Multi-indicators Multi-objective Evolutionary Algorithm with Q-Learning for Real-world Network Optimization

Tung Truong THANH, Rui WANG, Jia-hua LI and Lian-bo MA
College of Software, Northeastern University, Shenyang, China
*Corresponding author

Keywords: Multi-indicators, Multi-objective evolutionary algorithm, Q-learning.

Abstract. Aiming at the deployment optimization of complex Internet of Things (IoT) systems, we propose a new multi-objective optimization algorithm using multiple indicators with reinforcement learning, called MIEA-RL. In MIEA-RL, a set of evaluation indicators are employed to guide the evolution of population, while a Q-learning method is designed to manage these indicators in an efficient way during the search. To be specific, each candidate indicator is determined by the performance improvement of the population selected by the current indicator. Moreover, the search biases of different indicators can be adaptively balanced according to a Q-learning table. Accordingly, the convergence and diversity can be maintained effectively while the algorithm complexity is not increased. Finally, the MIEA-RL is applied to resolve the real-world IoT optimization instances in the experiment. Results show the proposed algorithm is effective and efficient to handle with these problems.

Introduction

With the rapid development of Internet of Things (IoT) in recent years, radio frequency identification (RFID) networks have become more and more prevalent in many practical applications [1-9]. In fact, this technology exhibits a powerful performance to detect and identify a large number of tags in the workspace with a full coverage via optimally deploying a certain number of readers. For this technology, the key issue is how to determine the optimal parameter configuration of these readers in order to obtain the expected performance. Generally, this problem is referred to as the RFID networks planning (RNP) problem [10]. However, due to the complexity of large-scale RFID network, RNP is still very challenging to be tackled because that: 1) the large number of readers and tags in real-world RFID systems leads to a high-dimensional optimization problem, which essentially increases the computation complexity, and 2) there are different optimization objectives to be tackled together properly, which usually conflict each other. It has been turned out that that the RNP problem is an NP-hard problem involving multi-objectives, mixed control variables and constrains [8, 10].

In recent years, several state-of-the-art algorithms have been proposed to resolve the RNP problem [10-15]. Conventional optimization methods usually formulate the RNP problem as an aggregation function, which is made up of a set of single-objective functions via the weighted-sum approach [14]. And then, they are optimized by evolutionary algorithms (EAs) and swarm intelligence (SI) techniques, such as genetic algorithms (GA), evolutionary strategy (ES), artificial bee colony Algorithm (ABC) [16,17], and particle swarm optimization (PSO). It is stressed that these methods cannot generate a set of appropriate Pareto optimal solutions, but only a single solution, which cannot provide a tradeoff between objectives. Moreover, it is very difficult for users to determine exactly how to assign the weight for the RFID network. In fact, these objectives in most real-world RFID applications are usually conflicted strongly with each other. This causes the ineffectiveness of conventional aggregation approaches on the large-scale multi-objective RNP problems. On the other hand, multi-objective optimization algorithms can be a straightforward yet effective approach to obtain a set of Pareto optimal solutions, becoming a powerful optimization tool to tackle the RNP
In multi-objective optimizations, a final solution set is usually evaluated according to a variety of indicators. Different indicators can access different aspects of the obtained solutions, e.g., the diversity and convergence. This motivates us to use multiple indicators in an efficient way to cope with the complex multi-objective optimization problems. [18-22]. Note that, a single indicator often misguides the search toward a certain subregion of Pareto solutions and then the search is stagnated. This means that, the algorithm based on a single indicator usually tends to obtain a set of local-optimal solutions rather than the global-optimal solutions. Some indicators favor the convergence more than the diversity, e.g., the binary additive $\varepsilon$-indicator [19], and the additive approximation $S\alpha$ indicator [23]. Some other indicators, e.g., the crowding distance [24], and the shift-based density estimation indicator [25], prefer the diverse solutions. There are some special indicators, e.g., maximin fitness [26] and the penalty-based boundary intersection [27], which are able to obtain the optimal solution better under some special Pareto optimal surface [28-35]. In principle, there is a greater probability for different biases of multiple indicators to complement each other. Therefore, it is unwise to use a single indicator rather than multiple indicators for the environmental selection.

Based on the above analysis, we propose a novel multi-indicator based evolutionary algorithm with reinforcement learning (MIEA-RL) for the RFID network optimization, which can achieve a better performance on the multi-objective RNP model. The main idea is to carry out an improved environmental selection using multiple indicators that are complementary with each other. In order to reduce the bias of the selected indicator, we use the Q-learning method to dynamically select an optimal indicator in the environment selection. By the above mechanisms, MIEA-RL can obtain a set of representative Pareto optimal solutions with a good convergence and an uniform distribution.

The remainder of this paper is organized as follows. Section II presents the multi-objective RNP problem. In Section III, the details of the MIEA-RL are presented and then give corresponding experimental studies. Section IV illustrates instantiation of MIEA-RL on a RNP and analysis of experimental results. Finally, Section V concludes this paper and indicates some future directions.

Multi-objective RNP Model

In real-world RFID network planning, many factors such as economic efficiency, tag coverage and load balance need to be considered. Based on the above factors, the multi-objective RNP model can be presented as below [1,2].

Tag coverage ($f_1$): To achieve optimum tag coverage, the received power $PR_t$ of any tag $t$ from reader $r$ should exceed its threshold $P_T$ to ensure a communication connection from reader to tag. Besides, the backscatter signal $PB_t$ received by reader $r$ should also surpass the threshold $P_r$ of the reader $r$ to establish the available tag-to-reader communication. Accordingly, the function of tag coverage is formulated as

$$f_1 = \max \sum_{t \in TS} \frac{C(t)}{NT}$$

where $TS$ is the set of tags located in the workspace, $NT$ is the number of the tags and $RS$ is the set of readers deployed.

Economic Efficiency ($f_2$): Based on the consideration of multi-path propagation loss, channel attenuation and random noise, it is recommended to deploy the reader near the center of tag clusters. Thus, this objective function is formulated as
\[ f_2 = \min \sum_{r \in RS} \text{dis}(L_r, BL_r) \]  

(2)

where \( \text{dis}(\cdot) \) is the distance function, \( L_r \) and \( BL_r \) are respectively the position of reader \( r \) and its best served reader namely the corresponding tag center. K-means clustering algorithm is adopted to find the tag cluster in this paper.

Load Balance \( (f_3) \): Reader evenly distributed networks generally have better performance than unevenly configured networks, especially in the large-scale RFID deployment scenario. For minimizing the variance of load conditions, the objective function is formulated as

\[ f_3 = \min \prod_{r \in RS} \left( \frac{D_r^{\text{max}}}{D_r} \right) \]  

(3)

where \( D_r \) is the number of tags that is assigned to reader \( r \) and \( D_r^{\text{max}} \) is the maximum number of tags that is interrogated by the reader \( r \) per unit of time.

Objective Constraint: In addition to optimize the above three objective functions, the model should also guarantee the full coverage of tags. In other words, each tag located in working region can be covered by at least one reader. This constraint is formulated as:

\[ \text{s.t. } PR_t \geq P_t, PB_t \geq P_t \quad \forall t \in TS, r \in RS \]

\[ \sum_{r \in RS} D_r^i \geq 1 \quad \forall t \in TS \]  

(4)

where \( D_r^i \) is a binary value, which denotes the number of available readers. If the reader cover the tag \( t \), that is \( D_r^i = 1 \), otherwise \( D_r^i = 0 \). Therefore, this objective constraint not only keeps the network efficient, but also ensures that the reader fully covers the tags.

**Algorithm 1** Main Loop of MIEA-RL

| Input: | population size \( N \) |
| Output: | approximation set \( A \) |
| 1. | Initiate the population \( P_0 \) randomly |
| 2. | Evaluate all individuals in \( P \) |
| 3. | Set the offspring population \( Q_0=\emptyset \) t=0 |
| 4. | Initiate the Q-table \( T_{\text{indicators}}=0 \) |
| 5. | Select an initial indicator \( I_{\text{current}} \) at random |
| 6. while | \( t < \text{MaxGen} \) do |
| 7. | \( Q=\text{Mating\_selection}(P_t) \) |
| 8. | \( Q=\text{Variation}(Q) \) |
| 9. | /* Environmental selection based Q-learning */ |
| 10. | \( [P_{t+1}, T_{\text{indicators}}, I_{\text{current}}]=\text{QPEPS}(P_t, Q, T_{\text{indicators}}, I_{\text{current}}) \) |
| 11. | \( t=t+1 \) |
| 12. end while |
| 13. | \( A = \text{Non-dominated-sort}(P_{t+1}) \) |
| 14. | Return \( A \) |

Multi-objective Evolutionary Algorithm with Reinforcement Learning

**Overview**

In order to effectively optimize the multi-objective RNP model, a new multi-objective optimization algorithm using multiple indicators with reinforcement learning (MIEA-RL) is proposed. The main framework of MIEA-RL is shown in Algorithm 1. First of all, \( N \) solutions are randomly generated as
initial populations. Random parent individuals are selected to generate offspring in each generation. The offspring population is aggregated with the parent population after fitness evaluation. And then, Q-learning selects an optimal indicator to evaluate each individual. During the environmental selection, N good individuals are selected as new parents based on selected indicator. When the optimization is termination, the nondominated solutions in the final population are used as the final output.

**Indicators**

Generally, the proposed framework can accommodate any reasonable indicators. However, We expect these indicators to compensate each other for better performance, intuitively they should have different biases. Hence, the indicators $I_{\varepsilon}$ [19], $I_{\text{Maximin}}$ [26] and $I_{\text{SDE}}$ [25] are chosen for MIEA-RL. These indicators are chosen mainly for the following reasons: 1) these indicators have been proved to be effective in terms of convergence or diversity in many related works [19-21] and 2) since there is no need to set appropriate reference set/point, they are very computationally efficient.

Suppose that there are two solutions $x$ and $y$, the quality indicator $I_{\varepsilon+}$ is formulated as

$$I_{\varepsilon+}(x, y) = \min_{\varepsilon} \{ f_i(x) - \varepsilon \leq f_i(y) \text{ for } i \in \{1, \ldots, m\} \}$$

(5)

where $m$ is the number of objectives. According to the formula, it can be deduced that $I_{\varepsilon+}$ shows the minimum shift weight of each dimension of the objectives. Then it is used to compose indicator $I_1$ for comparing solutions as

$$I_1(x) = \sum_{y \in P \setminus \{x\}} -e^{-I_{\varepsilon+}([x, y])/0.05}$$

(6)

where $P$ is the population that includes $x$ and $y$. Distinctly, $I_1(x)$ can be directly employed as the dominance relation.

The quality indicator $I_{\text{Maximin}}$ proposed by Balling [22] is defined as:

$$I_{\text{Maximin}}(x) = \max_{y \neq x, y \in P} \left( \min_i \left( f_i^x - f_i^y \right) \right)$$

(7)

Some interesting properties are found from eq. (7): 1) the dominant individual is the one whose maximum indicator is greater than zero, and 2) Individuals whose maximum indicator is less than zero are non-dominant individuals. In addition, for non-dominant individuals, clustering leads to the increase of indicator. The corresponding $I_2$ for comparing solutions are defined as

$$I_2(x) = \max_{y \neq x, y \in \text{ND}} \left( \min_i \left( f_i^x - f_i^y \right) \right)$$

(8)

where ND is the non-dominated individuals. By constraining $y$ to be a non-dominant individual, the indicator of a non-dominated individual is controlled only by non-dominated individuals.

The indicator $I_{\text{SDE}}$ and the corresponding $I_3$ for selecting better individual are defined as

$$I_{\text{SDE}}(x, y) = \sqrt{\sum \text{dist}(f_i(x), f_i(y))^2}$$

$$\text{dist}(f_i(x), f_i(y)) = \begin{cases} f_i(y) - f_i(x) & \text{if } f_i(x) < f_i(x) \\ 0 & \text{otherwise} \end{cases}$$

(9)

$$I_3(x) = \min_{y \in P} \{ I_{\text{SDE}}(x, y) \}$$

(10)
Intuitively, $I_{SDE}$ reflects the distribution information of individuals. In addition, it is obvious that individuals with poorly-converged will also get a high density value. Thus, $I_3$ reflects both the distribution and convergence information of individuals.

**Q-learning Procedure Based Environmental Selection**

Based on the above indicator, the environmental selection need to select $N$ individuals from $2N$ individuals. Intuitively, the proposed environmental selection can be divided into two steps. The first step is to select the optimal $N$ individuals according to the indicators of $2N$ individuals, namely the environment selection. And then the Q-table is updated based on the performance variation of population. Detailed procedure is given in Algorithm 2.

**Algorithm 2. QLES (environmental selection based Q-learning)**

| Input: Population $P_t$, Offspring $Q_t$, Q-table $T_{indicators}$, Indicator in the current state $I_{current}$ |
| Output: Next population $P_{t+1}$, Updated Q-table $T_{indicators}$, Updated indicator in the current state $I_{current}$ |

1. Select the best action indicator $I_{act}$ for the current state indicator $I_{current}$ according to Q-table
2. Calculate fitness values $I_{new}$ of individuals in $P_t$
3. Based on indicator $I_{new}$, better $N$ individuals make up new population $P_{t+1}$
4. Get a reward $r = HV(P_{t+1}) - HV(P_t)$
5. Update the data item ($I_{current}$, $I_{act}$) in the Q-table $T_{indicators}$
6. Update the current state $I_{current} = I_{act}$

In the environmental selection process, the proposed mechanism is similar to the classical selection process. That is, all the individuals are sorted by their fitness values and then the better $N$ ones are selected.

In order to select appropriate indicator at each iteration, the Q-learning is adopt in the environmental selection. Specifically, Q-learning selects an optimal indicator according to the current iteration states. First of all, The selection indicator operating space is abstracted as a $3 \times 3$ matrix namely Q-table, as showed in Table 1. Then, the indicator that is used to evaluate the individuals in each iteration is selected according to the Q-table. For example, suppose the current population is assessed based on indicator $I_3$, the optimal indicator that can achieve best performance in next iteration is performed as $I_1$ based on potential reward-maximization. Finally, the population gets a feedback based on the performance variation of population. In this paper, the hypervolume indicator (HV) is used to measure this performance variation. Then the corresponding reward function as following:

$$r = HV(P_{t+1}) - HV(P_t)$$  \hspace{1cm} (11)

where $P_{t+1}$ is the population after environmental selection and $P_t$ is the population before environmental selection.

The corresponding data item in the Q-table is updated as

$$Q(I_{state}, I_{act}) = Q(I_{state}, I_{act}) + \alpha[\Delta Q(I_{state}, I_{act})]$$

$$\Delta Q(I_{state}, I_{act}) = r + \beta \max Q(I_{state}, I) - Q(I_{state}, I_{act})$$

$$\alpha(t) = 1 - (0.9 \times \frac{iter}{\max Cycle})$$  \hspace{1cm} (12)

where $\alpha$ is the learning rate in $[0,1]$, $r$ is the immediate reward for using indicator $I_{act}$ after using indicator $I_{state}$ and $\beta$ represents the discount factor, denoting the extent to which current gains are sacrificed for long-term gains.

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Table 1. A specific example of the Q-table.

| current state | $I_1$ | $I_2$ | $I_3$ |
|---------------|------|------|------|
| $I_1$         | -0.2 | -0.5 | 0    |
| $I_2$         | 0    | 0.9  | 0.5  |
| $I_3$         | 0.5  | 0    | -0.3 |

**Computational Complexity Analysis**

Supposed an RNP problem with three objective functions and a population size of $N$, the time complexity of $T$ generation of MIEA-RL is as follows: $O(N)$ is used to generate a new population. Next, the time complexity of evaluating the fitness of the population and merging population need $O(mN)$ and $O(N)$ respectively. And finally, Q-learning procedure based environmental selection consumes $O(mN^2)$, in which the environment selection and update Q table consume $O(mN^2)$ and $O(N^2)$ respectively. In short, the computational complexity of MIEA-RL is $O(TmN^2)$. Compared with other popular algorithms[15,19,25,36-40], this performance is very competitive.

**RNP Simulation**

**Experiment Setup**

As is known to all, the task of RFID network planning is to deploy RFID readers in the working area to satisfy network requirements. A simulation experiment containing 100 clustered distributed tags and 10 RFID readers that Comply with EPC Class1 Gen 2 standards is implemented in the 30 m × 30 m working space, where the following three decision variables are chosen in this work: the x-axis coordinate value of the RFID reader, the y-axis coordinate value of the RFID reader and the read range of the RFID reader. The related parameters in the simulation RFID network are set as in [15]. The solution’s representation makes up of these variables. On that basis, each solution that represents a RFID network structure consists of a 30-dimensional vector in which 20 dimensions indicate the coordinates of the readers in the 2-dimensional working area, and the other 10 dimensions denote the interrogation range of each reader.

The proposed algorithm is applied to solve this RNP instance with multi-objective model. In order to verify the performance of the proposed algorithm, the state-of-the-art multi-objective evolutionary algorithms NSGAII[24], NSGAIII[45] and MOEAD[27] are considered. The population size of MIEA-RL and NSGAII is set to 100. The population size of NSGAIII and MOEAD is set to 91 and the number of weight vectors is the same. The crossover and mutation probabilities are fixed at 0.9 and $1/n$, respectively, where $n$ is the number of decision variables. The distribution indexes of SBX and polynomial mutation operators are both set to 20. To obtain statistically reliable results, the number of fitness evaluation is set to 100,000 and the independent run times are set to 30.

**Computation Results and Analysis**

![Figure 1. all obtained Pareto fronts by the algorithms.](image-url)
Three competing objectives in section II are optimized simultaneously by the above four algorithms. According to the RNP instance, all obtained Pareto fronts by the different algorithms are shown in Fig. 1. It clearly illustrates the relationships among all presented objective functions. According to the simulation data, without degrading the other related optimized objectives, it is impossible that each MORNP objective is further improved. Obviously, the tradeoffs given by MIEA-RL generally dominate the tradeoffs given by the other three algorithms. Furthermore, Table 2 shows the all compromise Pareto-optimal solutions in the three-dimensional Pareto front by MIEA-RL. Due to the limited layout, the Pareto-optimal solutions of other algorithms are not given.

A sample from Pareto-optimal solutions is selected to further analyze the algorithm performance in Fig. 2. A contour represents the same radiated power. It is shown in Fig. 2 that the power peaks in the working area are the positions where the readers are deployed, and the signal strength decreases with distance from the reader. Observing Fig. 2, we can draw conclusions: 1) MIEA-RL tries to generate an optimal reader network layout with high tag coverage rate; 2) a satisfactory economic efficiency by increasing the best-server areas is maintained by MIEA-RL; 3) according to the capacity of readers, the algorithm uses a load balancing strategy to configure the network so that each reader in the network has an optimal number of tags.

Table 2. Pareto optimal solutions for RFID network planning by MIEA-RL.

| No. | $f_1$   | $f_2$   | $f_3$   | No. | $f_1$   | $f_2$   | $f_3$   |
|-----|---------|---------|---------|-----|---------|---------|---------|
| 1   | 3.1E-01 | 2.6E-07 | 1.6E-01 | 11  | 9.0E-02 | 1.4E-04 | 1.2E-01 |
| 2   | 1.1E-01 | 1.5E-03 | 7.4E-02 | 12  | 6.5E-02 | 4.8E-04 | 7.8E-02 |
| 3   | 4.7E-02 | 1.2E-05 | 1.6E-01 | 13  | 1.7E-01 | 9.6E-07 | 1.4E-01 |
| 4   | 4.8E-02 | 1.1E-05 | 2.2E-01 | 14  | 2.1E-01 | 6.5E-04 | 6.5E-02 |
| 5   | 4.1E-01 | 3.6E-05 | 4.9E-02 | 15  | 6.2E-02 | 2.2E-06 | 2.0E-01 |
| 6   | 1.4E-01 | 1.2E-03 | 6.2E-02 | 16  | 2.9E-01 | 7.3E-05 | 5.3E-02 |
| 7   | 1.3E-01 | 7.7E-04 | 6.6E-02 | 17  | 1.3E-01 | 3.7E-04 | 9.0E-02 |
| 8   | 3.3E-01 | 5.2E-05 | 5.2E-02 | 18  | 1.3E-01 | 9.9E-07 | 1.8E-01 |
| 9   | 2.5E-01 | 2.8E-04 | 5.6E-02 | 19  | 6.0E-02 | 6.7E-04 | 1.0E-01 |
| 10  | 1.7E-01 | 1.3E-03 | 6.1E-02 | 20  | 1.4E-01 | 1.2E-04 | 1.1E-01 |

Summary

In this paper, in order to solve the RNP problem effectively, we propose a multi-objective optimization algorithm based on multiple indicators and reinforcement learning. The proposed algorithm, namely MIEA-RL, employs the Q-learning procedure to balance the search biases of different indicators. Specifically, the indicator used in the next iteration is determined by evaluating the performance improvement of the population that is selected by the current indicator. By maintaining a Q-table, the convergence and diversity are effectively maintained. Moreover, the
algorithm does not increase the computation complexity and it retains a good balance between performance and efficiency.

Since our new RNP model takes advantage of multi-objective algorithms to find all the Pareto optimal solutions and to accomplish the optimal planning solutions by simultaneously optimizing three conflicting objectives, this work is more novel than previous approaches to RFID network planning. To verify its validity, MIEA-RL is employed to solve a RFID network planning problem and gave the better performance. For future research, it is interesting to investigate the performance of MIEA-RL on the larger-scale RNP environments and the application of parallel or distributed techniques to improve MIEA-RL.

Acknowledgement
This work is supported by the National Natural Science Foundation of China under Grant No. 61773103 and 61503373; and Fundamental Research Funds for the Central Universities No. N161705001.

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