e-ISSN: 2349-9745
p-ISSN: 2393-8161

Scientific Journal Impact Factor (S

International Journal of Modern Trends in Engineering and Research

www.ijmter.com

Solving Nurse Rostering Problem Using Ant Colony Optimization Approach

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Abstract— The Nurse Rostering Problem consists of allocating nurses to workload according to their skill, experience and preferences with subject to given constraints. The difficulty of handling this problem is due to the high number of constraints to be satisfied. The benefit of automating the roster is to produce a roster having high quality as well as more flexibility. It also reduces workload of head nurses with minimizes time and effort. This paper presents the Ant Colony Optimization Algorithm for the problem of automatically creating nurse rosters. The ACO algorithm is tested on real world benchmark instance and compared against previously available approaches. Evolutionary Algorithms are robust and effective method to solve combinatorial optimization problems.

Keywords- Nurse Rostering Problem (NRP), Ant Colony Optimization (ACO), combinatorial optimization (CO), Evolutionary Algorithm (EA).

I. INTRODUCTION

Nurse Rostering Problem consists of placing nurses or employees into slots in a pattern, where the pattern denotes a set of possible shifts defined in terms of task to be done subject to given constraints [1]. Nurse Rostering Problem is highly constrained combinatorial optimization problem. Most health care systems have head nurses or nurse managers, who are regularly responsible for constructing schedules, generally which are manually done. Creating roster is very challenging and tricky task for head nurse which require to satisfy possible constraints as well as to balance all requirements of health care system. Due to this rather than concentrating on crucial work of caring for patients, head nurse spend lot of time and efforts for creating roster. Automated roster can improve quality of roster by saturating fairness issue, preferences of staff, reduces paper work, reduces stress on head nurse, avoid understaffing and overstaffing, improve good quality of service.

Nurse Rostering Problem usually classified into two categories: hard constraints and soft constraints [2]. Hard constraints must be satisfied under any circumstances. However, Soft constraints can be violate at some circumstances but tried to satisfy as closely as possible to get optimal roster. Depending on importance of constraints weight is assigned to different constraints are different. Basically, roster is either cyclic or acyclic. The drawback of cyclic roster is lack of flexibility while acyclic roster is more flexible. Most of the Nurse Rostering Problems belongs to constrained optimization problem because it is impossible to satisfy every constraint.

In this work we presented population based algorithm i.e. Ant Colony Optimization algorithm. The algorithm is comes under Evolutionary algorithm category and showed to be efficient for solving combinatorial optimization problems [3]. Compared to traditional optimization techniques, Evolutionary Algorithms has some features that encourage for solving NRP. Features are: Evolutionary algorithm has stochastic in nature, global search capability, ease for implementation, very few parameters needed to be tuned etc. Ant Colony optimization algorithm tested on real world dataset that is publically available on link *www.cs.nott.ac.uk/~tec/NRP/*.

Rest of the paper structured as follow. Section II describes literature Review in detail. Section III delivers formulation of Nurse Rostering Problem. In section IV we have implemented Ant Colony Optimization Algorithm for NRP. In section V we have discussed experimental settings and Result analysis. Finally, in section VI, we have discussed concluding remarks and future scope for further improvement.

II. LITERATURE REVIEW

In last few years, different approaches have been proposed to solve Nurse Rostering Problem. The Nurse Rostering Problem (NRP) is a complex optimization problem of allocating nurses to duty rosters in health care systems. The NRP is increasingly becoming a crucial point in the world because of there is an increasing pressure of work in healthcare organizations. One possible way of easing this pressure is to develop better nurse rostering decision support systems that can help to produce rosters which utilize resources more efficiently. The main goal of the system is to create a roster by assigning shift types to skilled personnel members, in order to meet the requirements in a certain planning period.

Nurse Rostering problems have been solved using a variety of different mathematical and artificial intelligence methods. Due to the combinatorial nature of NRPs, heuristic approaches may be more suitable than the exact methods like constrained programming, mathematical programming, goal programming etc. in terms of solution efficiency, particularly for large-sized problems. A.T. Ernst, H. Jiang, and M. Krishnamoorthy [4] presented review of staff scheduling and rostering problems. According to the organization, constructing schedule for staff satisfies the requirements of their services. The artificial intelligence approaches like constraint programming, Mathematical programming [5]-[7], and metaheuristics are used to solve staff scheduling problems. These methods were able to deal with smaller size problem instances which do not considered preferences of nurses', qualifications, shift types or used very few constraints. B. Cheang, H. Li b, A. Lim B. Rodrigues [8] have taken the review of Nurse Rostering Problem, they defined NRP with various problem type also defined solution approaches for NRP like Mathematical Programming, Artificial Intelligence, Heuristics with advantages and limitations. In [9] they presented a genetic algorithmic approach to the solution of the problem of personnel timetabling in laboratories in which the objective is to assign tasks to employees where the objectives are to assign staff to particular day in planning period and minimization of personnel cost by avoiding overtime pay. Hybrid GA approach used in which Canonical genetic algorithm demonstrated very slow convergence to optimal solution. Hence, in laboratory personnel timetabling problem knowledge augmented operator introduced in genetic algorithm framework. The hybridization approach helps to get the near-optimal solution quickly with partial feasible chromosome representation; initialization and operators have shown fast convergence towards optimal solution with comparatively small population size. Ivo Blochliger [10] had given an introduction to staff scheduling problem. According to hospital type author described constraint in different types like sequence constraints, job constraints, hard constraints, and soft constraints. In [11] they have briefly reviewed and discussed a wide range of nurse scheduling papers that have addressed a large variety of models, methods and approaches to the problem. They mainly presented an overview of nurse rostering problem formulation and different solution methods. Wan Rosmanira Ismail, Liong Choong Yeun [12] proposed a Tabu search approach to the nurse scheduling problem. Authors focused on both hospital objectives and nurses preferences. To build up a computerized nurse scheduling system that utilizes effectively the nursing personnel. The approach is capable to construct very good solutions with few constraints. John S. Dean [13] implemented two genetic algorithms based on chromosome representation for staff-scheduling at health care systems. One solution uses a traditional bit-string chromosome structure to represent each schedule. The other solution uses a two- dimensional array chromosome structure to represent each schedule. Experimental results demonstrated that his two-dimensional array staff-scheduling performance was better than the bit-string staff-scheduling execution. Uwe Aickelin and Kathryn A. Dowsland [14] implemented a Genetic Algorithms approach for a nurse scheduling problem. Authors recognized that their solution suffer from being too dependent on problem-specific knowledge. In [15] they presented an alternative solution an indirect genetic algorithm, in that they overcome the limitations of the classical GAs pattern in handling the conflict between objectives and constraints. Here they used a different strategy for a GA approach; the problem-specific knowledge is moved out of the genetic algorithm code in which the individuals in the population do not represent direct encodings of solutions. Instead, solutions are obtained via separate decoder heuristics that build solutions from permutations of the list of available nurses using the constraints as guides. The advantage of this strategy is that the GA can remain canonical, i.e. it solves an unconstrained problem and does not require a problem- specific knowledge. The approach taken here is to use an indirect coding based on permutations of the nurses, and a heuristic decoder that builds schedules from these permutations.

Tai-Hsi Wu, Jinn-Yi Yeh, Yueh-Min Lee [16] described a Particle swarm Optimization Approach for Nurse Rostering Problem. Working shifts and rest period have not been evenly and fairly assigned to nurses, establishing a fairness base among nurses is the primary purpose of this study. Author did not cover holidays and leaves. Walter J. Gutjahra, Marion S. Rauner [17] described the ant colony optimization (ACO) approach applied to nurse scheduling problem in Austria. They considered a variety of hard as well as soft constraints, nurses' qualifications as well as preferences of nurses. Experimental result shows that ACO approach provides high quality solutions within a reasonable computation time compared with greedy approach. Nikola Todorovic and Sanja Petrovic [18], proposed a novel bee colony optimization approach to the nurse rostering problem. The bee colony optimization algorithm is motivated by the foraging habits of honey bees. The satisfaction of soft constraints determines the quality of a solution. For each soft constraint, there is a penalty associated with its violation. The objective function is the sum of the penalties of the violated constraints. Performance of the algorithm was evaluated on real-world data from hospitals in Belgium. The result shows that the bee colony optimization is able to efficiently find solutions that are competitive compared to the solutions produced by other algorithms like Memetic algorithm, scatter search, shift sequence approach, and variable depth search. For instances of smaller and medium sizes, it requires more time compared to the other methods, but the amount of time is reasonable. However, for the largest instances with more than 40 nurses, it was between two and ten times faster than the other algorithms. In [19] particle swarm optimization algorithm is used to solve real Anesthesiology Nurse Scheduling Problem. Proposed PSO algorithm is compared with Integer Programming and Constraint Programming. PSO algorithm gives solution with better work distribution than compared techniques. Edmund K. Burke, Jingpeng Li and Rong Qu [20] solved highly-constrained Nurse Rostering problem using hybrid multi-objective model that combines integer programming (IP) and variable neighborhood search (VNS). This paper is primarily focus on nurse's requests and qualification is not considered.

Edmund K. Burke, Timothy Curtois, Rong Qu, Greet Vanden Berghe [21] proposed a scatter search approach for Nurse Rostering problem. The objective is to find a roster that satisfies all hard constraints while minimizing soft constraint violations. For experimental analysis authors used standard BCV instances for solving Nurse Rostering problem. The experimental result shows that the proposed algorithm is a robust and efficient method for variety of real world instances. Yassine Saji, Mohammed Essaid Riffi, Belaid Ahiod [22] proposed Ant colony optimization (ACO) algorithm to solve Nurse Scheduling Problem. The main goal is to minimize the violations of the objective functions. To compute the performance of ACO algorithm authors used real data from two units of Hotel-Dieu hospital: Intensive Care Unit (SI) and Emergency Unit (URG). The ACO approach gives a feasible schedule, in terms of execution time and quality of solutions compared to the genetic algorithm. Patrick De Causmaecker, Greet Vanden Berghe [23] described Categorization of nurse rostering problems. Nurse Rostering Problem is classified into α|β|γ notations. These three notations refers description of personnel environment with information about the number of staff, their skills and preferences, description of Work characteristics with actual services including range, time interval for certain coverage constraint, minimizing the personnel cost and permit the distinction between various types of decision support system. Authors concentrated on problem related features but not to deal with solution approaches, or models.

III. PROBLEM DESCRIPTION

Nurse Rostering Problem is defined as allocating each nurse in healthcare system to specific planning days satisfying all hard constraints and as many soft constraints as possible. Hard and soft constraints can be different from one organization to another according to rules and regulations of healthcare system. Hard constraints provide feasibility to roster while soft constraints give quality to the roster. In this section we discuss hard and soft constraints, function evaluation and weights assigned to the soft constraints according to importance of constraints.

3.1. Hard Constraints

HC1: Exact demand (No understaffing or overstaffing)
HC2: A nurse can work at most one shift per day
HC3: A nurse must match the skills required for the shifts they prefer to work

3.2. Soft Constraints

Soft constraints reveal personal requirements, preferences and hospital's requirements. Quality of created roster depends on how many we can satisfy those constraints. Soft constraints considered in BCV 1.8.1 instance are presented in Table I with penalty.

No.	Constraints	Weight
SC1	Complete weekend	**20**
SC2	Maximum consecutive free days	**1**
SC3	Alternative shifts	**1**
SC4	Maximum number of shifts	**5**
SC5	No night shift before free weekend	**10**
SC6	Maximum shift types	**5**
SC7	Minimum time between shifts	**10**
SC8	Avoid certain shift succession	**6**
SC9	Maximum consecutive working days in week	**5**
SC10	Maximum number of working weekends in four Weeks	**1**
SC11	Maximum hours worked	**1**
SC12	Number of consecutive shift types	**10**
SC13	Free days after series of night shifts	**0**
SC14	Maximum shift types per week	**10**
SC15	Minimum consecutive working days	**1**
SC16	Same shift types for the weekend	**5**
SC17	Personal requests for day on	**0**
SC18	Personal requests for day off	**180**
SC19	Requested holidays	**1**
SC20	Maximum shifts of day of week	**1**

TABLE 1. CONSTRAINTS AND ITS WEIGHT

3.3. Objective function

Objective function of this work is minimizing the total penalty cost of soft constraints violation and satisfaction of all hard constraints is mandatory.

$$Roster\ penalty = \sum_{i=1}^{k}\sum_{s=1}^{n} C_s . g_s(x) \qquad (1)$$

Where,

i= index of nurse
k= number of nurse
s= index of soft constraints
n= number of soft constraints
c_s = Penalty weight for violation of soft constraints
$g_s(x)$= total number of violations for the soft constraint *s* in solution roster *x*

IV. IMPLEMENTATION

Ant Colony Optimization

Ant colony optimization (ACO) is a swarm intelligence population-based search method motivated in the social behavior of real ants [3]. ACO was introduced by M. Dorigo in 1992. To compute the shortest path from food sources to nests, the ants drop pheromone trail while walking and all other ants choose to follow a path where the amount of pheromone is higher. When ants search a food source, they carry it back to the nest and starts depositing the chemical. Other ants will tend to select a shorter path between food source and their nest, where there is higher quantity of pheromone. ACO approach consists of a colony of artificial ants with the characteristics to search good solutions to discrete optimization problems.

ACO is applied to solve Nurse Rostering Problem. The NRP is a task of assigning shifts to nurses for the duties that have to carry out. The efficiency of this algorithm will depend on the selection of parameters, trail update method etc. The pheromone structure is used in order to build up the search around the most promising areas, i.e., those that development contains the best feasible solutions with respect to the objective function.

The ACO algorithms have main steps as follows:

1. Initialization: The choice of parameters has a significant role in the performance of the algorithm and depends primarily on a set of input data. These parameters are the number of ants per colony, number of iterations, the evaporation rate ρ, α and β.

The Mathematical representation of solutions: The number of solutions X = (x_{ij}) the schedule matrix (two- dimensional)

2. Construction of solution: The probability of planning that an employee *i* work the day *j* by an ant from colony c (1… c) is given by:

$$p_{i,j}(x_i) = \frac{(\tau_{i,j})^{\alpha}.(\eta_{i,j})^{\beta}}{\sum(\tau_{i,j})^{\alpha}.(\eta_{i,j})^{\beta}} \qquad (2)$$

The parameters α and β are two constants that control the relative importance of pheromone trails beside the heuristic information. When updating pheromone trails, it is essential to decide on which of the constructed solutions (x_i) a quantity of pheromone will be laid.

The pheromone factor depends on the definition of pheromone trails; the heuristic factor depends on the objective functions of the problem.

At each iteration, the colony builds a solution that minimizes the objective associated to that colony.

3. Pheromone Update: The quantity of pheromone τ_{ij}^{c} is associated with the planning of working day *j* for an employee *i* under constraint to minimize objective function F_s is defined by

$$\tau_{i,j} = (1-\rho).\tau_{i,j} + \Delta\tau_{i,j} \qquad (3)$$

Where $\rho \in (0,1)$ is a parameter. After all the ants finish building their own solutions, a global pheromone updating rule is applied to restore pheromone trials.
The main objective function is to minimize the violations of soft constraints as much as possible (i.e. minimizing the overall penalty of roster) objective function describe in section III.

Ant Colony Optimization for Nurse Rostering Problem
The algorithm starts with a randomly generated set of ants called a colony and then each ant calculate its probability with fitness function. Finally update pheromone to compute best solution.
Begin
Initialization
Initialize all parameters (the number of ants in a colony, number of iterations, the evaporation rate ρ, α, and β) and pheromone trail to *τmax*.
While stopping criterion not met **do**
Place each ant in a starting node;
Repeat
For each ant **do**
Choose next node by applying probability $P_{ij}(t)$ with objective function

$$(F_s) = Min \sum_{i=1}^{n} w_i . g_i(x)$$

Apply local pheromone update;
End for
Until each ant has built a solution
Update best solution (**S**);
Select random position from current solution (**S**).
Apply mutation operator to generate new solution (**S'**) from current solution (**S**);
Update S with (**S'**);
Apply global pheromone update;
End While
End

ACO differs itself from other conventional meta-heuristic methods with the following advantages:
- Inherent parallelism;
- Positive Feedback accounts for rapid discovery of good solutions
- It provides an effective way to combine global search experience with problem specific heuristics using pheromone sharing;
- It utilizes indirect communication in learning and employs positive feedback to achieve fast convergence.

Limitations of ACO
- Theoretical analysis is difficult;
- Probability distribution changes by iteration;
- Time to convergence uncertain (but convergence is guaranteed);

The algorithm converges to the optimal final solution, by gathering the most effective sub-solutions. But as the iterations goes on increases convergence rate slow down. The use of mutation operator is for enhancing the algorithm escape from local optima.

Steps for mutation operator:
1. Select any one nurse in the colony.
2. If selected nurse is head nurse then assign head shift.
3. If selected nurse is regular nurse then assign any other shift than head shift.

IV. RESULT ANALYSIS AND DISCUSSION

ACO algorithm is tested using the BCV 1.8.1 standard benchmark data sets which are available on http://www.cs.nott.ac.uk/tec/NRP/. BCV 1.8.1 instance consist of 8 nurses, 28 days planning period, 2 skills (primary or head nurse and secondary skill nurse) and 4 shifts (day (D), Night (N), Late (L), Vroage (V)) etc. The proposed algorithms was coded in C language and implemented on a i5 processor 2.5 GHz personal computer with 2 GB RAM. Due to nature of heuristic algorithm, ten independent runs were performed for instance. After intensive testing we are found following parameter setting which are shown in table II. The achieved results of our proposed ACO algorithm are shown in table III. After intensive testing we are found following parameter setting which are shown in table II.

Colony Size	Iteration	Pheromone Rate	Alpha	Beta	Mutation Rate
300	1300000	0.1	0.1	1	0.3

TABLE 2. PARAMETER SETTING OF ACO

The ACO algorithm was also compared against the algorithms that had already been evaluated on the same data. For each technique, best and average results are presented. The ant colony optimization on average beats Shift Sequence, Memetic Algorithm, Scatter Search (SS), Bee Colony Optimization approaches. The results of all algorithms are taken from [18]. Result analysis shown in Table III.

Instance BCV-1.8.1	Best found in literature	Shift sequence	Memetic algorithm	Scatter search	Bee colony optimization	Proposed Ant colony optimization
Best Results	252	323	275	263	261	**253**
Average Results	-	-	285	268	264	278

TABLE 3. RESULT ANALYSIS OF PROPOSED ACO

The proposed ACO algorithm produced roster with the objective function values equal and less to the best known solutions. The ACO algorithm requires more number of iterations to generate optimal solution with large amount of time.

	ACO
Best	**253**
Average	278
Worst	310
Time (Sec.)	32993
Standard Deviation	27.40

TABLE 4. RESULT ANALYSIS

V. CONCLUSION AND FUTURE DIRECTION

This paper presented the implementation of ACO algorithm for Nurse Rostering Problem. Heuristic techniques are efficient and robust method to solve optimization problems. Experimental results show that ACO gives feasible solution. But it easily stuck at the local optima; In order to prevent such a phenomenon, it is important to implement operators that preserve diversity in the population. The mutation operator in genetic algorithms is used for enhancing the algorithm escape from local optima. Although many times Heuristic algorithms face problems like premature convergence and curse of dimensionality due to this require long time to find optimal solution. Further research is needed to solve NRP on GPGPU. GPGPU is helpful to reduce the computational time and improve the speedup of large application. Also try to solve the remaining BCV instances for further research.

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