Volume 3, Issue 8, August 2013 ISSN: 2277 128X

International Journal of Advanced Research in Computer Science and Software Engineering

Research Paper

Available online at: www.ijarcsse.com

Multi-Objective Ant Colony Optimization Algorithm to Solve a Nurse Scheduling Problem

Yassine Saji *
Mathematics & Computer Science Dept
LABOMATIC, faculty of sciences
Chouaïb Doukkali El Jadida University Morocco

Mohammed Essaid Riffi
Mathematics & Computer Science Dept
LABOMATIC, faculty of sciences
Chouaïb Doukkali El Jadida University Morocco

Belaïd Ahiod
Computer Science Dept
LRIT, URAC-29 faculty of sciences
Mohammed V- Agdal University Morocco

Abstract— In this paper we deal with the Nurse Scheduling Problem (NSP) in a hospital. The problem aims to generate a feasible and a satisfactory schedule to the planners and the hospital staffs. Sometimes a large number of constraints are taken into account: preferences of staffs (vacation, public holidays, and special demands) and administrative or union obligations, in order to ensure a good working condition and consecrate more time to take care of the patients. To solve NSP, we use a multi-objective mathematical programming model, and for the based search method, we propose an adaptation of a Multi-Objective Ant Colony Optimization algorithm (MOACO). MOACO is extensively for solving multi-objective optimization problems, especially combinational ones. To demonstrate the efficiency of our proposed search method towards others algorithms such as genetic algorithm, some numerical tests based on real data from different units of a large hospital are also pre tutored.

Keywords— Nurse Scheduling Problem, Meta-heuristic, Multi-objective optimization, Ant Colony Optimization.

I. INTRODUCTION

Our automation is to provide for the planner a set of feasible solutions that would save a lot of time and money to the hospital, which the budgetary burden of the staff represents about 75% of the total hospital budget [1]. In addition our ambition is to propose powerful software to facilitate the affectation of the employees into different shifts over fifteen days planning horizon. Our research is carried out on real data from two main units of the hospital Hotel-Dieu from Montreal, and for the mathematical model has arising from the non-linear multi-objective mathematical programming proposed by Berrada [2].

Actually, the automatic planning of scheduling staff covers several fields: the hospital field, railway, airfield and others. In the present work we consider the nurse scheduling problem abbreviated NSP or NRP (Nurse Rostering Problem) [3], which consist in generating a schedule specifying for each employee working and rest days in a period of time, while respecting a set of constraints. This task is usually undertaken manually by the head nurse of the unit concerned and she spends, on average, between six to eight hours to prepare a schedule of three shifts over a period of one month, which is preliminary as it is often modified under many changes related to special demands of the staff. The nurse scheduling is a very difficult and very delicate task for the planners; difficult because it relies on finding a combinatorial solution, that answer to multiple and conflicting constraints, caused frequently by the absenteeism; delicate because it always imposes a negotiation between the staff and their direction service or the administration, which make the problem very difficult to solve. The NSP is well known as a combinatorial and NP-hard problem [4].

Although obtaining an optimal solution is not guaranteed, the use of a meta-heuristic provides many advantages over an exact method. In some practical applications the search of an optimal solution can be completely inappropriate due to many factors, the size of the problem, the dynamic that characterizes the work environment, the lack of precision in the data collection, the difficulty in formulating the constraints in explicit terms or the presence of conflicting objectives and sometimes a large number of real problems is not optimizable effectively by purely mathematical approaches, in this case the use of an exact method has been often much slower than meta-heuristics, which generates additional costs and difficulties on the level of the response time. The metaheuristics and especially ant colony algorithms can be easily adapted to a large number of combinatorial optimization problems, or combined with other methods. This flexibility explains the considerable success of the ant colony algorithms to solve many problems like dynamic, with real variables, stochastic, or multi-objective.

The rest of the paper is organized as follows: section 2 gives two little reviews of the nurse scheduling problem. Section 3 describes our proposed metaheuristic approach. In section 4 we will prove the performance of the used approach on real instances. Finally we conclude and give some perspectives of research.

© 2013, IJARCSSE All Rights Reserved

II. THE NURSE SCHEDULING PROBLEM

Generally, the "Nurse Scheduling Problem" is characterized by a large number of constraints and preferences to include in the generation of the schedule. To make a good schedule, the solution must satisfy these constraints and these preferences. The constraints are divided on two levels: the constraints of quotas that apply to general schedule or a set of individual schedules, and the intrinsic constraints or individual constraints [5]. Each one of these last constraints is hard or flexible [6]. The conflicting constraints of our problem lead to divide them into two types: rigid constraints which must be satisfied and others flexible which can be violated, however our goal is to try to minimize these violations. The rigid constraints correspond to administrative requirements and concern the working weekends, the weekly working days, the uniform distribution of lack or surplus of personnel on all week and holidays. The flexible constraints translate the wishes of nurse staff relating to the number of consecutive working days, to the holiday vacation and the weekly vacation.

For many years, several states of the art have been proposed on the subject [7], [3]. Several techniques have been used in the literature to manage this kind of problem, primarily metaheuristic such as hybrid tabu search [8] and the genetic algorithm [9], [10], linear programming [11], goal programming [6], constraint programming [12], [13], [14], the tabu search [15] or the simulated annealing algorithm [16].

In the literature, several types of schedules are presented: cyclic and noncyclic schedules. A most current approach is to build cyclic schedules, which a frame is repeated as long as the constraints remain unchanged over a defined period. These schedules present a facility of construction but a difficulty in taking into account the personal wishes of the staff. In a cyclic or individualized planning process, a new schedule is generated for each planning period. Although the time spent to making a planning is important and the personalization of the schedules increases the complexity of scheduling as well as the number of potential conflicts between personal demands [17], but it also has the advantage of being relatively flexible and being very interesting for employees in respect of their personal desires [18].

The following table shows an example of individualized schedule, where each line represents the schedule of an employee

TABLE 1 INDIVIDUALIZED SCHEDULE EXAMPLE

Timetable of the employee	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Sun**	**Mon**	**Tue**	**…**
A	D	D	D	L	E	L	L	N	N	…
B	E	E	E	L	N	L	L	L	L	…
C	L	N	N	N	L	L	L	D	D	…
D	N	L	L	D	D	L	L	E	E	…

D-Day; E-Evening; N-Night; L-Leave

An individualized schedule is formed by many personalized schedules of many employees, what makes schedules are difficult to interchange between the employees, thus it's about a noncyclic problem of planning that focuses our attention, and because the individualized schedules take into account the individual preferences, we worked on a general problem of individualized scheduling as presented into two units of the hospital Hôtel-Dieu of Montréal. Every day and on three shifts of eight hours each unit is in service: day shift (08:00 - 16:00), evening shift (16:00 - 00:00) and night shift (00:00 - 08:00). And for more flexibility and satisfaction of personal desires, these schedules are programmed for two weeks.

III. MULTI-OBJECTIVE ANT COLONY OPTIMIZATION

Ant colony optimization metaheuristic described in [19], [20] has been inspired by the behavior of real ant colonies [21], [22], [23]. Basically, the ant colony optimization was used for the first time to solve the traveling salesman problem (TSP) while each ant is considered like an agent [24]. The objective of this problem is to find the shortest path between a set of cities.

Dorigo and Gambardella [25] have proposed some improvements to the basic version described in [20] concerning the rule of transition, the local and the global update of the pheromone trails, the integration of improvement methods and the use of a list of candidates. Several other works Dorigo and Di Caro [26] add further explanations on the algorithm process, the notation and the choice of various parameters.

Recently several studies proposed algorithms based on ant colony optimization to solve MOP, called in the literature MOACO [27] algorithms. These algorithms differ with respect to the three following points:

Pheromone trails: The quantity deposing on a given component represents a previous experience of the colony in the choice of the preferred component. When there is only one objective function, this experience is defined with respect to this objective. However, if there are several objectives, one can consider two different strategies.

A first strategy is to consider a single pheromone structure as suggested in [28], [29], [30], [31]. In this case, the quantity deposited of pheromone corresponds to an aggregation between different objectives. A second strategy is to consider several pheromone structures, as proposed in [32], [33], [34], [35], [36]. Usually, each colony of ants associates with an objective different than the others colonies, in this case each colony having its own pheromone structure.

The choice of a solution: When updating pheromone trails, it is necessary to decide on which of the constructed solutions a quantity of pheromone will be laid. A first possibility is to choose the solutions that find the best values for each constraint in the current cycle, as proposed in [33], [34], [36]. A second possibility is to select the non-dominated

© 2013, IJARCSSE All Rights Reserved

solutions of the current cycle. In this case, one can is to take all the solutions in the Pareto set, as proposed in [31] or only the new non-dominated solutions which enter in the set of the current cycle, as proposed in [32].

Definition of the heuristic factors: During the construction of solutions, at each step a candidate is chosen relatively to a transition probability that depends on two factors: a pheromone factor and a heuristic factor. The definition of the pheromone factor depends on the definition of pheromone trails, as discussed in the first point. For the definition of the heuristic factor, two different strategies have been considered. A first strategy is to consider an aggregation of the various objectives into only single heuristic information, as proposed in [33], [35], [29]. A second strategy is to consider each objective into separated heuristic information, as proposed in [28], [32], [34], [31], [36].

Algorithms 1 and 2 describe a generic algorithm MOACO [27] used to construct solutions in a construction graph G whose definition depends on the MOP. At each iteration, a vertex of G is selected from a set of candidate vertices Cand; it is added to the solution S, and the set of candidate vertices is updated by removing vertices that violate constraints associated with the colony c. The vertex v_i added to the solution S by ants from colony c is chosen relatively to the probability:

$$P_S^c(v_i) = \frac{[\tau_S^c(v_i)]^\alpha . [\eta_S^c(v_i)]^\beta}{\sum_{v_j \in Cand} [\tau_S^c(v_j)]^\alpha . [\eta_S^c(v_j)]^\beta}$$

Where $\tau_S^c(v_i)$ and $\eta_S^c(v_i)$ are respectively the pheromone factor and heuristic factor of the candidate vertex v_i, α and β are two parameters which determine their relative importance. The definition of pheromone factor depends on the parameters *# Nc* the number of colony and *# Nτ* the number of pheromone structure.

The definition of heuristic factor depends on the objective functions of the problem. It must be defined during the application of the algorithm to a specific problem.

Algorithm 1: algorithm MOACO *(#Nc, #Nτ)* : Generic ACO algorithm for MOP

1. Initialize all pheromone trails to τ_{max}
2. **repeat**
3. **for** each colony c **in** 1..*# Nc*
4. **for** each ant *k* **in** 1..*nbAnts*
5. construct a solution
6. **for** *i* **in** 1.. *#Nτ*
7. update the ith pheromone structure trails
8. **if** a trail is lower than τ_{min} **then** set it to τ_{min}
9. **if** a trail is greater than τ_{max} **then** set it to τ_{max}
10. **until** maximal number of cycles reached

Algorithm 2: Construction of a solution *S*:

1. $S \leftarrow \emptyset$
2. $Cand \leftarrow V$
3. **while** $Cand \neq \emptyset$ **do**
4. choose $v_i \in Cand$ with probability $p_S(v_i)$
5. add v_i at the end of *S*
6. remove from *Cand* vertices that violate constraints
7. **end while**

IV. ADAPTATION OF MOACO TO NSP

To solve the problem our approach constructs a solution in two main phases. The first phase is used to distribute in a uniform manner the lack or surplus during the working week (excluding Saturday and Sunday) while satisfying the daily staff demand the day *j*, which was randomly selected, the process stops when reaching the number of days required to work of the last employee. This process is based on a heuristic similar to 'first-fit decreasing' [2] used to solve the problem of 'bin-packing'. The second phase is a variant of ant colony algorithm (MOACO) adapted to multi-objective NSP problem, aims to minimize the violations of the objective functions within an iterative process, based on the behavior of ant colonies to generate a set of feasible solutions.

The strategy of constructing a solution by MOACO algorithm is described in the following points:

-Consider a set of *m* artificial colonies of ants, and *m* pheromone structures, as $m = |F|$ is the number of objectives to be optimized. Each colony is associated with an objective which differs to other colonies. The ants from the same colony seek to minimize the objective associated with this colony, while using their own pheromone and heuristic structure. The parameters which enter into account of the resolution approach will be defined in the numerical results.

-**Constructing a solution**: the probability of planning that an employee *i* work the day *j* by an ant from colony c ∈ {1,.., *m*} is given by:

$$P_{ij}^c(t) = \frac{[\tau_{ij}^c(t)]^\alpha . [\eta_{ij}^c(t)]^\beta}{\sum_{N_{ih} \in D} [\tau_{ij}^c(t)]^\alpha . [\eta_{ij}^c(t)]^\beta}$$

© 2013, IJARCSSE All Rights Reserved

The parameters α and β are two constants that control the relative importance of pheromone trails against the heuristic information.

D: the set of possible decisions.

We mention that for each iteration, the colony builds a solution that minimizes the objective associated to this colony.

-The pheromone update: the quantity of pheromone τ_{ij}^{S} is associated with the planning of working day *j* for an employee *i* under constraint to minimize objective function f_s is defined by $\tau_{ij}^{S} = (1-\rho).\tau_{ij}^{S} + \Delta\tau_{ij}^{S}$

With $\Delta\tau_{ij}^{S}$ is the quantity of pheromone laying by ants of colony S, this quantity is defined by

$$\Delta\tau_{ij}^{S} = \begin{cases} \dfrac{1}{(1 + f_s(X^S) - f_s(X_{meilleur}^S))} & \textit{ant planned employee i work the day j} \\ 0 & \textit{else} \end{cases}$$

With ρ is the evaporation rate, and $X_{meilleur}^{S}$ is the best solution that minimizes the objective function f_s since the first iteration including the current cycle.

- **The heuristic information:** the heuristic factor η_{ij}^{S} which corresponds to the minimization of the objective f_s is given by:

$$\eta_{ij}^{S} = \frac{d'_j - \sum_{i=1}^{NE} x_{ij}^{S} + 1}{\sum_{j \in J} d_j + F_s}$$

Where d'_j daily residual demand and d_j Total number of employees required on the day *j*.

F_s: is the violation of the solution X_t^S at iteration *t* for the employee *i* work the day *j*.

$$F_s = f_s(X_t^S);\ x_{ij}^{S} = 1$$

-T**he initialization of parameters:** the choice of parameters has a critical role in the performance of the algorithm and depend principally a set of input data. We recall that these parameters are the number of ants per colony, number of iterations, the evaporation rate ρ, α and β.

-The mathematical representation of solutions: we note by X = (x_{ij}) the schedule matrix (two-dimensional) and we define its elements.

$$x_{ij} = \begin{cases} 1 & \textit{if employee i work the day j}, \forall\, i \in I, j = k, k+6 \\ 0 & \textit{else} \qquad \textit{and } k = 1{,}8. \end{cases}$$

Where *I*: set of employees of a shift over two week period

k: index of the week, *k* = 1.8 (the index of the first day of the working week)

This representation is the general form of this type of schedule in which rows represent the employees and columns the working days.

-The objectives of the problem: The objective functions of the considered problem are defined as follows:

f_0: the personnel lack or the surplus of staff must be uniformly balanced over each week.

f_1: the number of consecutive days of work must not exceed a fixed number succmax.

f_2: the number of consecutive days of work must be at least equal to 2.

f_3: the daily demand of staff from the same group of substitution must be satisfied.

f_4: the vacation days must be taken consecutively and attached to a weekend.

f_5: the special demands concerning the weekly vacation and/or the work days must be satisfied.

f_6: the daily demand of staff in specific days (Monday and Friday) must be satisfied.

-The choice of a solution: The strategy of choosing a solution is based on the fact to keep at the end of each iteration the solutions that minimize the objective associated with the current colony, and also which improves the best solution taken since the first iteration, while respecting the following lexicographical order of preferences relating to objectives:

$$f_0 > f_5 > f_6 > f_3 > f_1 > f_2 > f_4$$

Algorithm 3 : Algorithm MOACO for NSP

1. Initialize all parameters and all pheromone trails to τ_{max}
2. **repeat**
3. **for** each colony c **in** 1..*# Nc*
4. fix weekends for each solution X^c
5. **for** each employee *i* **in** 1..*nbEmployees*
6. **while**($\varphi_{ik} > 0$) k=1,8
7. choose a day $j \in J$ by probability:

$$P_{ij}^{c}(t) = \frac{[\tau_{ij}^{c}(t)]^{\alpha}.[\eta_{ij}^{c}(t)]^{\beta}}{\sum_{N_{ih} \in D}[\tau_{ij}^{c}(t)]^{\alpha}.[\eta_{ij}^{c}(t)]^{\beta}} \qquad k+1 \le j \le k+5, k = 1{,}8$$

8. **if**($\sum_{i=1}^{nbEmployees} x_{ij}^{c} - d'_j < 0$)
9. $x_{ij}^{c} = 1$
10. $\varphi_{ik} = \varphi_{ik} - x_{ij}^{c}$;

© 2013, IJARCSSE All Rights Reserved

```
            d'_j = d'_j − 1
            mark the day j as already assigned
        end if
      end while
    end for
  end for

  for each colony c in 1..# Nc
   for each employee i in 1..nbEmployees
      τ_ij^c = (1 − ρ).τ_ij^c + Δτ_ij^c ( For all days already assigned)

      if a trail is lower than τ_min then set it to τ_min end if
      if a trail is greater than τ_max then set it to τ_max end if
    end for
  end for
Select the best solution that improves the global solution and that respects the
  lexicographic order
until maximal number of cycles reached
```

V. NUMERICAL TESTS

A. The data of problem

To judge the performance of our algorithm, we use real data from two units of Hôtel-Dieu hospital: Intensive Care Unit (SI) and Emergency Unit (URG). The choice of these two units was not hazardous as they are the two largest units in the hospital where we find a very large number of special demands. In addition we consider the interval between 25th June and 16th September, where most employees prefer to go on vacation; this can increase the complexity of planning a schedule that satisfies multiple constraints.

Taking into account that the period of the schedule is two weeks, we define six categories of test problems C_i $(1 \leq i \leq 6)$. Each category corresponds to a shift (Day, Evening, or Night) of one among the two units mentioned previously for six distinct problems, which brings us to 36 problems to solve. In order to simplify the interpretation of the results we adopt the classification described in [37], then we compare our results with that obtained by using genetic algorithm with limited population (equal 10), and also to evaluate the quality of our solution and to simplify the comparison, we present some measures described in [37].

- The CPU time: is the time required to execute the search method.
- V_{moy}: weighted sum of the gap between the objective value and the ideal value is given by

$$V_{moy} = \frac{\sum_{i=0}^{p-1} \lambda_i (f_i - f_i^*)}{\sum_{i=0}^{p-1} \lambda_i}$$

  p = number of objectives (p = 7).
  λ_i = weight of the objective with priority i. It is equal to $(p - i + 1)$.
  f_i = value of the objective with priority i.
  f_i^* = ideal value of the objective of priority i, obtained by minimization of this objective under the rigid constraints.
- $\%Im$: Percentage improvement of the initial solution

$$\%Im = \frac{V_{moy}(Sol.Initiale) - V_{moy}(Sol.Finale)}{V_{moy}(Sol.Initiale)}$$

B. Results

The experiments prove that α = 1, it's the best value. Then after having fixed α we define the value of β. After five runs, the optimal value defines the value of β and we take the same procedure to define the other parameters. Taking as an example the problem P1 of the emergency unit during the night shift.

TABLE 2: THE VALUES OF PARAMETER β

Run	**β**					
	0.01	0.9	1	2	3	5
1	0.12	0.27	0.27	0.1	0.33	0.13
2	0.08	0.25	0.09	0.08	0.46	0.13
3	0.13	0.13	0.12	0.07	0.33	0.10
4	0.12	0.18	0.12	0.07	0.55	0.09
5	0.10	0.18	0.15	0.07	0.36	0.08
Average	0.13	0.20	0.15	0.072	0.40	0.10
Min(Aver)	0.072					
Minimum	0.07					

© 2013, IJARCSSE All Rights Reserved

After five runs, we take the parameter value corresponds to the minimum cost and also that corresponds to the minimum average cost. The minimum average value and the minimum value justify setting this parameter to 2.

Now we set $\alpha = 1$ and $\beta = 2$, then we define the value of ρ.

TABLE 3: THE VALUES OF PARAMETER ρ

Run	**ρ**				
	0.1	0.3	0.6	0.7	0.8
1	0.10	0.11	0.09	0.07	0.17
2	0.21	0.09	0.07	0.22	0.10
3	0.28	0.25	0.07	0.13	0.15
4	0.10	0.22	0.08	0.07	0.20
5	0.10	0.19	0.07	0.25	0.10
Average	0.15	0.17	0.076	0.14	0.14
Min(Aver)	0.076				
Minimum	0.07				

Finally, we find the best parameters which will be used after the adjustment are:

TABLE 4: THE PARAMETERS OF THE PROBLEM

Parameter	**Value**
# colony	# Objective= 7
# Ants	#Employees
# iteration	700
ρ	0.6
α	1
β	2

TABLE 5: RESULTS OF NIGHT SHIFT PROBLEMS OF THE EMERGENCY UNIT

Category C1	**Initial. Sol Vmoy**	**Final. Sol Vmoy**	**CPU (s)**
P1	0.12	0.07	49.8
P2	0.32	0	50.5
P3	0.22	0	48.65
P4	0.46	0	46.68
P5	0.10	0	48
P6	0.28	0	48.85
Average	0.25	0.011	48.74

TABLE 6: RESULTS OF NIGHT SHIFT PROBLEMS OF THE INTENSIVE CARE UNIT

Category C2	**Initial. Sol Vmoy**	**Final. Sol Vmoy**	**CPU (s)**
P1	1.34	0.15	56.48
P2	1.17	0.42	50
P3	1.30	0.47	56.24
P4	1.6	0.19	57.32
P5	1.08	0.10	52
P6	2	0.7	62.12
Average	1.41	0.33	55.7

TABLE 7: RESULTS OF EVENING SHIFT PROBLEMS OF THE INTENSIVE CARE UNIT

Category C3	**Initial. Sol Vmoy**	**Final. Sol Vmoy**	**CPU (s)**
P1	1.36	0.13	58.4
P2	2.20	0.04	65.6
P3	1.60	0.14	59.6

© 2013, IJARCSSE All Rights Reserved

P4	1.33	0.14	60.32
P5	2	0.82	59.68
P6	1.6	0.62	56.84
Average	1.68	0.31	60.07

TABLE 8: RESULTS OF DAY SHIFT PROBLEMS OF THE INTENSIVE CARE UNIT

Category C4	**Initial. Sol**	**Final. Sol**	**CPU (s)**
	Vmoy	**Vmoy**	
P1	2.05	0.07	60
P2	1.75	0.11	50.4
P3	1.84	0.46	51.6
P4	2.41	0.60	64.8
P5	1.48	0.12	48
P6	1.92	0.28	50.4
Average	1.9	0.27	54.2

TABLE 9: RESULTS OF EVENING SHIFT PROBLEMS OF THE EMERGENCY UNIT

Category C5	**Initial. Sol**	**Final. Sol**	**CPU (s)**
	Vmoy	**Vmoy**	
P1	3.17	0.63	68.44
P2	2.93	0.56	64.45
P3	1.91	0.056	65.76
P4	1.96	0.1	64.74
P5	3.35	0.38	69.42
P6	1.28	0.27	64
Average	2.43	0.33	66.13

TABLE 10: RESULTS OF DAY SHIFT PROBLEMS OF THE EMERGENCY UNIT

Category C6	**Initial. Sol**	**Final. Sol**	**CPU (s)**
	Vmoy	**Vmoy**	
P1	1.27	0.065	63.62
P2	0.75	0.045	65.8
P3	2.44	0.74	73.35
P4	3.75	1.01	70.61
P5	3.18	1.31	65.15
P6	3.9	1.91	67.66
Average	2.54	0.84	67.7

TABLE 11: RESULTS OF MOACO AND AG ALGORITHMS

Category	**MOACO**				**AG**			
	Initial. Sol	**Final. Sol**	**% Im**	**CPU**	**Initial. Sol**	**Final. Sol**	**% Im**	**CPU**
	Vmoy	**Vmoy**			**Vmoy**	**Vmoy**		
C1	0.25	0.011	96	48.74	1.53	0.07	96	49.81
C2	1.41	0.33	77	55.7	3.34	0.39	88	71.71
C3	1.68	0.31	82	60.07	3.31	0.32	90	87.26
C4	1.9	0.27	86	54.2	3.04	0.27	92	85.60
C5	2.43	0.33	86	66.13	3.17	0.34	90	98.80
C6	2.54	0.84	45	67	5.48	0.93	83	139.25

© 2013, IJARCSSE All Rights Reserved

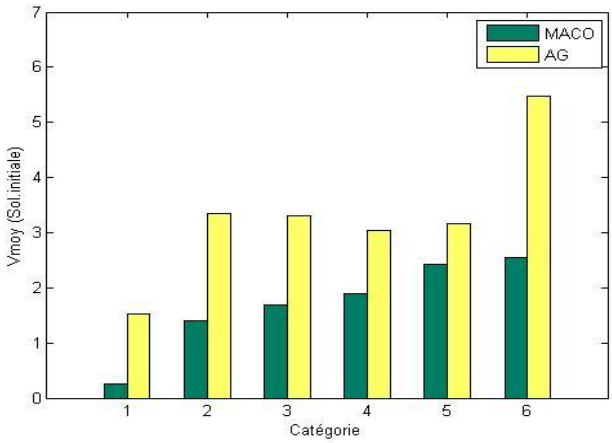

Fig 1: the average violation of the initial solution

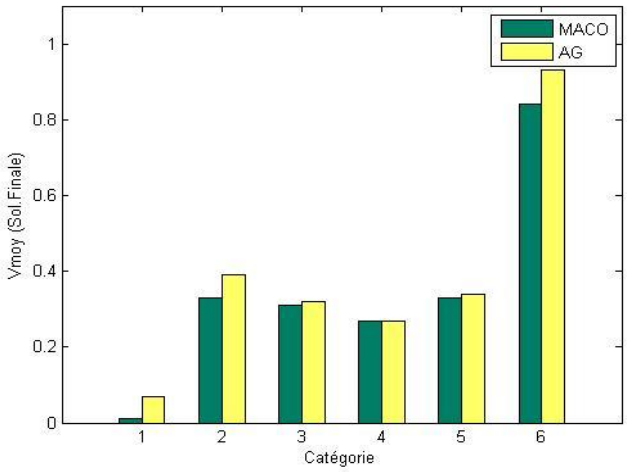

Fig 5: the average violation of the final solution

The proposed approach allows generating a feasible schedule, in terms of execution time and quality of solutions compared to the genetic algorithm. Indeed the quality of the solutions found can be explained, on the one hand, by the diversification adopted in the first phase of the algorithm, that aims to uniformly distribute the lack or the surplus, on the other hand, by the starting solution of each ant of the colony which differ from one colony to another, depending on the objective associated with this colony. That allows constructing initial solutions with less violation compared to the genetic algorithm. In this case the maximum number of iterations needed to improve the starting solution of a given colony does not exceed a hundred iterations, which reduces the computing time. So the speed of the proposed method allows to planners to run a large number of test sets, in order to ensure obtaining a good solutions according the preset criteria.

VI. Conclusion and Perspectives

We propose in this article an adaptation of MOACO algorithm to solve NSP problem. There are several variants of MOACO algorithm parameterized by the number of colonies and the number of pheromone structures, as there are several strategies to choose solutions. We are tested one of these variants of this algorithm on real instances of the NSP problem; this variant has demonstrated considerable effectiveness in relation to the genetic algorithm with a limited population. Our perspectives of this research are to use other variants to generate solutions as good quality as the genetic algorithm with a large population and within a sufficiently reasonable time.

Acknowledgements

The authors would like to thank the anonymous reviewers for careful reading and thoughtful review of our manuscript.

Special thanks to the group members of laboratory of Mathematics and Technologies of Information and Communication (LABOMATIC) Chouaïb Doukkali University.

References

[1] Chan, P. “ La planification du personnel: acteurs, actions et termes multiples pour une planification opérationnelle des personnes. ” Thèse de doctorat, Université Joseph Fourier de Grenoble 2002.

[2] I. Berrada, J.A. Ferland et P. Michelon, "Multi-objective Models and Techniques for Nurse Scheduling Problem", Publication No. 907, Université de Montréal. 1994.

© 2013, IJARCSSE All Rights Reserved

[3] Burke, E.K, Causmaecker, P.D.,Berghe, G. V.,Landeghem, H. V. The state of the art of nurse rostering. Journal of scheduling, vol 7 n°6, pp. 441-499. 2004.
[4] T. Osogami et H. Imai. Classification of Various Neighborhood Operations for the Nurse Scheduling Problem. Dans les actes de ISAAC '00: Proceedings of the 11th International Conference on Algorithms and Computation, London, UK, 72–83. Springer-Verlag. 2000.
[5] Pascal Labit IRIS : "Amélioration d'une méthode de génération de colonnes pour la confection d'horaires d'infirmières. " Master's thesis, Ecole Polytechnique de Montréal. La Bibliothèque nationale du Canada. 2000.
[6] I. Berrada, J.A. Ferland et P. Michelon, "A Multi-objective Approach for Nurse Scheduling with both Hard and Soft Constraints". Socio-Econ. Plann. Sci., 30, p. 183-193. 1996.
[7] Cheang, B., Li, H., Lim, A. & Rodrigues, B. Nurse rostering problems - a bibliographic survey, European Journal of Operational Research 151(3): 447–460. 2003.
[8] Burke, E. K., Causmaecker, P. D. & Berghe, G. V. A hybrid tabu search algorithm for the nurse rostering problem, Lecture Notes in Computer Science 1585: 187–194. 1999.
[9] Aickelin, U. & Dowsland, K. A. Exploiting problem structure in a genetic algorithm approach to a nurse rostering problem, Journal of Scheduling 3(3): 139–153. 2000.
[10] Aickelin, U.,Dowsland, K. A. An indirect Genetic Algorithm for a nurse scheduling problem. Computers and Operations Research, vol 31, pp. 761–778. 2004.
[11] B. Jaumard; F. Semet et T. Vovor, Generalized Linear Programming Model for Nurse Scheduling. Europen Journal Of Opeluitaonal Research, 107(1):1-18. May 1998
[12] Weil, G., Heus, K., François, P.,Poujade, M. Constraint Programming for Nurse Scheduling. IEEE Engineering in Medicine and Biology, vol 14 n°4, pp. 417-422. 1995.
[13] Cheng, B. M., Lee, J. H. & Wu, J. C. A nurse rostering system using constraint programming and redundant modeling, IEEE Trans Inf Technol Biomed 1(1): 44–54. 1997.
[14] Abdennadher, S.,Schlenker, H.. Nurse scheduling using constraint logic programming. Proceedings of Innovative Applications of Artificial Intelligence AAAI/IAAI-99, Orlando, Florida. 1999.
[15] Dowsland, K.A. Nurse scheduling with tabu search and strategic oscillation. European Journal of Operation Research, 106(2-3):393–407. 1998.
[16] Brusco, M. J.,Jacobs, L. W. Cost analysis of alternative formulations for personnel scheduling in continuously operating organisations. European Journal of Operational Research, vol 86, pp. 249–261. 1995.
[17] Ivo Erasmo Buzon Cantera. La confection des horaires de travail des médecins d'urgence résolue à l'aide de la recherche avec tabous. La Bibliothèque nationale du Canada. 2001.
[18] Valouxis, C.,Housos, E. Hybrid optimization techniques for the workshift and rest assignment of nursing personnel. Artificial Intelligence in Medicine, vol 20, pp. 155-175. 2000.
[19] Colorni, A., Dorigo, M. & Maniezzo, V. Distributed optimization by ant colonies, Actes de la première conférence européenne sur la vie artificielle, Paris, France, Elsevier Publishing, pp. 134–142. 1991.
[20] Dorigo, M. Optimization, Learning and Natural Algorithm, PhD thesis, Politecnico di Milano, Italy. 1992
[21] Deneubourg J.L., Pasteels J.M. and J.C. Verhaeghe. Probabilistic behaviour in ants: A strategy of errors?, Journal of Theorical Biology, 105, p. 259-271. 1983.
[22] Deneubourg J.L. and S. Goss. Collective patterns and decision-making, Ethology & Evolution, 1, p. 295-311. 1989
[23] Goss S., Beckers R., Deneubourg J.L., Aron S. and J.M. Pasteels. How trail laying and trail following can solve foraging problems for ant colonies, In: Behavioural Mechanisms of Food Selection, R.N. Hughes ed., NATO-ASI Series, vol. G20, Berlin: Springler-Verlag. 1990.
[24] Dorigo M., Maniezzo V. and A. Colorni. Positive feedback as a search strategy, Technical Report No 91-016, Politecnico di Milano, Italy, 20 pages. 1991.
[25] Dorigo M. and L.M. Gambardella. Ant colonies for the traveling salesman problem, BioSystems, 43, p. 73-81. 1997.
[26] Dorigo M. and . Di Caro. The Ant Colony Optimization Meta-Heuristic, In: D. Corne, M. Dorigo and F. Glover Editors, New Ideas in Optimization, McGraw-Hill. 1999
[27] Ch. Solnon, Kh. Ghédira. Ant Colony Optimization for Multi-objective Optimization Problems Inès Alaya SOIE/LIRIS, National School of Computer Sciences Manouba Campus. 2010
[28] C. E. Mariano, E. Morales, A Multiple Objective Ant-Q Algorithm for the Design of Water Distribution Irrigation Networks, Technical Report n HC-9904, Instituto Mexicano de Tecnologa del Agua, Mexico, June, 1999.
[29] M. Gravel, W. L. Price, C. Gagné, Scheduling Continuous Casting of Aluminium using a Multiple Objective Ant Colony Optimization Metaheuristic, European Journal of Operational Research, vol. 143, n1, 2002, p. 218-229.
[30] P. R. McMullen, An Ant Colony Optimization Approach to Addressing a JIT Sequencing Problem with Multiple Objectives, Artificial Intelligence in Engineering, vol. 15, n3, 2001, p. 309-317.
[31] B. Baràn, M. Schaerer, A Multiobjective Ant Colony System for Vehicle Routing Problem with TimeWindows, Proc. Twenty first IASTED International Conference on Applied Informatics, Insbruck, Austria, 2003, p. 97-102.
[32] S. Iredi, D. Merkle, M. Middendorf, Bi-Criterion Optimization with Multi Colony Ant Algorithms, First International Conference on Evolutionary Multi-criterion Optimization (EMO'01), vol. 1993, Lecture Notes in Computer Science, 2001, p. 359-372.
[33] K. Doerner, W. J. Gutjahr, R. F. Hartl, C. Strauss, C. Stummer, Pareto Ant Colony Optimization: A Metaheuristic Approach to Multiobjective Portfolio Selection, Annals of Operations Research, 2004.

© 2013, IJARCSSE All Rights Reserved

[34] L. Gambardella, E.D. Taillard, G. Agazzi, MACS-VRPTW: A Multiple Ant Colony System for Vehicle Routing Problems with Time Windows, in F. G. D. Corne, M. Dorigo (ed.), New Ideas in Optimization, McGraw Hill, London, UK, 1999, p. 63-76.

[35] B. Bullnheimer R.F. Hartl C. Strauss, An Improved Ant system Algorithm for the Vehicule Routing Problem, Annals of Operations Research, vol. 89, 1999, p. 319-328.

[36] K. Doerner, R. F. Hartl, M. Teimann, Are COMPETants More Competent for Problem Solving? The Case of Full Truckload Transportation, Central European Journal of Operations Research, vol. 11, n2, 2003, p. 115-141.

[37] B. Ahiod, I. Berrada, I. Kassou, Deux méthodes de recherche locale pour résoudre un problème d'horaire du personnel infirmier dans un établissement hospitalier, Investigacion Operativa, Volume 6, Numéro 1-2-3, 1998.

© 2013, IJARCSSE All Rights Reserved