COMPARING SCHEDULING APPOINTMENT RULES PERFORMANCE IN HEALTH CARE UNITS: A DISCRETE EVENT SIMULATION APPROACH

Thiago Nunes Klojda
Rio de Janeiro State University, Brazil
E-mail: thiago.klojda@gmail.com

Antônio Pedro de Britto Pereira Fortuna
Rio de Janeiro Federal University, Brazil
E-mail: antoniopfortuna@hotmail.com

Bianca Menezes Araújo
Rio de Janeiro State University, Brazil
E-mail: biancamearaujo@gmail.com

Daniel Bouzon Nagem Assad
Universidad Politécnica de Madrid, Spain
Rio de Janeiro State University, Brazil
E-mail: danielbouzon@gmail.com

Thaís Spiegel
Rio de Janeiro State University, Brazil
E-mail: thais@eng.uerj.br

Abstract

Health care systems are affected by sudden increases in demand that can be generated by factors such as natural disasters, terrorist attacks, epidemics, among others. Patient demand can be divided between scheduled and walk-in and, in pandemic scenarios, both of them must be managed in order to avoid higher patient waiting times or number in queue. A discrete event simulation model is proposed in order to evaluate critical indicators like: patient waiting times, number in queue, resource utilization (doctors), using four different patient schedule appointment rules. In this study it was also considered patients impunctuality, walk-in patients and no-show in different scenarios. The best schedule appointment rules for each demand scenario were evaluated. After comparing six performance indicators, four schedule appointment rules in nine different scenarios it was found that the most known scheduling rule had the lowest queue sizes at scenarios with low or no walk-in patients, whereas, as the unpredictability of the scenarios rose, other rules outperformed it. It was also presented to exist an inverse relation between queue size and the physician idle time.
Keywords: *discrete event simulation, idle-time, queue management, appointment scheduling, health care*.

Introduction

Since HIV in the 1980s and until Zika virus in 2015, emerging infectious diseases challenge health systems which leads to public health emergencies (Metcalf & Lessler, 2017). In late 2019 in China and February of 2020 in several countries, COVID-19 started to quickly spread (Ben Hu, 2020) and impact society in many areas (Horton 2020; Couto 2021).

https://doi.org/10.33225/pmc/21.16.28
ISSN 2029-6932 (Print) ISSN 2538-712X (Online)

Besides presenting a huge dissemination capacity, COVID-19, which is a viral disease caused by Sars-Cov-2, can also induce many clinical symptoms. One of the most relevant is severe acute respiratory syndrome, which requires intensive treatment and may overload health systems (Boban, 2020; Tu, 2020).

The Sars-Cov-2 transmission occurs mainly through direct human-to-human contact, via airborne droplets and aerosols from sneezing, coughing, and speaking (Oliveira, 2020; Lotfi, 2020). Transmission may also occur by indirect ways, such as contaminated objects and particles suspended in the ambient air (Lotfi, 2020). Therefore, crowded and closed environments are considered of high risk in the spread of the virus (Rader et al. 2020).

In this recent context of a highly contagious pandemic virus, it is necessary to reduce crowding in closed environments (Lotfi, 2020; Rader, 2020) such as in health care organizations, where there will potentially be a higher concentration of people from risk groups and infected people. Thus, the following research question is proposed:

How to reduce the risk of infection (caused by crowding) in health care organizations for elective (scheduled) appointments?

One way of trying to control the number of patients in queue in the waiting room of a service is to make changes in the scheduling rules and policies for clients/patients (Meza, 1998). Cayirli and Veral (2003) had stated that a scheduling rule is a combination of three variables:

(i) block size of scheduled patients per slot;
(ii) initial block of patients scheduled at the first operating time;
(iii) interval between appointments.

In the present work, performance indicators were evaluated in four scheduling rules and in nine scenarios of demand (varying no-show and walk-in patients' rate). These scenarios were compared using a discrete event simulation model built from data extracted from the research of Peres (2017) and Cayirli et al. (2006). The performance indicators evaluated are:

1) Number of patients in queue;
2) Patient's waiting time;
3) Resource utilization/idle time (doctor);
4) Patient total time in the unit.
5) Number of patients seen

All these indicators will be defined in the next paragraphs. It will also be presented why some definitions differ from other research.

The focus of present research is:

To evaluate the impact of the use of different scheduling rules on the number of people queued and on resource utilization in a pandemic context. Furthermore, variables such as no-show, walk-in and patient lateness will be considered.

Discrete event simulation aims to mimic the evolution of a system with state variables that change at discrete points in time (Banks, 2010; Law 2013). This tool can be used to simulate the operation of health care services such as: ophthalmological surgery (Peres et al., 2017), central sterile services department (Assad et al., 2018) and admission to primary care health care units (Klojda et al., 2021).

Within the scope of scheduling rules, research such as that of Bailey (1952), Welch (1964), Bosch and Dietz (2000), Harper and Gamlin (2003), Guo, Wagner and West (2004), Wijewickrama and Takakuwa (2005), Wijewickrama (2006), Kaandorp and Koole (2007), Zhu and Teow (2009), Anderson et al. (2015), Barghash and Saleet (2018) used different strategies aimed to:

1. Reduce waiting time (planned versus performed): Bailey (1952), Welch (1964), Bosch and Dietz (2000), Harper and Gamlin (2003), Wijewickrama and Takakuwa (2005), Zhu and Teow (2009) and Anderson et al. (2015), Klassen and Yoogalingam (2019)
2. Decrease idleness of resources (doctor): Guo etl al. (2004), Kaandorp and Koole (2007), Zhu and Teow (2009) and Anderson et al. (2015)

3. Reduce resource overtime (physician): Kaandorp and Koole (2007), Zhu and Teow (2009), Barghash and Saleet (2018).
4. Reduce queued patients: Wijewickrama (2006) and Zhu and Teow (2009)

Although minimizing waiting time is an issue well covered in literature, the indicator is usually calculated by making the difference between the scheduled time or when a patient arrives (in lateness cases) and the time when the patient is admitted in the consultation room. If on one hand this way brings a great efficiency measure, on the other hand, in a pandemic context, it does not allow the organization to consider the total patient waiting time that means exposure time which should be minimized.

Thus, in order to minimize the infection transmission risk, two key performance indicators (KPI) are mainly relevant, unfocused in previous research and are formally presented below:

1. total patient waiting time (exposure time): The difference between patient time arrival and the time when the consultation ends. This unusual interpretation of indicators therefore lends originality to the proposed study.
2. queue size (crowding): the number of queued patients all over the time which is equally unusual indicator adopted in previous research.

Other traditional performance indicators used in this research are formally presented below:

1. idle time: total time that a resource (doctor) was available, but there was no patient demand.
2. Patient total time in the unit: the difference between patient arrival and release from the unit.
3. Number of patients seen: total number of patients seen by the physician in workday

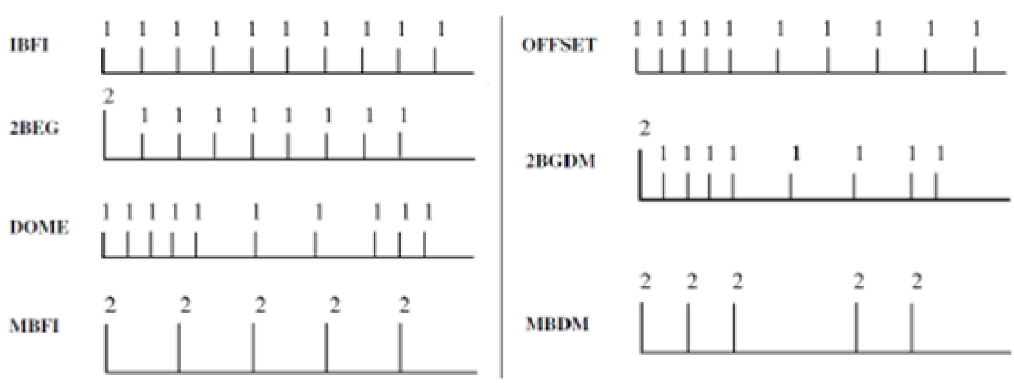
Research Methodology

General Background

The health care unit evaluated has 1 doctor and 1 receptionist. Patients are seen by appointment. There may be patients arriving without an appointment (walk-in) and scheduled patients may not appear (no-show). Finally, the scheduled patients can also arrive before or after the time scheduled following a certain probability distribution that will be mentioned below.

Cayirli et al. (2006) proposed seven scheduling appointment rules presented in the following figure 2, and here four of them were implemented in the Promodel software as described below:

Figure 1
Seven Scheduling Appointment Rules Proposed by Cayirli et al. (2006)

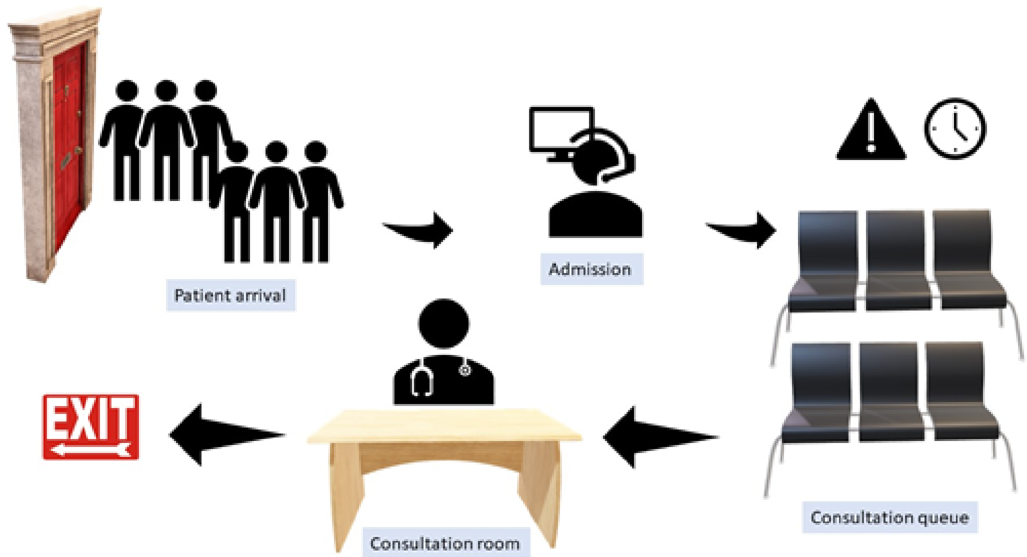


The scheduling appointment rules studied in this research were IBFI, 2BEG, OFFSET and DOME because they are more usual. Below is the explanation of each rule:

1. IBFI: (individual block/fixed interval): rule usually used by clinics that schedule patients individually at intervals equal to the average service time;
2. 2BEG: (individual block/fixed interval): same as the IBFI rule, but with an initial block of two patients;
3. OFFSET (individual block/variable interval): schedules the first patients between shorter intervals and the rest are scheduled between longer intervals, when compared to the IBFI rule;
4. DOME (individual block/variable interval): schedules the first patients between shorter intervals, patients in the middle of the shift are scheduled between longer intervals, and the rest are scheduled between shorter intervals, when compared to the IBFI rule.

Instrument and Procedures

Figure 2
The Model (Authors)



A model which simulates the operation of a health care unit was built in Promodel. The unit has two professionals: 1 receptionist and 1 physician. Both have the capacity to see one patient at a time.

Upon arrival at the unit, the patient waits his turn to be seen by the receptionist. After being seen, he goes to the waiting room until the doctor is available to see him in the consultation room. Patients are seen in arrival order. After the consultation, the patient is released and exits the system.

The unit's workday is from 8am to 5pm, with a break from 12pm to 1pm. Overtime is not allowed. If a patient arrives after 5pm he will not be seen. Every day starts with the entire agenda booked, with two shifts of 12 patients booked in each. In the model, patient admission has equal chances of being of the returning or new. Patients of these classifications have different times of attendance by the doctor.

Sample of Research and Data Analysis

The time values of the activity processes, as well as the patients` impunctuality, were input data extracted from the articles by Peres (2017) and Cayirli et al. (2006). They follow statistical distributions and are described below:

Table 1
Adapted from Peres (2017) and Cayirli et al. (2006)

Factor	Distribution
Patients' impontuality	Normal (-16.62, 27.07)
Service time at medical office for new patients	Lognormal (19.09, 6.85)
Service time at medical office for returning patients	Lognormal (15.50, 5.038)
Service time at the reception	Triangular (1, 1.5, 2)

The patients' impontuality will sum the random variable retrieved from a normal distribution with mean -16.62 and standard deviation of 27.07 to the planned schedule time for each patient.

The appointment schedules for the rules IBFI and MBFI follow the interval of 20 minutes between patients. The tables 2 and 3 explain further how the patients were scheduled for the Dome and Off-set rules. On them, it's stated the patient order on any given shift and the time interval to the previous scheduled patient.

Table 2
Interval between Appointments Using the Dome Rule

Patient	Interval (minutes)
1	-
2	15
3	15
4	15
5	15
6	15
7	25
8	25
9	25
10	25
11	20
12	20

Table 3
Interval between Appointments Using the Off-set Rule

Patient	Interval (minutes)
1	-
2	15
3	15
4	15
5	15
6	15
7	25
8	25
9	25
10	25
11	25
12	25

Nine different scenarios were tested with varying rates of No-show and Walk-in for each scheduling rule presented. These inputs variations among the scenarios are described in Table 4:

Table 4
Scenarios of Number of Walk-in Patients and Rate of No-show

Scenario	Distribution that represents time between walk-in patients (minutes)	Rate of no-show (%)
1	No Walk-in	10
2	No Walk-in	20
3	No Walk-in	30
4	Normal (140, 20)	10
5	Normal (140, 20)	20
6	Normal (140, 20)	30
7	Normal (70, 20)	10
8	Normal (70, 20)	20
9	Normal (70, 20)	30

Each combination of scheduling rule and scenario was simulated 100 times, and the results were exported and compiled utilizing the Rstudio software.

In each scenario seven performance indicators were collected.
1. Maximum queue size
2. Average queue size
3. Average waiting time
4. Physician idle time
5. Average crossing time
6. Average number of patients a day

Research Results

Considering four schedule appointment rules, six performance indicators and nine scenarios it is expected to present 216 results. But, in order to show how the best schedule appointment rules can change depending on walk-in and no-show scenarios, in this section, only the best rule and their value are presented by each scenario and performance indicator.

Table 5
Maximum Queue Size

Maximum queue size (MQS)		
Scenario	**Best performing scheduling rule**	**Value**
1	IBFI	2.69
2	IBFI	2.4
3	IBFI	2.19
4	Dome	3.36
5	IBFI	2.72
6	IBFI	2.4
7	Dome	3.89
8	Dome	2.97
9	Off-set	2.82

The IBFI scheduling rule performed best in average queue size and maximum queue size in 5 of the 9 scenarios, according to Tables 5 and 6. In the other scenarios, Dome and Off-set alternated in the position of best performing rule.

Table 6
Average Queue Size

Average queue size (AQS)		
Scenario	**Best performing scheduling rule**	**Value**
1	IBFI	0.55
2	IBFI	0.35
3	IBFI	0.32
4	Dome	0.77
5	IBFI	0.5
6	IBFI	0.37
7	Off-set/Dome	1.12
8	Dome	0.64
9	Off-set/Dome	0.52

The 2BEG rule proved to be the only one not to be the most advantageous for these parameters in any of the scenarios tested. The likely reason is that the rule consists of scheduling two patients at the very first time, which causes a queue to be scheduled from the very beginning of the clinic's operation.

It is emphasized that as the number of walk-in patients increases, IBFI stops being the most appropriate rule for these parameters. In the three scenarios in which there is a higher rate of walk-in patients, the IBFI rule is disadvantaged by the Dome and Off-set rules.

Table 7
Average Waiting Time

Average waiting time (AWT)		
Scenario	Best performing scheduling rule	Value (min)
1	Dome	10.36
2	IBFI	8.5
3	Off-set	8.58
4	Off-set	12.95
5	Dome	11.22
6	IBFI	10.15
7	Off-set	13.82
8	Dome	11.08
9	Off-set	9.44

Regarding the waiting time (Table 7) and total patient time (Table 8) indicators, Dome, IBFI and Off-set appear as the best choices, depending on the scenario. Once more, the 2BEG rule does not present the best performance in any of the proposed scenarios.

Table 8
Patient Total Time

Patient total time (PTT)		
Scenario	Best performing scheduling rule	Value (min)
1	Dome	34.24
2	IBFI	29.97
3	Off-set	30.52
4	Dome	36.45
5	IBFI	31.47
6	IBFI	28.83
7	Dome	40.77
8	Dome	32.32
9	Off-set	29.67

The Dome rule is the one that appears most frequently as the best choice, being indicated in 4 out of 9 scenarios in patient total time indicator, while Off-set appears in 4 out of 9 scenarios in Average waiting time.

ISSN 2029-6932 (Print) ISSN 2538-712X (Online) https://doi.org/10.33225/pmc/21.16.28

Table 9
Physician Idle Time

Physician idle time (IDT)		
Scenario	**Best performing scheduling rule**	**Value (%)**
1	2BEG	21.94
2	Dome	31.12
3	Dome	35.88
4	2BEG	16.32
5	IBFI	25.22
6	2BEG	33.65
7	2BEG	12.02
8	2BEG	21.47
9	2BEG	25.98

In the physician idleness indicator, the 2BEG rule stands out as the best choice in 6 of the simulated scenarios. This reflects the lack of the policy that allows on average more patients to be seen without overtime (Table 10) due to the loading of a scheduled queue at the beginning of each shift.

The Off-set rule does not provide the lowest physician idleness in any combination of no-show and walk-in scenarios.

Table 10
Average Number of Patients per Day

Average number of patients per day (ANPD)		
Scenario	**Scheduling rule with highest average**	**Value**
1	2BEG	21.58
2	Dome	18.88
3	2BEG	17.2
4	2BEG	24.54
5	2BEG	22.01
6	Off-set	20.3
7	2BEG	28.05
8	2BEG	25.36
9	2BEG	24.2

Table 11 summarizes the results presented in Tables 5 through 10 and then a comparison between scenarios, performance indicators, and rules is provided.

Table 11
Best Performing Rule for Each Indicator per Scenario

Scenario	MQS	AQS	AWT	IDT	PTT	ANPD
1	IBFI	IBFI	Dome	2BEG	Dome	2BEG
2	IBFI	IBFI	IBFI	Dome	IBFI	Dome
3	IBFI	IBFI	Off-set	Dome	Off-set	2BEG
4	Dome	Dome	Off-set	2BEG	Dome	2BEG
5	IBFI	IBFI	Dome	IBFI	IBFI	2BEG
6	IBFI	IBFI	IBFI	2BEG	IBFI	Off-set
7	Dome	Off-set/Dome	Off-set	2BEG	Dome	2BEG
8	Dome	Dome	Dome	2BEG	Dome	2BEG
9	Off-set	Off-set/Dome	Off-set	2BEG	Off-set	2BEG

Table 11 presents the best scheduling rule for each indicator and per simulated scenario. It is clear that there is a trade-off between physician idleness and queue size. The 2BEG rule, which on average offers less idle time to the physician, does not present better results regarding average and maximum queue size. On the other hand, the IBFI rule, which stands out in the number of queue patients results, in comparison to the idleness of the physician only appears better in one scenario.

Discussion

Previous research states that there is not a better appointment scheduling rule for all scenarios (Cayirli et al., 2006, Anderson et al., 2015, Peres, 2017 and Barghash and Saleet, 2018). This statement is enhanced by Table 11. In addition, the same table shows how the "best rule" depends on the set of crucial KPIs adopted by the decision makers.

Moreover, some "patterns" were found by using a discrete event simulation approach that are presented below:

1. The IBFI rule, the most traditional one, shows great results when there is little no-show and walk-in. That is, when there is high predictability in the schedule.
2. IBFI schedule appointment rule is not suggested by any indicators in all scenarios where there is a high walk-in rate (scenarios 7, 8 and 9). This result was also seen in Perez (2017) research.
3. As long as the number of walk-in patients increases, however, the IBFI rule is outperformed by the Dome or Off-set rules, which are more efficient in dealing with uncertainties.
4. The 2BEG rule maximized ANPD in 7 of 9 scenarios and reduced physician idle time in 6 of 9 scenarios. In practice, as 2BEG rule consists in allow a overbook (schedule 2 patients in 1 patient slot) in the first slot it is expected a worse result in comparison to other rules by evaluating the other performance indicators proposed.

Despite the intrinsic trade-off involved in the KPI's chosen, considering an infectious disease transmission context, it is suggested that managers should give a particular attention to MQS and AQS performance indicators. It also allows their operation to meet particular government recommendations about social distancing that has been taken in many countries (Masters et al., 2020).

Future Directions

To further works it is suggested:

1. Apply all seven schedule appointment rules proposed by Cayirli et al, (2006) and conduce literatures review to expand current schedule appointment rules in order to verify some changes in the patterns presented in Table 11 and discussed above;
2. Apply optimization techniques to find the best parameters used for each schedule appointment rules like proposed in Barghash and Saleet (2018);
3. Consider more resources or stages like other consultation rooms and imaging exams like in Klassen and Yoogalingam (2019) and then verify the KPI proposed at each stage;
4. Evaluate cost-effectiveness of adding resources or organizational changes using simulation models.

Conclusions and Implications

In view of the results generated by the simulations, some conclusions can be drawn. Considering an infectious disease pandemic scenario, it would be interesting to value scheduling rules that optimize the average and maximum queue size indicators. In this sense, in scenarios without walk-in or with low walk-in frequency, the IBFI rule performed best overall. However, in scenarios with high walk-in frequency, DOME and OFFSET alternated between the position of best rule.

On the other hand, taking into account time-related indicators such as patient waiting time in the queue and total waiting time in the unit, it can be seen that the Dome rule out performed in most scenarios (7 scenarios), followed by Off-set (6 scenarios) and then IBFI (5 scenarios).

Furthermore, considering the indicators of physician idle time and number of patients seen per day, one can observe that the 2BEG rule out performed in most scenarios. This rule particularly does not appear as best role in other performance indicators proposed because, in practice, it promotes overbooking in the first patients' slot.

It should be emphasized that the choice of a scheduling rule for a given health care unit should weigh these different performance indicators and consider the trade-off between them, and it may be valid, in a pandemic context, to give a greater weight to the indicators involving queue size.

Finally, to the practitioners, it is presented a possible strategy to achieve better operation indicator results that do not require organizational changes nor financial support. To current literature, it is enhanced the importance of queue management performance indicators in a transmissible disease context.

Acknowledgements

Thank you to the Laboratory of Engineering and Management in Health (LEGOS) from the Rio de Janeiro State University (UERJ)

Declaration of Interest

Authors declare no competing interest.

References

Anderson, K., Zheng, B., Yoon, S. W., & Khasawneh, M. T. (2015). An analysis of overlapping appointment scheduling model in an outpatient clinic. *Operations Research for Health Care*, *4*, 5-14. https://doi.org/10.1016/j.orhc.2014.12.001

Assad, D. B. N., Spiegel, T., & de Vasconcelos Silva, A. C. P. (2018). Improve center of sterilized material performance: A discrete event simulation model. In *Modeling and Simulation Techniques for Improved Business Processes* (pp. 113-139). IGI Global. https://doi.org/10.4018/978-1-5225-3226-2.ch005

Bailey, N. T. (1952). A study of queues and appointment systems in hospital out-patient departments, with special reference to waiting-times. *Journal of the Royal Statistical Society: Series B (Methodological)*, *14*(2), 185-199. https://doi.org/10.1111/j.2517-6161.1952.tb00112.x

Banks, J., Carson, J. S., Nelson, B. L., & Nicol, D. M. (2010). *Discrete-event System Simulation*. (5th ed. ed.) Prentice Hall.

Barghash, M., & Saleet, H. (2018). Enhancing outpatient appointment scheduling system performance when patient no-show percent and lateness rates are high. *International Journal of Health Care Quality Assurance*. Vol. 31 No. 4, pp. 309-326. https://doi.org/10.1108/IJHCQA-06-2015-0072

Boban, M. (2021). Novel coronavirus disease (COVID-19) update on epidemiology, pathogenicity, clinical course and treatments. *International Journal of Clinical Practice*, *75*(4), Article e13868. https://doi.org/10.1111/ijcp.13868

Bosch, P. M. V., & Dietz, D. C. (2000). Minimizing expected waiting in a medical appointment system. *Iie Transactions*, 32(9), 841-848. https://doi.org/10.1023/A:1007635012421

Cayirli, T., & Veral, E. (2003). Outpatient scheduling in health care: A review of literature. *Production and Operations Management*, *12*(4), 519-549. https://doi.org/10.1111/j.1937-5956.2003.tb00218.x

Cayirli, T., Veral, E., & Rosen, H. (2006). Designing appointment scheduling systems for ambulatory care services. *Health Care Management Science*, *9*(1), 47-58. https://doi.org/10.1007/s10729-006-6279-5

Couto, M. T., Barbieri, C. L. A., & Matos, C. C. D. S. A. (2021). Considerations on COVID-19 impact on the individual-society relationship: From vaccine hesitancy to the clamor for a vaccine. *Saúde e Sociedade*, 30, Article e200450. https://doi.org/10.1590/S0104-12902021200450

Guo, M., Wagner, M., & West, C. (2004, December). Outpatient clinic scheduling-a simulation approach. In *Proceedings of the 2004 Winter Simulation Conference, 2004.* (Vol. 2, pp. 1981-1987). IEEE. https://doi.org/10.1109/WSC.2004.1371559

Harper, P. R., & Gamlin, H. M. (2003). Reduced outpatient waiting times with improved appointment scheduling: A simulation modelling approach. *Or Spectrum*, *25*(2), 207-222. https://doi.org/10.1007/s00291-003- 0122-x

Horton, R. (2020). Offline: COVID-19 and the NHS- "a national scandal". Lancet (London, England), 395(10229), 1022. https://doi.org/10.1016/S0140-6736(20)30727-3

Hu, B., Guo, H., Zhou, P., & Shi, Z. L. (2020). Characteristics of SARS-CoV-2 and COVID-19. *Nature Reviews Microbiology*, 1-14. https://doi.org/10.1038/s41579-020-00459-7

Kaandorp, G. C., & Koole, G. (2007). Optimal outpatient appointment scheduling. *Health Care Management Science*, 10(3), 217-229. https://doi.org/10.1007/s10729-007-9015-x

Klassen, K. J., & Yoogalingam, R. (2019). Appointment scheduling in multi-stage outpatient clinics. *Health Care Management Science*, *22*(2), 229–244. https://doi.org/10.1007/s10729-018-9434-x

Klojda, T., de la Vega, R., e Alvim Alexandre, R., & Spiegel, T. (2021). Análise por simulação de melhoria de processos na entrada de unidade de atenção primária de saúde. *Revista Gestão & Saúde*, *12*(01), 92–107. https://doi.org/10.26512/gs.v12i01.32821

Law AM. (2013). *Simulation modeling and analysis*. McGraw-Hill.

Lotfi, M., Hamblin, M. R., & Rezaei, N. (2020). COVID-19: Transmission, prevention, and potential therapeutic opportunities. *Clinica Chimica Acta*. https://doi.org/10.1016/j.cca.2020.05.044

Masters N.B., Shih S.F., Bukoff A., Akel K.B., Kobayashi L.C., Miller A.L., Harapan, H., Lu, Y., Wagner, A.L. (2020) Social distancing in response to the novel coronavirus (COVID-19) in the United States. *PLOS ONE* 15(9), Article e0239025. https://doi.org/10.1371/journal.pone.0239025

Metcalf, C. J. E., & Lessler, J. (2017). Opportunities and challenges in modeling emerging infectious diseases. *Science*, 357(6347), 149-152. https://doi.org/10.1126/science.aam8335

Meza, J. P. (1998). Patient waiting times in a physician's office. *The American Journal of Managed Care*, *4*(5), 703–712.

Oliveira, H. M. J. (2020). A disseminação da covid-19: um papel expectante e preventivo na saúde global [The spread of covid-19: An expectant and preventive role in global health]. *Journal of Human Growth and Development*, *30*(1), 135-140. http://dx.doi.org/10.7322/jhgd.v30.9976

Peres, I., Veiga, S. G., Hamacher, S., Oliveira, F. L. C., & Spiegel, T. (2017). Simulação de políticas de agendamento de pacientes no ambulatório de oftalmologia de um hospital público. In: *XLIX Simpósio Brasileiro de Pesquisa Operacional, 2017*.

Peres, IT (2017). *Simulação de políticas de agendamento em serviços ambulatoriais* [Simulation of scheduling policies in outpatient services]. Rio de Janeiro.

Rader, B., Scarpino, S. V., Nande, A., Hill, A. L., Adlam, B., Reiner, R. C., ... & Kraemer, M. U. (2020). Crowding and the shape of COVID-19 epidemics. *Nature Medicine*, *26*(12), 1829-1834. https://doi.org/10.1038/s41591-020-1104-0

Tu, H., Tu, S., Gao, S., Shao, A., & Sheng, J. (2020). Current epidemiological and clinical features of COVID-19; a global perspective from China. *Journal of Infection, 81*(1), 1-9. https://doi.org/10.1016/j.jinf.2020.04.011

Welcht, J. D. (1964). Appointment systems in hospitals and general practice: Appointment systems in hospital outpatient departments. *Journal of the Operational Research Society*, *15*(3), 224-232. https://doi.org/10.2307/3007210

Wijewickrama, A. K. A. (2006). Simulation analysis for reducing queues in mixed-patients' outpatient department. *International Journal of Simulation Modelling*, *5*(2), 56-68. https://doi.org/10.2507/IJSIMM05(2)2.055

Wijewickrama, A., & Takakuwa, S. (2005, December). Simulation analysis of appointment scheduling in an outpatient department of internal medicine. In: *Proceedings of the Winter Simulation Conference, 2005*. (pp. 10-pp). IEEE. https://doi.org/10.1109/WSC.2005.1574515

Zhu, Z. C., Heng, B. H., & Teow, K. L. (2009). Simulation study of the optimal appointment number for outpatient clinics. *International Journal of Simulation Modelling (IJSIMM)*, *8*(3). https://doi.org/10.2507/IJSIMM08(3)3.132

Received: *May 05, 2021*　　Accepted: *June 18, 2021*

Cite as: Klojda, T. N., Fortuna, A. P. B. P., Araujo, B. M., Assad, D. B. N., & Spiegel, T. (2021). Comparing scheduling appointment rules performance in health care units: A discrete event simulation approach. *Problems of Management in the 21st Century*, *16*(1), 28-41. https://doi.org/10.33225/pmc/21.16.28

PROBLEMS
OF MANAGEMENT
IN THE 21st CENTURY
Vol. 16, No. 1, 2021

Thiago Nunes Klojda *(Corresponding author)*	BSc, Rio de Janeiro State University, R. São Francisco Xavier, 524 - Maracanã, Rio de Janeiro - RJ, 20550-013, Brazil. E-mail: thiago.klojda@gmail.com Website: http://lattes.cnpq.br/1226846513452195 ORCID: https://orcid.org/0000-0003-4352-8019
Antônio Pedro de Britto Pereira Fortuna	Undergraduate, Rio de Janeiro Federal University, R. Prof. Rodolpho Paulo Rocco, 255 - Cidade Universitária da Universidade Federal do Rio de Janeiro, Rio de Janeiro - RJ, 21941-617, Brazil. E-mail: antoniopfortuna@hotmail.com Website: https://www.linkedin.com/in/antônio-pedro-fortuna-620957200/ ORCID: https://orcid.org/0000-0003-4650-3490
Bianca Menezes Araujo	Undergraduate, Rio de Janeiro State University, R. São Francisco Xavier, 524 - Maracanã, Rio de Janeiro - RJ, 20550-013, Brazil. E-mail: biancamearaujo@gmail.com Website: http://lattes.cnpq.br/1385492783893941 ORCID: https://orcid.org/0000-0002-4916-4917
Daniel Bouzon Nagem Assad	MSc, Polytechnic University of Madrid, José Gutiérrez Abascal, 2, 28006 Madrid, Spain. E-mail: danielbouzon@gmail.com Website: http://lattes.cnpq.br/0258423859812498 ORCID: https://orcid.org/0000-0003-3911-4323
Thaís Spiegel	DSc, Rio de Janeiro State University, R. São Francisco Xavier, 524 - Maracanã, Rio de Janeiro - RJ, 20550-013, Brazil. E-mail: thais@eng.uerj.br Website:http://lattes.cnpq.br/8880192361495671 ORCID: https://orcid.org/0000-0002-7801-8492

ISSN 2029-6932 (Print) ISSN 2538-712X (Online) https://doi.org/10.33225/pmc/21.16.28