A Genetic Approach for Joint Link Scheduling and Power Control in SIC-enable Wireless Networks

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Abstract

Successive interference cancellation (SIC) is an effective means of multi-packet reception to combat interference at the physical layer. We investigate the joint optimization issue of channel access and power control for capacity maximization in SIC-enabled wireless networks. We propose a new interference model to characterize the sequential detection nature of SIC. Afterward, we formulize the joint optimization problem, prove it to be a nondeterministic polynomial-time-hard problem, and propose a novel approximation approach based on the genetic algorithm (GA). Finally, we discuss the design and parameter setting of the GA approach and validate its performance through extensive simulations.

Keywords: network capacity, link scheduling, power control, successive interference cancellation, genetic algorithm

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1. Introduction

In the last decade, wireless networks have gained worldwide popularity and has attracted considerable industrial and research attention. However, the congestion issue in which tens or hundreds of links contend for a common channel has become a network bottleneck and severely limits the applications of wireless networks, particularly in overloaded traffic scenarios.

The emerging successive interference cancellation (SIC) [1], one of the advanced signal-processing techniques, can decode multiple concurrent signals and exhibits a potential to mitigate the congestion issue in wireless networks. The principle of SIC is described as follows:

(1) A signal can basically be extracted when the signal-to-interference-plus-noise ratio (SINR) is larger than a given threshold even when some interfering signals exist;

(2) When a new signal is successfully decoded, the corresponding received signal can be regenerated and removed from the received composite one to reduce the interference in the remaining signals;

(3) The SIC-enabled receiver repeats these two steps until the desired signals are all successfully decoded or the decoding process is interrupted.

Compared with other multi-packet reception (MPR) techniques, the SIC-enabled receiver utilizes a single decoder iteratively, which reduces the hardware cost significantly. However, several urgent issues need to be considered seriously in the deployment of SIC [2]. First, the design of link scheduling is challenging because too few links selected to transmit simultaneously would waste the concurrent opportunity, whereas too many links or wrong selection would produce considerable interference, such that the desired signals cannot be extracted. Second, the power control for the selected links is also challenging because it determines the feasible data transmission rate.

The relationship between link scheduling and power control is interactive, that is, pure link scheduling cannot realize the concurrent potential of the SIC technique thoroughly, whereas the combination of link scheduling and power control can improve the concurrent feasibility of link sets and enhance the transmission rate of concurrent links. However, the interplay between link scheduling and power control renders the situation highly complicated.

In this study, the two dependent issues of link scheduling and power control are unified with a genetic algorithm (GA)-based framework [3]. First, a new physical interference model referred to as SIC-PHY is proposed to characterize the sequential detection nature of SIC. Second, an algorithm is presented to evaluate the transmission capacity of a link in the SIC-enhanced decoding process. Third, considering that the joint link scheduling and power control issue is proven to be a nondeterministic polynomial-time (NP)-hard problem, a novel GA-based solution is proposed. Finally, various simulations are conducted to show the advantage of the proposed solution.

The remainder of this paper is organized as follows. Section 2 summarizes related work, and Section 3 presents the physical interference model and problem formulation. Section 4 introduces the design of the GA-based approach. Section 5 provides the simulation and numerical results, and Section 6 presents the conclusions.

2. Related Work

SIC has been implemented in the software-defined radio platform and nearly achieved the Shannon capacity of multi-user additive white Gaussian noise (AWGN) channels [4].

However, several stringent SINR constraints and hard limits need to be addressed by SIC; hence, careful transmission scheduling and assignment are required. In [5], Gelal et al. proposed a topology-control framework that greedily forms and activates sub-topologies in a manner that exploits successful SIC decoding. In [6], Lv et al. studied the link-scheduling problem for SIC-enabled wireless networks, and an independent set-based greedy scheme was proposed to construct a maximal feasible schedule. In [7], Jiang et al. introduced a crosslayer optimization framework that incorporates variables at physical, link, and network layers in the context of multi-hop SIC-enabled wireless networks.

Only a few existing studies have considered the issue of power control [8-10]. Although power control can significantly enhance the transmission capacity of SIC-enabled networks, the corresponding complexity remains an issue.

3. System Model and Problem Formulation

3.1 SINR-based Interference Model

Considering a wireless network consisting of n nodes and N transmission links in the link set $\mathcal{L}$, we let N_0 denote the average AWGN power, P_i the transmission power of the i-th link, and $S_{ij} = P_i/(\vartheta \cdot |d_{ij}|^{\eta})$ the received signal power of the i-th link at the receiver side of the j-th link, where ϑ is the path-loss constant, η is the path-loss exponent ($2 \le \eta \le 6$), and d_{ij} is the distance between the transmitter of the i-th link and the receiver of the j-th link. Signal S_{ij} is successful if the SINR is above a certain reception threshold β, that is,

$$SINR_{ij} = \frac{S_{ij}}{\sum_{k\neq i} \alpha_k \cdot S_{kj} + N_0} = \frac{P_i/(\vartheta \cdot |d_{ij}|^{\eta})}{\sum_{k\neq i} \alpha_k \cdot P_k/(\vartheta \cdot |d_{kj}|^{\eta}) + N_0} \ge \beta, i \in \mathcal{L}, \quad (1)$$

where $\alpha_k \in \{0,1\}$ is the variation denoting whether the j-th link is in activation ($\alpha_k = 1$) or not ($\alpha_k = 0$). The feasible data rate of the j-th link is provided as follows:

$$r_j \le log_2(1 + SINR_{jj}) = log_2\left(1 + \frac{\frac{P_j}{\vartheta \cdot |d_{jj}|^{\eta}}}{\sum_{k\neq j} \frac{\alpha_k \cdot P_k}{\vartheta \cdot |d_{kj}|^{\eta}} + N_0}\right), j \in \mathcal{L}. \quad (2)$$

For simplicity, the bound in Equation (2) is approximated as an equation. Equations (1) and (2) show that a few links can be transmitted simultaneously and that network transmission performance is severely limited by the traditional reception techniques.

3.2 SIC-enabled Interference Model (SIC-PHY)

By utilizing SIC, a novel MPR technique that cancels the decoded signals to improve the SINR value of the remaining signal iteratively, the decoding constraint of Equation (1) can be relaxed significantly, and more concurrent links are enabled in the same transmission time slot.

We consider the SIC sequential detection nature of two concurrent links, the i-th and j-th links. The transmission of the i-th link cause much interference to the j-th link because the

SINR-decoding constraint of the j-th link cannot be satisfied, that is, $SINR_{jj} = \frac{S_{jj}}{S_{ij}+N_0} < \beta$. Meanwhile, in SIC-enabled networks, the concurrent transmission of the i-th and j-th links can be successfully decoded as follows:

1) Decoding strong interference: when S_{ij} is sufficiently strong to tolerate the interference from the j-th link, the receiver of the j-th link can decode the signal of the i-th link, which is the strong interference of the j-th link;
2) Decoding the desired signal: when the transmission of the i-th link is decoded, the corresponding interference can be removed from the original received signal, and the desired signal of the j-th link may be successfully decoded from the remaining signal.

In each single iterative process of SIC-enabled decoding, the SINR constraint is still assumed to be satisfied, that is,

$$(SINR_{ij} = \frac{S_{ij}}{S_{jj}+N_0} \geq \beta) \ \&\& \ \left(SINR_{ij}^{SIC} = \frac{S_{jj}}{N_0} \geq \beta\right), i, j \in \mathcal{L}. \tag{3}$$

The SIC sequential detection nature can be generalized to an arbitrary number of concurrent links, and the relaxed decoding constraint with SIC can be expressed as follows:

$$\begin{aligned}(SINR_{ij}^{SIC} &= \frac{S_{ij}}{\sum_{k\neq i, k\notin L_{ij}^{SIC}} \alpha_k \cdot S_{kj} + N_0} \\ &= \frac{P_i/(\vartheta \cdot |d_{ij}|^{\eta})}{\sum_{k\neq i, k\notin L_{ij}^{SIC}} \alpha_k \cdot P_{kj}/(\vartheta \cdot |d_{kj}|^{\eta}) + N_0} \geq \beta, \forall i \in L_{jj}^{SIC}) \ \&\& \\ &\left(SINR_{jj}^{SIC} = \frac{S_{jj}}{\sum_{k\neq j, k\notin L_{jj}^{SIC}} \alpha_k \cdot S_{kj} + N_0} = \frac{\frac{P_j}{\vartheta \cdot |d_{jj}|^{\eta}}}{\sum_{k\neq j, k\notin L_{jj}^{SIC}} \frac{\alpha_k \cdot P_{kj}}{\vartheta \cdot |d_{kj}|^{\eta}} + N_0} \geq \beta, j \in \mathcal{L}\right),\end{aligned} \tag{4}$$

where L_{ij}^{SIC} is the link set denoting the corresponding signals decoded successfully and removed from the composite received signal before the decoding process of signal S_{ij}. The feasible data rate of the j-th link in SIC-enabled networks can be extended to

$$r_j^{SIC} \leq log_2\left(1 + SINR_{jj}^{SIC}\right), j \in \mathcal{L}. \tag{5}$$

3.3 Achievable Transmission Capacity Calculation

Equations (2) and (5) show two issues related to improving network performance. These two are the link-scheduling mechanism, which determines the links that access the common channel by adjusting parameter $\alpha_i (i \in \mathcal{L})$, and the power control mechanism, which selects the appropriate transmission power $P_i (i \in \mathcal{L})$ to increase the data rate or reduce the interference. Given that the interplay between link scheduling and power control is complicated, coordinating them independently is challenging.

In this study, we construct a unified framework for link scheduling and power control. N transmission links in the wireless network, with a given discrete transmission power set $P = \{\wp_1, \ldots, \wp_s\}$ $(0 \leq \wp_j \leq \wp_{max}, 1 \leq j \leq s)$, are assumed to be scheduled in m $(N > m)$ time slots, and each link is scheduled exactly once.

Given a solution of link scheduling and power control $\mathcal{P} = \{(t_i, P_i) | i \in \mathcal{L}, 1 \leq t_i \leq m, P_i \in P\}$, which schedules the i-th link in time slot t_i with transmission power P_i, by denoting the active link set in time slot t_i by $L_a(t_i)$, we can calculate the achievable transmission capacity of the i-th link in the solution $\mathcal{P}$, $r_i(\mathcal{P})$ as the following Algorithm 1:

Algorithm 1. Achievable Transmission Capacity $r_i(\mathcal{P})$
Input: $\mathcal{L}$, P, $\mathcal{P}$
Output: $r_i(\mathcal{P})$

01 $SEN \leftarrow NULL$; $REC \leftarrow NULL$;
02 For each $l_{SR} \in L_a(t_i)$ (l_{SR} is the link with sender S and receiver R)
03 If $S \in SEN$ or $S \in REC$
04   Return 0;
05 End if;
06 $SEN \leftarrow SEN \cup \{S\}$;
07 If $R \in SEN$
08   Return 0;
09 End if;
10 $REC \leftarrow REC \cup \{R\}$;
11 End for;
12 Calculate $S_{ji} = \frac{P_{ji}}{\vartheta \cdot |d_{ji}|^{\eta}}, (j \in L_a(t_i))$;
13 Generate the link set: $L_{ii}^{SIC} = \{j | j \in L_a(t), S_{ji} > S_{ii}\}$;
14 Reorder L_{ii}^{SIC} to satisfy $\left(j, k \in L_{ii}^{SIC}\right) \& (j > k) \rightarrow S_{ji} \geq S_{ki}$;
15 For each $j \in L_{ii}^{SIC}$
16   If $SINR_{ji}^{SIC} = \frac{P_{ji}/(\vartheta \cdot |d_{ji}|^{\eta})}{\sum_{k>j, k \in L_{ii}^{SIC}} P_{ki}/(\vartheta \cdot |d_{ki}|^{\eta}) + \sum_{k \in L_a(t_i) \backslash L_{ii}^{SIC}, k \neq i} P_{ki}/(\vartheta \cdot |d_{ki}|^{\eta}) + N_0} < \beta$
17   Return 0;
18   End if;
19 End for;
20 If $SINR_{ii}^{SIC} = \frac{P_{ii}/\vartheta \cdot |d_{ii}|^{\eta}}{\sum_{k \in L_a(t_i) \backslash L_{ii}^{SIC}, k \neq i} P_{ki}/\vartheta \cdot |d_{ki}|^{\eta} + N_0} < \beta$
21   Return 0;
22 Else
23   Return $log_2(1 + SINR_{ii}^{SIC})$;
24 End if.

The first part of Algorithm 1, lines 1 to 11 pseudocode, checks the half-duplex restriction of the concurrent link set $L_a(t_i)$. On the one hand, any two concurrent links cannot share the same sender node; on the other hand, the sender node of one link cannot be the receiver node of another concurrent node. Considering that the SIC technique aims to resolve collision capability, concurrent links can share the same receiver node.

3.4 Formulization of the Maximum Capacity Problem (MCP)

MCP with joint link scheduling and power control can be formulized as follows:

$$max_{\mathcal{P}} \quad \sum_{i \in \mathcal{N}} r_i(\mathcal{P}), \tag{6.a}$$
$$subject\ to \quad \sum_{t=1}^{m} \alpha_i(t) = 1, i \in \mathcal{L}, \tag{6.b}$$
$$r_i(\mathcal{P}) > \gamma, \ i \in \mathcal{L}, \tag{6.c}$$
$$P_i \in P, \ i \in \mathcal{L}, \tag{6.d}$$

where Equation (6.a) illustrates that the objective of MCP is to maximize the total achievable transmission capacity of the scheduling links in the considered network, Equations (6.b) and

(6.c) demonstrate that all links are scheduled exactly once with minimum transmission capacity threshold γ, and Equation (6.d) restricts the range of transmission power.

Proposition 1: MCP is NP-hard.

Proof: The proof is that the special case of MCP with $\gamma = 0, m = 2, P_i = P\ (i \in \mathcal{L})$ can be reduced from the partition problem, a well-known NP-complete problem [11], in a polynomial time. The proof detail is similar to that in [12], and interested readers can refer to this reference. Given that a special case of the problem is NP-hard, the general case is NP-hard as well. ■

4. GA-based Approach

4.1 Design Challenges

As one of the most popular stochastic optimization algorithms and a powerful solution to NP-hard problems, GA is introduced to solve MCP in this study.

The principal ideas of the GA approach are to represent the solutions of the target problem as chromosome-like codes; evaluate the chromosome codes with genetic mechanisms [3], such as individual selection, crossover, and mutation; and determine the optimal solution with the maximum fitness index.

4.2 Chromosome Coding

We employ a bit string to code the solution in MCP, as shown in **Fig. 1**.

(1) A chromosome-like individual consists of N strings $\{str\ i: \underline{(\alpha_i; P_i)}, i \in \mathcal{L}\}$.

(2) Each individual string is divided into two sub-strings, $\alpha_i = \{\alpha_i^1, \alpha_i^2, \ldots, \alpha_i^t\}$ and $P_i = \{P_i^1, P_i^2, \ldots, P_i^s\}$, and presents an instance of link scheduling and power control for a link.

(3) A link scheduling (or power control) sub-string $\alpha_i^j (1 \le j \le m)$ (or $P_i^k (1 \le j \le s)$) consists of some bits, the length of which is determined by the number of time slots, m (or candidate transmission power, s).

(4) If a bit in a sub-string α_i^j (or P_i^j) equals 1, then the corresponding time slot j (or transmission power $\wp_j$) is selected for the i-th link; otherwise, the i-th link is silent in time slot j (or transmission power $\wp_j$ is not selected for the i-th link).

(5) The restriction $(\sum_j \alpha_i^j = 1)$ && $\left(\sum_k P_i^k = 1\right), \forall\, i \in \mathcal{L}$ should be satisfied to guarantee that each individual string coding is a feasible solution of the optimization problem.

As an example, we consider a wireless network that consists of 12 communication links. A chromosome-like individual then comprises 12 sub-strings, and the string $str\ 1 = \underline{(00100; 00010)}$ denotes that the first link is scheduled in time slot 3 with transmission power $\wp_4$.

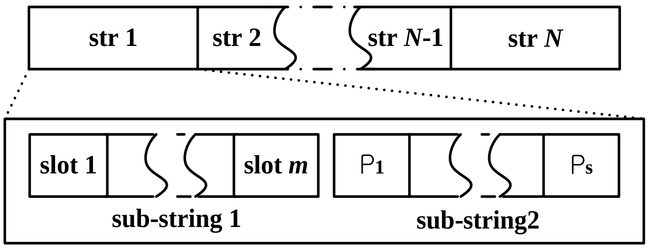

Fig. 1. Chromosome-like individual of MCP

4.3 Fitness Function

The fitness value of a chromosome-like individual determines the probability of the individual to participate in the reproduction process. Given that the objective of MCP is to determine the optimal solution of link scheduling and power control, the fitness value is supposed to characterize the feasibility of joint scheduling solution and the total achievable transmission capacity as follows: if the solutions do not satisfy Constraints (6.b), (6.c), and (6.d), then their corresponding fitness values are set to 0; otherwise, the fitness value of a feasible solution is set to the total achievable transmission capacity of concurrent links.

Fitness function $F(X)$ can be expressed as

$$F(X) = \begin{cases} 0, & \textit{the corresponding solution is infeasible} \\ \sum_{i \in \mathcal{N}} r_i(\mathcal{P}_X), & \textit{otherwise} \end{cases}, \tag{7}$$

where X is a chromosome-like individual and $\mathcal{P}_X$ is the corresponding scheduling solution.

4.4 Genetic Operations

The initial individuals are randomly produced, and only the individual strings that satisfy the restriction $(\sum_j \alpha_i^j = 1)$ && $\left(\sum_k P_i^k = 1\right), \forall\, i \in \mathcal{L}$ can be reserved in the initial generation. A new generation of offspring individuals with high fitness values is reproduced by using several basic genetic operations, such as individual selection, crossover, and mutation. When the number of evolution steps exceeds a predefined threshold $\mathcal{G}_m$ or the fitness value stops to refresh in predefined evolution steps a (the improvement of optimal fitness is less than predefined threshold $\mathcal{T}$), the evolution process is interrupted, and the individual with the highest fitness value in the last generation is determined to be the optimal solution of MCP.

(1) **Individual Selection**: From the current generation of chromosome-like individuals, the size of which is denoted by S_C, a part of individuals, S_P, with a relatively high fitness value is selected to form the basis of a new generation.

(2) **Individual Crossover**: From the individuals selected by step (1), several individuals with probability p_c are selected to perform the crossover operation illustrated in **Fig. 2**. That is, a pair of individuals exchange some strings, the crossover point is randomly selected in the intersection positions of two strings, and the new produced individuals are added to the new generation.

(3) **Individual Mutation**: From the individuals selected by step (1), several individuals with probability p_m are selected to perform the mutation operation. That is, some bits in the individual substrings are randomly changed. Given that the newly generated solution may be infeasible, an additional repair step is executed to accelerate the convergence process. With the link string $str\ 1 = \underline{(00100; 00010)}$ as an example, if its second bit turns to "1" from "0," $str\ 1 = \underline{(01100; 00010)}$, then link 1 is scheduled to two time slots, namely, slots 2 and 3. The third bit should turn to "0," $str\ 1 = \underline{(01000; 00010)}$, to ensure the feasibility of the new solution.

The condition $S_C = (1 + p_c + p_m) \cdot S_P$ should be satisfied to guarantee the stability of the evolution process.

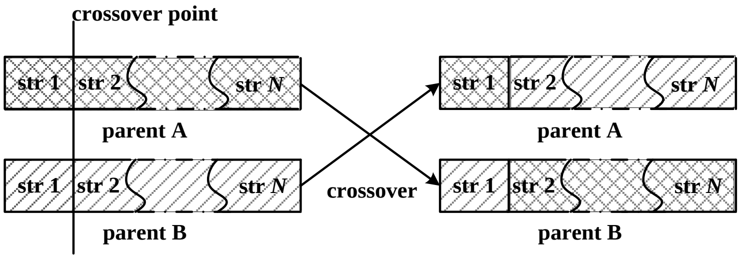

Fig. 2. Illustration of the crossover process

4.5 GA Process

Given the algorithm designs presented in Sub-sections 4.2, 4.3, and 4.4, GA-SIC is proposed as follows:

Algorithm 2. GA-based approximate algorithm (GA-SIC)
Input: genetic operation parameters $\mathcal{M}$, $\mathcal{G}_m$, p_c, p_m
Output: optimal individual string X^*

Randomly produce the initial individual group: $\mathcal{C}(g = 0)$;
$\psi_{counter} \leftarrow 0$; //the refresh generation counter
While $g < \mathcal{G}_m$
  selection($\mathcal{C}(g)$); //selection operation
  crossover($\mathcal{C}(g)$); //crossover operation
  mutation($\mathcal{C}(g)$); //mutation operation
  replace($\mathcal{C}(g)$); //replace operation
  If $\frac{\mathcal{F}\left(arg\, max_{X\in\mathcal{C}(g+1)}\mathcal{F}(X)\right)-\mathcal{F}\left(arg\, max_{X\in\mathcal{C}(g)}\mathcal{F}(X)\right)}{\mathcal{F}\left(arg\, max_{X\in\mathcal{C}(g)}\mathcal{F}(X)\right)} < T$
    $\psi_{counter} \leftarrow \psi_{counter} + 1$;
  Else
    $\psi_{counter} \leftarrow 0$;
  End if;
  If $\psi_{counter} > a$
    Break; //jump the while loop.
  End if;
  $g = g + 1$;
End while;
Return $arg\ max_{X\in\mathcal{C}(g)}\ \mathcal{F}(X)$.

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5. Experimental Results

We evaluate the proposed GA-SIC algorithm by implementing it on our customized C++ platform. Without loss of generality, 50 homogeneous nodes in our network are randomly deployed in a 1200 × 1200 m square shape, and 35 point-to-point links are selected to be scheduled in 10 transmission time slots with five different transmit power levels. All transmissions are implement in a half-duplex model. The path-loss constant ϑ, path-loss exponent η, and reception threshold β are set to 2, 2, and 10, respectively.

We set generation threshold $\mathcal{G}_m = 300$. Many numerical experiments are executed to investigate five performance-related effect factors, namely, population size S_P, crossover probability p_c, mutation probability p_m, network size N, and network topology (rand or grid). The default parameters are set to $S_P = 50$, $p_c = 0.5$, $p_c = 0.3$, and $N = 35$. The default network topology is rand.

The results of the simulation experiments are discussed below.

5.1 Effect of Genetic Operation Parameters

As shown in **Fig. 3**, when the population size is small ($S_P < 50$), the capability of searching for optimized solutions and the achievable fitness value increases rapidly with the population size. When the population size reaches 50, the difference between the achievable fitness value and the global optimal one is only 2.40%. Thus, continuously increasing the population size would not increase the performance considerably but would introduce additional complication.

The effects of crossover and mutation probabilities are presented in **Figs. 4** and **5**, respectively. When the crossover or mutation probability is too small, GA is premature; when the crossover or mutation probability is too large, the stability of GA decreases. The achievable fitness values in both cases are not satisfactory. In summary, the reasonable genetic operation parameters in our network scenario are population size $S_P = 50$, crossover probability $p_c = 0.5$, and mutation probability $p_m = 0.3$.

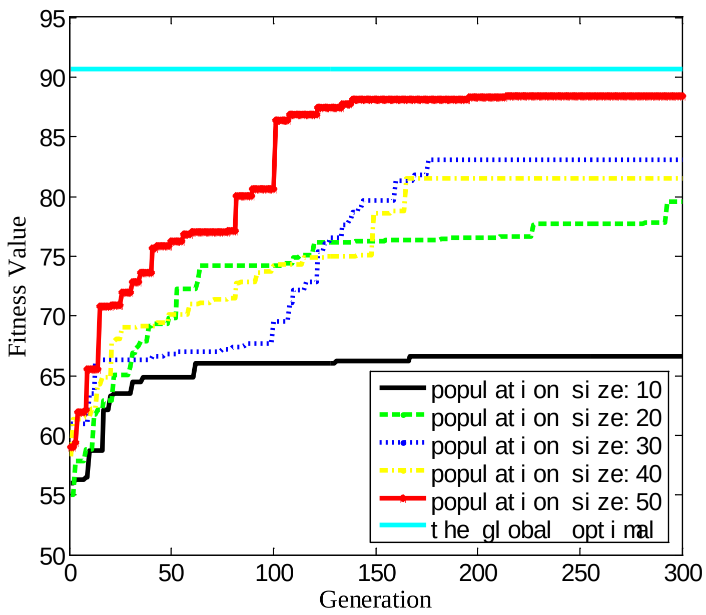

Fig. 3. Effect of population size

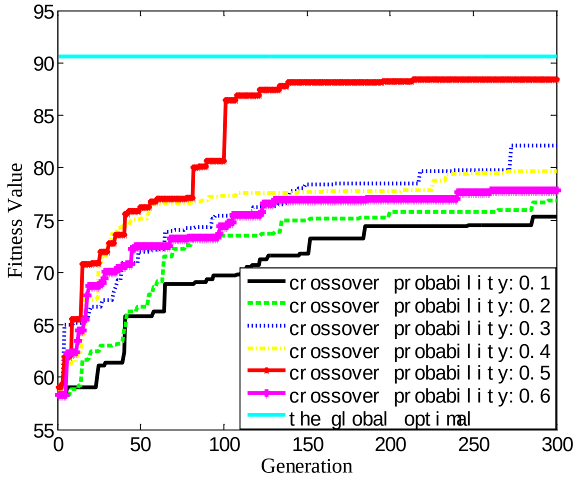

Fig. 4. Effect of crossover probability

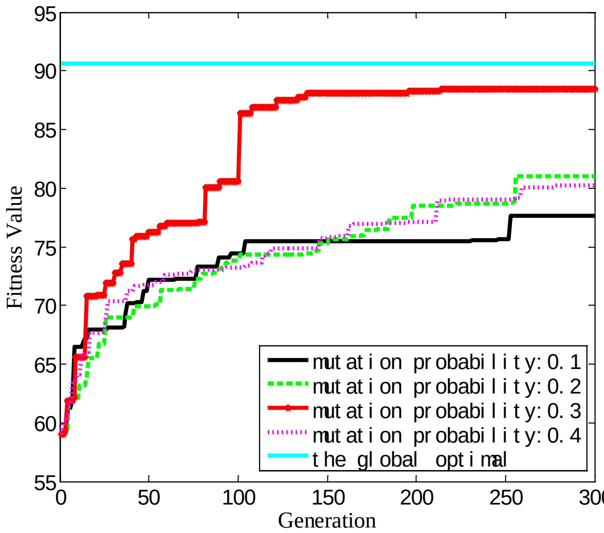

Fig. 5. Effect of mutation rate

5.2 Effect of Network Parameters

The effects of network size and topology are presented in **Figs. 6** and **7**, respectively. The following findings are obtained.

(1) When the network has a relatively small size ($N < 35$), improving the number of communication links can provide new concurrent opportunities and thus enhance the total network transmission capacity; however, a large number of links will introduce considerable interference among concurrent links and cause damage to network transmission performance.

(2) The network transmission performance of the rand network remarkably exceeds that of the grid network, and the performance gain can reach almost 40%; the rand network has higher diversity of communication links, which provides more concurrent opportunities.

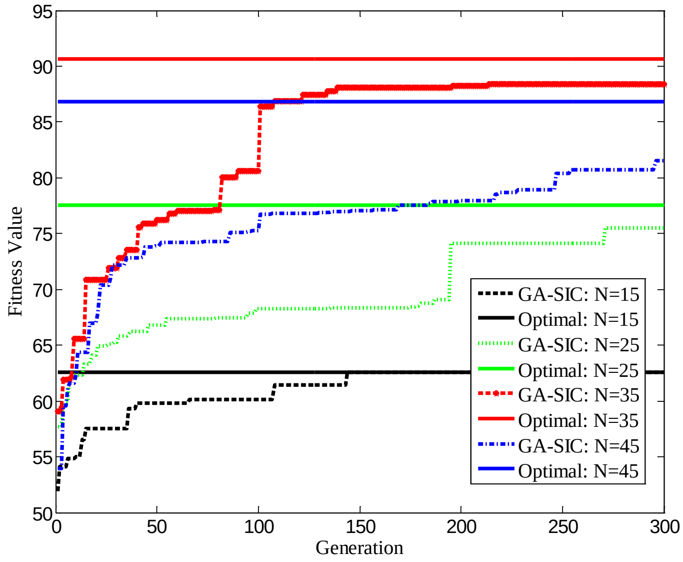

Fig. 6. Effect of network size

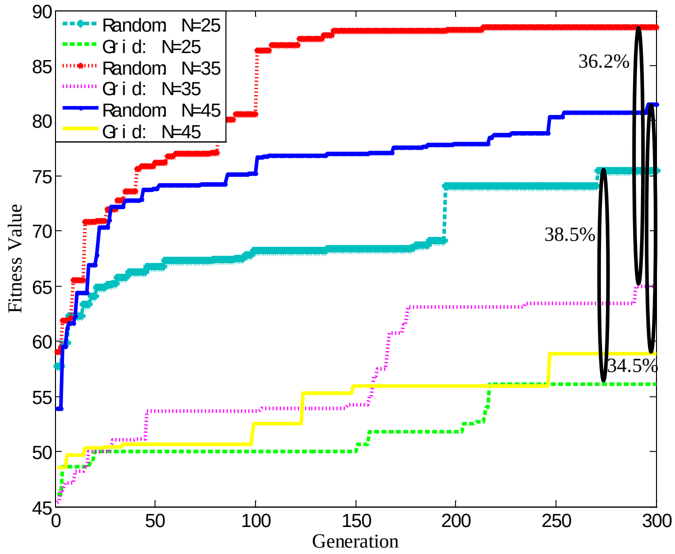

Fig. 7. Effect of network toplogy

6. Conclusions

We investigated the joint optimization issue of channel access and power control for capacity maximization in SIC-enabled wireless networks. First, we formulized the joint optimization problem under a new physical interference model to characterize the sequential detection nature of SIC and proved it to be an NP-hard problem. Second, we introduced a GA-based approach. Finally, extensive simulations were performed to demonstrate that our GA-based approach is promising in solving the joint optimization problem.

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