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An Effective Multi-Objective Optimization Algorithm for Spectrum Allocations in the Cognitive-Radio-Based Internet of Things

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ABSTRACT The continuous growth of interconnected objects in the Internet of Things (IoT) raises a challenge to the wireless communication technology. Cognitive radio could make full use of the dynamic spectrum access and spectrum diversity over wide spectrum to alleviate the spectrum scarcity problem and satisfy the enormous connectivity demands in IoT, which has garnered significant attention over the last few years. This paper addresses the spectrum allocation problem with respect to both spectrum utilization and network throughput in the cognitive-radio-based IoT. On the one side, each link in a transmission path intends to improve the transmission performance on the assigned spectrum channel to maximize the end-to-end throughput. On the other side, these links share the same spectrum channel to concurrently transmit as much as possible to achieve the maximum spectrum utilization. In order to solve the problem, we propose a concurrent transmission model in the network which reveals the constraints of mutual interference and resource competition in links concurrent transmissions. Based on this model, we formulate the spectrum allocation plan for links as the chromosome (solution) in genetic algorithms. Then, we apply the nondominated sorting genetic algorithm-II to solve the multiobjective spectrum allocation problem. Simulation results validate that the proposed strategy can search the optimal solutions efficiently and satisfy the requirements of spectrum allocation in various cases.

INDEX TERMS Internet of Things, cognitive radio, spectrum allocation, multi-objective optimization.

I. INTRODUCTION

Internet of Things (IoT) is a worldwide network of interconnected objects uniquely addressable, based on standard communication protocols, and allows people and things to be connected any-time, anyplace, with anything and anyone, ideally using any path/ network and any service [1]. In the network, all these objects will have to exchange information, most of the time by making use of wireless communications [2]. Therefore, the proliferation of objects in the IoT naturally results in the increasing demands for spectrum resources, which will likely exacerbate the problem of spectrum scarcity in wireless communications. Traditionally, the spectrum licenses have been allocated for specific radio services, operating in specified frequency bands. Recent studies have shown that such static strategy of spectrum allocations causes inefficient and unbalanced utilization of the spectrum. Cognitive radio [3], a promising technology to improve spectrum utilization, has aroused significant attention over the last few years. Cognitive radio allows unlicensed users, also called Secondary Users (SUs), to access licensed spectrum bands as long as they do not cause intolerable interference to Primary Users (PUs). The attractive technology can make full use of the dynamic spectrum access and spectrum diversity over wide spectrum. Therefore, applying cognitive radio technology into the IoT could alleviate the spectrum scarcity problem and achieve higher spectral efficiency and network performance, which will contribute to a great boom in the IoT.

The cognitive-radio-based IoT is desired that IoT objects should have cognitive facility to make smart decisions about the spectrum and perform intelligent operation by analyzing network conditions [4], [5]. In this paper, we consider the spectrum allocation for the cognitive-radio-based IoT. In such network, there exist some multi-hop data flows in concurrent transmissions, which match the information exchanges of the IoT objects. Each flow crosses a routing path constituted by some consecutive links, which are active communication pairs formed by objects. Each of these links is assigned a spectrum channel elaborately to support flow transmission. On the one hand, to pursue the ''always connected'' paradigm in the IoT [2], the objective of optimizing spectrum allocation should should be concentrated on maximizing the multi-hop flow rates. On the other hand, to play the advantages of cognitive radio, an excellent spectrum allocation strategy should achieve efficient utilization on the assigned spectrum channels. Therefore, considering multi-objective optimization problem (MOP) in the procedure of spectrum allocation is significant and indispensable.

In this paper, we focus on the spectrum allocation strategy with respect to maximizing both network throughput and spectrum utilization in the cognitive-radio-based IoT. This problem is challenging due to the following reasons. Spectrum allocation in such multi-hop cognitive radio network scenarios should take more influential factors into consideration than that in the single-hop scenario. An effective end-to-end throughput should be allowable for all links composing the routing path of the flow. That means the capacity varying of any link can potentially affect the throughput of the whole path. Moreover, link transmission is influenced by not only the interference on the assigned channel, but also the resource competition in the network. Multi-objective spectrum allocation strategy accompanies the high computational complexity and thus the efficient algorithm should be explored to achieve optimal results in all cases.

In this paper, we consider the link as the elementary unit in spectrum allocation and multi-hop flow transmission. The link transmits on an assigned spectrum channel. Co-channel interference constraints are proposed based on a realistic interference model, and the link capacity is educed according to the Shannon model [6]. Then we explore the resource competition in the link transmissions. There exist that multiple concurrent flows share the same link or multiple links share the same SU node. The victim links are unable to give full play to the performance to transmit the flow. We formulate the resource competition problem and propose a fair resource sharing policy. Based on the model, each link can evaluate the transmission performance upper bound when transmitting the flow. By jointly considering transmission performances of all links in the routing path, the maximum allowable end-to-end throughput should be achieved.

We concentrate the optimal spectrum allocation strategy for all links on duty of flow transmissions in the cognitive-radio-based IoT. The strategy aims at two objectives, maximizing the aggregate end-to-end throughput in the network and maximizing spectrum utilization (measured by average number of links on each assigned spectrum channel). In the procedure of the spectrum allocation, each link on duty of the flow transmission can share a spectrum channel with other links or monopolize a new channel. Therefore, the search space of the spectrum allocation solution gets an exponential growth as the network size (number of links) increasing. The problem is classified as an NP-hard problem in the view of computational complexity. Thus, the heuristic algorithm with low complexity should be explored to seek the optimal solutions for the problem.

We apply the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [7] to solve the multi-objective spectrum allocation problem. NSGA-II algorithm is considered as manifesting the high performance in MOP, which is a Pareto-based algorithm and searches the whole feature space effectively. Fast non-dominated sorting approach characterizes low computational complexity while maintaining the good performance. NSGA-II adopts the elitist-preserving strategy, which contributes to excellent chromosomes (solutions) increasing rapidly in the population. So the algorithm is suitable to deal with the spectrum allocation problem. We formulate a spectrum allocation plan as a solution in the genic algorithm. A large population is adopted to accelerate the convergence to Pareto front. The simulation results validate that the strategy has a good balance between convergence rate and population diversity, which provides optimal spectrum allocation plans efficiently in various cases.

The rest of the paper is organized as follows. The next section summarizes the previous work on related topics. Section III defines the interference model and resource competition model in link transmissions. The multi-objective spectrum allocation in the cognitive radio network is presented in section IV. Simulations and analysis are shown in section V. Finally, section VI concludes the paper.

II. RELATED WORKS

In cognitive-radio-based systems and networks, maximizing a single performance metric is generally accompanied by the ignorance to the degradations of other performance metrics. Thus, in recent years, some researchers begin to employ MOPs in their researches to achieve balanced network performances.

Bedeer *et al.* [8] investigated the optimal link adaptation problem of OFDM-based cognitive radio systems and formulated this problem with two conflicting objectives, maximizing the system throughput and minimizing its transmit power. The proposed approach optimizes bit and power allocations per SU subcarrier under the constraints of the predefined interference thresholds for PUs and the spectrum sensing errors. In [9], an approach based on the concept of cat swarm optimization was proposed to optimize the parameter adaptation of an OFDM based cognitive radio engine. The spectral interference between primary and cognitive users is taken into consideration. A fuzzy logic based strategy is shown in order to find out a compromised solution on the Pareto front.

Power control is an important optimization objective and Some MOPs in cognitive radio networks refer to it. The power control approach for SUs can be represented by three objectives: first, minimizing the transmit power; second, keeping the SINR as close as possible to the target SINR; third, limiting the interference power at the primary receiver to some predefined constraint [10]. Naeem *et al.* [11] applied the cross-entropy optimization (CEO) to the problem of joint multiple relay assignment and source/relay power allocation in green cooperative cognitive radio (GCCR) networks. Monte-Carlo-based CEO algorithm is used to optimize two conflicting objectives: maximizing the total rate and the minimizing the greenhouse gas emissions in GCCR networks. Bedeer *et al.* [12] investigate multi-objective optimization for bit and power allocation problem in the OFDM system. An evolutionary algorithm is adopted to solve the convex problem. Moreover, the constraint on the average bit error rate (BER) is replaced by a BER per subcarrier constraint. According to the situation, an equivalent convex optimization method is proposed to deal with the problem and global optimality of the Pareto solutions is achieved. An Adaptive Multi-objective Optimization Scheme (AMOS) was proposed in [13]. The objective functions used in AMOS are comprehensive by incorporating throughput, delay, bit error rate, spectral efficiency, power, and interference. The weights and priorities of objective functions are adapted automatically according to the environment conditions and system capabilities.

Spectrum sensing directly affects the performance of the cognitive radio network. Some studies have focused on the joint optimization of spectrum sensing and other performance metrics. Balieiro *et al.* [14] investigated an adaptive sensing period optimization, which aims at minimizing the incurred sensing overhead and maximizing the spectrum opportunities. In [15], SUs form the clusters to make cooperative spectrum sensing. The objectives of the clustering optimization include total energy consumption minimization, total throughput maximization, and inter-cluster energy and throughput fairness. The NSGA-II is used to solve the optimization problem. Kulkarni and Banerjee [16] investigate the optimal allocations of limited time and energy for tasks of sensing and transmission to maximize average SU throughput and sum-throughput of SU network respectively.

Some performance metric optimization problems can be decomposed into MOPs. Mili and Musavian [17] introduced a novel performance metric called interference efficiency (IE) which shows the number of bits transmitted per unit of interference energy imposed on the PU receivers. The IE optimization problem is solved through a MOP that jointly maximizes the ergodic sum rate of multiple SUs and minimizes the interference power imposed on the Pus. In order to increase the energy efficiency in cognitive radio networks, the paper [18] provides a MOP that jointly maximizes the ergodic capacity and minimizes the average transmission power.

The spectrum allocation with multi-objective optimization is of great importance and has attracted many researchers [19]–[23]. Martínez-Vargas *et al.* [19] formulated the spectrum assignment problem for an underlay spectrum sharing network as an MOP to maximize throughput and spectral efficiency. They defined some cases and solved them using a proposed algorithm based on NSGA-II to search for the Pareto optimal solutions. The spectrum allocation was considered in the view of economics theory [21], [22]. The spectrum selection optimization is introduced with multi-objective portfolio function based on return and risk values of transmissions in primary and secondary frequency bands. In [23], the forced termination probability is considered as one objective function along with three network utility functions namely Max-Sum-Reward, Max-Min-Reward and Max-Proportional-Fair. The spectrum allocation process is formulated as a MOP consisting of the functions mentioned above and solved by using multi-objective differential evolution algorithm. In this paper, we introduce multi-objective spectrum allocation in the multi-hop cognitive-radio-based IoT. We focus on jointly optimizing the sum of end-to-end throughputs and the spectrum utilization which was not fully researched in existing works.

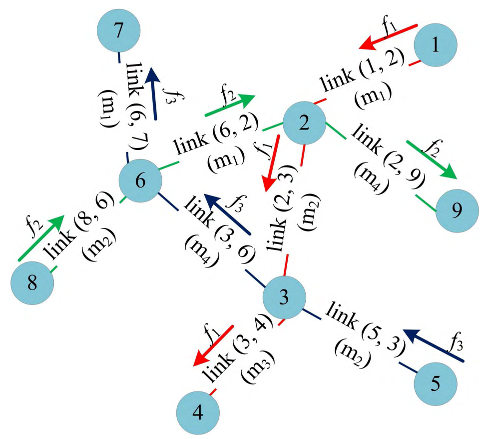


FIGURE 1. System model.

III. SYSTEM MODEL

In the cognitive-radio-based IoT, there exist some multi-hop concurrent data flows. The routing paths of these flows are composed of some successive object links. The links do not possess any of their own licensed channel and access the available spectrum channels offered by PUs to support their transmissions. We model the network formulated by a quadruplet $G = (V, L, M, F)$. V is the set of nodes in the network. To express more appropriately and accurately, hereafter the term node is used as a synonym of the term object. L is the set of links which are feasible communication pairs on duty of transmissions. For a link $(i, j) \in L$, i is the sending side (node) and j is the receiving side (node). Each link needs to be assigned to a spectrum channel for the transmission. M is the set of spectrum channels that are currently assigned to the links in L. F is the set of multi-hop concurrent data flows in the network. For detailed descriptions, an instance of the model is shown in Fig. 1. The network is composed of 9 nodes ($V = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$) and 9 links ($L = \{(1, 2),$ $(2, 3)$,$(3, 4)$,$(8, 6)$, $(6, 2)$, $(2, 9)$, $(5, 3)$, $(3, 6)$, $(6, 7)\}$). The set of spectrum channel includes 4 assigned channels ($M = m_1$,

m_2, m_3, m_4). There are 3 concurrent flows ($F = \{f_1, f_2, f_3\}$) in the network. Each flow crosses a sequence of links which constitute a routing path. For example, the routing path of f_1 consists of links (1, 2), (2, 3) and (3, 4). Respectively, these links are assigned to spectrum channels m_1, m_2 and m_3 so that they can achieve efficient transmission performances to support the stable end-to-end throughput.

A. TRANSMISSION IN THE COGNITIVE-RADIO-BASED IoT

In the cognitive-radio-based IoT, links have an effective strategy of spectrum selection to support their flow transmissions. Different links can choose various spectrum channels. But spectrum sharing among some links is promoted in the network, because raising spectral efficiency is the original intention of cognitive radio technology. Moreover, in a multi-hop cognitive radio network, there exit some links share the same spectrum channel while maintaining their desired transmission performances. Therefore, we need to investigate the constrained conditions of concurrent transmissions in multi-hop cognitive radio networks G.

In concurrent transmissions, the performance of a link not only depends on its own setup but also the influence factors from other links sharing the same channel. Signal-to-interference-plus-noise ratio (SINR) is used to measure the quality of communications. In link transmissions, SINR can be considered as the received power of the intended signal at the receiver divided by the sum of received powers of unintended signals (interferences) from other links on the same spectrum channel. For a link (i, j) on spectrum channel m, its SINR can be calculated as follows:

$$SINR_{ij}(m) = \frac{h_{ij}p_i}{\sigma^2 + \sum\limits_{(a,b)\in I(m),(a,b)\neq(i,j)} h_{aj}p_a} \tag{1}$$

where p_i denotes transmission power of sender i. In this paper, we assume that the transmission power of all links is at the fixed level. h_{ij} represents the channel gain between sender i and receiver j, which can be denoted by k/d_{ij}^{α}. Here k is the path loss constant. d_{ij} is the distance between i and j. α is the path loss exponent. σ^2 is the thermal noise that can be considered as a constant, and sigma notation presents the aggregate interference at receiver j, which is generated by the links transmitting concurrently on the current spectrum channel. Here, $I(m)$ presents the set of links sharing spectrum channel m. To guarantee the effective link transmission, each intended signal should be successfully decoded at the receiver. For the SINR, there exists a desired value denoted by β, which indicates the threshold of successful decoding. So, if link (i, j) intends to access spectrum channel m for its transmission, the constraint is satisfied as follows:

$$SINR_{ij}(m) \geq \beta \tag{2}$$

If the Equation (2) is satisfied, the link (i, j) can transmit data flow on the channel m. In accordance with the Shannon theorem, the capacity of link (i, j) on channel m is represented as follows:

$$C_{ij}(m) = W\log_2(1 + SINR_{ij}(m)) \tag{3}$$

where W is the spectrum bandwidth of channel m. The link capacity is considered as the upper bound of data rate that the link can support on the current channel.

B. RESOURCE COMPETITION IN CONCURRENT TRANSMISSIONS

In the cognitive-radio-based IoT, each link should be assigned a spectrum channel on which it transmits data flow. Let $x_{ij}^{f}(m) = 1$ indicate that link $(i, j) \in L$ chooses spectrum channel $m \in M$ for transmitting flow $f \in F$. Otherwise, $x_{ij}^{f}(m) = 0$, Note that each link can choose only one spectrum channel for a flow transmission. Thus there exists the constraint in the spectrum allocation as follows:

$$\sum_{m\in M} x_{ij}^{f}(m) = 1 \tag{4}$$

We further investigate that the flow transmission is restricted by the resource competition. In the network, there exists some links share a node as their common sender or receiver. Let L_i represent the set of all links sharing node i as follows:

$$\begin{aligned} L_i = &\{(i,k)|x_{ik}^{f}(m) = 1, m \in M, f \in F, (i,k) \in L\} \\ &\bigcup \{(t,i)|x_{ti}^{f}(m) = 1, m \in M, f \in F, (t,i) \in L\} \end{aligned} \tag{5}$$

We consider that each node in the network is mounted with only one transceiver, which results in the node severs for only one link transmitting the data flow at a time. Therefore, each link only applies a portion of the per unit time for its flow transmission, which is represented in terms of transmission opportunity. In this paper, we employ the fair transmission opportunity assignment strategy. In other words, the transmission opportunity is the average distribution among the links sharing the same node. Let T_i denote the transmission opportunity of each link in L_i, and $T_i = 1/|L_i|$. Here $|L_i|$ is the cardinality of L_i.

We further investigate the maximum data rate that can be supported by a link. For link (i, j), the efficient link transmission opportunity T_{ij} is defined as follows:

$$T_{ij} = \min\{T_i, T_j\} \tag{6}$$

T_{ij} evaluates the transmission opportunities on both sides of link (i, j). If the link transmits the data of flow f on spectrum channel m, the maximum data rate that the link can maintain is denoted by the following:

$$R_{ij}^{f}(m) = T_{ij} \times C_{ij}(m) \tag{7}$$

Thus, due to the constraint of the resource competition, link (i, j) only applies a portion of its link capacity for the flow transmission. A feasible data rate of flow f on the link must not exceed $R_{ij}^{f}(m)$.

After determining the maximum data rate on each link, we investigate the end-to-end throughput of the flow in the network. L^f is the set of links that compose the routing path of flow f, and defined by the following:

$$L^f = \{(i,j)|x_{ij}^f(m) = 1, m \in M, (i,j) \in L\} \quad (8)$$

We consider the effective end-to-end throughput R^f, the maximum allowable data rate in the routing path of flow f. Notice that all links in L^f must support the R^f, we have:

$$R^f = \min R_{ij}^f(m) \quad \forall (i,j) \in L^f \quad (9)$$

The value of R^f depends on the link with the minimum value of maximum data rate. Therefore, improving transmission performance of the link contributes to increasing the end-to-end throughput.

IV. PROBLEM FORMULATION

As mentioned above, a proper spectrum access of a link can capture higher capacity, which potentially help to maintain the higher end-to-end throughput. Therefore, harvesting the optimal flow transmission performance in the whole network is the important target of the spectrum allocation strategy. On the other hand, due to the scarcity of spectrum resources, efficient spectrum utilization is emphasized in the view of spectrum allocation. In dynamic spectrum access environment, the efficient spectrum allocation can make best use of the current spectrum access opportunity, which reduces the cost of spectrum sensing used to seek the new opportunities. In the condition of spectrum auction, efficient spectrum utilization means higher economic benefits. Moreover, it is feasible that multiple links with the elaborative planning can share the same spectrum channel to transmit concurrently in the network. Therefore, the spectrum allocation strategy intends to take full advantage of each assigned spectrum channel. Consequently, we focus on the spectrum allocation strategy with respect to jointly optimizing transmission performance and spectral efficiency in the cognitive-radio-based IoT. The MOP problem can be written as:

$$Max \sum_{f \in F} R^f \quad (10)$$

$$Max \frac{|L|}{|M|} \quad (11)$$

$$\begin{aligned} s.t.\ & SINR_{ij}(m) \geq \beta \\ & \left(x_{ij}^f(m) = 1,\ (i,j) \in L,\ f \in F,\ m \in M\right) \\ & \sum_{m \in M} x_{ij}^f(m) = 1 \\ & ((i,j) \in L,\ f \in F,\ m \in M) \end{aligned} \quad (12)$$

Equation (10) indicates maximizing the network throughput which is the sum of end-to-end throughputs of the concurrent flows and calculated according to Eqs. (3) and (5)-(9). Equation (11) indicates maximizing the spectrum utilization in the network, which is measured by the average number of the links on each assigned spectrum channel. L is the set of links on duty of flow transmissions, and $|L|$ is the cardinality of L. M is the set of spectrum channels assigned to links in L and determined by the result of the spectrum allocation. $|M|$ is the cardinality of M. Equation (12) indicates the constraint for the spectrum allocation in the network, which has already been elaborated in Eqs. (2) and (4).

We further analysis each spectrum allocation plan for the MOP problem formulated by Eqs. (10)-(12) which can be translated into a partition of link set L. A feasible spectrum allocation plan must assign a spectrum channel for every link in set L to support its transmission. The links assigned the same channel can be defined as a spectrum sharing set which is a subset of set L. Due to the constraint of Equation (4), a link is included in one and only one spectrum sharing set, which means any two spectrum sharing sets have no common elements. Consequently, the set of these spectrum sharing is a partition of set L, which corresponds to a spectrum allocation plan. In order to get the optimal solutions for the the multi-objective spectrum allocation problem, all partitions of set L need to be evaluated. The computational complexity of the problem is no less than $O(2^N)$, where N is the size of set L. However, in the situation of massive number of links in the network, it is still inefficient. Besides, in the cognitive-radio-based IoT, it is imperative to propose a more efficient spectrum allocation algorithm in accord with the dynamic spectrum access environment. Thus, the heuristic algorithm with low complexity should be considered for the problem.

In the paper, we apply the algorithm NSGA-II [7] to solve the multi-objective spectrum allocation problem formulated by Eqs. (10)-(12). NSGA-II is an improved version of NSGA [24] based on Pareto optimal set. Compared to the non-Pareto-based algorithms, such as the Vector Evaluated Genetic Algorithm (VEGA) [25], the algorithm overcomes the disadvantages of converging easily to local-best, and searches the whole feature space effectively. Fast non-dominated sorting approach is proposed in NSGA-II which efficiently sorts all solutions in the population and classifies them into multiple nondominated fronts. The computational complexity is reduced to $O(mN^2)$ in the proposed approach in contrast to $O(mN^3)$ in the naive nondominated sorting approach, where m is the number of objective functions and N is the population size [7]. NSGA-II algorithm introduces the elitist-preserving strategy that designs a mating pool by combining the parent and offspring populations, and then competes to produce the next generation population. It chooses the excellent individuals in the parent population to add them into the next generation. The excellent individuals won't be abandoned. Subsequently, the excellent individuals in population will be improved rapidly.

Due to the advantages mentioned above, NSGA-II is suitable to tackle with the multi-objective spectrum allocation problem. An alternative valid spectrum allocation plan at least satisfies that each link with the duty of the flow transmission is supposed to be assigned a spectrum channel to maintain concurrent transmissions of flows in the networks. The plan is represented by a list with the size equal to the number of all links in the network. Each element in the list corresponds to a link, and the value of the element is the serial number of

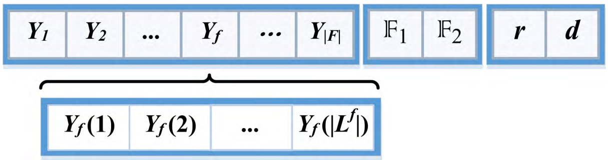


FIGURE 2. Composition of the solution in the spectrum allocation.

the channel assigned to the link. We map the list to the chromosome (solution) in the genetic algorithm. The essential factors in the proposed spectrum allocation approach based on the NSGA-II algorithm are shown in Fig. 2. The left part is a solution which is formed by sequentially placing the spectrum channel assignment for links in the routing paths of the flows next to each other. For a flow f, Y_f is the spectrum channel vector $(Y_f(1), Y_f(2)Y_f(|L^f|))$ of length $|L^f|$, which lists the serial number of assigned channel corresponding to the links comprising the routing path of flow f. In the solution, if a link serves for two or more flow transmissions, it can be assigned to the different spectrum channels for these transmissions respectively. Multiple solutions form a population which can be considered as the set of spectrum allocation plans.

$\mathbb{F}_1$ and $\mathbb{F}_2$ in Fig. 2 are the optimization objectives indicated in Eqs. (10) and (11) respectively, according to which the solutions in the population can be compared with each other and nondominated fronts can be ensured with various ranks through the nondominated sorting. For any two solutions p and q, p dominates q if one of the following conditions is satisfied:

$$\begin{aligned}&\mathbb{F}_1(p) > \mathbb{F}_1(q) \textit{ and } \mathbb{F}_2(p) > \mathbb{F}_2(q)\\&\mathbb{F}_1(p) > \mathbb{F}_1(q) \textit{ and } \mathbb{F}_2(p) = \mathbb{F}_2(q)\\&\mathbb{F}_1(p) = \mathbb{F}_1(q) \textit{ and } \mathbb{F}_2(p) > \mathbb{F}_2(q)\end{aligned} \tag{13}$$

Where $\mathbb{F}_1(p)$ and $\mathbb{F}_1(q)$ are the values of $\mathbb{F}_1$ under solutions p and q respectively, the same as $\mathbb{F}_2(p)$ and $\mathbb{F}_2(q)$. In the nondominated sorting, nondominated fronts are created according to the following steps. (1) For each solution p,compare with the rest solutions in the population and calculate two entities. One is the domination count n_p, the number of solutions which dominate p. The other is S_p, a set of solutions that p dominates. (2) Put each solution p with $n_p = 0$ into the first nondominated front with rank 1. Meanwhile, visit each member q in S_p and implement the operation $n_q = n_q - 1$. (3) Repeat the operations in step (2) to create the next nondominated front until all fronts are identified.

The right part in Fig. 2 is the crowding distance, which is the efficient approach to make comparison between solutions belonging to the same nondominated front. The crowding distance can be achieved as the following steps. (1) Sort the solutions in the nondominated front according to $\mathbb{F}_1$. (2) Assign an infinite distance value to the boundary solutions. (3) For each of the rest solutions p, its crowding distance can be calculated by the following equation:

$$\sum_{k=1}^{2} \frac{\mathbb{F}_k(p+1) - \mathbb{F}_k(p-1)}{\mathbb{F}_k^{\max} - \mathbb{F}_k^{\min}} \tag{14}$$

Where $\mathbb{F}_k(p+1)$ and $\mathbb{F}_k(p-1)$ are the values of $\mathbb{F}_k$ $(k \in 1, 2)$ under solutions $p+1$ and $p-1$ respectively. $\mathbb{F}_k^{\max}$ and $\mathbb{F}_k^{\min}$ are the maximum and minimum values of $\mathbb{F}_k$ respectively.

Algorithm 1 Seek the Optimal Solutions

$t = 0$, set the number of generations $t_{\max}$
Initialize a random parent population P_t of size N
Sort P_t based on the nondominated sorting and then obtain the crowding-distance for each solution in P_t
repeat
  Perform binary tournament selection over P_t to create mating pool
  Apply the genetic operators to obtain the new offspring Q_t of size N
  $R_t = P_t \cup Q_t$
  Sort R_t based on the nondominated sorting and then obtain the crowding-distance for each solution in R_t
  Select the population P_{t+1} from R_t based on the Pareto rank and the crowding-distance of size N
  $t = t + 1$
until $t \geq t_{\max}$

Based on the essential factors in Fig. 2, we can apply the NSGA-II algorithm in the spectrum allocation problem to seek the optimal solutions, which is given in Algorithm 1. The algorithm creates a random population P_t of size N. Each solution in P_t should satisfy the constraints indicated in Eq. (12). Then, an offspring population Q_t of size N is created by using binary tournament, mutation operators and recombination. Thereafter, P_t combines Q_t to form a new population R_t of size $2N$. Then population R_t is sorted according to nondomination. In the procedure, each solution in R_t is added into a certain nondominated front with the corresponding nondomination rank (1 is the best level, 2 is the next-best level, and so on). A new population P_{t+1} of size N is generated from R_t. Firstly, the nondominated fronts in R_t are added into P_{t+1} consequently according to their ranks in ascending order until the size of the current nondominated front exceeds the size of the remaining slots in R_t. Then, the solutions in the front are sorted according to crowded-comparison operator in descending order and the best solutions are selected to fill all remaining slots in R_t. Repeat the above procedure until reach the upper bound of generations.

V. EXAMPLES AND SIMULATION RESULTS

In this section, we evaluate the simulation results of the proposed spectrum allocation strategy in different scenarios. The topology of the cognitive-radio-based IoT in the simulation is depicted in Fig. 3 where 60 nodes are randomly deployed over a $1000m \times 1000m$ area. Each node is mounted with only one transceiver. There exist at most 5 data flows simultaneously in

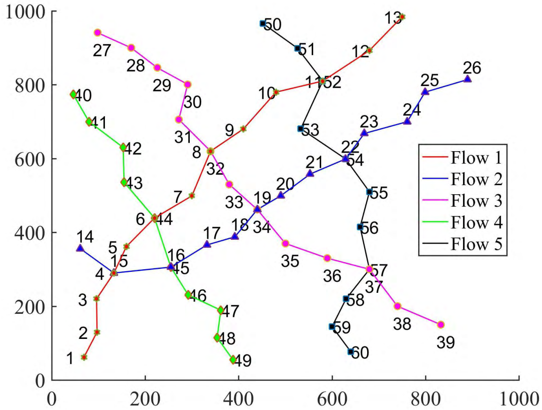


FIGURE 3. Network topology.

the network. The transmission power of each link is fixed to $13dBm$ and the thermal background noise σ^2 is $-100dBm$. The channel gain is defined as $h_{ij} = k/(d_{ij})^{\alpha}$, where d_{ij} is the distance between two nodes. We adopt the path loss constant $k = 1$ and path loss exponent $\alpha = 3$. For simplicity, we assume that all available spectrum channels have the same bandwidth. But the proposed model and algorithm can be easily extended to the case when the bandwidths vary. We consider the available spectrum channels to be assigned to links have a uniform bandwidth $5MHz$.

As shown in Fig. 3, the scenario indicates the data transmission between the nodes in different edges of the network. The data flows with long routing paths cross the whole space that the network lies in and intersect with each other in the central region of the network. As a result, co-channel interference and resource competition become severer. We evaluate the performance of the proposed multi-objective spectrum allocation strategy in this case. The parameters used for the algorithm are indicated in Table 1. There are 55 links need to be allocated spectrum channels, which also means that the length of each solution is 55. We design the population to contain 100 solutions, and operate the gene evolution for 100 generations. The algorithm is executed for 10 times. In each experiment, a Pareto front is achieved, which is the nondominated front with highest rank in the population of the last generations.

TABLE 1. Parameters used in the simulation.

Parameter	Value
Number of flows	5
Number of links	55
Population size	100
Number of generations	100
Crossover probability	0.9
Mutation probability	0.1

Figure 4 illustrates the Pareto fronts under varying SINR thresholds ($4dB$, $6dB$, $8dB$ and $10dB$). The distribution of the solutions in each Pareto front depicts that the network throughput and the spectrum utilization are conflicting performance metrics in the spectrum allocation. Under the low Transmission SINR constraint such as $4dB$ and $6dB$, more links can be assigned to concurrent transmit on the same spectrum channel, which causes the serious co-channel interfere and sharp decline of the link capacity. Consequently, the whole network throughput is at a low level. As shown in Figs. 4(a) and 4(b), the experiment results exactly reflect the fact that some solutions with high spectrum utilizations are obtained. Thus, there is a widespread distribution of solutions in the Pareto front. With the SINR threshold growing, link transmissions are more sensitive to the co-channel interference and spectrum channel sharing by multiple links becomes more difficult. When SINR threshold is set to $8dB$ or $10dB$, maximal value of spectrum utilization drops down and the size of the Pareto fronts become small relatively, which are shown in Fig. 4(c) and 4(d). We also notice that in the condition of low spectrum utilizations the solutions in Fig. 4(c) and 4(d) are better than the counterparts in Fig. 4(a) and 4(b). One possible reason is that the algorithm can converge to the Pareto front effectively in a smaller search space.

In order to further evaluate the performance of the proposed spectrum allocation algorithm, we adopt the improved Strength Pareto Evolutionary Algorithm (SPEA-II) [26] to deal with the multi-objective spectrum allocation problem for comparison. SPEA-II is regarded as an efficient elitist multi-objective evolutionary algorithm and validated the effective performance for the multi-objective optimizations in wireless networks [27], [28]. In Figs.5(a) and 5(b), the Pareto fronts obtained by the SPEA-II are shown under SINR thresholds $8dB$ and $10dB$ respectively. Correspondingly, Fig. 4(c) and 4(d) show the Pareto fronts obtained by the proposed algorithm under the same settings of SINR thresholds. It can be observed that the proposed algorithm reveals better performances than the SPEA-II. Under the same conditions, the Pareto fronts obtained by the proposed algorithm have more excellent solutions than their counterparts obtained by SPEA-II. Moreover, the proposed algorithm demonstrates the superiority in both the searching efficiency and the diversity of population through adopting larger population. The near-optimal and near-complete Pareto front of the problem is obtained at a rapid pace, which has considerably practical significance for spectrum allocation decision. Generally, converging to the true Pareto front while maintaining the diversity of the population is at the expense of time. Therefore, spectrum allocation decision needs to be made as soon as possible. Especially, in the case of dynamic spectrum environment or varying transmission tasks, the decision maker should adjust the spectrum allocation schedule timely to satisfy network transmission requirements. So, the approximate true Pareto fronts with the fast convergence are adopted.

To harvest the optimal spectrum allocation plans, we can jointly consider the results of multiple experiments and select the best solutions from these Pareto fronts to form an optimal solution aggregate. In Figs. 6(a) and 6(b), optimal solution aggregates are generated from Pareto fronts of

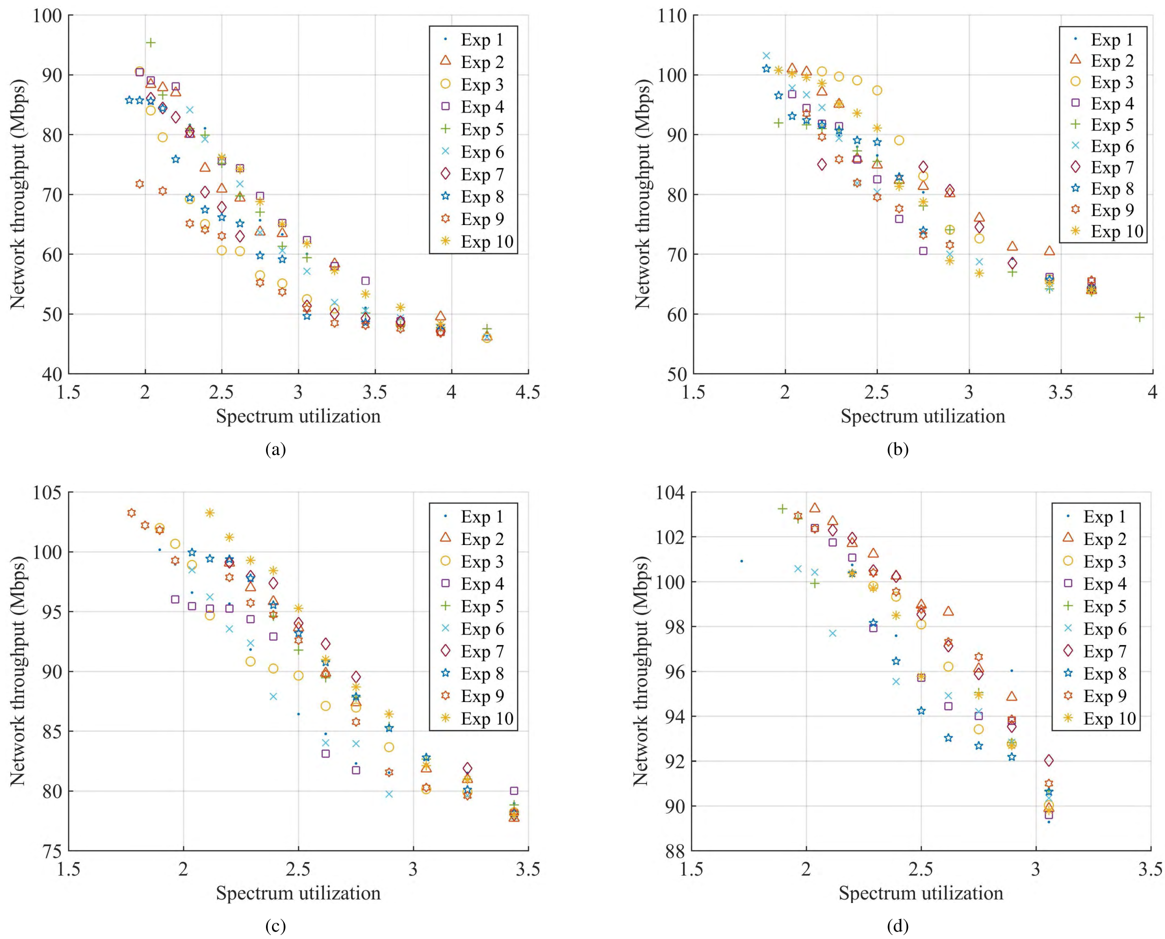


FIGURE 4. **Pareto fronts vs. varying SINR thresholds. (a) SINR threshold β is 4dB. (b) SINR threshold β is 6dB. (c) SINR threshold β is 8dB. (d) SINR threshold β is 10dB.**

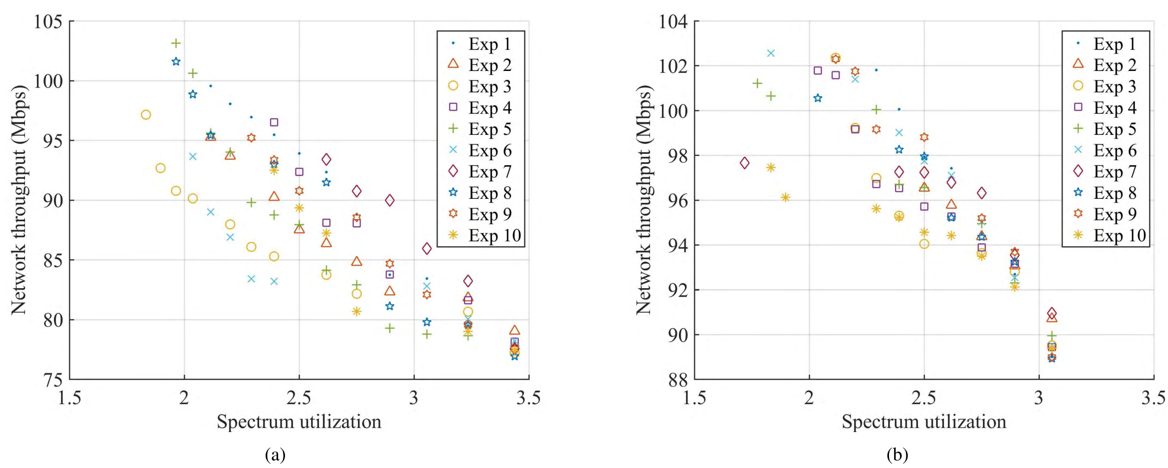
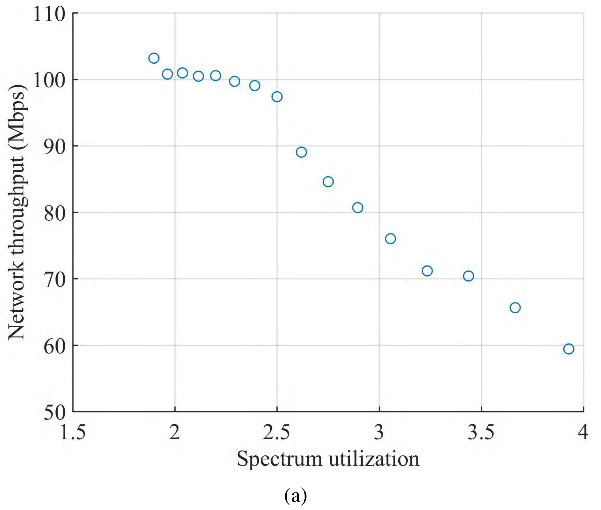


FIGURE 5. **Pareto fronts with varying SINRs obtained by SPEA-II. (a) SINR threshold β is 8dB. (b) SINR threshold β is 10dB.**

10 experiments under SINR threshold 6dB and 8dB respectively. Under each certain spectrum utilization, travel corresponding solutions in the Pareto fronts and add the one with the highest network throughput into the optimal solution aggregate. The optimal solution aggregate is not a Pareto-optimal set, but it has the best solutions and the most widespread distribution of solutions in current situation, which is superior to single Pareto front. The decision maker can obtain more effective spectrum allocation plan based on the optimal solution aggregate.



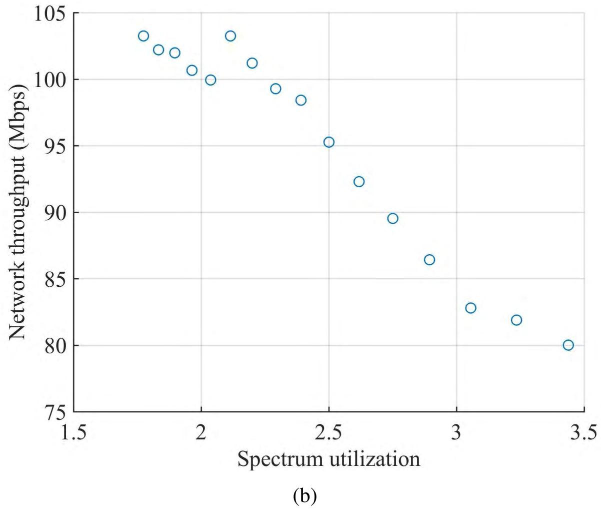


FIGURE 6. Optimal solution aggregates. (a) SINR threshold β is 6dB. (b) SINR threshold β is 8dB.

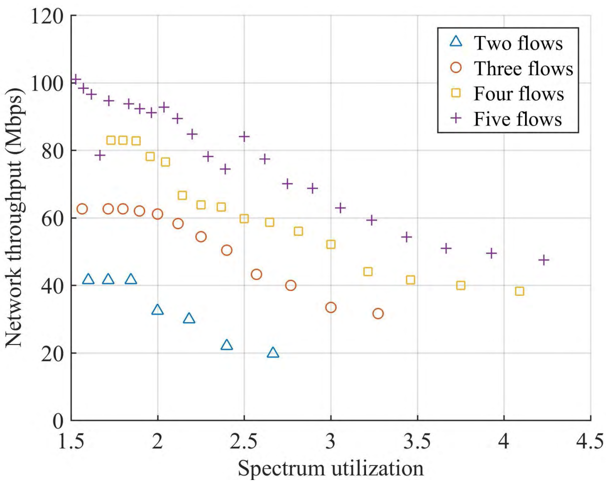


FIGURE 7. Optimal solution aggregates with varying number of concurrent flows.

We further analyze the spectrum allocation with respect to network throughput and spectrum utilization under varying number of concurrent flows. In order to achieve the maximum efficiency, each optimal solution aggregate in Fig. 7 is generated from 10 experiments. Under small number of concurrent flows, there is not a high Spectrum utilization. With the growth of flows, spectrum utilization can be raised effectively. The factor reveals that spectrum sharing is more feasible among links belonging to different routing paths. In such a condition, some links are quite far apart, and can transmit concurrently with low co-channel interference. We notice that when the spectrum utilization drops below 2 the network throughput will not have a remarkable improvement. In such conditions, enough spectrum channels are assigned to the links, and co-channel interference is reduced effectively. Thus, resource competition is the primary influential factor for the transmission performance and continued increase of spectrum channel is less well to the network throughput. The fact may help to enhance the spectrum allocation strategy. We can control the diversity of the population, and the condition of allocating a large number of spectrum channels to links is considered little in the strategy.

VI. CONCLUSION

In this paper, we investigate the optimal spectrum allocation with respect to network throughput and spectrum utilization in cognitive-radio-based IoT. Since links in the network are elementary units in spectrum allocation and data transmission, we propose a concurrent transmission model which reveals the constraints of mutual interference and resource competition in link concurrent transmissions. Based on this model, we formulate the spectrum allocation problem as a MOP and transform the spectrum allocation plan into the solution in genic algorithms. Then the NSGA-II algorithm is adopted to explore the optimal solutions to the multi-objective spectrum allocation problem. Simulation results corroborate that the proposed approach performs well in harvesting the optimal solutions in various cases. We will further apply the proposed approach into the design of cognitive radio protocols to achieve a balanced network performance. In addition, issues such as fairness and quality of service (QoS) will be further studied in our future work.

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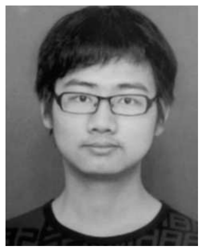

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