

# A Genetic Algorithm Solution for the Doctor Scheduling Problem

Abir Alharbi and Kholood AlQahtani

Mathematics Department, King Saud University, Riyadh, Saudi Arabia

e-mail: abir@ksu.edu.sa , 432201096@student.ksu.edu.sa

**Abstract**—In this study, we present a genetic algorithm solution to the scheduling problem for doctors in the Pediatric Department of Prince Sultan Military Medical City (PSMMC) in Riyadh Saudi Arabia. The genetic algorithm approach uses a cost bit matrix where each cell indicates any violation of constraints. The experimental results show that the suggested method generated a doctor schedule faster and with less violated constraints compared to the traditional manual methods.

**Keywords**- Doctor Scheduling Problem, Genetic Algorithms, cost bit matrix.

## I. INTRODUCTION

A hospital providing around-the-clock services divides its daily work into consecutive shifts, and a shift is a period of time in which a group of employees is in-service. A doctor is assigned to a set of shifts, and this assignment satisfies several constraints that may be set up by staffing requirements, rules by the administration, and labor contract clauses. In a Doctor Scheduling Problem (DSP), each doctor is assigned to the set of shifts and rest days in a timetable called a doctor roster. DSP was proven to be NP-hard even with only a subset of real world constraints [4]. In the literature, many research works were done on DSP or the similar Nurse Scheduling Problem (NSP). Miller et al. [13], and Warner et al. [14] formulated Nursing Schedule Problem as the selection of a timetable that minimized an objective function that balanced the trade-off between staffing coverage and nurses' preferences. Abdannadher et al. [2], applied Constraint Logic Program (CLP) framework and Li et al. [11], employed Bayesian optimization algorithm. Jan et al. [9], and Aickelin et al. [3] applied the genetic algorithms (GA) to NSP. Kundu et al. [10] applied genetic algorithm and simulated annealing to the same problem instances and compared their performances with others, and [6] applied coloring graph theory to solve NSP.

In DSP, there are many constraints and there can be several different instances with different set of constraints. In this study, we consider the cyclic Doctor Scheduling Problem with the following constraints. An instance includes three components:

- (1) the personal preference of each doctor to work on particular days and shifts,
- (2) the minimal coverage constraints of the minimal required number of doctors per shift and per day,

- (3) the case-specific constraints specified by personal time requirements, specific workplace conditions, etc.

The objective of this problem is to satisfy doctors' requests as much as possible while fulfilling the employers' requirements. In this paper, we apply a genetic algorithm with a cost bit matrix that penalizes the solution of the DSP if the constraints are violated, and hence find a schedule solution that optimizes the doctors' rosters and satisfies the constraints. In the next section, we will briefly introduce the genetic algorithms, DSP, its cost function, and the cost bit matrix. In Section III the GA results are discussed. Finally, conclusions and future work are discussed in Section IV.

## II. GENETIC ALGORITHMS

Genetic Algorithms (GA) are adaptive heuristic search algorithms [12] premised on the evolutionary ideas of natural selection and genetics. The basic concepts of the GA were designed to simulate those processes in natural evolution system, and survival of the fittest. GA are a powerful tool to solve optimization problems with multiple variables [1][7]. GA were applied to several scheduling problems [3][5][8][9]. GA use a search algorithm to simulate the process of natural selection. GA start with the set of potential solutions called population and evolves toward more optimal solutions. The solutions are evaluated by a fitness function. The fitness value represents the quality measure of a solution so that the algorithm can use it to select ones with better genetic material for producing new solutions and further generations. The selection chooses superior solutions in every generation and assures that inferior solutions become extinct. The crossover operator chooses two solutions from the current population and generates a new solution based on their genetic material. Selection and crossover operators will expand the good features of superior individuals through the whole population. They will also direct the search process towards a local optimum. The mutation operator changes the value of some genes in a solution and helps to search other parts of the problem space. The main disadvantage of GA is the requirement for a large computation time.

### A. Doctor Scheduling Problem

DSP consists of creating weekly or monthly schedules for N doctors by assigning one out of a number of possible shift patterns to each doctor. These schedules have to satisfy working contracts and meet the requirements for the number

of doctors of different grades for each shift, while being seen to be fair by the staff concerned. Therefore, DSP is essentially a scheduling problem that suits a number of constraints. The constraints are usually categorized into two categories: soft and hard constraints. Hard constraints should always be satisfied in any working schedule so that there will be no breaches. Any schedule that does not satisfy all of the hard constraints cannot be a feasible one. Possible examples include restrictions on the number of doctors for each shift; the maximum number of shifts in a week, a month, etc. On the contrary, soft constraints can be violated but as minimal as possible. In other words, the soft constraints are expected to be satisfied, but violation does not make it an infeasible solution. We confined the constraints as follows:

(a) Hard constraints

(i) There are constraints on the number of doctors for each working shift per day. The number of doctors for morning, evening, and night shift should be between the minimum and maximum values.

(ii) There are constraints for the working patterns. Morning after night shift, evening after night, morning after evening shift and three consecutive night shifts are restricted combination of working patterns.

(b) Soft constraints

There are constraints for the total number of off-days (o), night (n), morning (m) and evening (e) shifts during a certain period of days for each doctor.

In this project, we consider a scheduling problem for the Pediatric Department of Prince Sultan Military Medical City (PSMMC) in Riyadh/ Saudi Arabia. Monthly doctors' rosters are made manually before the end of each month. Figure 1 shows original hospital rosters for the month of February 2016. Even though making monthly rosters manually required great effort and time, it did not resolve all conflicts, and sometimes it had created more tedious adjustments to accomplish needed tasks. There are consultants, senior and junior doctors working in this department. This project is concerned with scheduling shifts for junior doctors in two of the department wards for one month only. A major problem with any scheduling problem is the allocation of resources in an effective way, and violating constraints will be affecting the quality of the solution.

### B. The Cost Function

We have to define a cost function which, after optimization, will obtain optimal schedules for each doctor. Let  $N$ ,  $D$  be the number of doctors and days. Then, DSP may be represented as a problem to find a schedule matrix, so that each element of the matrix,  $X_{ij}$  expresses that doctor  $i$  works on day  $j$  where  $X_{ij} = (m, e, n, o)$ .

(a) To evaluate the violation of hard constraint (i), we define  $m, e, n$  as the total number of doctors for morning, evening, and night shift on day  $j$ . If any of these numbers are not between the minimum and maximum number of doctors for each shift ( $m_{min}, m_{max}, e_{min}, e_{max}, n_{min}, n_{max}$ ), cost  $C_1$  will be incremented by 1.

(b) To evaluate the violation of hard constraint (ii), working patterns are examined. Any violation of the working patterns specified (such as  $n$  after  $m$ ,  $e$  after  $n$ ,  $m$  after  $e$ , or consecutive  $n, n, n$ ) will increment cost  $C_2$  by 1.

(c) To evaluate the violation of soft constraint, we define  $M, E, N, O$  as the total number of the corresponding shifts, morning, evening and night and off-days for doctor  $i$  during the period of  $D$  and  $M_{req}, E_{req}, N_{req}, O_{req}$  as the required number of morning, night and night shifts and off-days for all doctors during the period of  $D$ . If any of these numbers  $M, E, N, O$  does not meet,  $E_{req}, N_{req}, O_{req}$  respectively, cost  $C_3$  will be incremented by 1.

Different weight values can be assigned for the costs  $C_1, C_2$  and  $C_3$ . Then, the final cost function is

$$f = C_1 * w_1 + C_2 * w_2 + C_3 * w_3$$

where  $w_1, w_2$  and  $w_3$  are weight values for  $C_1, C_2$  and  $C_3$ , respectively. Our goal is to minimize the cost function  $f$  so as to find an optimal doctor schedule. The simplest method to find the solution is a brute force approach (manually) evaluating all possible doctor schedules and finding the feasible one with the minimum cost among them. However, if the number of all possible doctor's increase, this approach is intractable. This is a class of problems schedules for which it is believed that no efficient algorithm exists, called NP-hard. In other words, the algorithms that guarantee to find an optimal solution with the size of  $D$  and  $N$  in reasonable time may not exist. To overcome this problem, we use a genetic algorithm which is an approximation algorithm. GA provide an approximate solution rather than an optimal one in acceptable time.

### C. GA Parameters for Selection and Crossover

The initial population ( $n$ ), are the first  $n$  schedules for doctors that are  $N \times D$  matrices, is generated randomly assigning each doctor to one of the three shifts with a day-off on each day, Table I shows a sample of a week schedule for 5 doctors (a  $5 \times 7$  matrix). The costs of these schedules are calculated by cost functions  $C_1, C_2$  and  $C_3$ . The method of selection in this study, is the roulette wheel selection that is the most common type of selection method. Two schedules,  $P_1$  and  $P_2$ , are chosen randomly based on their costs and are used to produce an offspring. One schedule can be selected for a parent more than once. The crossover between the two chosen parents genome is done at a single point randomly chosen with probability 0.8 to produce the new generation offspring, and with 0.01 Mutation rate. The remaining initial

parameters are set as given by the PSMHC hospital for Feb 2016,  $N=24$ ,  $D=29$ ,  $mmin=8$ ,  $mmax=10$ ,  $emin=6$ ,  $emax=10$ ,  $nmin=6$ ,  $nmax=10$ , and soft constrains for each week  $Mreq=Ereq=Nreq=2$ , and  $Oreq=1$ . The method was activated to reach an optimum cost=0 ( $f=0$ ) using Matlab genetic algorithm toolbox with Intel Core™ i5-250M 2.5 Ghz CPU and 4GB.

TABLE I. SAMPLE WEEK OF HOSPITAL SCHEDULE FOR 5 DOCTORS

Doctor	M	T	W	TH	F	S	SU
1	m	e	n	o	m	m	n
2	e	m	m	n	o	m	n
3	n	n	o	m	e	e	e
4	m	m	e	e	n	o	m
5	e	e	e	n	m	n	o

### III. GA RESULTS

The genetic algorithm started with a population size of 60 individuals, with the size of each genome  $N \times D$  matrix (24 doctors for 29 days). The algorithm terminates when the maximum number of generations reaches 300, or when the increase in fitness of the best individual over five successive generations falls below a certain threshold, set at  $2 \times 10^{-6}$ . Our fitness function  $f$  is set to the final cost function as  $f = 5C_1 + 5C_2 + C_3$ , which penalizes systems violating the constrains with the assigned weights. The GA runs throughout the generations to find the best genome in this population. The best genome is the one, which violates the least number of constrains. After all 300 generations (repeated 50 times), the genetic algorithm finds the optimum genome; hence, it finds the best doctor schedule table which violates the least constrains. The proposed GA results are compared to the hospital manual roster tables derived from Fig. 1. Table III shows the incident matrix for the 24 doctors in PSMHC for the month of February, 2016. Fig. 2 shows the GA results as plots of the best fitness value over the generations, and average distance between individuals for the 4 weeks. The best doctor schedule produced from the GA is given in Table IV. Table II shows a comparison of the performance results of the two methods. Both methods solved each of the given problem instances and the results did not violate any of hard constrains in all periods. GA generated schedules with optimal cost in all periods, also, the optimal costs from GA is smaller than that of the manual tables. The average execution time of GA is around 3.45 minutes which is much faster than those of manual tables

which takes a few hours to accomplish. Hence, GA are very effective compared to traditional manual methods based on time and least constrains violation.

TABLE II. COMPARISONS OF GA AND TRADITIONAL HOSPITAL SCHEDULE

period	Method	$f_{opt}$	T (min)
1week	GA	2	2.6
	Manual	7	
2weeks	GA	5	3.2
	Manual	11	
3weeks	GA	4	3.75
	Manual	12	
4weeks	GA	3	3.96
	Manual	10	

### IV. CONCLUSION AND FUTURE WORK

In this paper, we proposed a Genetic Algorithm approach with a cost bit matrix to solve a DSP in PSMHC hospital. The genetic algorithm found solutions satisfying all the constrains. This approach generated a doctor schedule faster in speed and better in quality than traditional manual methods. Although we have presented this work in terms of doctor scheduling, it should be noted that the main idea of the approach could be applied to many other scheduling problems. Future research aims at experiments on the nurse’s schedule in PSMHC hospital with more constrains and a diversity of requirements. Our future plans also include producing a software that helps hospitals design schedules with their constrains for their doctors and nurses with simple inputs and less time to avoid manual schedule making.

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GENERAL PAEDIATRIC ON-CALL ROTA									
February 2016									
Date	Day	1 <sup>st</sup> On-Call (Bleep 0344)	PGICU 1.6	2 <sup>nd</sup> On-Call (Bleep 0271)	1 <sup>st</sup> On-Call (Bleep 0240)	1 <sup>st</sup> On-Call (Bleep 0340)	2 <sup>nd</sup> On-Call (Bleep 0304)	Consultant	
		PGICU 3.1	PGICU 1.6	PGICU 1.6 & 3.1	Admission & A&E Interns (Bleep 0232)	Wards 3.3, 4.1, 4.2 & 4.3 Interns (Bleep 0236)	Admission/ Wards	General	PGICU
1	Mon	ELGAWHARAH	MALIK	Rizwan	AZIZ MUSAINED	ALANOUD M	FARHOOD	A Hilwa	Chehab
2	Tues	QASSIM	KHALED	Warwar	HEBA	HAMZAH	MARAM	A Fawaz	Chehab
3	Wed	M. ASIRI	HAMDAN	Yacoub	HISHAM	FAHAD	GHADAH	R Asiri	Chehab
4	Thu	GRACE	NOURAH	Inayat	FADIAH	ALANOUD K	MANAR	H Ahmari	Mohaimed
5	Fri	TAGHREED	A. JABER	Rizwan	BASHAYER M	ALANOUD M	BIN HUSSAIN / FARHOOD	H Ahmari	Mohaimed
6	Sat	ELGAWHARAH	MALIK/ Asim S	Ahmed	KHALED	AZIZ MUSAINED	MARAM / GHADAH	H Ahmari	Mohaimed
7	Sun	AMAL	HISHAM	Warwar	HAMZAH	HEBA	M. ASIRI	A Hilwa	Thabet
8	Mon	NADA ALHARBI	NOURAH	Yacoub	ALANOUD K	FADIAH	NOUR	R Asiri	Thabet
9	Tues	RAED	Asim S	Inayat	ALANOUD M	BASHAYER M	FARHOOD	M Hijazi	Thabet
10	Wed	BODOUR	HISHAM	Rizwan	FAHAD	AZIZ MUSAINED	BIN HUSSAIN	H Ahmari	Thabet
11	Thu	MUJAHID	MALIK	Yaser	HAMZAH	HEBA	SAEED	A Hilwa	Bafaqih
12	Fri	NADA	KHALED	Warwar	AHMED	ALANOUD K	GHADAH / MARAM	A Hilwa	Bafaqih
13	Sat	ESRAA M	HAMDAN	Yacoub	FAHAD	A. JABER	M. ASIRI / FARHOOD	A Hilwa	Bafaqih
14	Sun	EBTISAM	Asim S	Inayat	ALANOUD M	FADIAH	RAED	H Ahmari	Mohaimed
15	Mon	TAGHREED	MALIK	Rizwan	BASHAYER M	AZIZ MUSAINED	NOUR	A Fawaz	Mohaimed
16	Tues	NADA	KHALED	Yaser	ALANOUD K	HAMZAH	MARAM	R Asiri	Mohaimed
17	Wed	QASSIM	NOURAH	Yacoub	FADIAH	HEBA	GHADAH	M Hijazi	Mohaimed
18	Thu	ESRAA M	Asim S	Ahmed	ALANOUD M	BASHAYER M	MANAR	R Asiri	Thabet
19	Fri	MUJAHID	FAHAD	Inayat	NADA ALHARBI	HANEM	RAED / NOUR	R Asiri	Thabet
20	Sat	SARAH F	GRACE	Warwar	HISHAM	AHMED	QASSIM / BIN HUSSAIN	R Asiri	Thabet
21	Sun	RAED	Asim S	Rizwan	AHMED	ALANOUD K	GHADAH / MARAM	A Hilwa	Bafaqih
22	Mon	TAGHREED	MALIK	Ahmed	BASHAYER M	AZIZ MUSAINED	NOUR	H Ahmari	Bafaqih
23	Tues	AMAL	HISHAM	Inayat	ALANOUD K	FADIAH	NOUR	A Fawaz	Bafaqih
24	Wed	QASSIM	KHALED	Warwar	HAMZAH	HEBA	M. ASIRI	M Hijazi	Bafaqih
25	Thu	NADA ALHARBI	NOURAH	Rizwan	FADIAH	ALANOUD K	MANAR	A Fawaz	Chehab
26	Fri	EBTISAM	Asim S	Yacoub	BASHAYER M	AZIZ MUSAINED	NOUR	A Fawaz	Chehab
27	Sat	MUJAHID	FAHAD	Yaser	HISHAM	AHMED	QASSIM / BIN HUSSAIN	A Fawaz	Chehab
28	Sun	QASSIM	NOURAH	Inayat	AZIZ MUSAINED	ALANOUD M	FARHOOD	R Asiri	Chehab
29	Mon	M. ASIRI	HAMDAN	Warwar	HEBA	HAMZAH	MARAM	A Hilwa	Chehab

Department of Paediatrics									
Paediatric ICU Team									
Division Mobile: 0504585767									
February 2016									
		1-6 PICU On-call Team A 08:00-08:00			3-1 PICU service Team B 08:00 - 16:00			PRRT & Transportation 08:00-08:00 Team C	
Date	Day	Consultant	Fellow / Registrar	Resident	Consultant	Fellow	Registrar/Resident	Consultant	Fellow /Registrar
1	Mon	Chehab	Rizwan	ELGAWHARAH	Mohaimeed	Rizwan	NOUR S	Mohaimeed	Rizwan
2	Tues	Chehab	Warwar	QASSIM	Mohaimeed	Rizwan	NOUR S	Mohaimeed	Rizwan
3	Wed	Chehab	Yacoub	M. ASIRI	Mohaimeed	Rizwan	NOUR S	Mohaimeed	Rizwan
4	Thu	Mohaimeed	Inayat	GRACE	Mohaimeed	Inayat	GRACE	Mohaimeed	Inayat
5	Fri	Mohaimeed	Rizwan	TAGHREED	Mohaimeed	Rizwan	TAGHREED	Mohaimeed	Rizwan
6	Sat	Mohaimeed	Ahmed	ELGAWHARAH	Mohaimeed	Ahmed	ELGAWHARAH	Mohaimeed	Ahmed
7	Sun	Thabet	Warwar	AMAL	Bafaqih	Warwar	MALIK	Bafaqih	Warwar
8	Mon	Thabet	Yacoub	NADA ALHARBI	Bafaqih	Warwar	MALIK	Bafaqih	Warwar
9	Tues	Thabet	Inayat	RAED	Bafaqih	Warwar	MALIK	Bafaqih	Warwar
10	Wed	Thabet	Rizwan	BODOUR	Bafaqih	Warwar	MALIK	Bafaqih	Warwar
11	Thu	Bafaqih	Yaser	MUJAHID	Bafaqih	Yaser	MUJAHID	Bafaqih	Yaser
12	Fri	Bafaqih	Warwar	NADA	Bafaqih	Warwar	NADA	Bafaqih	Warwar
13	Sat	Bafaqih	Yacoub	ESRAA M	Bafaqih	Yacoub	ESRAA M	Bafaqih	Yacoub
14	Sun	Mohaimeed	Inayat	EBTISAM	Chehab	Inayat	HAMDAN	Chehab	Inayat
15	Mon	Mohaimeed	Rizwan	TAGHREED	Chehab	Inayat	HAMDAN	Chehab	Inayat
16	Tues	Mohaimeed	Yaser	NADA	Chehab	Inayat	HAMDAN	Chehab	Inayat
17	Wed	Mohaimeed	Yacoub	QASSIM	Chehab	Inayat	HAMDAN	Chehab	Inayat
18	Thu	Thabet	Ahmed	ESRAA M	Thabet	Ahmed	ESRAA M	Thabet	Ahmed
19	Fri	Thabet	Inayat	MUJAHID	Thabet	Inayat	MUJAHID	Thabet	Inayat
20	Sat	Thabet	Warwar	SARAH F	Thabet	Warwar	SARAH F	Thabet	Warwar
21	Sun	Bafaqih	Rizwan	RAED	Thabet	Yaser	Abdullah S	Thabet	Yaser
22	Mon	Bafaqih	Ahmed	TAGHREED	Thabet	Yaser	Abdullah S	Thabet	Yaser
23	Tues	Bafaqih	Inayat	AMAL	Thabet	Yaser	Abdullah S	Thabet	Yaser
24	Wed	Bafaqih	Warwar	QASSIM	Thabet	Yaser	Abdullah S	Thabet	Yaser
25	Thu	Chehab	Rizwan	NADA ALHARBI	Chehab	Rizwan	FATIMAH	Chehab	Rizwan
26	Fri	Chehab	Yacoub	EBTISAM	Chehab	Yacoub	HALA	Chehab	Yacoub
27	Sat	Chehab	Yaser	MUJAHID	Chehab	Yaser	NADA ALHARBI	Chehab	Yaser
28	Sun	Chehab	Inayat	QASSIM	Mohaimeed	Ahmed	Yosef	Mohaimeed	Ahmed
29	Mon	Chehab	Warwar	M. ASIRI	Mohaimeed	Ahmed	Yosef	Mohaimeed	Ahmed

Figure 1. Example of a Hospital Manual Doctor schedule.

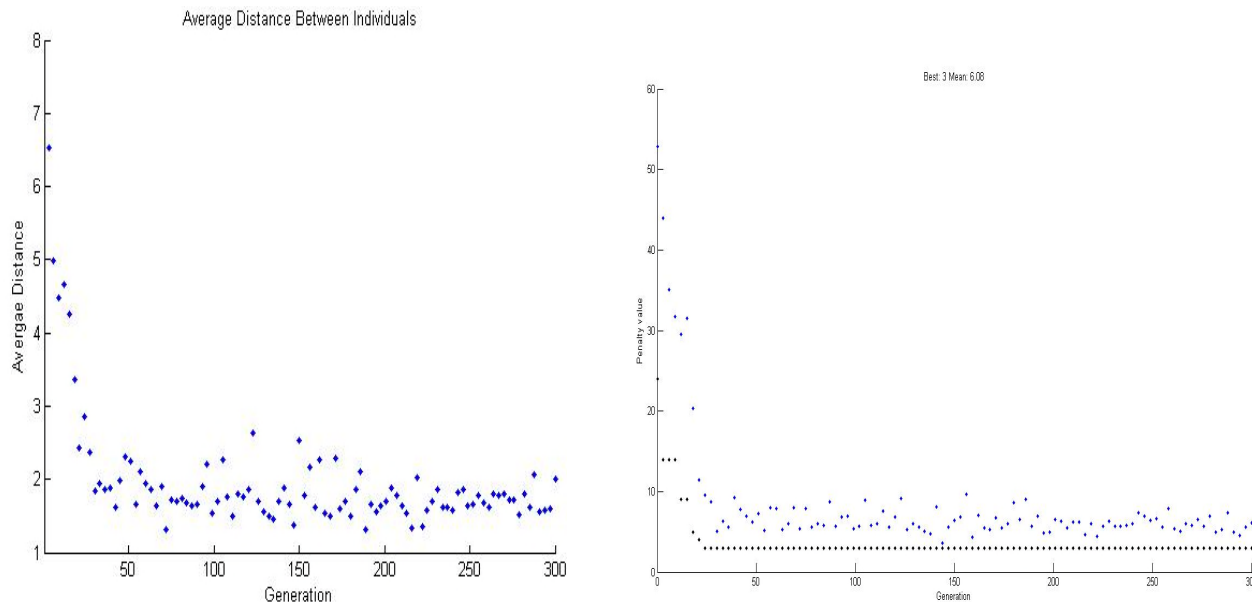


Figure 2. GA results showing the average distance between the individuals, and the best fitness value for 4 weeks.

TABLE III. THE HOSPITAL INCIDENT MATRIX FOR DOCTORS WORKING IN SAME GROUP AND WARD FOR N=25.

	R31	R41	R11	R15	R24	SUB1	R32	R42	R12	R21	R25	SUB2	R33	R43	R13	R22	R26	SUB3	R34	R44	R14	R23	R27	SUB4
R31	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R41	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R11	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R15	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R24	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
SUB1	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R32	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R42	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R12	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R21	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R25	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
SUB2	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R33	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R43	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R13	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R22	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R26	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
SUB3	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R34	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R44	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R14	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R23	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
R27	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
SUB4	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■

TABLE IV. GENETIC ALGORITHM BEST DOCTOR SCHEDULE N=24, D=29.

Dr #/day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m
2	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e
3	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n
4	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m
5	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e
6	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m
7	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e
8	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n
9	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m
10	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e
11	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m
12	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e
13	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n
14	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m
15	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e
16	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m
17	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e
18	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n
19	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m
20	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e	e	e	n	m	n	o	e
21	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m	e	n	o	m	m	n	m
22	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e	m	m	n	o	m	n	e
23	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n	n	o	m	e	e	e	n
24	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m	m	e	e	n	o	m	m