DISCRETE EVENT SIMULATION OF THE COVID-19 SAMPLE COLLECTION POINT OPERATION

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ABSTRACT

The year 2020 was very challenging for everyone due to the COVID-19 pandemic. Many people turn their lives upside down from day to day. Politicians had to impose completely unprecedented measures, and doctors immediately had to adapt to the huge influx of patients and the massive demand for testing. Of course, not all processes could be planned completely efficiently, given that the situation literally changes from minute to minute, but sometimes better planning could improve the real processes. This contribution deals with the application of simulation software SIMUL8 to the analysis of the COVID-19 sample collection process in a drive-in point in a hospital. The main aim is to create a model based on the real data and then to find out the suitable number of other staff (medics) helping a doctor during the process to decrease the number of unattended patients and their waiting times.

INTRODUCTION

Although simulation modeling is a relatively widespread tool and the use of ICT in developed countries is a common part of everyday life, in reality we still face problems in which simulation modeling could help avoid unpleasant effects - and yet no similar analysis has been made. Even at a time when we face many restrictions related to the COVID-19 pandemic and when the implementation of various measures and changes is often very rapid, we should not forget the benefits of simulation modeling and discrete event simulation before launching new projects or processes. Due to its probabilistic and dynamic aspects, a realization of experiments with the simulation model helps the decision-maker set the processes in a better way than without the model, especially when no previous similar situation was not tested.

In the Czech Republic, unlike other countries, simulation modeling in the healthcare environment is not a common part of introducing new processes and changes. According to the review of approximately 250 high-quality journal papers published between 1970 and 2007 on healthcare related simulation made by Katsaliaki and Mustafee (2011), no paper was connected with the Czech Republic healthcare system. Most of the papers used Monte Carlo simulation models, but discrete event simulation was also mentioned in 20 % of the papers analysed. Brailsford, Carter and Jacobson (2017) commented the situation of 50 years of simulation modelling in healthcare context – they agreed that healthcare was a prolific application area for simulation modeling ever since the very early days of computer simulation and during the 5 decades a lot of models using Monte Carlo simulation and discrete event simulation was done, mainly in USA and UK. Walsh et al. (2018) showed that among the 100 most cited articles on simulation in healthcare, 88% of articles are from the USA, UK and Canada. So there is still much space for improvement in other countries, including the Czech Republic.

Most of the papers used Monte Carlo simulation models, but discrete event simulation was also mentioned in 20% of the papers analysed by Katsaliaki and Mustafee (2011). Van Buuren et al. (2015) presented a detailed discrete event simulation model for emergency medical services call centers. As Hamrock et al. (2013) stated, discrete event simulation in healthcare commonly focuses on improving patient flow, managing bed capacity, scheduling staff, managing patient admission and scheduling procedures, and using ancillary resources (e.g., labs, pharmacies).

This paper focuses on improving patient flow and better staff scheduling in the drive-in COVID-19 sample collection point. Our goal is to analyze the situation and verify whether certain aspects of the process could not be better addressed or whether it was not possible to propose an alternative approach. The main aim is to create a simulation model and analyze the impact of the number of resources' changes on queuing time. For the model, SIMUL8 software is used.

SIMUL8

SIMUL8 is a software package designed for Discrete Event Simulation or Process Simulation and developed by the American firm SIMUL8 Corporation (www.simul8.com). The software started to be used in 1994, and every year a new release has come into being.

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A visual 2D model of an analyzed system can be created by placing objects directly on the screen. This software is suitable for discrete event simulation (Shalliker and Ricketts 2002). SIMUL8 uses 2D animation only to visualize the processes, but for the given problem, this view is sufficient, especially because queue analysis is important.

SIMUL8 belongs to the simulation software systems widely used, especially in industry (Greasley 2003), but several case studies were aimed at analysing the queues in the healthcare processes. Pisaniello et al. (2018) used SIMUL8 to develop the simulation model of the call center in the children's hospital, they demonstrated the meaning of the application of validation and verification techniques as the most critical aspects of the simulation modelling process. Viana et al. (2014) showed the usage of SIMUL8 for discrete event simulation in combination with system dynamics in VENSIM software to analyze how the prevalence of Chlamydia at a community level affects (and is affected by) operational level decisions made in the hospital outpatient department.

SIMUL8 main components

SIMUL8 operates with 6 main parts out of which the model can be developed: Work Item, Work Entry Point, Storage Bin, Work Center, Work Exit Point, Resource (Concannon et al. 2007).

Work Item: dynamic object(s) (customers, products, documents or other entities) that move through the processes and use various resources. Their main properties that can be defined are labels (attributes), an image of the item (showed during the animation of the simulation on the screen) and advanced properties (multiple Work Item Types).

Work Entry Point: an object that generates Work Items into the simulation model according to the settings (distribution of the inter-arrival times). Other properties that can be used in this object are batching of the Work Items, changing the Work Items Label or setting the following discipline (Routing Out).

Storage Bin: queues or buffers where the Work Items wait before the next processes. It is possible to define the capacity of the queue or the shelf life as time units for the expiration.

Work Center: main object serving for the activity description with the definition of the time length (various probabilistic distributions), resources used during the activity, changing the attributes of entities (Label actions) or setting the rules for the previous or following movement of entities (Routing In / Out).

Work Exit Point: an object that describes the end of the modeled system in which all the Work Items finish their movement through the model.

Resource: objects that serve to model limited capacities of the workers, material or means of production used during the activities.

All objects (except resources) are linked together by connectors that define the sequence of the activities and also the direction of movement of Work Items.

After the system is modelled, the simulation run follows. The animation shows the flow of items through the system and for that reason the suitability of the model can be easily assessed. When the structure of the model is verified, several trials can be run and then the performance of the system can be analyzed statistically. Values of interest may be the average waiting times or utilization of Work Centers and Resources (Shalliker and Rickets 2002). SIMUL8 can be used for various kinds of simulation models (Concannon et al. 2007). The case studies can also be seen on the website www.simul8.com.

Our experience shows that SIMUL8 is easy to learn when only the main components are used (without the necessity to use Visual Logic with different programming functions). It can serve not only for the modelling of different services but also for the simulation of various production processes (Fousek et al. 2017).

PROBLEM DESCRIPTION

The impetus for the creation of the model presented in this paper was the experience of one of the authors in the test for COVID-19 as there were long queues at a selected drive-in center in one of Prague's hospitals. Therefore, we decided to analyze the problem and use a simulation model to assess the number of service personnel changes to reduce customer waiting time.

HOSPITAL DATA

The model is focused on the analysis of the drive-in COVID-19 sampling point in one of the Prague's hospitals. The drive-in collection point is used for patients arriving for the test by car. The hospital allows people to order a test using the online form (e-request) only. Examination for coronavirus infection is performed either on the basis of an indication by a general practitioner or the Regional Hygiene Station or without any indication as a self-payer. A patient who orders a drive-in test at their own expense must pay for the test online, and a patient who has a test request from a general practitioner does not have to pay. Therefore, payment is not included in the model at all, because it takes place when ordering (online), or it does not take place at all.

Each patient must be booked, the collection point does not accept unordered patients. Unfortunately, there are still cases where an unordered patient appears in the

queue. The hospital also offers a walk-in collection point, and occasionally a patient who goes for a walk-in test also appears at the drive-in collection point. All these situations must be included in the model.

According to the hospital's information, tests are performed from 8:00 to 11:55 and from 13:00 to 16:55 at intervals of five minutes, or from 18:00 to 21:56 at four minute intervals (FNKV.cz 2021). Based on the experience of the hospital's doctor (obtained from the authors' interview with the doctor), patients arrive at the collection point approximately at the time of order, but the order of the cars may not match the order of ordering, as some patients arrive in advance, some on time and some even with a delay. However, it is not possible to change the order in the car queue, so patients are admitted in the order in which they arrived. Upon arrival at the collection site itself, the doctor first finds out whether the patient has been ordered, whether all necessary data is in the patient form and whether a request has been sent from a general practitioner or a patient is a self-payer. If everything is in order, the doctor will take a sample and store it. Then the patient leaves the drive-in. Occasionally, there may be complications when the patient is ordered for a walk-in and not for a drive-in, or he/she is not ordered at all, a request is not sent from a general practitioner. The differences are also when the patient is a child and not an adult. It takes longer to take samples with a child, as it is more difficult to take samples.

Based of our knowledge of the process and according to the discussion with a doctor and patients' interviews (interviews with several patients were conducted by the authors at the sampling site) we collected these kind of data:

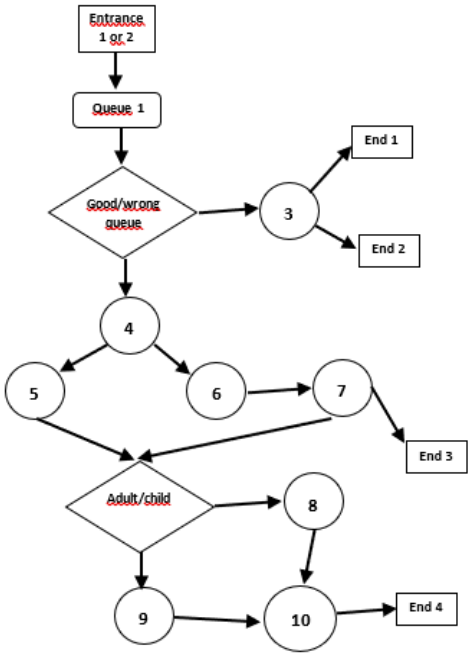
- No request for a doctor or a payment from the self-payer can be found in 5% of the patients ordered. If a practitioner has to be called, the problem will be solved in 80% of patients, so the request will be sent immediately. In 20% of cases, the patient must go either to the end of the queue or home again and order for another day.
- 4% of patients are in the wrong queue, half of them should be in the walk-in and half is not ordered.
- 85% of patients are adults and 15% of patients are children.
- Doctors and medics also work during the lunch and evening breaks plus overtime (50 minutes of service) if patients are still waiting in line.
- Although patients are booked on a specific time, they do not always arrive on time, so an exponential distribution can be used for the intervals between arrivals.

The model should include only activities related to the process at the drive-in collection point. The list of activities, including probability distributions for durations, is given in Table 1. Symbol EXP is used for exponential distribution with the mean value for interarrival times. T is used for the triangular distribution with lower, mode and upper time limits. U is for uniform distribution with minimum and maximum duration, N for normal distribution with mean value and standard deviation of the duration.

Table 1: List fo Activities and Probability Distributions

Activity No.	Probability distribution and times in minutes
1.arrivals during the day	EXP (5)
2.arrivals during night	EXP (4)
3. wrong queue activities	T (1;2;6)
4. database search	T (0,5;1;3)
5. well entered form	T (1;3;5)
6. badly entered form	T (3;5;7)
7. calling a practitioner	U (1.5;3)
8. adult sampling	T (0.5;1;2)
9. child sampling	T (2;2.5;4)
10. sample storage	N (1;0.25)

The scheme of the process with all 10 activities is on the Figure 1.



Figures 1: Scheme of the Process

The patient comes to the drive-in center and stands in Queue 1. Afterward, the doctor or medic controls the ordering form in the database. If there is some problem (activity 3; 4% of patients) - a patient is in the wrong queue (he/she should be in the Walk-in instead) or if he/she is not ordered – the doctor or medic sends the patient to the Walk-in center (50%; end1) or home to order electronically (50%; end2). For those correctly ordered for the drive-in (96%), the request/order form is

checked (activity 4). Patients, who have everything correctly filled in, are prepared for sampling. (activity 5) For those who do not have the correct request from a general practitioner, it is necessary to try to supplement the information by calling a general practitioner (activities 6 and 7). When successful, the patient is ready and continues testing (activities 8 or 9). If the information cannot be completed, the patient is sent re-ordered for another day (end3). Finally, after testing, the sample is stored (activity 10) and the patient can go home (end4).

MODEL IN SIMUL8

The simulation model was developed in SIMUL8 software. The aim of the simulation is to find a suitable number of doctors and medics to serve patients so that the queue length does not exceed 30 cars and the waiting time is acceptable. We have tested 3 models:

- Model 1 – 1 doctor, no medic – this model corresponds to the real situation in the selected hospital
- Model 2 – 1 doctor, 1 medic
- Model 3 – 1 doctor, 2 medics

Entities in all 3 models are patients generated via the exponential distribution with 5 minutes or 4 minutes interarrival times during the working hours. According to Table 1, activities are modeled as work centers (as an example of activity 5 see Figure 2). In Model 1 only 1 resource (doctor) is used (see Figure 3), in Model 2 one medic is added. The so-called pooled resource is created – it means doctor and medic together when part of the activities can be done by any of them (see Figure 4). Only the sample collection and storage activities are made by a doctor. Model 3 is similar to Model 2, only 2 medics instead of 1 are used.

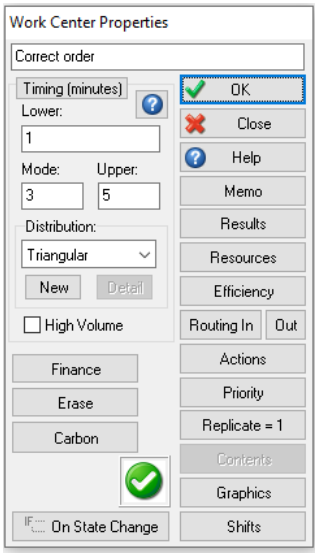


Figure 2: Activity Settings

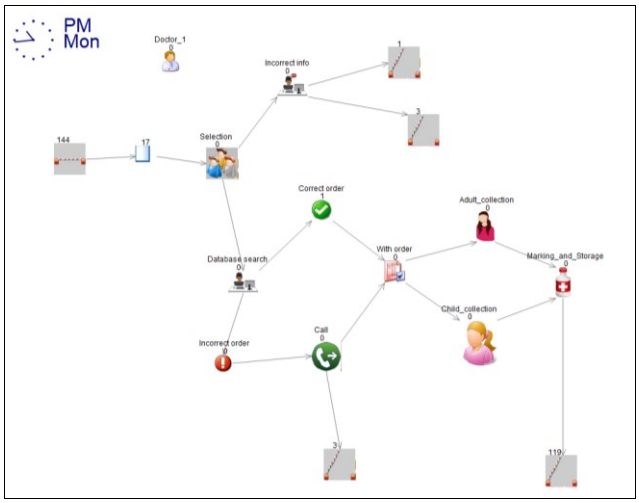


Figure 3: Model 1

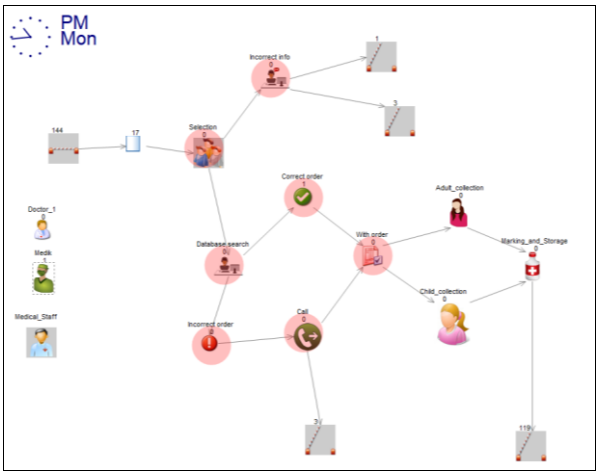


Figure 4: Model 2

RESULTS

After 1000 experiments with Model 1 the average of 30.7 unattended patients at the end of the day (see Figure 5) was identified, with a 95% confidence interval (29.96; 31.40). This is an alarming result, as this system would not be sustainable - if about 30 patients were not served every day, they would have to book another day and the demand for consumption would increase very quickly.

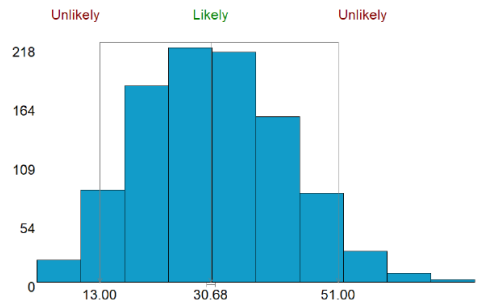


Figure 5: Model 1 - Curent Content of the Queue 1 (1000 runs)

The average queue length is 15.7 cars. Although this means a relatively long line, it would not cause serious problems in traffic. However, when we focus on the maximum queue length, we find that the 95% confidence interval is (37.04; 38.46). This means that there is a high chance that a queue could be longer than 30 cars, which will significantly complicate traffic.

The average time spent in the queue is about 83 minutes (see Figure 6) which is not acceptable.

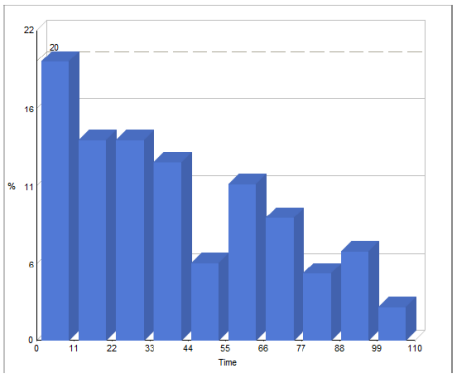


Figure 6: Time in the Queue 1

A doctor occupancy is on average up to 98%. This unfavorable result means that a doctor should work up to 14: 45h a day without any breaks, and yet patients remain unattended after the closing time. Definitely, this result is not satisfactory even if the doctors take turns. We recommend including the medic in the model to help with the administration.

In Model 2 a medic was added. He/she, however, cannot take samples and then label and store samples, these activities will remain with the doctor. Other activities can be performed by both a medic and a doctor. This allows two patients to be served at the same time (eg, the doctor takes a sample from the first patient while the medic checks the second patient's request).

The average number of unattended patients dropped rapidly to just 0.12 per day. Also, the estimate of the average queue length (see Figure 7) was reduced to only 1.05.

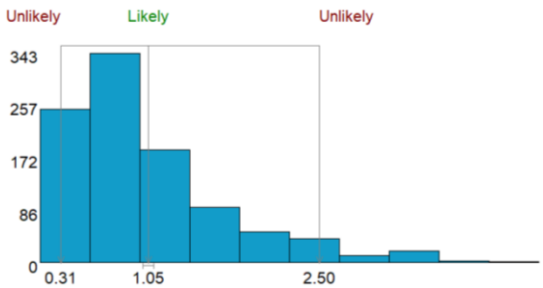


Figure 7: Model 2 - Curent Content of the Queue 1 (1000 runs)

The average workload of the doctor decreased to 68.44%, the confidence interval is (68.11; 68.76). We consider this workload reasonable, as the doctor is not busy all day and has time for lunch/dinner or a short rest. The workload of the medic can also be considered reasonable (see Figure 8). The model estimates the average workload of the medic to be 58.87%.

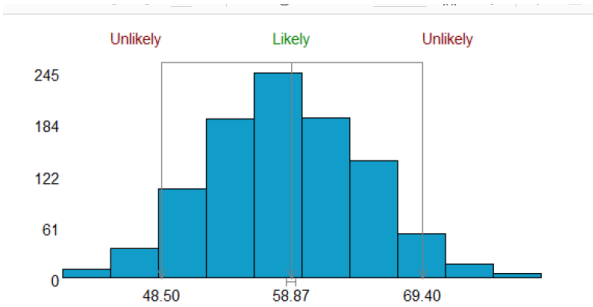


Figure 8: Model 2 – Medic Usage (1000 Runs)

The average time in the system was significantly reduced to 17.76 minutes. At the same time, the average time in the queue was shortened to 5.78 minutes. The estimate of the 95% confidence interval of the average time in the queue is then (5.57; 6.00). The average waiting time in the queue can thus be considered acceptable.

Model 3 included two medics. In this case, the doctor only take samples and then mark and store the sample. Other activities are in charge of two medics. This allows up to three patients to be served at the same time, which of course shortens the queue and speeds up the system. Other settings remain the same as in Model 1.

With this solution, in no simulation experiment did an unattended patient remain in the queue for 50 minutes after the end of working hours. The average queue length was about 0.194 cars. Of course, the average time in the queue was also reduced to 1.08 minutes. The average time in the system of the patient who was sampled is 11.02 minutes. The workload of the doctor is the lowest in this model, about 34.16% on average. The workload of medics has also decreased compared to the previous model, as there are now two administrative activities, so the workload was 43.16% on average.

Finally, we compare the results of the individual models. Estimates of all significant average characteristics are worst for Model 1, while best for Model 3 (see Table 2). The basic model (Model 1) is very bad in all respects – but unfortunately it corresponds to the reality that one of the authors experience. The differences between the average time spent in the system and in the queue, the average queue length, or the number of unattended patients are not significant between the remaining models. Both Model 2 and Model 3 are acceptable with regard to queue length and waiting time. If the hospital wants to speed up the process with patients not spending

more than a quarter of an hour on the tests, Model 3 is more appropriate, provided that the hospital has 2 medics available to involve in the process. When 1 medic is involved, his/her workload and the doctor's workload will be higher but still acceptable. Patients would spend a little longer in the process, but still, that time would be much shorter than in real practice shown in Model 1.

Table 2: Comparison of the Average Results of All Models

Average results	Model 1	Model 2	Model 3
No. of doctors	1	1	1
No. of medics	0	1	2
Unattended patients	30.78	0.12	0.00
Queue length	15.70	1.05	0.19
Busy doctor	97.91	68.44	34.16
Busy medics	x	58.87	43.16
Patient time in system (minutes)	91.57	17.76	11.02
Queuing time	83.53	5.78	1.08

CONCLUSION

The aim of the contribution was to demonstrate the applicability of SIMUL8 on the drive-in COVID-19 sample collection point process in a hospital. The model was based on available information given by patients and doctors of the hospital and one author's experience. The simulation model shows the real situation with very long queues, a lot of unattended patients and a long time spent in the hospital. Only a small change – adding 1 medic to help the doctor – could rapidly improve both hospital time and queue length. Unfortunately, the deployment of doctors and medics is done on an ad hoc basis.

Our results show that only a small change in the system can significantly benefit the situation. In this case, it is a more efficient division of labor into the administrative part and the sample collection itself. We demonstrate that the use of simulations has a real use even in crisis situations where there is not enough time to analyze the impacts of the selected system. Thanks to the simulation, it is possible to see whether the proposed change would have a large or negligible impact on the overall societal benefit, whether in terms of doctor's workload, time spent in the queue, or a negative impact on traffic in adjacent streets.

As Brailsford, Carter and Jacobson (2017) mentioned: active stakeholder engagement in the modeling process is a critical success factor for a healthcare simulation model to be useful in practice and despite major advances in both software and hardware, there is still a general lack of implementation of simulation in healthcare, compared with other sectors such as manufacturing industry or defense. As this paper describes, a relatively simple simulation model can very quickly show the effects of changes and its use would be beneficial to both doctors and patients, and thus for the hospital as a whole.

It would certainly be interesting to analyze the situation in other hospitals, but this would require access to data, which is not always easy or possible. However, the presented analysis can also help raise awareness of the possibilities of using simulation models in healthcare.

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