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A Combinatorial Algorithm of Ant Colony Optimization and Neural Network Algorithm for Channel Assignment Problem

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Abstract—Recently, demands for cellular radio network are increasing cellular devices such as smart phones or wireless sensor devices. Channel Assignment Problem(CAP) are becoming more important in order to make the most of limited channels. This paper proposes a combined method of Ant Colony Optimization(ACO) and Neural Network Algorithm(NAA) for the CAP. ACO is utilized for explore large solution space and NNA is used for getting into a local optimum solution immediately. The proposed method can achieve similar solution ability in some instances as an existing method, and can acquire 2% smaller interference solution in 3 benchmarks in average and the same interference solutions in 2 benchmarks compared with an existing method. We expect that a larger number of ants and better parameter tuning can achieve better solution using our proposed method.

1. Introduction

Recently, there has been an increase in demand for cellular radio network with increasing cellular devices such as smart phones or wireless sensor devices. Besides, sophisticated services of mobile phones often require more frequent network connections and more transmission data. Although the number of available channels in each cellular radio network has been increasing, the numbers of channels is limited and can be exhausted [1]. The channels will need to be more carefully assigned so that larger number of cellular devices can utilize cellular radio network. This problem is called Channel Assignment Problem (CAP). Available channel is assigned to each user when the users make connection requests. Total interference among assigned channels is desired to be as small as possible. The assignments to neighboring cells need to be taken into consideration so that interference by other assignments in the neighboring cells can be smaller. The CAP is known to be NP-complete problem [2] and requires quite large computational complexity to solve exact solutions. Various heuristic techniques have been proposed for the CAP. The CAP first appeared in the 1960s [3]. Most contributions on the CAP used heuristics based on the related graph coloring problem until 1980s[4]. Afterward, some heuristic algorithms were proposed to achieve better performance such as Simulated Annealing, Neural Network Algorithm(NNA)s, Genetic Algorithms and so on [5] [6] [7] [8].

In this paper, we propose a combined method of Ant Colony Optimization(ACO) [9] and NNA [10] for the CAP for cellular radio network. ACO is adopted because it can yield diverse solutions and has memory of searching. ACO is based on random searching, and therefore has large searching space. NNA, on the other hand, is chosen due to rapid convergence. An adopted Hopfield NNA is based on steepest descent method, and employment of expanded maximum neuron can obtain further calculation speed. In our proposed method, ACO is utilized to acquire various solutions, and NNA is for gaining a local optimum solution quickly. Only ACO is executed in the beginning of the proposed algorithm. NNA turns over the solution generated by ACO and goes on until getting into a local optimum solution and the best solution by NNA is the final solution of the proposed algorithm. The proposed method can acquire 2% smaller interference solution in 3 benchmarks in average and the same interference solutions in 2 benchmarks compared with Ikenaga et al. [5] We expect that a larger number of ants and better parameter tuning can achieve better solution using our proposed method.

2. Channel Assignment Problem

A coverage area of Cellular Radio Network (CRN) is theoretically divided into hexagonal compartments called cells and each cell has a base station as shown in Figure 1. Users in each cell send the base station a connection request, and the base station assigns a channel so that CRN can become available for the users.

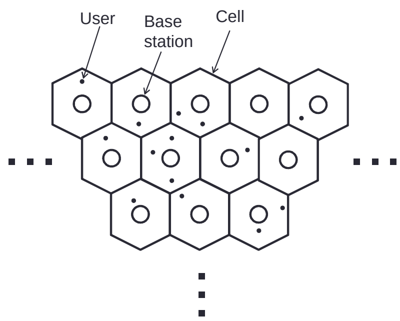

Figure 1: Cell structure of Cellular Radio Network

Some channel assignments cause interference each other. Total interference value among assignments is desired to be the minimum and ideal total interference value is zero. Following three types of conditions are considered as interference.

(1) Co-channel constraint: The same channel is not desired be simultaneously assigned to certain pairs of cell.

(2)Co-site constraint: Any pair of channels assigned to a cell is desired to maintain a certain interval. Required interval is be defined in the compatibility matrix.

(3) Adjacent channel constraint: Adjacent channels in the frequency are not desired to be simultaneously assigned to neighboring cells.

The values of interference in these cases are defined in a compatibility matrix C , one of inputs of Channel Assignment Problem(CAP). The CAP requires four inputs, one output and one internal parameter. The inputs of CAP are the number of cells(N),the number of channels(M), a compatibility matrix (C), and a demand vector (D).

A compatibility matrix C is a symmetric matrix and the size of the compatibility matrix depends on cells N. Each value of compatibility matrices represents required channel interval k to assign channel without causing any interference. An example of a compatibility matrix C is shown in Expression (1). C_{01} and C_{10} equal four and C_{02} and C_{20} equal zero. This example shows assignments in *cell*0 and *cell*1 need four channel intervals and the interference value between the assignments in *cell*0 and *cell*1 is 4. On the other hand, the same channel can be assigned in *cell*0 and *cell*2 without any interference. Five channel intervals are required to assign channels in the same cell in this example because C_{ii} always equals five. Demand vectors represent the numbers of connection requests by users in each cell. Expression (2) shows an example demand vector V as well. *Cell*0, *cell*1 and *cell*2 have one connection demand and *cell*3 has three connection demands.

$$C = \begin{pmatrix} 5 & 4 & 0 & 0 \\ 4 & 5 & 0 & 1 \\ 0 & 0 & 5 & 2 \\ 0 & 1 & 2 & 5 \end{pmatrix} \quad (1), \qquad D = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 3 \end{pmatrix} \quad (2)$$

Each interference value between two assignments is represented in an interference matrix E, which is derived from the C. The E is a three dimensional($N \times N \times M$) matrix and derived from a corresponding as shown in Expression (3). Elements of the E_{ijk} in Expression (4) represent interference values when two assignments are made in cell i and cell j with k channel intervals.

$$E_{ij0} = C_{ij}, \quad E_{ijk} = \left\{ \begin{array}{ll} 0 & (C_{ij} \leq k) \\ C_{ik} - k & (C_{ij} > k) \end{array} \right) \quad (3)$$

$$E_{ij1} = \begin{pmatrix} 4 & 3 & 0 & 0 \\ 3 & 4 & 0 & 0 \\ 0 & 0 & 4 & 1 \\ 0 & 0 & 1 & 4 \end{pmatrix}, \qquad E_{ij2} = \begin{pmatrix} 3 & 2 & 0 & 0 \\ 2 & 3 & 0 & 0 \\ 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 3 \end{pmatrix}$$

$$E_{ij3} = \begin{pmatrix} 2 & 1 & 0 & 0 \\ 1 & 2 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 2 \end{pmatrix} \quad (4)$$

Output result of CAP is an assignment table V to express which channels are assigned in each cell. The V is an $N \times M$ matrix and the elements of V are Boolean type as shown in Expression (5).

$$V_{ij} = \left\{ \begin{array}{ll} 1 & (\text{channel} \quad j \quad \text{is assigned in cell} \quad i) \\ 0 & (\text{otherwise}) \end{array} \right. \quad (5)$$

Figure 2 (a) is an undesired result of channel assignments, where N and M are 4 and 10, C and D is Expression (1) and (2), respectively. Black circles represent that the values of V_{ij} equals 1, otherwise 0. Total interference is calculated by summing up elements of E corresponding to every pair of assignments. The example in Figure 2 has some interference among assignments, which are circled with dashed line. The total interference in Figure 2(b) equals 5 because e_{010} and e_{231} are 4 and 1 respectively. Figure 2(b) shows a desired result of channel assignment under the same conditions mentioned above. The total interference in Figure 2(b) equals 0.

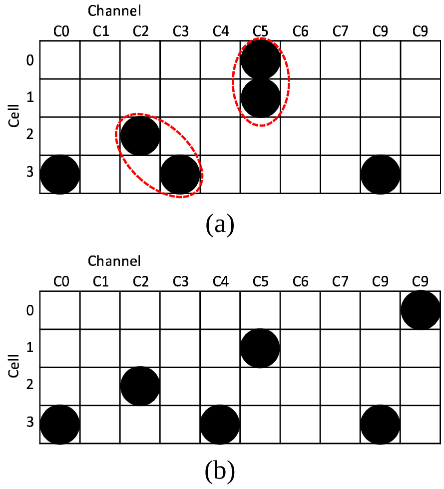

Figure 2: An undesired (a) and a desired (b) examples of channel assignment tables V

3. Proposed Method

In this paper, we propose a combined method of Ant Colony Optimization(ACO) and Neural Network Algorithm(NNA) for solving the CAP. Some problems including the CAP are known as NP-complete problems, and the exact solution cannot be found in polynomial time. Heuristic algorithms can be used in order to gain relatively good solutions in practical time.

ACO is a heuristic algorithm, and derived from foraging behavior of ant to find a path between an ant colony and food [9]. Ants deposit chemical agent, *pheromone*, on the traced path. Each ant decides which way to go based on strength of pheromone. Higher pheromone on a path increases the probability that ants follow the path, and finally a route with the highest pheromone can be an optimum solution or close to the optimum solution. ACO is based on biased random searching and has large searching space, therefore, can yield different solutions.

NNA is a heuristic algorithm, and is a mathematical model of neurons. NNA can internally develop information processing for solving a problem by giving appropriate information. Hopfield NNA(HNNA) is adopted in our proposed algorithm. HNNA has an energy function, and each neuron works to make the energy minimum when the solution is optimal. HNNA is based on the steepest descend method and converges on local optimum solution from current solution immediately.

Procedure of the proposed method is shown in Figure 3. Only ACO constitutes beginning of searching, and the remaining part of searching consists of one step of searching by ACO and some iterations of searching by NNA.

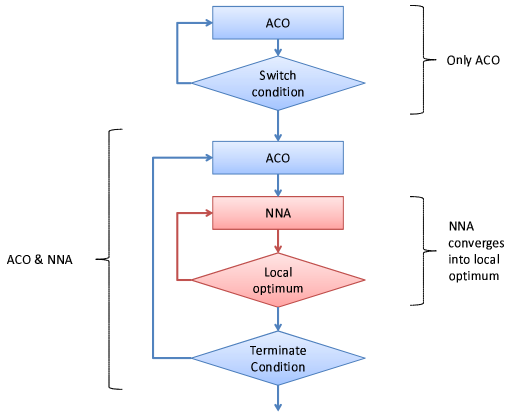

Figure 3: Flow chart of proposed method

(1) ACO Step

At first, the proposed method runs only ACO and goes on searching until a condition is satisfied. The proposed ACO has a $M \times N$ float type matrix, a pheromone table T, for the sake of possessing pheromone information corresponding to an assignment table V, $M \times N$ Boolean matrix.

Regular interval assignments are introduced in order to improve channel assignments result[11]. In the most congested cell, channels with regular intervals are assigned to minimize the total interference.. The remaining cells are randomly chosen and pheromone biased random assignments are made.

Artificial ants decide which ways to go depending on both randomness and pheromone values in T. Channel assignments are made based on pheromone weighted random. Initial value of every element in pheromone table $[\tau_{ij}]$ equals to 1.0 and therefore the initial assignment is always complete random assignment except for the most congested cell. Pheromone increase is executed after every assignment is made as shown in Expression (6). Pheromone values are updated only when V_{lm} equals 1, that is to say V_{lm} is assigned to a user. Pheromone increment depends on whether the total interference value of the assignments is a minimum value so far or not. When smaller interference assignment is found, corresponding pheromone values increase more. Otherwise, pheromone increment is smaller. W_{inc} is a constant number and an amount of increase, and W_{bet} is a constant number as well and a weight to bias the increment.

$$\tau_{lm} \leftarrow \begin{cases} \tau_{lm} + W_{inc} \times W_{bet} & \text{(interference is minimum so far)} \\ \tau_{lm} + W_{inc} & \text{(otherwise)} \end{cases}$$
$$\text{where} \quad W_{inc} > 0 \quad \text{and} \quad W_{bet} > 1 \qquad (6)$$

Some pheromone values are decreased after one channel is assigned because channels corresponding to decreased elements of pheromone table have potential to cause interference. Decrement of pheromone depends on interference matrix E. Expression (7) shows decrease of pheromone. When e_{ijk} equals 0, that is to say the corresponding assignment does not have potential to cause interference, pheromone is not updated. W_{dec} is a constant number to weight decrement in Expression (7).

$$\tau_{ij} \leftarrow \tau_{ij} \times W_{dec}^{e_{ijk}}, \quad where \quad 0 < W_{dec} < 1 \qquad (7)$$

(2) ACO + NNA Step

After only ACO step, NNA is called in order to find local optimum solutions, which starts from the solution acquired by ACO. Searching by NNA continues until a local optimum solution is found. The proposed algorithm iterates one ACO search and NNA searches until a terminate condition is satisfied.

The NNA in proposed algorithm has a $M \times N$ integer type matrix U in order to represent neurons input corresponding to an assignment table V, $M \times N$ Boolean matrix V. Output of NNA is an assignment table V as well as ACO. When an algorithm is switched from ACO to NNA, the result of ACO is reflected to initial input values U of neurons in NNA as shown in Expression (8).

NNA takes over searching from ACO by initializing neuron's input table U with a solution generated by ACO. W_{neu} is an integer constant number of weight for the solution by ACO, V_{ij}^{ACO}. The larger initial U_{ij} becomes, the longer the solution tends to hold the solution by ACO rather than converges into a local optimum solution.

$$U_{ij} = V_{ij}^{ACO} \times W_{neu}, \quad where \quad W_{neu} > 1 \qquad (8)$$

An expanded maximum neuron model is introduced into the NNA in proposed method. The proposed method adopts HNNA and proposes to minimize an energy function shown in Expression (9). This energy function contains only a factor to represent total interference. NNA is terminated when the energy equals 0 or static terminate condition is satisfied.

$$E = \frac{A}{2} \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{p=1}^{N} \sum_{q=1,(i,j)\neq(p,q)}^{M} e_{ip|j-q|} V_{pq} V_{ij} \qquad (9)$$
$$A \quad \text{is a coefficient}$$

A motion equation (Expression(10)) is derived if Expression (9) is partially differentiated and is used for neuron's input update. Expression(10) does not have any factor to get out from local optimum solution. Neuron update by the motion equation, therefore, can get into a local optimum solution immediately. Neuron update is carried out as shown in Expression (11).

$$\frac{dU_{ij}}{dt} = -\frac{\partial E}{\partial V_{ij}} = -A \sum_{p=1}^{N} \sum_{q=1,(i,j)\neq(p,q)}^{M} e_{ip|j-q|} V_{pq} \qquad (10)$$
$$\text{where A is a coefficient}$$
$$U_{ij} \leftarrow U_{ij} + \frac{dU_{ij}}{dt} \qquad (11)$$

The best solution by NNA is the final solution of the proposed algorithm.

4. Evaluation

The proposed method is evaluated about execution time and total interference, with C language, GCC 4.1.2, Linux 2.6.18, CPU Intel Xeon X5450 3.0GHz, and Memory 16GB. We do not adopt parallel programming approaches. Each value of the parameters in ACO is followings. W_{inc} = 1.2, W_{bet} = 10, $MaxLoop$ = 300, and $SwitchCondition$ = 100. And one in NNA is followings. A = 1, W_{neu} = 1, and $TerminateCondition$: energy = 0 or the number of loop is 25. 10 benchmarks in Table 1 are used. EX1 and EX2 are small examples. HEX1, HEX2, HEX3 and HEX4 are based on 21-cell hexagonal [12] examples. KUNZ1, KUNZ2, KUNZ3 and KUNZ4 are derived from topographical data, and morphostructures are taken into consideration.

Name	N	M	# of demands	D	C
EX1	4	5	6	D_1	C_1
EX2	5	17	13	D_2	C_2
HEX1	21	37	120	D_3	C_3
HEX2	21	91	120	D_3	C_4
HEX3	21	21	112	D_4	C_3
HEX4	21	56	112	D_4	C_4
KUNZ1	10	30	72	$[D_5]_{10}$	$[C_5]_{10}$
KUNZ2	15	44	113	$[D_5]_{15}$	$[C_5]_{15}$
KUNZ3	20	60	140	$[D_5]_{20}$	$[C_5]_{20}$
KUNZ4	25	73	167	D_5	D_5

Table 1: 10 benchmarks

The proposed algorithm has one ant and 10 times execution corresponds to searching by 10 ants. Best one among 10 solutions, therefore, corresponds to a solution gained by 10-ant algorithm. Table 2 shows the smallest total interference among 10 solutions in each benchmark. Result achieved by Ikenaga [5] is shown in the last column of Tableinterference. Total execution time of 10 times execution is shown in Table 2.

Our proposed method achieved smaller interference solution in EX2, HEX1 and KUNZ4, and the same interference solutions in EX1 and KUNZ3 when our 10 ants' result is compared with result by Ikenaga et al.

5. Conclusion

We propose a heuristic algorithm which consists of ACO and NNA for the CAP. The proposed method shows 2% smaller interference solution in 3 benchmarks in average and the same interference solution in 2 benchmarks compared with Ikenaga et al. Some results of ours is inferior to that of Ikenaga et al. A larger number of ants can achieve smaller interference solution rather than searching is carried out by just one ant.

For better performance, further parameter tuning and hardware implementation. Connection demands by users change continuously in a realistic situation. Dynamic demands, therefore, need to be considered. Memory of searching, pheromone in our proposal, can be exploited to find a solution rather than starting over from scratch.

Name	Min.	Ave.	Ikenaga.	Exe.(sec)
EX1	0	0.0	0.0	1.36
EX2	0	2.9	0.1	11.2
HEX1	46	47.2	46.2	1238
HEX2	18	20.5	16.7	7556
HEX3	80	82.5	78.6	363
HEX4	20	23.0	17.0	2582
KUNZ1	22	23.2	20.8	157
KUNZ2	32	33.1	31.2	752
KUNZ3	13	13.0	13.0	2662
KUNZ4	0	0.0	0.6	6440

Table 2: Interference and Execution time

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