CHAPTER II

LITERATURE REVIEW

2.1. Importance of Healthcare Services

Healthcare is one of the important factors in public services. It receives focused attention from both international institutions and national government. The United Nation (UN) through its World Health Organization (WHO) has put up proposals for Sustainable Development Goals (SDG), with focus on health as one of the target achievements (Schmidt et al., 2015). All countries around the world, including Indonesia, are well aware of healthcare importance for their citizens.

The government of Indonesia has raised healthcare awareness in the country by providing increased healthcare budget. In 2015, out of the National Budget, the budget for healthcare was increased by 43% from IDR 74.3 trillion IDR to 106.1 trillion IDR (Kompas Health Care: 2015). The Minister of Health, Nila Djuwita F. Moeloek has emphasized that from 2015 onwards, the government has declared the focus on preventive actions in order to maintain people's health. The preventive actions have increased the life expectancy of people, i.e. the average number of years of people's life. In 2002, life expectancy is around the age of 68, whereby in 2012, it has increased to the age of 71 (Kompas Health Care: 2015).

2.2. Importance of Scheduling

Scheduling has contributed a significant factor in many of manufacturing and service industries (Pinedo et al., 2015). Pinedo in his paper categorizes scheduling into static and dynamic. Static scheduling is the kind of schedule that is least likely to change over a certain period of time. Real life examples of static scheduling are in transportation service, particularly flight schedules of airlines. Given that static schedules remain unchanged for a long period of time, a long processing time is acceptable in order to achieve optimized schedules. To the contrary, dynamic scheduling is expected to change dynamically in a shorter period of time, for example weekly, thus processing time is expected to finish in a shorter time. Real life examples of dynamic scheduling are workforce scheduling in consulting firms, call centers, support centers and hospitals.

Ineffective or over/under assignment of resources have impact on resources' performance and operational costs. Over the last decade, hospitals have to deal with financial pressure due to the rising cost of hospital operations (Erhard et al., 2017). On average, more than 50% of hospital services expenses are derived from the costs of workforces (Bolt, 2014). Therefore, optimal resources allocation will benefit the hospital and its operation.

There are many resources involve in providing services to patients in hospitals, i.e. physicians, residents, nurses and administrative staffs. Each role has its designated function, in which all functions together to compose an integrated service to patients.

2.3. Scheduling for Physicians

Physicians' contributions to hospitals are crucial, thus scheduling for physicians plays a significant factor to hospital's healthcare service. Physician scheduling stands out from other resources in hospitals due to multiple aspects involved (Erhard et al., 2017):

- Physicians, by law, are eligible to have collective labor contracts with several hospitals.
- Physicians' turnover in a hospital has become one of the most critical challenge (Gunawan & Lau, 2009).

Physicians' scheduling fall under the category of dynamic scheduling. It is important in the scheduling that physicians' constraints are captured and addressed accordingly in order to provide excellent service to patients. There are implications of balancing between physicians' obligations, preferences and fairness that make physicians' scheduling becomes critical to hospital operations. (Erhard et al., 2017). Inefficient scheduling of physicians can also cause bottleneck in the healthcare services (Santos & Eriksson, 2014).

According to Aiken et al. (2002), resources dissatisfaction and absences due to illness or burnout are potential consequences of unmanageable workload. Therefore, it is crucial for healthcare providers to optimize their existing resources while delivering healthcare services to patients. One of the important elements is through optimum schedule of hospital resources.

2.4. Mathematical Models for Physician scheduling

Erhard et al. (2017) in his review paper summarizes approach of previous researches in solving physicians' scheduling problem. The use of Mathematical Programming that includes Linear Programming (LP), Integer Programming (IP) and Mixed Integer Programming (MIP) are mostly applied by popular researches, especially to solve scheduling problems. Physician scheduling problem is considered a tactical task that involves physicians' assignments for their duties over a horizon of time with some constraints to be considered (Gunawan & Lau, 2010). Objective of the scheduling is to fulfill the constraints and duty requirements imposed by the hospital and regulations and come up with an optimal schedule to utilize resources and to balance their assignments . Parameters affecting scheduling can either be hard or soft constraints; financial or non-financial. Erhard et al. (2017) specify contributing parameters involve:

- People related measures; such as reduction of overtime hours, fair distribution of workload, unfavorable shift or weekends off, fulfillment of preferences for days off duty and job satisfaction.
- Patients related measures are relevant for patients' handoffs, which should be avoided as much as possible or minimized. Examples of handoffs are cancellation of surgery appointment or waiting time.
- Hard constraints enforced by legislation or hospital management, such as:
    - Meeting demand, where certain level of care has to be covered in every period in the planning horizon.

- One shift restriction, where a physician could only be assigned to one shift in each period, at most.
- Avoid backward rotation, such as night shifts followed by morning shift on the next day.
- Window of minimum rest, i.e. a minimum duration of rest between two shifts.
- Shift limits, i.e. limitation on max number of shifts in a period.
- Working hours, i.e. number of working hours regulated by Ministry of Manpower.

- Soft constraints are associated to personnel's preferences with examples below:
    - Stable rosters, i.e. no or minimum roster changes preferred.
    - Stretched working hours, i.e. preferred stretched hours before taking days off.
    - Weekends off.
    - Weekdays off after working on weekends.
    - Night shift limits, i.e. setting max night shifts preferred.
    - Forward rotations, with day-shift following morning shift, or night shift following evening shift.
    - Shift duration limit i.e. preferred max duration.
    - Fairness, by fair assignment to all team members on unfavorable shifts.
    - Approved requests, i.e. vacation/days off requests.

    - Joint weekends i.e. preferred both Saturday and Sunday on duty.
    - Equal distribution of weekends.

Physicians level of seniorities and specialties in a hospital ranges from juniors, seniors to professors. Each level of seniorities has specific assignments involved. For example, juniors will be assigned for more tasks' rehearsals than the senior ones, to exhibit competency over tasks repetition. Thus, competency learning and team composition is often included in the physician scheduling model (Erhard et al., 2017).

Erhard et al. (2017) in his review paper suggests modeling approaches as follows:

- Physician categories: general and specialized doctors.
- Shift types: predefined.
- Break window.
- Fairness: evenly distributed workloads, shifts and balanced soft constraints fulfillments.
- Uncertainty, e.g. personal emergencies, extended surgery durations, absence, stochastic demands.

2.5. Methods for Solving Physician Scheduling Models

Erhard et al. (2017) in their review paper conclude that there are two options to solve physician scheduling problem:

1. Using exact algorithm provides high optimization. For small number of constraints and simple model, exact algorithm can be applied.

However, for complex and huge number of constraints, the trade-off for optimal solution is long processing time.

2. On the other hand, heuristic approach provides solution to problems with complexity and huge number of constraints in much less time compared to exact algorithm. However, the trade-off is less optimal solution.

As the size of constraints and the complexity of problems increase, exact algorithm takes considerable amount of time to solve. Therefore, heuristic algorithm is proposed, which can considerably reduce the processing time significantly. In the following sub sections, we will review some heuristic algorithms in order to understand strengths and weaknesses of each algorithm and find the most suitable one applicable to the model that will be composed for the physicians' scheduling problem in the selected hospital for this research.

2.5.1. Genetic Algorithm (GA)

Alharbi & Alqahtani (2016) in their study presented a Genetic Algorithm (GA) to solve physician scheduling problem in the Pediatric Department of Prince Sultan Military Medical City (PSMMC) in Riyadh Saudi Arabia. The physician scheduling model is defined with number of doctors (D) for number of days (N), where a day is split into 3 shifts of Day (d), Evening (e) and Night (n). Each doctor will have some Off-Days (o) also. Hard constraints are defined to regulate restrictions of 'd', 'e', 'n' and 'o' for each physician.

GA uses cost bit matrix that plots a violation in each cell. Whenever a violation exist, penalty applies. Each violation has some Cost (C_i) and Weight (W_i) associated to it. Total Penalty (P) is a function of:

$$P = \sum_{i=1}^{n} (C_i \times W_i) \tag{1}$$

The goal of GA algorithm is to obtain the minimum value of Penalty (P) that suits the physician scheduling problem.

The study shows that the automated scheduling using GA algorithm has improved the processing time for physicians' scheduling that adhere to the constraints, i.e. mandatory fulfillment of hard constraints and optional fulfillment of soft constraints. Average processing time using GA takes around 3.45 minutes compared to few hours of processing time using the traditional manual approach. The study concluded that GA is proven faster than the traditional manual approach and the quality of the schedule satisfying the constraints is better.

2.5.2. Particle Swarm Optimization (PSO)

Lo & Lin (2011) conducted a research on Physician Scheduling for a Hospital Emergency Room in Taiwan using Discrete Particle Swarm Optimization (DPSO) approach. Discrete approach is chosen over the original PSO since physician scheduling problem is considered non-continuous optimization problem, thus Discrete PSO is more appropriate. The goal of algorithm is to automate physician scheduling process and produce shift assignments for physicians that fulfill hard constraints mandatorily and fulfill soft constraints optionally.

PSO core technology is inspired by the behavior of birds or fish that flock around, moving from one place to another. PSO algorithm starts with random population which will then be generated iteratively until an optimum result is achieved. The population moves in the trajectories with the velocity computed by the equation below:

$$V_{s,t} = w_t\, V_{s,t-1} + c_1\, r_1 \left(P_{sbest} - P_{s,t-1}\right) + c_2\, r_2 \left(P_{gbest} - P_{s,t-1}\right) \qquad (2)$$

where:

$V_{s,t}$: velocity of particle-*s* at iteration-*t*

w_t : inertia weight at iteration-*t*

$V_{s,t-1}$: velocity of particle-*s* at previous iteration *t-1*

c_1, c_2 : constant values

r_1, r_2 : random values generated between 0 and 1

$P_{s,t-1}$: position of particle-*s* at iteration *t-1*

P_{sbest} : local best for particle-*s*

P_{gbest} : global best for the entire swarm

The original PSO algorithm is developed to solve continuous optimization problem, with dimension value ranges from 0 to 1. However, in the case of physician scheduling, the dimension of the space in which swarm particle flies are not continuous. Therefore, Lo and team decided to use Discrete PSO, which was proposed by Kennedy & Eberhart (1997).

Using Discrete PSO to solve physician scheduling problem can be done in two approaches:

1. Use constraint handling method that reject infeasible solutions until feasible one is achieved. This approach normally takes quite long duration to reach to feasible and optimal/near optimal solution because there are many constraints, both hard and soft.

2. Use penalty function method to charge for some penalty when violations of constraints are encountered. With this approach, constraints/restrictions can be weighed according to their importance. Those constraints that are more critical to be fulfilled can be weighed higher than the ones less critical, particularly for soft constraints which are optional. The goal of running the algorithm is to minimize total penalty charged from violating soft constraints.

The formula for Total Penalty (Z):

$$\min Z = \sum_{k=1}^{n} (Rule_k \times \text{penalty}_k) \qquad (3)$$

where:

Rule_k: the number of times Rule_k is being violated.

penalty_k: the cost of violating the Rule_k

Table 2.1 below illustrates sample of Restriction Rules (constraints) and the penalty charge when a rule, being a hard/soft constraint, is violated.

Table 2.1. Physician Scheduling Constraints

Rule ID	Constraint	Rule Definition	Penalty
Rule 1	Hard	Physicians' working hours cannot exceed 8 hours/day	100
Rule 2	Hard	Max working hours for physicians is 48 hours/week	1000
Rule 3	Hard	Total working hours of physicians per week cannot be less than 16 hours	1000
Rule 4	Hard	Physicians cannot work straight in 6 consecutive days	1000
Rule 5	Soft	After a night shift, physicians are recommended to take 2 days-off, when possible	10
Rule 6	Soft	Avoid pattern of off-day-working day-off day, if possible	10
Rule 7	Soft	Standard deviation of bonus for each medical dept. should be less than 50	1000
Rule 8	Soft	Pre-reserved shift requests should be fulfilled as much as possible	1000

Rule 9	Hard	Consecutive off-days cannot be more than 5 days	MAX
Rule 10	Hard	Minimum manpower demand per shift must be met	MAX

The research conducted by Lo and team confirmed that using penalty method indeed speed up the processing time in finding optimal/near optimal physician scheduling solution using Discrete PSO algorithm.

2.5.3. PSO Advantages Over GA

Shen et al. (2004) study the two heuristic algorithms and suggest that PSO has advantages over GA. In GA, there are evolution parameters such as crossover and mutation involved. In PSO, particles fly in the search space according to their local and social (global) experiences, based on the calculation of the velocities. They move and adjust their positions based on their local (neighbor) position and the global best position. Therefore, PSO is proven to have more profound intelligent background compared to GA (Wang et al., 2008). In recent decade, PSO has been recognized as one of the promising algorithms due to its characteristics of simple concept, easy implementation, fast convergence, robustness to control parameters and its computation efficiency (Bansal et al., 2011, Patwal & Narang, 2018). PSO has the potential to be processed quickly to find optimal solution in a limited space (Lo & Lin, 2011).

2.6. Binary Particle Swarm Optimization Algorithms

Provided that the model of physician scheduling is in binary bits of 1s and 0s, further studies are done on binary PSO. There have been several researches conducted on BPSO. The particles move in the direction of velocity vector that will change a bit from 0 to 1, vice versa or unchanged (Camci, 2008, Kennedy & Eberhart, 1997).

2.6.1. Binary PSO with Sigmoid Logistic Transformation

Kennedy & Eberhart (1997) introduce binary PSO to optimize pure discrete binary combinatorial problem. The search space in BPSO is illustrated as in hypercube, where a particle may move near to or farther apart from the corners of the cube by flipping the bit values (Hossein, Majid, & Malihe, 2008). They design the particles to take the values of binary vectors and the velocity to determine probability of bit-x to take the value of 1. Sigmoid Logistic transformation is performed on the velocity through below equation (4) and the next bit value is determined by x, defined in equation (5).

$$S\left(V_{s,t}\right) = 1/(1 + e^{-V_{s,t}}) \tag{4}$$

$$x = \begin{cases} 1 & if\ r_3 \le S(V_{s,t}) \\ 0 & otherwise \end{cases} \tag{5}$$

Binary PSO with Sigmoid Logistic Transformation has been implemented in various problems, such as Maintenance Scheduling for generators (Kumarappan, 2015), Unit Commitment of power systems (Shi & Eberhart, 1998), wind power and energy storage systems (Tan, 2014).

2.6.2. Novel Binary PSO

Novel Binary PSO differs from the native BPSO with Sigmoid Logistic Transformation in the formulation of the velocity that determines the probability of changing the next bit (Camci, 2008). Novel BPSO introduces two velocity values $\left(V^1_{s,t}, V^0_{s,t}\right)$ defined in equations (6) and (7) below. When bits of particle $P_{s,t}$ are 1s, $V^0_{s,t+1}$ is used. When bits of particle $P_{s,t}$ are 0s, $V^1_{s,t+1}$ is used:

$$V^1_{s,t} = w_t\ V^1_{s,t-1} + (-1)^{1-P_{sbest}}\ c_1\ r_1 + (-1)^{1-P_{gbest}} c_2\ r_2 \quad (6)$$

$$V^0_{s,t} = w_t\ V^0_{s,t-1} + (-1)^{P_{sbest}}\ c_1\ r_1 + (-1)^{P_{gbest}} c_2\ r_2 \quad (7)$$

where:

V : velocity
w : inertia weight for iteration-t
s : particle-s
t : iteration-t
c_1 , c_2 : positive constant values
r_1 , r_2 : random numbers between 0 and 1
P_{sbest} : bit value of local-best position of particle-s
P_{gbest} : bit value of global-best position

Once the velocity is calculated, the new value of the particle bit is set. If the randomly generated r_3 is less than the velocity $V_{s,t}$ then the bit is defined as the complement of previous value. Otherwise, the bit is unchanged. Refer to equation (8) below.

$$x_{i,j,k}(t) = \begin{cases} \overline{x_{i,j,k}(t-1)} & if\ r_3 < V_{s,t} \\ x_{i,j,k}(t-1) & otherwise \end{cases} \quad (8)$$

2.7. Conclusion

Metaheuristic algorithms have been widely used by researches to solve optimization problems. Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are being reviewed and it is proven that PSO has more advantages than GA due to ease of implementation, robustness and computational efficiency. Provided that the physician scheduling is implemented in binary, Binary PSO is applied. Two BPSO algorithms of Native BPSO with Sigmoid Logistic Transformation and Novel BPSO are experimented. Each algorithm has its own formula to calculate velocity vector of the particle's movement and its own unique definition to determine its next bit position.