# Patient Scheduling in Hemodialysis Unit Using Simple Heuristic

A. Sundar <sup>1, a)</sup>, N. A. A. Rahmin \*, 1, b), C. Y. Chen <sup>1,c)</sup> and M. A. Nazihah <sup>1,d)</sup>

<sup>1</sup> Mathematics Department, Faculty of Science, University of Putra Malaysia, 43400, Serdang, Selangor.

<sup>a)</sup>ashweenasundar@gmail.com, <sup>b)</sup>aliza@upm.edu.my, <sup>c)</sup>cychen@upm.edu.my, <sup>d)</sup>nazihah@upm.edu.my

\*Corresponding author

## **ABSTRACT**

This paper study a patient scheduling and nurse assignment problem in the hemodialysis unit. A long waiting time can cause dissatisfaction among patients, and it might affect their health condition. We aim to minimize the waiting time before and after the dialysis treatment by considering patients' satisfaction. As the model consumes a high computational time to solve for a large-scale instance, we developed a simple heuristic to deal with the problem. The results show that solutions obtained by the simple heuristic are of good quality and has significantly reduced the computational time even when considering more patients on the waiting list.

Keywords: Patient Scheduling, Nurse Assignment, Simple Heuristic, Multi-Objective Model

#### INTRODUCTION

(Coresh et al., 2007) highlighted that recent research has reported an increased prevalence of chronic kidney disease (CKD) worldwide. CKD consists of five stages and the last stage is end-stage renal disease (ESRD). These ESRD patients mostly rely on dialysis treatments for their survival. Hemodialysis (HD) is a common treatment among ESRD patients, and it is performed in a clinical setting thrice a week for several hours where the patient is connected to a machine via vascular access. In treatment, a patient should be served for various types of dialysis treatment as per their health requirement. Additionally, the patients may have their preferences including the desire for short treatment times and preferred starting times during the day. On the other hands, dialysis facilities pursue planning the treatment efficiently by optimizing resource utilization for the best patient outcomes. These requirements make the patient scheduling process very challenging. Patient scheduling which is done in dialysis units worldwide can be defined as assigning patients to scarce resources and time slot to achieve some objectives. This paper focused on patient scheduling and nurse assignment to minimize the waiting time before and after the dialysis treatment by considering patients' satisfaction. A multi-objective model from (Fleming et al., 2019) is referred to develop a heuristic to solve the patient scheduling problem. A simple heuristic (SH) is used to solve the patient scheduling problem and a backtracking heuristic (BH) is used to solve the nurse assignment problem.

The scheduling problem is one of the combinatorial optimization problems (COP). Even though there is various research conducted on scheduling problem in the healthcare field, however, there is a lack of literature considered patient scheduling problem in the hemodialysis unit. (Holland, 1994) compare two scheduling models of a hemodialysis center by considering the device utilization, length of service and capability of the dialysis unit. The researcher

suggested that a flexible start time is better than the fixed start time for dialysis treatment. (Pena & Tolentino, 2013) investigated inpatients dialysis scheduling problem for ESRD patients. Each patient requires a different number of time slots to be treated and the dialysis devices are partitioned into blocks according to the needs of the patients.

Some of the researchers solved patient scheduling problem by using metaheuristic methods. (Saremi et al., 2015) mentioned the challenges of scheduling patients with stochastic service times and heterogeneous service sequences in multi-stage facilities by proposing an optimization method termed multi-agent tabu search (MATS). (Choi et al., 2017) used a mathematical model of the dialysis patient for each conventional regular dialysis schedule meanwhile genetic algorithm (GA) is used to search for the optimal HD schedule using the model and the algorithm was able to find the optimized schedule for patients and duration for each session. GA also improved the adequacy of conventional HD schedule and proved that frequent dialysis is more physiological and effective compared to conventional regular dialysis schedule. In another study, where (Liu et al., 2019) developed a basic heuristic and a rollout algorithm to solve three-level of treatment schedule problem. The results showed that the rollout algorithm able to schedule patient efficiently with the increasing demands of medical service and extensive use of advanced medical equipment by developing an optimization model. The researchers suggested that other approaches such as metaheuristics or hyperheuristics can be considered for solving this model. An analytical model and a decision support tool developed by (Fleming et al., 2019) for meeting the complex challenge of scheduling dialysis patients. The model considered clinical pathways, a limited number of nurses managing the patients and dialysis stations and the result showed a schedule can be computed efficiently using the decision support tool. However, the researchers suggested that patientrelated objective functions should be considered.

Another significant study in patient scheduling is involving dialysis machine utilization and patient satisfaction. Few studies have been carried out on this matter. For instance, (Wu et al., 2014) studied a patient scheduling problem with periodic deteriorating maintenance that aims to minimize the number of tardy medical treatment of all the patient. An earliest due date (EDD) rule-based heuristic is developed to consider fairness among patients. (Azadeh et al., 2015) addressed a semi-online patient scheduling problem in a pathology laboratory and proposed mixed-integer linear programming (MILP) to maximize the level of patient satisfaction. Apart from that, (Yan et al., 2015) proposed a sequential appointment scheduling method to balance the benefits of clinic and patient's satisfaction considering the patient choice and service fairness simultaneously.

Based on the literature review discussed above, (Fleming et al., 2019) involves both patient scheduling and nurse assignment problems. Therefore, in this paper, we refer to their model and solve the problem by considering their suggestion for future researchers and use other methodologies to improve the quality of the solution. A simple heuristic is used to obtain the solution. Several sets of generated data are used to test the performance of the proposed heuristic.

The remainder of this paper is as follows. Section 2 formulated the studied problem multiobjective model and explained the proposed algorithms. Section 3 deals with the computational experiments and finally, Section 4 concludes the paper.

## **METHODOLOGIES**

This section will discuss the methodologies for the patient scheduling and nurse assignment problem. A multi-objective model (MOM) is used for the patient scheduling problem. A simple heuristic (SH) algorithm is developed as the initial solution for this problem. A backtracking heuristic is applied to solve the nurse assignment problem.

## PATIENT SCHEDULING PROBLEM

Based on the information from (Fleming et al., 2019), the hemodialysis unit in the United Kingdom (UK) operates from 7:00 am till 11:00 pm and there are six dialysis stations available for the treatment along with three nurses for each morning and evening shift. This case may vary with Malaysia, however, to test the model, we follow the UK style. Patients can be classified into six types according to their health plan and we indicate them from 1 to 6 and for the chronic kidney disease (CKD) stages, we indicate them from 1 to 5, where 5 is the last stage of CKD.

## MATHEMATICAL MODEL

The table below are the parameters used in the model based on (Fleming et al., 2019):

Parameter	Description
A	Set of activities
$A_p$	Set of activities corresponding to patient $p \in P$
$\boldsymbol{\partial}_{m{p}}$	Dialysis activity of patient $p$ which excludes the setup and finish
$d_{i,j}^{min}$	Minimum time lag for precedence relation $(i,j) \in \varepsilon$
ε	Set of precedence relations
$\boldsymbol{E_i}$	Earliest period to schedule activity $i \in A$
$L_i$	Latest period to schedule activity $i \in A$
P	Set of patients
$oldsymbol{arphi}_p$	Dialysis finish activity of patient $p \in P$
$p_i$	Duration of activity i
$r_i^{nurse}$	Nurse demand by activity $i \in A$
$r_i^{room}$	Room demand by activity $i \in A$
$R_i^{nurse}$	Nurse capacity in period $t \in T$
$R_i^{room}$	Room capacity in period $t \in T$
$\sigma_p$	Dialysis setup activity of patient $p \in P$
T	Set of periods
$W_{i}$	Set of consecutive periods to schedule activity $i \in A$

The MOM involving the parameters in the above table is formulated as follows:

$$minimize z = \max_{p \in P} \sum_{t \in W_{\sigma_P}} t * x_{\sigma_p,t}$$
 (1)

$$minimize z = \max_{p \in P} \sum_{t \in W_{\varphi_p}} t * x_{\varphi_p,t}$$
 (2)

s.t:

$$\sum_{t \in W_j} t * x_{j,t} \ge \sum_{t \in W_i} t * x_{i,t} + d_{i,j}^{min} \qquad \forall p \in P, (i,j) \in \varepsilon_p$$
 (3)

$$R_t^{nurse} \ge \sum_{i \in A: t \in W_i} r_i^{nurse} * \sum_{\tau = \max(E_i, t - p_i + 1)}^{\min(L_i, t)} x_{i,\tau} \quad \forall t \in T$$
 (4)

$$R_t^{room} \ge \sum_{i \in A: t \in W_i} r_i^{room} * \sum_{\tau = \max(E_i, t - p_i + 1)}^{\min(L_i, t)} x_{i,\tau} \quad \forall t \in T$$
 (5)

$$\sum_{t \in W_i} x_{j,t} = 1 \qquad \forall i \in A \tag{6}$$

$$x_{i,t} = \{0,1\} \qquad \forall i \in A, t \in W_i \tag{7}$$

The objective function (1) minimizes the maximum waiting time for patients to start the dialysis session and the objective function (2) minimizes the maximum scheduled finish time of the treatments. Constraint (3) use the information from the clinical pathways and ensure that the minimum time lags between all consecutive activities are guaranteed. Nurse constraint (4) ensure that the demand for nurses does not exceed the nurse capacity. Constraint (5) ensure that the demand for the treatment rooms does not exceed the treatment room capacity. Constraint (6) ensure that each activity is scheduled exactly once and constraint (7) is the decision variable for this model,

$$x_{i,t} = \begin{cases} 1, & \text{if clinical activity } i \in A \text{ starts in period } t \in W_i \\ 0, & \text{otherwise} \end{cases}$$

## SIMPLE HEURISTIC

As the number of patients increases, the MOM becomes time-consuming. Therefore, we proposed a heuristic to solve the problem. A simple heuristic (SH) is developed to schedule the dialysis treatment and we want to make sure patients with critical stage will get their treatment as soon as possible. The level of the stage will determine the scheduling of the treatment on each day. The SH start by sequencing the waiting list. We sequence the patient with a high level of CKD stage over the patient with a lower level of CKD stage. If the level of CKD stage, we will sequence the patient based on their duration in increasing order.

Finally, we will schedule the patients based on the list. The table below is the notation used in the Simple Heuristic Algorithm

Notations	Description
i	Index of the patient where $i = 1,, N$
j	Index of treatment room where $j = 1,, R$
stages[i]	Level of stages for the patient, i
duration[i]	Duration of treatment for the patient, i
system[i]	If the value equal to 1, the patient $i$ is in the list, otherwise equal
	to 0
sum[i]	The total duration of treatment for patient $i$

**Algorithm 1** explains the SH procedure for patient scheduling problem based on their level of CKD stage (LOS). In Step 1, we will choose two patients, i and j. If the level of the stage of patient i is lower than patient j, we will swap the position of the patient (Step 2). But if the level of the stage for both patients i and j are the same, we will check the duration of treatment (Step 3). If the duration of patient i is higher than patient j, we will swap the position of the patients. This algorithm will be stopped when all the patients on the list are considered. After we have obtained the initial list, we will proceed to Step 4 where all the patients will be scheduled to room, r on the day, d. In Step i), we declare all patients, i with System(i)=0 to indicate the treatment not yet be scheduled. After that, we will choose treatment, i to be scheduled in the room, r on the day, d (Step 4(ii),4(iii),4(iv)). In Step 4(v), for every treatment, i with System(i)=0, we will calculate the summation of treatment time until it is less than or equal to.

	Algorithm 1: Simple Heuristic (LOS)			
Step 1	Set patient $i = 1$ and $j = i + 1$			
	If $stages[i] < stages[i+1]$ ,			
	swap TRUE			
Step 2	If $stages[i] = stages[i + 1]$ ,			
	then if $duration[i] > duration[i+1]$ ,			
	swap = TRUE			
Step 3	Else, repeat Step 1			
Step 4	Stop when $i \geq N$			
Step 5	Assign patient $i$ to room $j$			
	i. Declare $system[i] = 1$			
	ii. For $j = 1$ , let $sum = 0$ . If			
	system[i] = 1, then calculate			
	sum += duration[i]			
	iii. Let $sumt[i] = sum$ . If $sum >$			
	480, then break. Else repeat Step			
	(ii)			
	iv. Let $system[i] = 0$			
	v. Repeat for $j + 1$			

Algorithm 2 explains the SH procedure considering duration from long to short (DLS). In Step 1, we will choose two patients with different stages, i and j. If the level of the stage of patient i is lower than patient j, we will swap the position of the treatment. If the duration of treatment patient i is lower than patient j, we will swap the position of the patient. (Step 2). But if the duration for both patients i and j are the same, we will repeat step 1 (Step 3). This algorithm will be stopped when all the patients on the list are considered. After we have obtained the initial list, we will proceed to Step 4 where all the patients will be scheduled to room, r on the day, d. In Step i), we declare all patients, i with System(i)=0 to indicate the treatment not yet be scheduled. After that, we will choose treatment, i to be scheduled in the room, r on the day, d (Step 4(ii),4(iii),4(iv)). In Step 4(v), for every treatment, i with System(i)=0, we will calculate the summation of treatment time until it is less than or equal to.

	Algorithm 2: Simple Heuristic (DLS)					
Step 1	If $stages[i] < stages[i+1]$ ,					
	swap TRUE					
Step 2	If $duration[i] < duration[i+1]$ ,					
	swap = TRUE					
Step 3	Else, repeat Step 1					
Step 4	Stop when $i \geq N$					
Step 5	Assign patient $i$ to room $j$					
	i. Declare $system[i] = 1$					
	ii. For $j = 1$ , let $sum = 0$ . If					
	system[i] = 1, then calculate					
	sum += duration[i]					
	iii. Let $sumt[i] = sum$ . If $sum >$					
	480, then break. Else repeat Step					
	(ii)					
	iv. Let $system[i] = 0$					
	v. Repeat for $j + 1$					

Algorithm 3 explains the SH procedure considering duration from short to long (DSL). In Step 1, we will choose two patients with different stages, i and j. If the level of the stage of patient i is lower than patient j, we will swap the position of the treatment. If the duration of treatment patient i is higher than patient j, we will swap the position of the patient. (Step 2). But if the duration for both patients i and j are the same, we will repeat step 1 (Step 3). This algorithm will be stopped when all the patients on the list are considered. After we have obtained the initial list, we will proceed to Step 4 where all the patients will be scheduled to room, r on the day, d. In Step i), we declare all patients, i with System(i)=0 to indicate the treatment not yet be scheduled. After that, we will choose treatment, i to be scheduled in the room, r on the day, d (Step 4(ii),4(iii),4(iv)). In Step 4(v), for every treatment, i with

System(i)=0, we will calculate the summation of treatment time until it is less than or equal to.

	Algorithm 3: Simple Heuristic (DSL)
Step 1	If $stages[i] < stages[i+1]$ ,
	swap TRUE
Step 2	If $duration[i] > duration[i+1]$ ,
	swap = TRUE
Step 3	Else, repeat Step 1
Step 4	Stop when $i \geq N$
Step 5	Assign patient $i$ to room $j$
	i. Declare $system[i] = 1$
	ii. For $j = 1$ , let $sum = 0$ . If
	system[i] = 1, then calculate
	sum += duration[i]
	iii. Let $sumt[i] = sum$ . If $sum >$
	480, then break. Else repeat Step
	(ii)
	iv. Let $system[i] = 0$
	v. Repeat for $j + 1$

Simple Heuristic (FCFS) has no step for this procedure. The treatment will be arranged based on the order of patients in the list. Patients who come first will be considered to carry out their dialysis treatment and the process will be repeated until it satisfied all the constraints.

## NURSE ASSIGNMENT PROBLEM

In this section, we will discuss the nurse assignment problem after the treatment is scheduled. Based on the information from (Fleming et al., 2019) and (Liu, et al., 2018), the nurse will be assigned based on their shift and availability for that day. The first condition that we need to know is for each treatment scheduled, at least two nurses needed to handle the treatment. The lead nurse will be the one responsible for any decision making during the treatment and the assistant nurse will assist the lead nurse during the treatment. Secondly, the nurse rotation for nurse assignment is that the lead nurse will be free from participating in the next treatment while the assistant nurse will be the lead nurse on the next treatment.

A backtracking heuristic (BH) is used to determine if there is another treatment of the same type has been selected in another room simultaneously. This is to prevent from the nurse being assigned to a different room at the same time. We will use this heuristic to solve the nurse assignment problem.

The table below is the notation used in the Backtracking Heuristic Algorithm

Notations	Description
j	Index of treatment room where $j = 1,, R$
h	Index of nurse
TYPE1[h]	Type of patients' background
STATUS[h]	Status for the nurse, if 'Y' the nurse is available and if 'N' the
	nurse isn't available
sum[i]	The total duration of treatment for patient <i>i</i>

**Algorithm 4** explains the BH procedures for nurse assignment problem. Step 1, we declare status for the nurse as 'Y' to indicate that nurse is available. Then, for each patient i, check for the treatment room availability. If patient is scheduled for that treatment room and status of nurse available, assign nurse[h] to patient[i]. If the nurse is not available, assign nurse[h+1] to patient[i] (Step 2). The algorithm will be stopped when all the nurse is assigned to room, R.

	Algorithm 4: Backtracking Heuristic				
Step 1	Declare $STATUS[h] = 'Y'$				
Step 2	For $i = 0 < N$ ,				
	Check for treatment room $j = 1$ and				
	type[i] = 1,				
	If $TYPE1[h] = '1'$ and $STATUS[h] =$				
	'Y', then assign nurse[h] to patient[i].				
	Declare $STATUS[h] = $ 'N'				
	Assign nurse[h+1] to patient[i]				
Step 3	Else, repeat Step 2 for $j + 1$ up to $R$ .				

#### **RESULT & DISCUSSIONS**

## **GENERATED DATA**

To test the efficiency of the proposed method, we generated the different size of data. We created the data since we want to test for a bigger sample size of data. We interviewed few dialysis patients about their experience during dialysis treatment to get to know the real scenario in Malaysia. We generated three sets of data by using a Uniform Distribution with the notation  $U \sim [a, b]$  where the data is generated randomly from integer value of uniform distribution defined on the interval [a, b].

We vary the number of patients, i that need to be scheduled for each set,  $N_i$  for 20,30, 40, 50 and 100 patients. The number of treatment room available for scheduling,  $N_{Room}$  and number of days to schedule the treatment,  $N_{Day}$  are random to test our proposed method in the limited amount of capacity. The level of stages for each patient i, stages[i] is randomly

generated from a uniform distribution of [1,5] as an integer value where 5 indicates the last stage of CKD. The patient type, Type<sub>i</sub> is randomly generated from the uniform distribution of [1,6] as an integer value. **Table 1** shows the details of nurse lists for five-set of generated data. For each set of data, we vary the total number of nurses for patients type,  $N_{nurses}$  for 12, 24 and 36 nurses with each patient type having the same number of nurses ( $N_{NursesType1}$ ,  $N_{NursesType2}$ ,...,  $N_{NursesType6}$ ).

The treatment duration is assumed between 179 to 229 minutes based on the information from (Jefferies, et al., 2011). We randomly generated the treatment duration, duration[i] from uniform distribution of [179,229]. **Table 2** present the details of the patient lists for three sets of generated data.

Set N<sub>Nurses</sub> N<sub>Nurses</sub>, Type1 N<sub>Nurses</sub>, Type2 N<sub>Nurses</sub>, Type3 N<sub>Nurses</sub>, Type4 N<sub>Nurses</sub>, Type6 N<sub>Nurses</sub>, Type5 12 2 2 2 2 2 2 2 24 4 4 4 4 4 4 3 36 6 6 6 6 6 6

**Table 1:** Details of the nurses' lists for three sets of generated data.

<b>Table 2:</b> Details of the patient lists for three	ee sets of generated data.
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Set	$N_{i}$	N <sub>Room</sub>	$N_{Day}$	Stages <sub>i</sub>	Type <sub>i</sub>	Duration <sub>i</sub> (min)
1	20	3	2			
2	50	6	4	[1,5]	[1,6]	[179,229]
3	100	10	6			

## **COMPUTATIONAL RESULTS**

To analyze the quality of the solutions and computational time for simple heuristics (SH), we need to obtain the optimum values for each size of the problem. Previous research solved the MOM model by using a decision support tool based on Open Solver. Thus, we solved the MOM model using goal programming based on excel solver. The heuristics are coded in C language programming software. Tests were performed on a computer with an intel® Core<sup>TM</sup> i3-27020U processor of 2.30 GHz and 4 GB of RAM. The performance of the results obtained are measured by the percentage of level of stages for scheduled and unscheduled treatment and the computational time.

We run the heuristics for ten times to get the average of computational time for each set of data. The average computational time for the patient scheduling (Time<sub>Sc</sub> in seconds) and nurse assignment (Time<sub>A</sub> in seconds) problem is presented in **Table 3(a)** and **Table 3(b)**. By referring to **Table 3(a)** and **Table 3(c)**, the total computational time (Time<sub>Tot</sub> in seconds) to obtain the final solution using MOM is higher compared to SH. In **Table 3(a)**, we cannot obtain the computational time for Set 3 as the size of data is larger and Solver (MOM) cannot solve the model. However, by using simple heuristic, we able to obtain computational time

for Set 3.

We present the results for scheduled and unscheduled patients obtained by the model and heuristics in **Table 4(a)** and **Table 4(b)**. These scheduled patients list is for one day basis and for the following day treatment, those who is in unscheduled list will be scheduled for that day.

Figure 1(a) and Figure 1(b) present the total computational time of MOM and proposed heuristics. Figure 2(a) and Figure 2(b) present the number of patients scheduled and unscheduled for the treatment.

**Table 3(a)**: Average computational time for patient scheduling and nurse assignment problem using MOM.

Set	MOM				
	$Time_{Sc}(s)$	$Time_A(s)$	$Time_{Tot}(s)$		
1	1500	0.114	1550.114		
2	2100	0.121	2100.121		
3	-	-	-		

**Table 3(b)**: Average computational time for patient scheduling and nurse assignment problem using four types of simple heuristic.

Set	LC	OS	DI	LS	DS	SL	FC	FS
	$Time_{Sc}(s)$	$Time_A(s)$	$Time_{Sc}(s)$	$Time_A(s)$	$Time_{Sc}(s)$	$Time_A(s)$	$Time_{Sc}(s)$	$Time_A(s)$
1	0.210	0.219	0.265	0.260	0.242	0.250	0.279	0.250
2	0.337	0.002	0.367	0.001	0.344	0.001	0.324	0.001
3	0.524	0.005	0.496	0.003	0.549	0.004	0.507	0.003

**Table 3(c)**: Average total computational time for patient scheduling and nurse assignment problem using four types of simple heuristic.

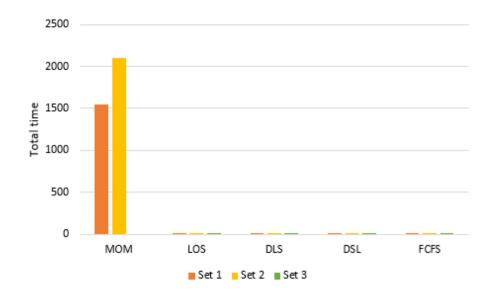
Set	LOS	DLS	DSL	FCFS
	$Time_{Tot}(s)$	$Time_{Tot}(s)$	$Time_{Tot}(s)$	$Time_{Tot}(s)$
1	0.429	0.525	0.492	0.529
2	0.339	0.368	0.345	0.325
3	0.529	0.499	0.553	0.510

Table 4(a): Number of patients scheduled for a day.

Set	LOS	DLS	DSL	FCFS
1	6	6	6	6
2	13	11	13	11
3	20	21	21	14

Table 4(b): Number of unscheduled patients in the list.

Set	LOS	DLS	DSL	FCFS
1	14	14	14	14
2	37	39	37	39
3	80	79	79	86



**Figure 1(a)** shows the overall average total computational time of MOM and the proposed heuristics.

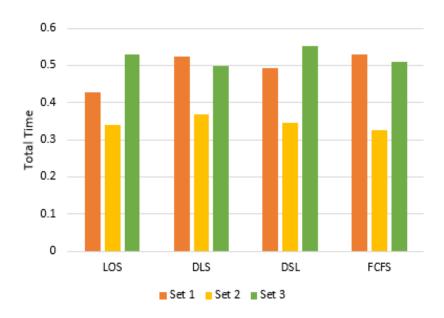


Figure 1(b) shows the closeup of average total completion time of proposed heuristic.

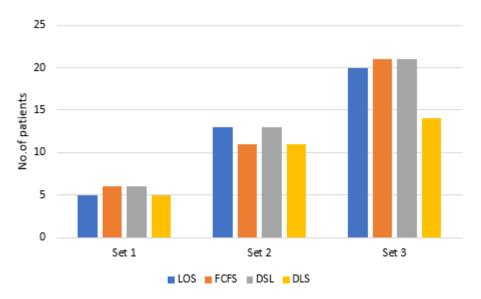


Figure 2(a) shows number of patients scheduled for a day.

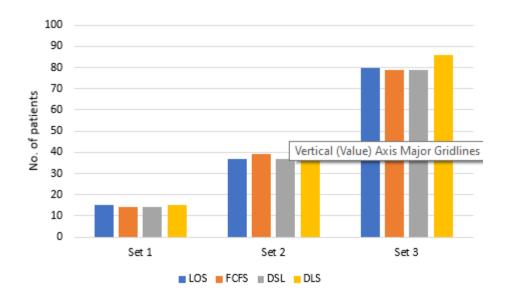


Figure 2(b) shows remaining unscheduled patients for a week.

#### **CONCLUSION**

In this paper, we developed simple heuristics to solve patient scheduling problem with nurse assignment. As the number of patients increase in the waiting list, the model failed to solve the problem and/or consume high computational time. Therefore, we used a Simple Heuristic to obtain the feasible solutions. To prove the efficiency of our proposed heuristics, we compared the solutions from the mathematical model with the solutions obtained from the heuristics.

Based on the results, simple heuristics are very good in reducing the large running time of the model. Our main objective to minimize the waiting time for patients to start dialysis session and to minimize the maximum scheduled finish time of the treatments are achieved. Since the proposed heuristic is efficient, this is a very good procedure to be implemented in solving the patient scheduling problem. In this work, we estimated the duration of the treatment based on the information from the paper that we are referred. It is important that the prediction of the treatment duration used for the heuristics should be as accurate as possible. Since the duration of the treatment is stochastic, it is difficult to obtain a good estimation. The failure to do so might affect the scheduling process in real life situation. Therefore, a detailed study for the treatment duration should be make in the future work. Another future work that can be done is improving the model by extend the problem that includes clinician guidelines and targets and by considering inpatient cases and bed occupancy. The method used can be improved to metaheuristic or hyper-heuristic for future work.

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