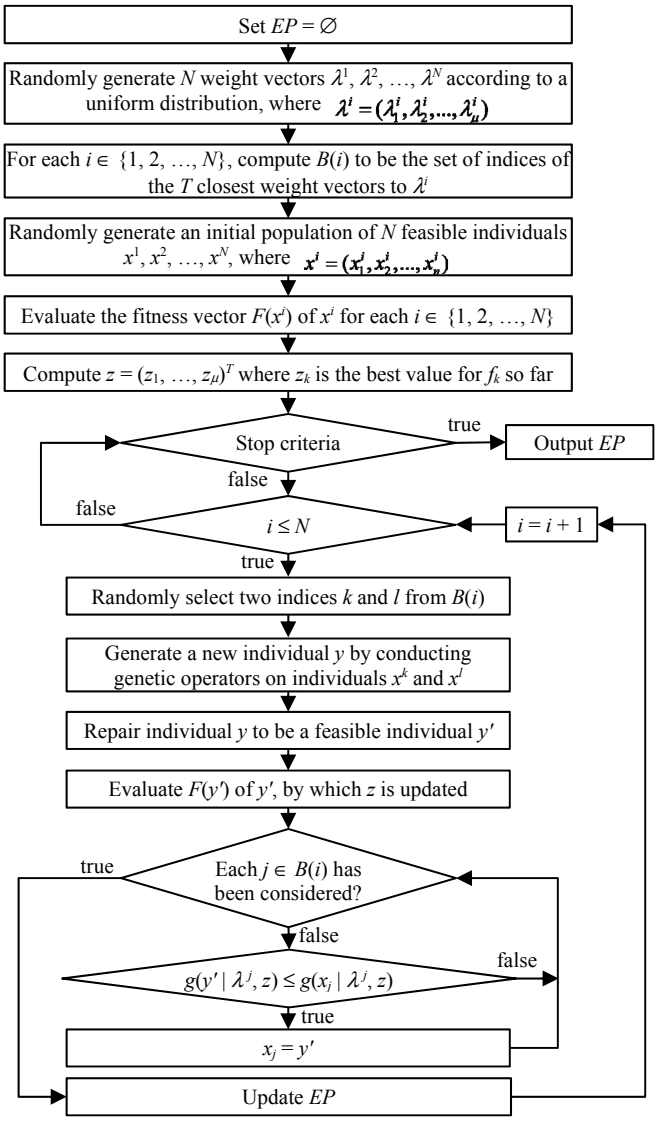

Fig. 2. Flowchart of the MOEA/D.

SIMULATION RESULTS AND DISCUSSION

To evaluate performance, the proposed MOEA/D is implemented in C++ programming language, and the simulation runs on a PC with Intel Core i7-6700 CPU and 8 GB memory with the following parameter settings. The number of objectives μ is 5 as detailed above. In the target environment, number of landmarks ν is 10, and the number of components allowed to be allocated to a device is ranged from 3 to 5 randomly. For the objective of minimizing the total communication energy consumption and balancing the energy among sensor devices, both the transmission energy and the receiving energy are random numbers from {20, 21, …, 100}. For the objective of maximizing the QoS, the sensor device cost, the failure probability, and the availability probability follow uniform distributions of [5, 30], [0.01, 0.3], and [0.8, 0.99], respectively. For the objective of maximizing number of EH services, a half of the sensor devices are EH sensors, and the others are comment sensors. For the objective of minimizing the total pollution level, the pollution level of each sensor follows a uniform distribution of [0.1, 0.3]. In the proposed MOEA/D, the number of neighboring subproblems to be considered (T) is 20, and the number of weight vectors (N) is 210.

On the communication energy consumption, 20 different runs of the MOEA/D for each problem instance do not differ a lot, so that each box in Fig. 3(a) looks narrow. On average, the energy consumption of C300 is less than that of C400, followed by C500. That is, when the problem size increases (by setting numbers of components and devices), the total communication energy consumption increases. Similar conclusions can be obtained for the results for number of EH services (Fig. 3(d)) and the total pollution level (Fig. 3(e)).

To analyze performance of the proposed MOEA/D on different-scale problems, we consider three different-scale problem instances, i.e., setting numbers of components and devices ($|C|$, $|D|$) = (300, 180), (400, 240), and (500, 300), which are labeled by 'C300', 'C400', and 'C500', respectively. The box plots of five objectives of the experimental results of running 20 times of the proposed MOEA/D on three problem instances are shown in Fig. 3.

On energy balancing among sensor devices, each box in Fig. 3(b) is wide, and each of the results of three problems shows a right-skewed distribution, meaning that the data skews to the lower-level values, and the mean value is greater than the median. However, a larger problem size still leads to a larger value for energy balancing. On maximizing the QoS, each box in Fig. 3(c) is wide, but the problem size does not have an obvious influence.

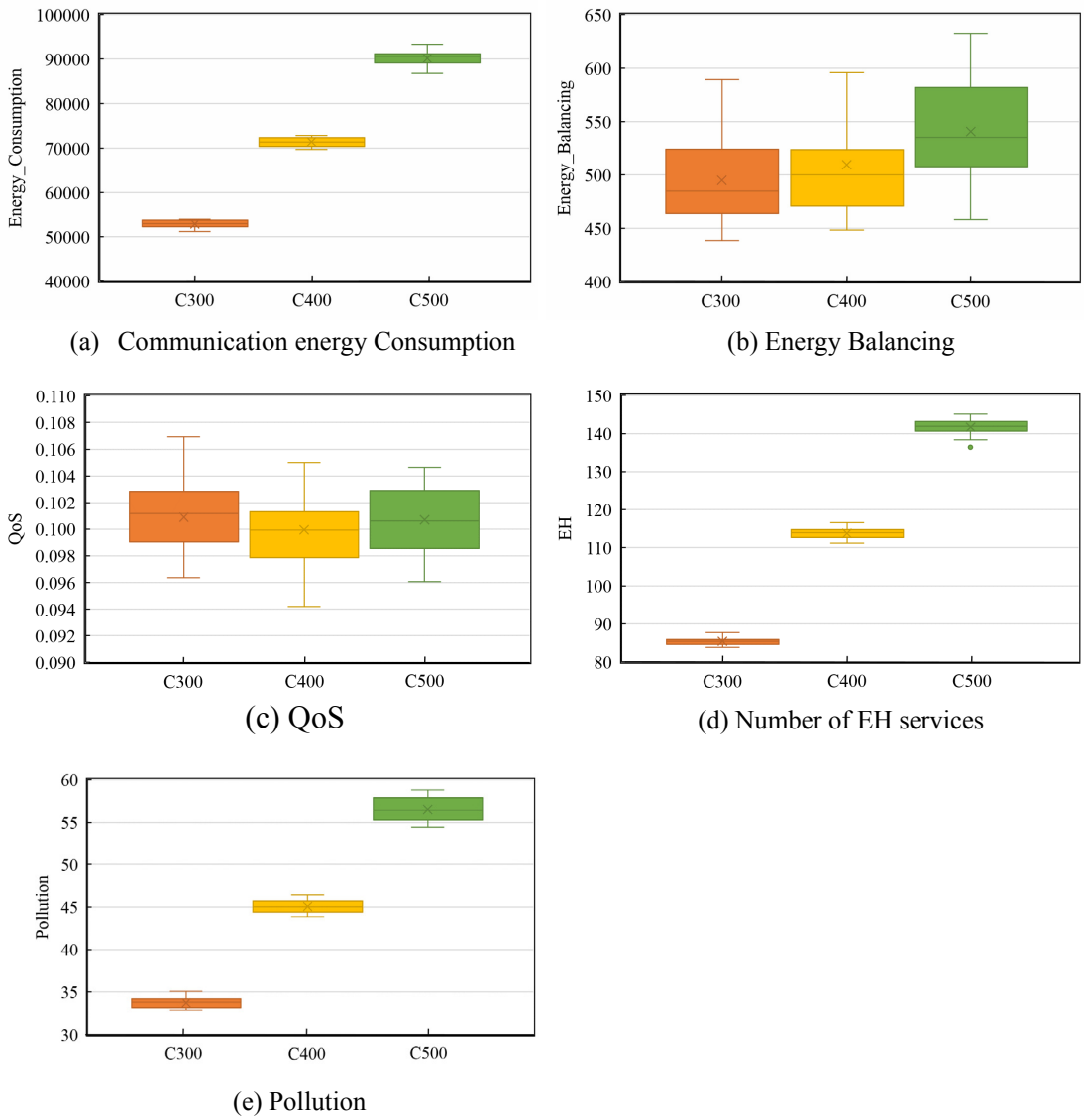

Fig. 3. Box plots of five objectives of the experimental results on three different-scale problems.

In summary, the problem size has a remarkable influence on optimizing communication energy consumption, energy balancing, number of EH services, and pollution level; but no obvious influence on the QoS.

A lot of previous works have shown that the MOEA/D can run more efficiently than other previous notable approaches, e.g., MOGLS, NSGA-II, MOPSO, PESA-II, and SPEA-II. The average CPU times of running 20 times of the MOEA/D for different-size problems under ($|C|$, $|D|$) = (500, 300), (1000, 600), (5000, 3000), and (10000, 6000) are 2.59 s, 4.57 s, 46.3 s, and 107.34 s, respectively. These results show that the CPU time displays a trend of linear relation in terms of the problem size. Therefore, the MOEA/D can efficiently solve the concerned problem.

In what follows, we analyze the 2D scatter chart for each pair of objectives for the

results of C500 in Fig. 4. Figs. 4(a), 4(b), 4(c), and 4(d) show weak correlations between energy balancing and the other objectives. We speculate that the objective of energy balancing has no significant correlation with the other four objectives.

Next, to analyze the objective of energy consumption, Figs. 4(e), 4(f), and 4(g) show some linear trends. That is, these non-dominated solutions show substitutional relationship of energy consumption optimization with the optimizations of QoS, number of EH services, and pollution level. It is intuitively reasonable that higher QoS (Fig. 4(e)) and fewer EH services (Fig. 4(f)) lead to more energy consumption. However, the pollution level and the energy consumption show a negative linear relationship (Fig. 4(g)). That is, optimization of concurrently minimizing communication energy consumption and pollution level cannot be achieved by the MOEA/D. Furthermore, the negative linear relations between QoS and number of EH services (Fig. 4(h)), between QoS and pollution level (Fig. 4(i)), and between number of EH services and pollution level (Fig. 4(j)) can be derived from Figs. 4(e) and 4(f), Figs. 4(e) and 4(g), and Figs. 4(f) and 4(g), respectively.

To analyze multiple objectives in a global view, the parallel coordinates of five objectives of the experimental result of C500 are shown in Fig. 5.

In comparison between energy balancing and power consumption, the data on the energy balancing axis shows a larger cluster (between 709 and 670) and three smaller clusters (between 515 and 592.6). The larger cluster on the energy balancing axis is mapped to a wide distribution with larger values on the energy consumption axis; whereas the two clusters with smaller values are mapped to a narrow distribution with smaller values. Although there are some exceptions, Fig. 5 shows a partially positive correlation between the two objectives, which cannot be observed from Fig. 4(a). Next, the values on the energy consumption and QoS axes in Fig. 5 show a positive linear mapping, which confirms the linear correlation as shown in Fig. 4(e). Similarly, the mappings between QoS and pollution axes and between pollution and EH axes in Fig. 5 confirms linear correlations as shown in Fig. 4(i) and Fig. 4(j), respectively.

By tracking a data across the five objective axes in Fig. 5, we can obtain a mapping relation across the five objectives. For instance, a lower energy balancing data is mapped to lower energy consumption, lower QoS, higher pollution level, and more EH services. In addition to Fig. 5, we also check parallel coordinates of various combinations of the five objectives, and confirm reasonability of all results.

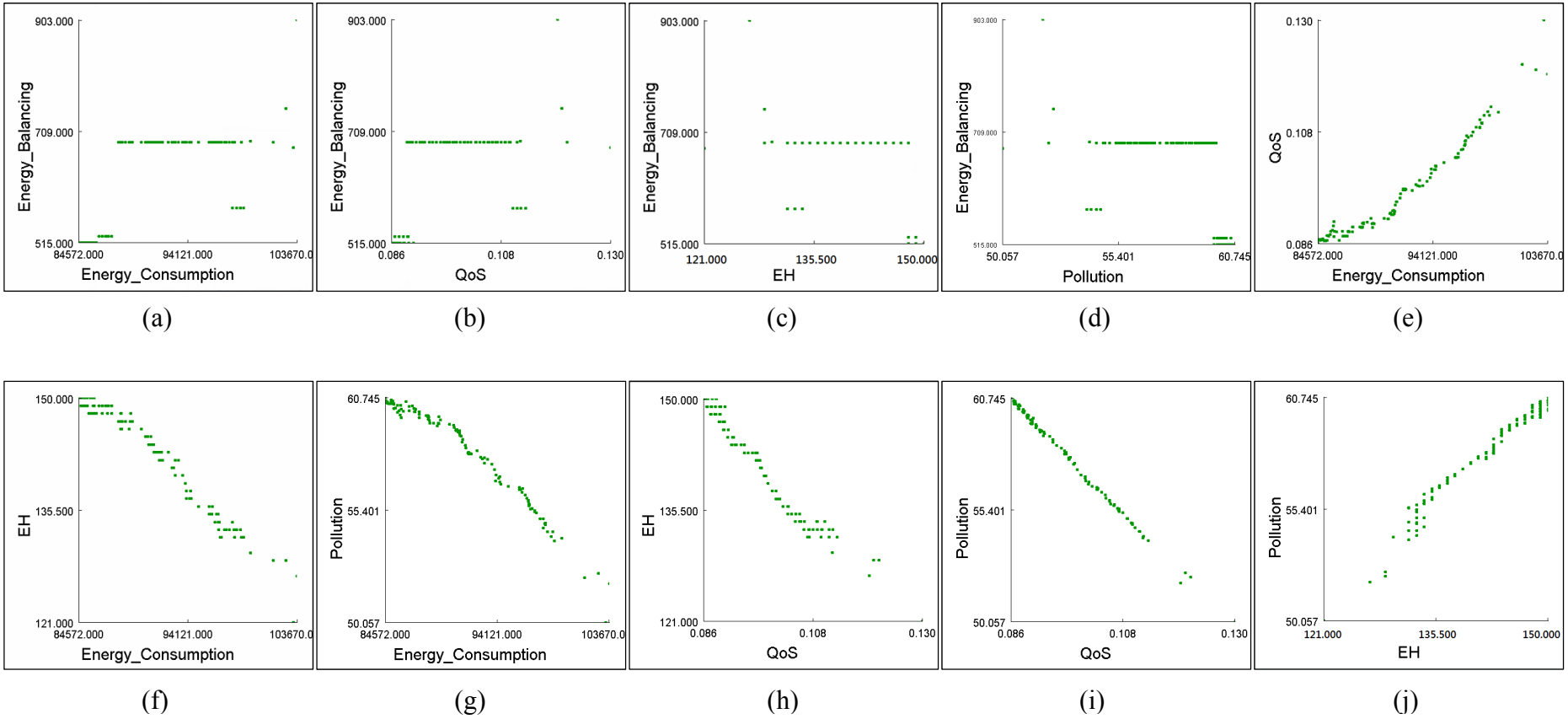

Fig. 4. Scatter chart of each pair of objectives of the experimental result of C500.

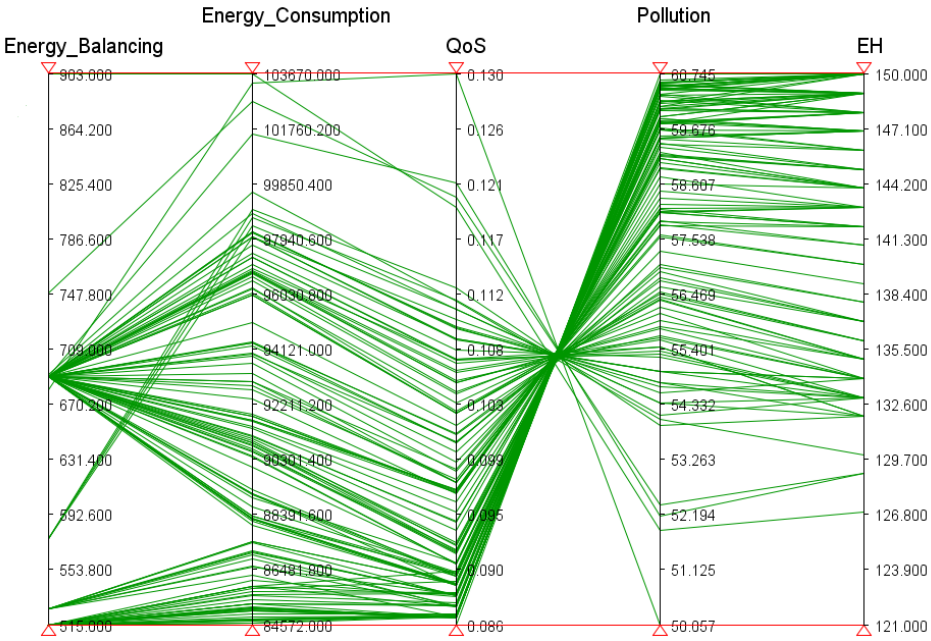

Fig. 5. Parallel coordinates of five objectives of the experimental result of C500.

CONCLUSION

The recent advance in EA has shifted from the paradigm of multi-objective optimization to many-objective optimization. Therefore, this article has made a comprehensive review on various sensor selection problems in IoT systems, and proposed a sensor selection problem with five objectives in IoT systems. Then, we solved the problem by an MOEA/D. The major contributions of this work are summarized as follows: 1) This work is the first to propose the MaOP for sensor selection in IoT systems. 2) An MOEA/D approach is proposed for addressing the problem. 3) To evaluate performance of the proposed approach, detailed experimental analysis is conducted through box plots, scatter charts, and parallel coordinates. Box plots of simulation results showed that increase of the problem size leads to increase of energy consumption, energy balancing, number of EH services, and pollution level, while it does not affect QoS remarkably. Scatter charts and parallel coordinates of simulation results show that the lower energy balancing, the lower energy consumption, the lower QoS, the higher pollution level, and the more EH services.

Future challenges still exist in extending sensor selection problems to various applications, e.g., smart home, healthcare, vehicular networks, and other Industrial 4.0 applications. It is also of interest to collect big data from sensor devices to assist in dynamic sensor selection, or to integrate social coordination and user interaction to achieve autonomous sensor selection. In addition, it is also challenging to consider more objectives and constraints from practical applications, including internet of

energy, internet of vehicles, fairness due to heterogeneity, and cross-layer designs.

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