Hybrid Ant Colony Optimization for the Channel Assignment Problem in Wireless Communication

Peng-Yeng Yin and Shan-Cheng Li
Department of Information Management, National Chi Nan University
Taiwan

1. Introduction

Wireless communication is a central technology to many applications such as wireless TV, radio broadcasting, global positioning, satellite-based cellular systems, mobile telephony, wireless LAN, to name a few. The research and development of wireless products have also bloomed the wireless communication applications to a new era. However, the available bandwidth does not grow as fast as the exploding demands from the consumer markets, so we need an algorithm to effectively and repetitively assign the available channels to multiple demanding cells such that no electromagnetic interference is induced. The aim of the *channel assignment problem* (CAP) is to minimize the span, the spectrum between the maximum and minimum used frequency, of allocated channels with an associated assignment that satisfies the bandwidth demands without incurring electromagnetic interference among them. The CAP can be polynomially reduced to the graph-coloring problem which has been known to be NP-hard. This means the derivation of the exact solution to the CAP in the general case is computationally prohibitive.

Most existing methods for tackling CAP are based on three approaches, namely, *mathematical programming*, *heuristics*, and *metaheuristics*. The mathematical programming techniques such as *integer linear programming* (Janssen & Kilakos, 1999; Mathar & Schmeink, 2002) and *branch-and-bound* (Tcha et al., 1997) are efficient in finding the exact solutions, however, they are limited to the application of small-sized problems only. Heuristics such as *ordering* technique (Sivarajan et al., 2000) and *sequential packing* technique (Sung & Wong, 1997) use a heuristic function for determining the order or packing of radio cells to allocate channels. These methods can quickly obtain a feasible solution even for a large problem but the solution quality varies a lot with the instances of the problem. Alternatively, more and more CAP researchers are attracted by the promising results on some applications using metaheuristics including genetic algorithms (Ngo & Li, 1998; Ghosh et al., 2003), simulated annealing (Aardal et al., 2003), tabu search (Hao & Perrier, 1999), and ant colony optimization (Montemanni, 2002). Their results have demonstrated some advantanges in problem scalability, easy implementation, economic computation, and high quality solutions over other approaches.

Inspired by the success of metaheuristics, in this chapter we present a hybrid ant colony optimization (HACO) algorithm embodied with several problem-dependent heuristics to

Source: Swarm Intelligence: Focus on Ant and Particle Swarm Optimization, Book edited by: Felix T. S. Chan and Manoj Kumar Tiwari, ISBN 978-3-902613-09-7, pp. 532, December 2007, Itech Education and Publishing, Vienna, Austria

take advantages of various approaches. The HACO algorithm provides an elegant framework for maintaining a good balance between *exploration* and *exploitation* trajectories in the solution space during the search, while the embedded heuristics are customized to the properties of CAP and is helpful in intensifying the promising area previously found in the search history. The performance of our algorithm is evaluated using a set of benchmark problems named *Philadelphia* that has been broadly used in early literature. Compared to existing approaches, our algorithm manifests the robustness and efficicency in solving the tested problems.

The remainder of this chapter is organized as follows. Section 2 presents the formulation of CAP considered in the chapter. Section 3 renders the details of the proposed HACO algorithm. In Section 4, the experimental results and discussions are presented. Finally, a conclusion is given in Section 5.

2. Problem Formulation

The objective of the CAP is to find an economic channel assignment with the minimum span of frequency spectrum to a number of demanding cells such that no electromagnetic interference is induced. There are three broadly considered electromagnetic compatibility (EMC) constraints as described as follows.

- Co-channel constraint The same channel cannot be assigned simultaneously to certain pairs of cells that are within a stipulated distance.
- Adjacent channel constraint The adjacent channels are not allowed to be assigned to adjacent cells simultaneously.
- Co-cell constraint The separation in channel units between any pair of channels assigned to a cell should be larger than a minimum separation threshold.

This chapter considers the CAP scenario involving the three EMC constraints. Assume that we are given n radio cells and m available channels, the three EMC constraints can be described together by a compatibility matrix $C = \{c_{ij}\}_{1\le i,\, j\le n}$ which stipulates the minimum separation in channel units between any pair of channels assigned to cell i and cell j simultaneously. The demands of the n radio cells can be described by a demanding vector $D = \{d_i\}_{1\le i\le n}$ where d_i indicates the amount of channels requested by cell i. The decision variables can be defined as $F = \{f_{ij}\}_{1\le i\le n, 1\le j\le d_i}$ where f_{ij} denotes the index of the jth allocated channel to cell i. The addressed CAP can be formulated as follows.

$$\text{Min} \max_{\forall i,j,k,l} \left| f_{ij} - f_{kl} + 1 \right| \tag{1}$$

subject to

$$\left| f_{ij} - f_{kl} \right| \ge c_{ik} \quad \forall\ i, j, k, l \text{ and } (i, j) \ne (k, l). \tag{2}$$

The objective function (1) describes the goal of the optimization problem that is to minimize the span in the channels assigned to the demanding cells. The constraint (2) stipulates that the channel assignment must satisfy all of the three EMC constraints described in terms of the compatibility matrix C.

3. Hybrid Ant Colony Optimization for the CAP

In addition to the good generalization of metaheuristics, many successful applications using metaheurisitcs rely on an elaborately designed procedure for handling the problem-specific constraints. There are two different approaches for constraint handling. The *relaxation* method releases the constraints by adding a penalty to the objective value where the penalty is a monotonically increasing function of the degree of the solution infeasibility with respect to the constraints. The *hybrid* method employs a problem-specific heuristic to guide the generation of new solutions that satisfy the constraints. As the convergence rate of the relaxation method could be slow if the constraints are too complicate, we adopt the hybrid method to design our algorithm. In particular, the ordering technique (Sivarajan et al., 2000) and the sequential packing technique (Sung & Wong, 1997) that have been developed for solving the CAP are embedded into an ant colony optimization framework to create an efficient hybrid algorithm. Moreover, a local optimizer is proposed to improve the candidate solutions generated in each iteration such that the quality of the candidate solutions is guaranteed.

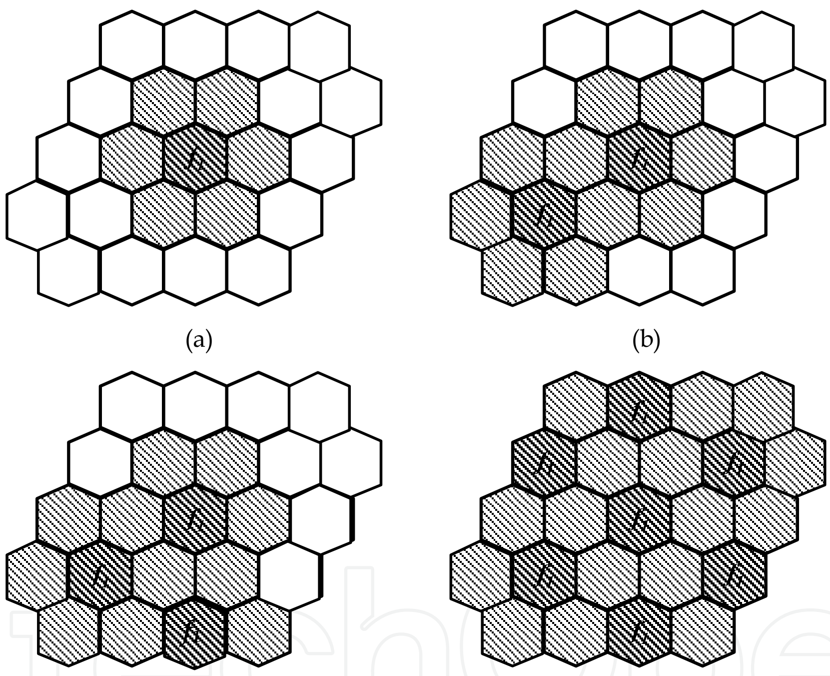


Figure 1. Illustration of the sequential packing method

3.1 Ordering and sequential packing

The ordering heuristic (Sivarajan et al., 2000) determines the order of the cells with which the channels are assigned in turn. In particular, the order of the cell is given according to the cell sequence in decreasing value of the cell degree, which is defined as $\delta_i = \sum_{j=1}^{n} d_j c_{ij} - c_{ii}$ taking into account the demands and the EMC constraints. The cell with a greater demand

and inducing more EMC interference with its surrounding cells is associated with a greater degree and will be considered for assigning channels earlier.

The sequential packing heuristic (Sung & Wong, 1997) sequentially packs the cells that are the "best" for the assignment of a particular channel considering the partial channel assignment already done. The "best" criterion is according to the heuristic that maximizes the overlap between the interfering area induced by the next cell which the channel is assigned to and that by the cells already been assigned channels. Fig. 1 gives an illustration of the sequential packing procedure. Assume that we start with packing with frequency f_1 and it is first assigned to the central cell as shown in Fig. 1(a). The interfering area induced by the electromagnetic effect is marked by light stripes. It should be noted here, although there is only one assigned channel shown in this illustration, the interfering area induced by all of the already assigned channels should be marked. Thus, the unmarked cells are interference free and are candidates for the next cell to assign the channel. The sequential packing heuristic arbitrarily selects one from those that have the maximal interfering overlap with the marked area such that the usage of the assigned channel is maximized. All the unmarked cells surrounding the marked area in Fig. 1(a) are candidates for selecting the next cell to assign the same channel except the bottom-left and upper-right cells. Thus, we can select an arbitrary one as shown in Fig. 1(b). Again, the interfering area due to the new assignment of the channel is marked with light stripes. The process is iterated until all the cells are marked and no interference free cells can be selected, as shown in Figs. 1(c) and 1(d). The sequential packing heuristic starts with the assignment of the first channel and continues with the assignment of the rest channels in turn until the demands of all cells are fulfilled.

3.2 The HACO algorithm

Dorigo developed the first framework of ant colony optimization (ACO) in his Ph.D. dissertation (Dorigo, 1992). He related his ant algorithm to the natural metaphor that ants are able to construct the shortest feasible path from their colony to the feeding source by the use of pheromone trails. An ant leaves some quantities of pheromone on the path it walks along, the next ant senses the pheromone laid on different paths and chooses one to follow with a probability that is proportional to the intensity of pheromone on the path, then leaves its own pheromone. This is an autocatalytic (positive feedback) process that is prone to select the preferable path along which more ants have previously traversed. The ACO has manifested successful applications such as the travelling salesman problem (Dorigo & Gambardella, 1997), quadratic assignment problem (Maniezzo et al., 1994), combined heat and power economic dispatch problem (Song et al., 1999), and the digital curve segmentation problem (Yin, 2003).

To circumvent the CAP problem by using the ACO, we propose a hybrid framework that embodies the ordering and sequential packing heuristics and a local optimiser into the ACO iterations. The details will be articulated in the following subsections.

3.2.1 Graph representation

ACO is a solution-construction algorithm that enables each of the artificial ants (which will be called ants hereafter for simplicity) to sequentially construct a solution by traversing a path on a problem-dependent graph. By iterating the solution construction process, the graph forms a pheromone field contributed by all the ants. Therefore, near-optimal solution can be constructed according to the pheromone attractiveness.

The conversion of a CAP problem to a corresponding graph is straightforward. Assume there are n radio cells, we can construct a graph G = <S, E>, where $S = (s_1, s_2, \ldots, s_n)$ is the set of all radio cells and $E = \{e_{ij} | 1 \le i, j \le n,\ i \ne j\}$ is the set of edges connecting any pairs of cells. Note that there is no loop, i.e., the edge connecting a cell to itself, in E because the co-cell constraint prohibits the same channel to be assigned twice within a cell.

3.2.2 Node transition rule

To allow the ant to traverse a path (in fact, it is to construct a solution), a node transition rule needs to be devised. The node transition rule is a probabilistic function which is defined on a biased probability distribution that is proportional to the product values of the pheromone intensity τ_{ij} and the visibility value η_{ij} associated with the edges. The value of τ_{ij} is initially set equal to a small constant and is iteratively updated using the pheromone updating rule as will be noted. While the value of η_{ij} is determined by a greedy heuristic $\eta_{ij} = A_{ij}\delta_j$ where A_{ij} is the overlap area of the electromagnetic interference if cell j is selected as the next cell to assign the channel as explained in the sequential packing heuristic, and δ_j is the degree of cell j defined in the ordering heuristic. Hence, the visibility greedily prefers to transit to the next cell which causes a greater overlap interference area and has a larger demand and is located in a more complex topology with its surrounding cells.
We now define the probability p_{ij} with which the ant transits from node i to node j as

$$p_{ij} = \frac{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}}{\sum_{h \notin tabu}(\tau_{ih})^{\alpha}(\eta_{ih})^{\beta}}, \tag{3}$$

where $tabu$ is the set of cells containing those violating the EMC constraints and those whose demands have been fulfilled (so there is no need to be considered for channel assignemnt further), parameters α and β are the weights for the relative importance of pheromone and visibility. The ties with respect to p_{ij} are broken randomly.
The solution construction process starts with the assignment of the first channel. When all cells are marked as interfering area due to this channel, the algorithm clears all the marks and continues with the assignment of the next channel. The assignment process is iterated until the demands of all the cells are fulfilled. As such, a feasible channel assignment is obtained.

3.2.3 Pheromone Updating Rule

After each ant has finished constructing a solution by traversing a path, the pheromone field (the pheromone intensity at the edges of the graph) should be updated according to the quality of the constructed solutions. As such, the experience can be accumulated in order to guide the future traverse conducted by the ants. In particular, the pheromone intensity at edge e_{ij} is updated by

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \sum_{k=1}^{P} \Delta\tau_{ij}^{k}, \tag{4}$$

where $\rho \in (0,1)$ is the evaporation rate of previous pheromone trails, and P is the number of ants used in the algorithm. We define $\Delta\tau_{ij}^{k}$ as the quantity of new pheromone trails left at edge e_{ij} by the kth ant and it is computed by

$$e_{ij} = Q/Span_k, \text{ if } e_{ij} \text{ was traversed by ant } k \text{ at the current iteration;} \quad (5)$$
$$= 0, \quad \text{otherwise,}$$

where Q is a constant and $Span_k$ is the span of the channel assignment constructed by the kth ant. Therefore, the edges that constitute shorter spans will receive greater amount of pheromone and serve as building blocks for constructing elite solutions in future iterations. This is an autocatalytic process and the near-optimal solution is more likely to be constructed as the pheromone field converges.

3.2.4 Local optimizer

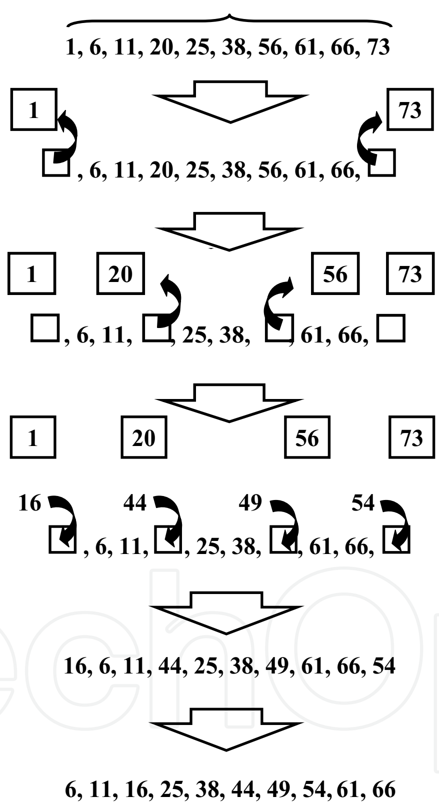


Figure 2. Illustration of the local optimizer process

In order to ensure the quality of the solution that is used for pheromone updating, a local optimizer is devised to modify the solution found by each ant to a local optimum in a definite local neighborhood. The local optimizer randomly selects certain allocated channels and replaces them with the best available channels under the EMC constraints. As the span can be shorten only when the least indexed and the greatest indexed allocated channels are replaced, we always include the two channels for replacement. An illustration of the local optimizer process is given in Fig. 2. Assume that the span of the currently allocated channels is equal to 73. The local optimizer will move the first (1) and the last indices (73) of the allocated channels to a tempary memory. However, the indices of the rest of the allocated channels are moved subject to a replacement probability. In this illustration, say, channels 20 and 56 are selected for replacement. Then, for each of the holes left by the moves, the local optimizer tries to fill it with the best among available channels under the EMC constraints. In this illustration, say, the holes are filled with channels 16, 44, 49, and 54, respectively. After re-sorting the allocated channels, we observe that the span is equal to 61 which is shorter than that of the previous channel assignment.

3.2.5 The algorithm

The pseudo code of the HACO algorithm for the CAP problem is summarized in Fig. 3.

```
1.  Initialize
    Convert the CAP problem into the corresponding graph G = <S, E>
    Set the initial pheromone to a constant value
2.  Repeat
        For each ant do
            Randomly select a starting node
            Repeat
                Move to the next node according to the node transition rule
            Until the demands of all radio cells are fulfilled
            Improve the channel assignment using the local optimizer
        End For
        For each edge do
            Update the pheromone intensity using the pheromone updating rule
        End For
    Until a maximal number of iterations are experienced
3.  Output the minimal span channel assignment found
```

Figure 3. Pseudo code of the HACO algorithm

4. Experimental Results and Discussions

In this section, we present the computational results and evaluate the performance of the HACO algorithm. The platform of the experiments is a PC with a 2.4 GHz CPU and 256 MB RAM. The algorithm is coded in C++.

4.1 Benchmark instances

The Philadelphia benchmark is one of the most widely used testing set of instances in the literature. It contains 21 hexagonal cells of a cellular phone network in Philadelphia. The hexagonal network structure is shown in Fig. 4. Following the literature, we use two nonhomogeneous demand vectors D_1 and D_2 detailed in Table 1 and four different settings of EMC constraints C_1, C_2, C_3 and C_4 in terms of specific values of the minimum separation threshold, as shown in Table 2. With the combinations of these settings, we get a set of eight problem instances shown in Table 3.

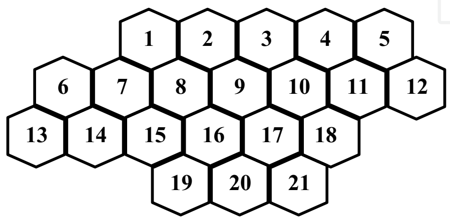


Figure 4. Hexagonal network structure of Philadelphia

Cell	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
$\mathbf{D_1}$	**8**	**25**	**8**	**8**	**8**	**15**	**18**	**52**	**77**	**28**	**13**	**15**	**31**
$\mathbf{D_2}$	**5**	**5**	**5**	**8**	**12**	**25**	**30**	**25**	**30**	**40**	**40**	**45**	**20**
Cell	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**					
$\mathbf{D_1}$	**15**	**36**	**57**	**28**	**8**	**10**	**13**	**8**					
$\mathbf{D_2}$	**30**	**25**	**15**	**15**	**30**	**20**	**20**	**25**					

Table 1. Two nonhomogeneous demand vectors

	$\mathbf{C_1}$	$\mathbf{C_2}$	$\mathbf{C_3}$	$\mathbf{C_4}$
$\mathbf{S_0}$	**5**	**5**	**7**	**7**
$\mathbf{S_1}$	**1**	**2**	**1**	**2**
$\mathbf{S_2}$	**1**	**1**	**1**	**1**

Table 2. Four different settings of EMC constraints

Problem	1	2	3	4	5	6	7	8
EMC constraints	C_1	C_2	C_3	C_4	C_1	C_2	C_3	C_4
Demand vectors	D_1	D_1	D_1	D_1	D_2	D_2	D_2	D_2

Table 3. Eight testing problem instances

4.2 Comparative results

As we use the benchmark instances, the comparative performances of the proposed HACO algorithm and some representitives in the literature can be evaluated. The parameters involved in the HACO algorithm are optimally tuned based on intensive experiments. They are set as the values tabulated in Table 4. For the application of the HACO algorithm in real-world cases, we set the stopping criterion of the algorithm to a fixed execution time intead of setting to different execution times according to the hardness of the problems because it is hard to know in advance the hardness of the problem in hand by observing on the compatibility matrix and the demand vectors. For example, it is hard to know which of the eight problems listed in Table 3 is the most difficult at this stage, although it turns out that problems 2 and 6 are the most difficult in this set after conducting the experiments as will be noted. In the following, the maximal execution time of the HACO algorithm for each of the benchmark problems is set to 10 min.

Parameter	Value
Number of ants (*P*)	20
Pheromone weight (α)	2
Visibility weight (β)	9
Evaporation rate (ρ)	0.2

Table 4. Parameter values used in the HACO algorithm

Ghosh et al. (2003) summarized the numerical results of a number of representitives in the literature tested on the same eight instances listed in Table 3. We only quoted the most recent results no earlier than 1999 from their report. Table 5 shows the comparative performances of the competing algorithms. The lower bound for each of the problems is also listed. It is seen that the methods proposed by Ghosh et al. (2003) and Beckmann & Killat (1999) are able to solve each of the benchmark problems optimally. Both of the two approaches are based on genetic algorithms, manifesting the promising direction of solving CAP using metaheuristics. The HACO can optimally solve problems 1, 3, 4, 5, 7, and 8, but obtains near-optimal solutions for problems 2 and 6, which have been known to be the most difficult problems in Philadelphia dataset. Nonetheless, the HACO spent 10 min for solving either problem 2 or problem 6, the GA-based method in Ghosh et al. (2003) spent 12-80 h for solving the two problems. The method in Beckmann & Killat (1999) starts with a lower bound and increases one channel at a time if a feasible channel assignment cannot be found by their algorithm, however, a reachable lower bound is not available in the general cases. The rest of the competing algorithms are based on heuristics, their performances are not comparable to those based on metaheuristics such as GA or ACO. While the heuristic proposed in Battiti et al. (2001) can obtain competitive results, the method they adopted involves randomisation process, which is a central feature of metaheuristics.

Problem	1	2	3	4	5	6	7	8
Lower bound	381	427	533	533	221	253	309	309
HACO	381	433	533	533	221	258	309	309
Ghosh et al., 2003	381	427	533	533	221	253	309	309
Chakraborty, 2001	381	463	533	533	221	273	309	309
Battiti et al., 2001	381	427	533	533	221	254	309	309
Tcha et al., 2000	381	433	533	533	-	260	-	309
Beckmann & Killat, 1999	381	427	533	533	221	253	309	309

Table 5. Comparative performances of the HACO algorithm and a number of representative algorithms in the literature

4.3 Convergence analysis

It is important to analyze the convergence behavior of the practiced algorithm because even a pure random search can report a solution improving with elapsed execution time, but the explored solutions never converge. The information entropy was used here to measure the amount of information observed in the pheromone field. The expected information entropy E over all radio cells is defined as

$$E = -\sum_{i=1}^{n}\sum_{\forall j} p_{ij}\log_2 p_{ij} \Big/ n \tag{6}$$

where p_{ij} is the node transition probability defined in Eq. (3). Hence, the less the value of E, the purer the information exhibited by p_{ij} related for each cell, which means the node transition rule becomes more deterministic due to a dominating probability and less information can be explored further.

Fig. 5 shows the variations of the expected information entropy as the number of HACO iterations increases. It is observed that the value of the expected information entropy decreases rapidly during the first 20 iterations (note that, to clearly demonstrate this phenomenon, the scale on the x-axis is varied in different intervals). This is because the node transition probabilities are uniformly distributed at the initialization phase of the algorithm and the transition probabilities related to the preferable paths (with shoter frequency span) are reinforced by the pheromone updating rule during the iterations, thus the expected information entropy is quickly decreased. After the 20th iteration, the decreasing rate of the expected information entropy becomes moderate, and gradually reaches stagnation as the number of iterations approaches 2000. This is due to the fact that the node transition rule becomes more deterministic and guides the ants to the paths corresponding to elite solutions. Although the information (building blocks) exchange among the elite solutions is still ungoing in order to finely improve the best solution found, the information gain is less than that obtained at the earlier iterations, because there is a large overlap at the building blocks of the elite solutions. So the solution improving ratio per unit time becomes less economic as the elapsed execution time increases. The practitioners must determine the best stopping criterion according to the allocated computational resource for their applications.

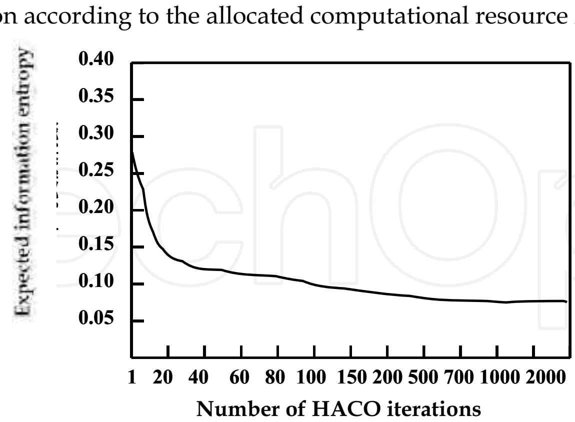


Figure 5. Variations of the expected information entropy as the number of HACO iterations increases

5. Conclusion

In this chapter, we investigate the channel assignment problem (CAP) that is critical in wireless communication applications. Researchers strive to develop algorithms that are able to effectively assign limited channels to a number of cells with nonhomogeneous demands. Inspired by the recent success of metaheuristics, a hybrid ant colony optimisation (HACO) is proposed in this chapter. The HACO embodies several problem-dependent heuristics including ordering, sequential packing, and a local optimiser into an ACO framework. The advantages of this hybrid are two-fold. First, the EMC constraints can be effectively handled by the problem-dependent heuristics instead of using a penalty function as observed in other works which may lengthen the elapsed time in order to reach convergence. Second, the embedded heuristics serve as intensification strategies conducted by the metaheuristic framework and help improve the generated solutions from different view points.

The performance of the HACO algorithm is evaluated on the Philadelphia benchmark set, such that it can be compared to that of existing approaches. It is observed from the experimental results that the HACO algorithm can solve optimally six of the eight benchmark problems and obtain near-optimal solutions for the other two problems which have been known to be the most difficult in the literature. For practical reasons, we only allow the HACO algorithm to run for a relatively short time compared to that used by other approaches. It is plausible to get a better result if more computational time is allocated.

6. References

Aardal, K. I.; Hoesel, P. M.; Koster, M. C. A.; Mannino, C. & Sassano, A. (2003). Models and Solution Techniques for Frequency Assignment Problems. A slightly revised version appeared in: *4OR: A Quarterly Journal of Operations Research*, Vol. 1, 261-317.

Battiti, R.; Bertossi, A. & Cavallaro, D. (2001). A randomized saturation degree heuristic for channel assignment in cellular radio networks. *IEEE Transactions on Vehicular Technology*, Vol. 50, pp. 364-374

Beckmann, D. & Killat, U. (1999). A new strategy for the application of genetic algorithms to the channel-assignment problem. *IEEE Transactions on Vehicular Technology*, Vol. 48, pp. 1261-1269

Chakraborty, G. (2001). An efficient heuristic algorithm for channel assignment problem in cellular radio networks. *IEEE Transactions on Vehicular Technology*, Vol. 50, pp.1528-1539

Dorigo, M. (1992). *Optimization, learning, and natural algorithms*. Ph.D. Thesis, Dip. Elettronica e Informazione, Politecnico di Milano, Italy

Dorigo, M. & Gambardella, L. (1997). Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Transaction on Evolutionary Computation*, Vol. 1, pp. 53-66

Ghosh, S. C.; Sinha, B. P. & Das, N. (2003). Channel Assignment Using Genetic Algorithm Based on Geometric Symmetry. *IEEE Transactions on Vehicular Technology*, Vol. 52, No. 4, pp. 860-875

Hao, J. K. & Perrier, L. (1999). Tabu search for the frequency assignment problem in cellular radio networks. Technical report LGI2P, EMA-EERIE, Parc Scientifique Georges Besse, Nimes, France.

Janssen, J. & Kilakos, K. (1999). An optimal solution to the "Philadelphia" channel assignment problem. *IEEE Transactions on Vehicular Technology*, Vol. 48, No. 3, pp. 1012-1014

Maniezzo, V.; Colorni, A. & Dorigo, M. (1994). The ant system applied to the quadratic assignment problem. Universite Libre de Bruxelles, Belgium, Technical Report IRIDIA/94-28

Mathar, R. & Schmeink, M. (2002). Optimal base station positioning and channel assignment for 3G mobile networks by integer programming. *Annals of Operations Research*, Vol. 107:1-4 , pp. 225-236

Montemanni, R.; Smith, D. H. & Allen, S. M. (2002). An ANTS Algorithm for the Minimum-Span Frequency Assignment Problem With Multiple Interference. *IEEE Transactions on Vehicular Technology*, Vol. 51, No. 5

Ngo, C. Y. & Li, V. O. K. (1998). Fixed channel assignment in cellular radio networks using a modified genetic algorithm. *IEEE Transactions on Vehicular Technology*, Vol. 47, pp. 163-172

Sivarajan, K. N.; McEliece, R. J. & Ketchum, J. W. (2000) Channel assignment in cellular radio. *Proceedings of the 39th IEEE Transactions on Vehicular Technology* to appear

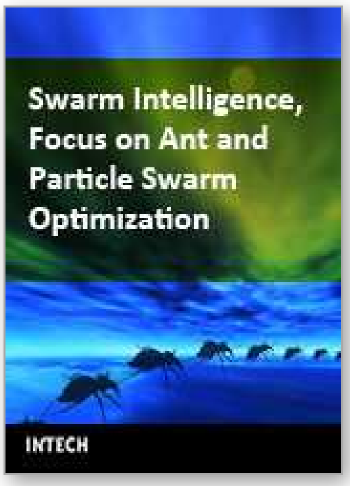
Song, Y. H.; Chou, C. S. & Stonham, T. J. (1999). Combined heat and power economic dispatch by improved ant colony search algorithm. *Electric Power Systems Research*, Vol. 52, pp. 115-121

Sung, C. W. & Wong, W. S. (1997). Sequential Packing Algorithm for Channel Assignment under Cochannel and Adjacent Channel Interference Constraint. *IEEE Transactions on Vehicular Technology*, Vol. 46, pp. 676-685.

Tcha, D. W.; Chung, Y. & Choi, T. J. (1997). A new lower bound for the frequency assignment problem. *IEEE/ACM Transactions on Networking*, Vol. 5, pp. 34-39

Tcha, D. W.; Kwon, J. H.; Choi, T. J. & Oh, S. H. (2000). Perturbation-minimizing frequency assignment in a changing TDMA/FDMA cellular environment, *IEEE Transactions on Vehicular Technology*, Vol. 49, pp. 390-396

Yin, P.Y. (2003). Ant colony search algorithm for optimal polygonal approximation of plane curves. *Pattern Recognition*, Vol. 36, pp. 1783-1797



Swarm Intelligence, Focus on Ant and Particle Swarm Optimization

Edited by FelixT.S.Chan and Manoj KumarTiwari

ISBN 978-3-902613-09-7

Hard cover, 532 pages

Publisher I-Tech Education and Publishing

Published online 01, December, 2007

Published in print edition December, 2007

In the era globalisation the emerging technologies are governing engineering industries to a multifaceted state. The escalating complexity has demanded researchers to find the possible ways of easing the solution of the problems. This has motivated the researchers to grasp ideas from the nature and implant it in the engineering sciences. This way of thinking led to emergence of many biologically inspired algorithms that have proven to be efficient in handling the computationally complex problems with competence such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), etc. Motivated by the capability of the biologically inspired algorithms the present book on "Swarm Intelligence: Focus on Ant and Particle Swarm Optimization" aims to present recent developments and applications concerning optimization with swarm intelligence techniques. The papers selected for this book comprise a cross-section of topics that reflect a variety of perspectives and disciplinary backgrounds. In addition to the introduction of new concepts of swarm intelligence, this book also presented some selected representative case studies covering power plant maintenance scheduling; geotechnical engineering; design and machining tolerances; layout problems; manufacturing process plan; job-shop scheduling; structural design; environmental dispatching problems; wireless communication; water distribution systems; multi-plant supply chain; fault diagnosis of airplane engines; and process scheduling. I believe these 27 chapters presented in this book adequately reflect these topics.