Recent Advancements of Nurse Scheduling Models and A Potential Path

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Abstract. Nurse scheduling problem (NSP) has been a subject that is being studied broadly by both academician and practitioners, over the years. Nurse scheduling concepts are varied due to sophisticated and challenging real world scenarios in nurse management system. Moreover, the importance of solving nurse scheduling problems has triggered various approaches or techniques to solve these scheduling problems. In order to develop a good nurse scheduling model, it is crucial to comprehend the problem and the characteristics of the potential techniques so as to cope with the complex scheduling problem. Hence, the main purpose of this paper is to provide a rich literature on the diverse recent solution techniques in the NSP. Subsequently, an evolutionary trend of nurse scheduling models is identified as fruitful and thus, future directions of the scheduling technique are discussed. Finally, a potential algorithm is proposed to solve a nurse scheduling problem.

Keywords: Nurse scheduling, Personnel scheduling, Scheduling techniques, Hybrid Evolutionary Algorithm, Healthcare management

1 Introduction

Nurse scheduling concepts are varied due to the ongoing nurse shortage accompanying sophisticated and challenging real world scenarios in nurse management system. [13, 34] have same consensus that the seriousness of job dissatisfaction may improve turnover and absenteeism rate thus, may impose undesirable work schedules. Therefore, the importance of solving nurse scheduling problems has triggered various approaches or techniques to mitigate these scheduling problems. This paper is to provide a literature on the diverse classification of recent solution techniques in nurse scheduling problem.

Briefly, [40, 64] identifies 28 different categories of methods that have been used in personnel scheduling problems. These methods include optimization approaches (i.e. mathematical programming), constraint logic programming, constructive heuristic, expert systems, genetic algorithms, simple local search, simulated annealing, tabu search, knowledge based systems, artificial neural networks and hybrid systems. Based on [55], this wide range of approaches and techniques has been performed in nurse scheduling and classified into four categories which are optimization, search, constructive heuristics, and hybrid techniques. However, knowledge-based approaches are generally getting popular to solve rescheduling in 2000s. Hence, our research has added a line of artificial intelligent (AI) approach into [55] Razamin's four categories technique as discuss in the following sections.

2 Scheduling Techniques in NSP

2.1 Optimization Techniques

Optimization approaches are to perform optimization concepts which either maximizing or minimizing some objectives via mathematical programming (MP) [33]. For instance, MP approaches are able to achieve the lowest cost solutions for set covering scheduling problems [6, 50, 51, 62].

Single-objective mathematical programming such as integer programming (IP) [46, 13, 14, 16], linear programming (LP) [26, 50], nonlinear programming, and mixed-integer programming (MIP) [17, 22] are a technique which only optimizing a goal that is preferred by a decision maker. Essentially, single-objective MP methods have been preferably used in NSP since 1970s and 1980s which it can be referred in [33] work.

Typically, Linear programming is usually associated to operation research (OR) method in order to produce better exact solution. For instance, [3] applies bayesian optimization and do classifier systems for similar nurse rostering problems. The results were merely close to those produced by an optimal integer programming. Besides, the best known exact algorithm for linear integer programs is the branch-and-bound method due to the lower bounds can be found by linear programming relaxations or Lagrangian relaxations [15, 40]. For branch-and-bound method, branching on constraints as 'follow-on' branching strategy has been stated more efficient than branching on single variables in Ernst et al. paper. Furthermore, branch-and-price (B&P) approaches [13, 22, 11] have emerging as powerful techniques for solving large scale linear integer programs. Basically, part of these good performances [22, 15, 54] are due to the aid of decomposition approach. [22] used branch-and-price algorithm that repeatedly solves two different pricing problems. The first one involves the generation of the individual roster lines which is done using dynamic programming. For the second pricing problem, mixed integer programming model is used to search for a surgery schedule, with a corresponding workload pattern that appropriately fits the generated set of roster lines. As is known, mixed-integer programming (MIP) is used when the variables are mixed with real-valued and integer-valued. However, MIP is less efficient to treat the integer variable as real.

Typically, multi-objective approaches are viable for realistic aspect. It is flexible in weighting objectives by some priorities. In this sense, Goal programming (GP) is a better approach when they are multiple objectives or priorities that need to be achieved in a problem. As [6] applies 0-1 Linear GP model to account both hospital objectives (nursing skill and staffing size) and nurses preferences (fairness considerations). The hard constraints must be satisfied while soft constraints treated as goals to be achieved as many as possible.

2.2 Constructive heuristics

Constructive heuristics approach has no initialization solution and variables (staff) added in an iterative trial-and-error manner in order to satisfy every requirement [5]. For instance, [44] has developed a general project schedule based on the framework of Resource-Constrained Project Scheduling Problem (RCPSP/τ) model. Generally, RCPSP/τ can be applied to various types of scheduling problems. It has three main features. The first feature is the availability of the resources within a schedule horizon varies at unit time. The following feature is the consumption of the activity within its duration time varies at unit time. The last feature is the generalized precedence constraints. Horio has solved the 3-shifts nurse scheduling problem (NSP) and satisfied all the constraints.

Moreover, [52] has added constructive heuristics (CH) into several versions of Gas to solve reactive scheduling problem. Specific encoding and operators for sequencing problems are applied to the nurse rescheduling problems. Overall, it has proved successfully in nurse rescheduling. Nevertheless, the limitation was the problem of rescheduling must be tackled with both hard and soft constraints by developing multi-objective versions of the heuristics.

2.3 Search Techniques

Search Techniques have been widely studied and applied in nursing administration. Classical heuristics are attempted to heal worst schedule by exchanging a part of a schedule with a part from other person's schedule. Basically, they start with an initial solution then develop a greedy neighborhood search (traditional heuristic or classical heuristic) procedure to find local optima. Nevertheless, more recent, the modern metaheuristics have been used extensively to solve various scheduling problems. Metaheuristics approaches consist of tabu search (TS), simulated annealing (SA), genetic algorithms (GA), constraint programming (CP), problem space search, greedy random adaptive search procedure (GRASP), neural networks (NN), machine learning, reinforcement learning and ant colony optimization (ACO).

Tabu search (TS) is searching iteratively from one solution to another by moving in a neighborhood space with the assistance of an adaptive memory. Down to the adaptive memory function of tabu search, TS or TS based in hybrid technique has found more recent acceptance in solving nurse scheduling problems [38, 31, 53, 18, 23, 36]. During nurse scheduling implementation, tabu is proclaimed if the nurse does not belong to the skill category requirement or if the shift is already assigned. TS may effectively improve objective function value of subsequent solutions but its computational time used is much larger partly because its implementation is very much experimental. Besides, [36] had compared TS with GA in NSP. The result proved that genetic approaches are able to get slightly better quality of solutions then TS. However, what advance for TS is its more time efficient.

Simulated annealing (SA) is a generalization of a Monte Carlo method for examining the equations of state and frozen states of n-body systems. The physical process of annealing which liquids freeze or metals recrystalize in the process of annealing is an inspiration to SA method [46]. The slower the cooling schedule (rate of decrease) may direct the algorithm to a near optimal solution. However, the slow cooling process may be the cause of heavy computational time and thus less likely to be used in 2000s NSP. But still, SA is able to handle mixed discrete and continuous problem with its simple formulation, low memory requirement and efficient step-by-step cooling concept. For instances, [59] paper investigates the effectiveness of metaheuristic techniques based on local search in producing suitable schedules. This neighbourhood search uses a weighted cost function with the weights dependent on the importance of each objective. Moreover, it has also compared two methods which are Sawing and Noising with simulated annealing. The result demonstrates that Noising produces better schedules to overcome the difficulties of searching good solutions while setting the constraints' weights. Besides, [58] presented a comprehensive review of three single objective optimization algorithms (SA, SA with TS, and chaos simulated annealing (CSA)) and five multiobjective optimization algorithms based on SA. Basically, SA takes less CPU time than GA. However, this point-based method is more time-consuming than TS on complicated example. In all, SA is less successful to find feasible solution.

In an essential thought, Evolutionary algorithm (EA) can be described as Genetic algorithm (GA). They are a genetic evolution starting with a population by generating genetic representation of a problem (so that characteristics can be inherited), then randomly changing available solutions (parents) to generate and improve new solutions (strings, chromosome or individual) via simple operators (selection, crossover and mutation) [33, 4, 49]. The whole process is guided by the idea of the survival of the fittest and it is repeated until it met stopping criteria (for example a preset number of generations, CPU time, or limit population diversity to a certain threshold). In a nutshell, exploring the three simple operators is in light of the GA development [32, 49, 2, 39]. For instance, [49] has been introduced two new crossover (matrix binary crossover (MBX), whole arithmetical crossover) schemes and two new mutation (interchange between two rows, interchange two sites along a row) schemes. [2] evaluated three different decoders (cover decoder, contribution decoder, and combined decoder) with varying levels of intelligence and four well-known crossover operators (PMX, uniform order based crossover, CI crossover, and order-based crossover) in GA technique.

Essentially, there is no pre-defined way of including constraints into GA and feasibility cannot be guaranteed as well [2, 4]. Hence, there exist three common constraint handling methods in NSP which are special representation (encoding) and operators (crossover), repair function, and penalty functions [1]. Besides these common ways, multi-objective optimization techniques and stochastic ranking [7] are also used to deal with constraints. Since GA is a wary search technique in generating (by operators) and filtering solutions (by fitness evaluation). Thus, this approach has take times to produce feasible solutions. Among the comparison of search techniques, GA [2, 36] is proved to construct quite reliably work schedules with more flexible implementation but less time efficient than TS. However, GA and SA have equally computational time response. While both are unable to produce optimal solutions in every run but they do provide good enough solutions [8, 55]. Hence, the reviews show that GA is capable searching large search space but the limitation is less effective in identifying local optima in term of computational time and the quality of solutions. Therefore, few previous research are vigorously proposed hybrid of GA to cover its drawback, especially hybridizing with classical heuristic (local search, variable neighborhood search (VNS), etc) [1, 24].

Other search technique like scatter search is similar to memetic algorithms (MA) except the random decisions are replaced with intelligently designed rules, and solutions may be created from more than one parent [30]. [30] compared scatter search approach with constructive method (CH) and memetic algorithm (MA) in solving nurse scheduling problem. During the CH comparison, scatter search used the variable depth search as an improvement method. It found a better solution and less computational times. In addition, when compared with MA, the scatter search with hill climber improvement method found better solutions for 7 out of 10 instances in less time as well. These conclude that scatter search is a robust and effective method on a wide variety of real world instances.

Constraint programming (CP) has the propensity to work on highly constrained problems. In the 1990s, a number of papers used Constraint programming (CP) methods to model the complicated rules associated with nurse rosters [33, 60]. The methods were applied to problems which involving cyclic and non-cyclic rosters. In an advancement, Constraint logic programming (CLP) is a generational of CP, in which aided with logic programming to include concepts from constraint satisfaction. [61] states that high-level nature of logic programming is augmented by the seamless integration of one or more constraint solvers thus allowing the ease of modeling the problem and its constraints declaratively. In depth, the power of constraint logic programming is relative easily to express complex constraints and construct suffice feasible solutions, although it is not really optimal [33, 40]. Lack of effectiveness in finding an optimal or near optimal solution from a vast number of feasible solutions is an undesirable drawback. And thus, this reflex the fact that [40] affirms more research is required to hybrid the flexibility of constraint logic programming with optimization techniques to conquer CP's weakness.

An unfamiliar approach, Hyper-heuristic, is a high-level heuristic approach which adaptively chooses low-level heuristics in order to solve a given optimization problem. This generic method is easily re-usable for other problems and other domains [57, 35, 7]. For instance, [57] has applied a choice function hyperheuristic for an NP-hard problem in scheduling nurses. In this study, highly problem-specific information is utilized to compare both tabu search and genetic algorithms performance. As the result, the choice function hyperheuristic proved to be more reliable than both direct and indirect genetic algorithms and as robust as tabu search. Unfortunately, thus far the hyperheuristic may only include low-level heuristic but not sophisticated low-level heuristics.

2.4 Knowledge-based approaches

Knowledge-based approaches are increasingly used in health care industry that critically relies on knowledge management activities. Knowledge-based technique collects data that representing related experiences. Solution is supported and enhanced by retrieving from the storage that is related to the problems [45]. Hence, the whole process idea is deal with creation, storage, transfer, and application. Below are some knowledge-based approaches that have been applied in nurse scheduling and rescheduling problems.

Neural network (NN) is simulating intelligence by attempting to reproduce the types of physical connections. [5] used Hopfiled neural network with binary neurons whose output states take values either 0 or 1 as a new procedure for solutions which satisfies the indispensable requirements of Nurse Scheduling Problem (NSP). Nevertheless, the scheduling results may merely support constraints that are limited to basic requirements. Additionally, it is difficult to apply in NSP because nurse scheduling table requires three-dimensional allocation. Hence, it is reasonable that some combinatorial optimization problems as Traveling Salesman Problem can be solved easily by plane structured neural networks due to some similar network characteristics.

Generally, case-based reasoning is done by storing observed scheduling matters, retrieving and performing these moves or repairs whenever the situation is encountered again [20]. Hence, it is more likely to be used for rescheduling problem. For example, case-based reasoning has been tested on complex real-world data from a UK hospital [21]. However, this approach avoids the use of evaluation functions, but it aims to imitate how an expert human scheduler would produce a good schedule. Hence, the authors suggested a method in which it could be combined with a metaheuristic approach to solve nurse scheduling problems effectively. Furthermore, in 2006, Beddoe and Petrovic [19] used this novel method again to capture nurse rostering decisions and adapt it in new problems solving. This method stores examples of previous encountered constraint violations and the operations that were used to repair those problems.

2.5 Hybrid techniques

As is known, every technique has its pro and con. Taking its consideration of each good element to a combination will produce a better outcome. Hence, generally, hybrid techniques are more efficient to solve NSP in this decade. As [27] cited there is always the possibility of hybridizing early approaches (or some features of early approaches) with more sophisticated modern techniques to produce even better methods.

Essentially, TS approaches have widely been hybridized to solve many combinatorial problems [33, 37] overcame nurse scheduling problem by using a hybrid systems which is the combination of classical Integer Programming (IP) algorithms and tabu search (TS) heuristic. This algorithm has successfully released the manually burdens of senior nursing staff from handling a time-consuming administrative task. Furthermore, there was a paper presented a hybrid AI approach for a class of over-constrained NSP. This local search and tabu search hybrid approach were applied to improve the solution which satisfies all hard rules and the preference rules as far as possible. This hybrid approach is based on a neighborhood structure for vertical exchange of shifts. The study shows that this hybrid approach is able to solve this class of NSP quickly [48]. Besides, [28] proposed a hybrid memetic algorithm which is integrating TS procedure within the framework of GA into NSP.

Besides, [43] states local search techniques have used in GA as mutation operator, create offspring solutions by means of elaborated encodings and crossover operators. It additionally applies diversification strategies to the algorithm to avoid premature convergence. Moreover, a hybrid GA is used in [1] to obtain solutions for nurse scheduling problems. This approach has further sophisticated to an Indirect Genetic Algorithm. It was also proposed by [2] to solve constrained problems and evaluated three different decoders with varying levels of intelligence as well as four well-known crossover operators. This approach used an indirect coding based on permutation of the nurses and a heuristic decoder that builds schedules from these permutations. The result found that indirect GA proved to be more flexible and robust than Dowsland's Tabu Search in 1998 [38]. However, the results of the parameterized uniform order crossover (PUX) operator experiments suggested that more disruptive operators may help out feasibility, but it also may affect solution quality if it is too much disruption. Hence, this appears a question of balance between disrupting long sub-strings and inheriting absolute positions from parents.

Moreover, there is a new hybrid technique namely GCS/Simplex solver which is incorporating Simplex method into the Guided Complete Search (GCS) framework for some difficult nurse rostering problem instances. This hybrid technique [41] is a general constraint satisfaction problems solver and it solved NSP via evaluating both computational time and number of fails. Hence, GCS/Simplex solver is viable to solve all different and cardinality constraint efficiently.

[29] hybridized heuristic ordering with variable neighbourhood search (VNS) for shift un-assignment and repair task in NSP. The used of heuristic ordering method has been shown to be an efficient and effective method of exploring the search space. High quality schedules can be found when it has combined with the VNS. In the study, back-tracking was able to find fast and better solutions by reducing the exploration of paths which only led to poor quality solutions. Even though the results produced by this algorithm are good, still there are areas that could possibly need to be improved and explored. Especially if it was being designed to run over a longer time period than one hour. Generally, it is often difficult for heuristics to cope with conflicting hard and soft constraints in a computationally efficient manner.

For the objective of utilizing available nurse and quantify the resultant benefits, hybrid case-based Reasoning (CBR) with integer programming (IP) has been used in [9]. In this paper, the problem is modeled by IP and at last solved with CBR technique that relies on intelligent heuristics to identify better candidate solutions. Besides, [19] integrate CBR and GA to solve unexpected changes problems for nurse's schedule management. Case-based repair generation (CBRG) increased the quality of repair by ensuring the repair types, and the subsequent nurses, days and shift involved are more likely to the constraint violations. Conversely, the GA technique is developed for off-line feature selection and weighting using the complex data types needed to represent real-world NSP. It significantly improves the accuracy of the CBR method and reduces the number of features that need to be stored for each problem. However, the efficiency of the method must be gained by improving the fitness evaluation for approximating chromosome fitness.

Table 1: Techniques for nurse scheduling and rescheduling problem

Year	Authors	Optimization	Construc-tion based	Search	Knowledge based AI	Hybrids
2000	Aickelin & Dowsland					GA+H
	Dowsland & Thompson					TS+IP
	Cai & Li			GA		
01	Burke et al.			MA		
	Brusco & Jacobs	ILP				
03	Soubeiga			HH		
	Li et al.					H+LS+TS
	Dias et al.			TS, GA		
04	Aickelin & White					GA+IP
	Aickelin & Dowsland			IGA		
	Isken	IP				
	Winstanley					CLP+AB
	Moz & Pato	binary LP				
	Bard (04b)	MIP				
	Bard (04a)	IP				
05	Bard & Purnomo (05a)	IP (B&P)				
	Azaiez & Al Sharif	0-1LinearGP				
	Bard & Purnomo (05c)					CGB+IP
	Bard & Purnomo (05d)					CGB+IP+H
	Matthews	LP				
	Bard & Purnomo (05b)	IP				
	Horio		CH			
	Fung et al.					GCS/SS
	Akihiro et al.				NN	
	Brucker et al.		CH			
06	Beddoe & Petrovic					CBRG+GA
	Suman & Kumar			SA		
	Belien	MIP(B&P),DA				
	Bard & Purnomo	IP(B&P)				
	Belien & Demeulemeester	IP(B&P)				
	Dowsland et al.			GA		
07	Moz & Vaz Pato					GA+CH
	Bard & Purnomo	IP(LR)				
	Burke et al.			EA(SS)		
	Burke et al.					H+VNS
	Punnakitikashem	DA				
	Thompson			LS,SA		
	Bai et al.					GA+SA HH
	Baumelt et al.			TS		
	Beddoe & Petrovic					CBR+TS
	Bester et al.			TS		
	Majumdar & Bhunia			GA		
08	Chiaramonte				AB	
	Vanhoucke & Maenhout	IP				
09	Brucker et al.					CH+LS
	Goodman et al.					GRASP

Representations of abbreviations: GA=Genetic algorithm, H=Heuristic, TS=Tabu search, IP= Integer programming, LP= Linear programming, MA=Memetic algorithm, ILP=Integer linear programming, HH=Hyper-heuristic, IGA=Indirect GA, CLP=Constraints logic programming, AB=agents-based, LP=Linear programming, MIP=Mixed integer programming, B&P=Branch & Price, CGB=Column generation based, GCS/SS=Guided complete search/Simplex solver, NN= Neural network, CH=Constructive heuristics, CBRG= Case-based repair generation, CBR=Case-based reasoning, SA=Simulated annealing, DA= Decomposition approach, SS=Scatter search, VNS=Variable neighborhood search, LS=Local search, GRASP= Greedy random adaptive search procedure

3 Future directions of scheduling techniques

In 1990s, local neighborhood search or extensions such as simulated annealing can be imbedded in genetic algorithm to enhance performance [56]. By the late 1990s, Evolutionary Algorithms (EAs) are majority used in tour scheduling heuristics. However, in 2000s, the development of EA for tour scheduling problems has been changed as showed in [34]. Presently, the EA hybridization has not only with local search series but also been expanding to Particle swarm optimization (PSO), Case based reasoning (CBR), Ant colony optimization (ACO) and others. The hybridization of evolutionary algorithms is getting popular and is carried out in various ways due to the challenging of formulating a universal optimization algorithm that able to solve variety problems. As [27] clearly exhibited the incorporation concepts of modern hybridized artificial intelligence (AI) and operations research techniques. With some problem specific information, they are able to form out successful solutions for real world implementations. Thus, based on the problem solving perspective, hybridization may be the key to solve practical problems and acquire the attention of future schedulers.

4 Proposed a potential algorithm

Cooperative architecture is a minor hybridizing system where the hybrid method is not required for proper functioning of the system. It is only aided in parameters determination or the initialization phase of Evolutionary algorithm (EA). Though, it seems like merely a small part of hybridization. However, this architecture may obtain flexible ability to include different techniques' greatness into evolutionary approach. Therefore, our proposed model is classified as cooperative model.

Moreover, EA can operate more than one solution at a time. This is because the technique explores different regions of search space to gradually enhance performance. The search operators are always deal with the population selective pressure, convergence issue, randomization and diversity, which all are merely committed to exploration and exploitation. In fact, these two strategies are contradictory. Therefore, a balanced employ of them is essential for achieving an efficient cautious search. Attributable to these principles and concepts, EA has potential to support the difficulties of scheduling and rescheduling task.

In depth, we propose a hybridization technique to solve nurse scheduling and rescheduling problem. EA will be the well suit preprocessor method of choice, and a promising technique cuckoo search component of [63] is incorporated. The purposes are to improve the performance of the EA (such as speed of convergence, reliability and accuracy) but not re-invent wheel, and to improve the solutions' quality. This proposed model will focus on enhancing the initial population and crossover operator performance. It is envisioned that the hybrid EA would remain diversity of search but forsake the high frequent of producing infeasible solution, and may inherit high properties of their parents.

The model will randomly generate initial solutions for the initial population. The chromosome representation is non-binary matrix representation. Both hospital requirements and nurse preferences are considered in the system thus, fitness values, objectives and constraints are defined. Next, a new cuckoo parent selection operator is used to select potential parents in order to get high diversity by undergoing a low selective pressure. If cuckoo egg (individual, Ic) is not discovered (Rand $\geq P_a$), the higher fit individual is accepted as parent1, whereas P_a is a fix number of fitness increasing rate, Rand is calculated by $[(I_c - I_A)/I_A]$. Else, retune I_C to the population and random pick again for parent2. Subsequently, the pair of selected parents is passing to crossover operator to form new children. In this stage, we propose a new crossover operator named Block-wise crossover operator which is randomly crossed by a block or sector of the chromosome. The randomly selected blocks are based on workstretch (excluding night stretch and weekend off shift). Moreover, guided mutation and steady-state replacement as had been used in [53] will be adopted in this on-going research. The following is a general structure chart of our proposed algorithm for nurse scheduling problems.

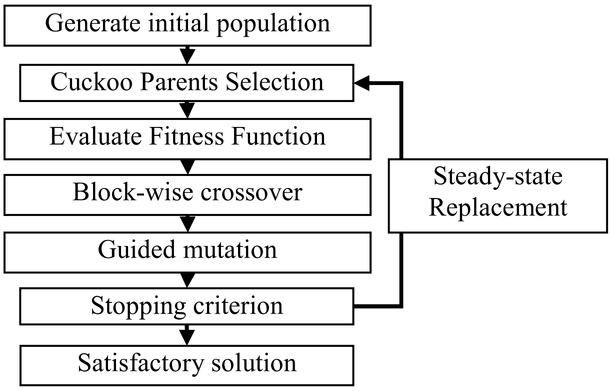

Fig. 1. Hybridization of Evolutionary Algorithm and Cuckoo Search structure chart

5 Conclusion

In all, with no doubt, nurse scheduling process is playing an important role in healthcare institutions around the world. Hence, they are few decades of studies that applying various techniques or algorithms to develop effective nurse schedule which from exploring optimization methods to search methods. Thus far, hybridization search techniques are the most well-liked approaches for nurse scheduling arena in 2000s.

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