Mass testing against COVID-19: a logistic simulation model to design and manage swab test clinics

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Abstract: COVID-19 pandemic caused several million deaths worldwide since the beginning of 2020. One of the most effective activities to contrast its diffusion is the execution of mass testing campaigns to track the virus spread. To design an efficient logistic system for such purpose, it is important to correctly plan the clinic layout and size the medical resources involved in the swab testing campaign, to avoid long patient queues or personnel underutilization. This paper describes the development of an original logistics simulation model to support the planning and design of clinics for the walk-in mass testing campaign against COVID-19 performed by South Tyrol Health Agency in just one weekend in November 2020 which involved more than 350'000 citizens. The developed model represents the targeted physical system considering all the different phase of such healthcare process. Furthermore, the duration of the multiple process phases is statistically distributed according to a large dataset collected during the COVID-19 testing campaign for touristic operators conducted in September and October 2020 in South Tyrol. The simulation model virtually evaluates the swab testing clinics with different parameters to determine the best scenario to be implemented. It concerns the number of medical resources allocated, the necessary clinic spaces and the time spent inside the clinic by each patient. The obtained results suggest that the so-defined configuration is distinguished by an average throughput of 8.8 minutes per patient. This clinic prototype has been replicated and set-up all over South-Tyrol territory to reach the targeted number of tested citizens. Indeed, 362'050 people were effectively tested from 20th to 22nd November 2020 leveraging 184 clinics and about 1400 healthcare co-workers, both medical and non-medical personnel. 3'615 Covid-positive people were detected and the virus transmission index of this Province fell from 1.22 to 0.74 just in the following 2 weeks.

Keywords: discrete-event simulation; facility layout; COVID-19; mass testing; logistics

1.Introduction and literature review

COVID-19 pandemic was officially registered for the first time at the end of 2019 in Wuhan, China. Since that moment, it caused more than 76 million cases and 1.7 million death in the world until the end of 2020 (European Centre for Disease Prevention and Control, 2020). In particular, Italy has been one of the most afflicted countries, with two million cases and more than 70 thousand people dead until 28th December 2020 (Italian Ministry of Health dashboard, 2020).

In order to contrast the virus, several European countries established local lockdown in the most critical areas, integrating it with mass testing campaigns involving large percentage of the population. The most relevant campaign was built in Slovakia at the end of October 2020 with the aim to test all the adult population in three consecutive weekends. To reach that goal, several clinics has been set up all over the country and a huge number of resources and personnel has been recruited for this purpose. One of the issues occurred concerned the availability of medical staff. Indeed, due to lack of these resources the first two days of the mass testing campaign encountered multiple problems and inefficiencies as people queued outside clinics for hours (The Lancet Report, 2020).

COVID-19 mass screening campaigns traditionally adopt rapid antigen tests (RATs) due to multiple reasons. First of all, these tests are nasopharyngeal swab tests that do not need a laboratory analysis to provide a result. For this reason, RATs provide a result in just 15-20 minutes which is a great advantage in circumstances which require a short turnaround time. Therefore, RATs allow prompt and timey contact tracing of COVID-19 infected people, who can be isolated soon to avoid a wide spread of the virus (European Centre for Disease Prevention and Control Report, 2020).

In scientific literature, different studies have been carried out to solve healthcare organizational problems with mathematical and quantitative methods. For example, linear programming was used to determine the optimal resource allocation in a Thorax Centre to operate a target number of patients. A model was developed which calculates the best mix of patients categories and number of patients in each of them to be operated each day. This linear programming algorithm was applied for 4 different scenarios to find the best solution in terms of accuracy of resources utilization (Vissers et al., 2005). However, fixed average values for hours allocation of the surgery were inserted in the model, while in reality the schedules can vary according to several parameters. To solve decision problems, operations research can adopt quantitative methods as simulation models. Since there are different kind of simulation models, each one can manage a specific healthcare problem. In particular, while agent-based simulation is more suited to manage quarantine strategies at local level, discrete-event simulation helps to allocate scarce resources, as bed or medical operators, by changing some parameters like patients schedule (Currie et al., 2020). A simulation model is proposed by Weiss et al. (2010) to evaluate patient condition with a drive-through clinic during an influenza pandemic. The authors assess the feasibility of such drive-through system and measure the throughput times of simulated patients. Different phases are established for the considered healthcare process, from screening to discharge, but duplicated in two identical testing lanes, reducing the overall healthcare system efficiency. Another discrete-event simulation model is recently developed by Beeler et al. (2014) to support decision-makers in medical staffing decisions for a vaccination campaign. Indeed, though the adoption of such model, the planners could define how the most relevant healthcare system parameters, like total performed vaccinations or patient wait times, change in relation to the available medical resources. Multiple timestamps are recorded to evaluate the durations of the different process phases considering different patient arrivals to clinic in batches sized from 1 to 5 people. This patient group arrival is modelled through interarrival times exponentially distributed to increase the reliability of the developed simulation model.

All these efforts have been resumed for COVID-19 studies. Firstly, coronavirus pandemic affects several sectors, as airports. Here, discrete-event simulation models are implemented to study the impact of social distancing on control lanes. Several scenarios are tested to find how COVID-19 changes airport performances and how to configure the new lanes to obtain similar results as before. The model demonstrated that the optimal design of the control lane also depends on the mix of passengers that comes to the airport (Kierzkowski et al., 2020). Simulation has been used also to predict the spread of the infection during the following months. Ferrari et al. (2021) developed a Susceptible-Infectious-Recovered (SIR) model to simulate the impact of contact tracing apps on the COVID-19 spread in Italy. They simulated several scenarios, according to some factors which can vary among regions, and found that the effective reproductive number (R_t) and the sum of infected gradually decrease if always more people use those kinds of tools. Rifanti et al. (2021) expanded the SIR model adding the new patient condition "hospitalized" and creating a Susceptible-Infectious-Hospitalized-Recovered (SIHR) model. Through this model, they compared the number of infected, hospitalized and dead people between the large-scale social restrictions (LSSR) period and the new normal period without restrictions in Indonesia. They were also able to find the transmission rate of both the periods and predict the end of the pandemic both if the restrictions were always kept and if these restrictions are reduced during the summer. Asgary et al. (2020) developed a simulation model to design a drive-through clinic for mass vaccination against the new SARS-CoV2. In particular, the proposed model evaluates the number of vaccinated patients and their time spent inside the clinic varying a defined set of relevant parameters as the number of medical resources or the patient arrival rate. Unfortunately, also this research is affected by a significant weakness represented by the duplication of queuing lanes for every process phase assigning one queue for every medical resource involved (e.g., a specific queue for every vaccinating nurse). Finally, to contrast the spread of COVID-19, in South Korea a mass testing campaign is designed by means of proper simulation model and efficiently delivered in March 2020. In particular, four specific testing phases are defined and modelled to design the optimal layout of small COVID-19 testing clinics to be replicated all over the country, even in locations distinguished by a limited space availability (Lee et al., 2020).

The aim of this research is the development of a logistic simulation model to support the design and planning of clinics for the mass testing campaign against COVID-19. The effort consists in finding the best solution in terms of space, times and resources starting from real data collected on the field, in order to define an ideal clinic to replicate all over the region according to the necessity.

2. Problem description and simulation model developed

The problem addressed consists in sizing scarce medical resources and design a specific layout for a clinic which should test against COVID-19 most people as possible keeping an accepted process and waiting time. In particular, the targeted testing process is distinguished by several phases linked to each other since each patient must complete one phase to proceed towards the next one (Figure 1). The first two phases which constitute the check-in part are form hand-out (A, index $_{\text{hand-out}}$) and form fill-in (B, index $_{\text{fill-in}}$). In the former, an operator gives patients the privacy policy and the module to fill in. In the latter activity, patients complete the form with their personal information. The third phase of the process is the acceptance (C, index $_{\text{acc}}$). Here, an operator scans patients health card to ease the search of their profile on the informatic system of the healthcare agency. Moreover, the operator inserts the patients personal information of the module on the computer database. The following phase is the performance of the antigen swab test by a nurse (D, index $_{\text{test}}$). Since there is only one nurse for each station, he/she should, firstly, complete the administrative activities like writing the exact hour of the test and controlling the patient information, and, then, carry out the test. The last phase is not linked to the patients and so it is performed by an operator independently letting the patients leave the clinic and go home. This phase consists in the registration of the antigen swab test results on the informatic system and the communication of these to the patients (E, index $_{reg}$). Indeed, after being tested, people must go home and wait for a SMS which informs them about the test result, in order to avoid gathering outside the clinic.

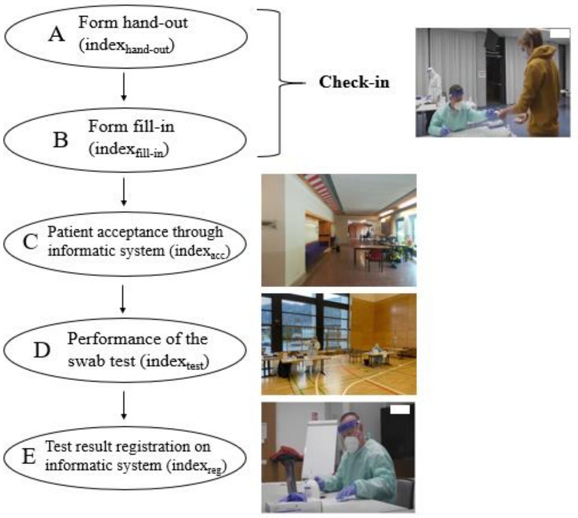

Figure 1: Process flowchart of the antigen swab test

To create a virtual environment which better represent the targeted healthcare physical system, it has been developed a discrete-event simulation model. It consists in a virtual model which can be run with different parameters until the best scenario is determined. The model is built as a group of modules all linked to each other to represent the testing process flowchart (Figure 2). The entities of the model represent the patients while the resources reflect both medical and non-medical operators. The first module creates the group of patients who arrive simultaneously at the clinic. Since people are scheduled according to a constant time window, the number of patient scheduled in each interval is set with variable S^{pat}. The group size can vary stochastically and it is a percentage of S_{pat} in order to differentiate each time window. The probability to create a specific size of each group is represented by the variable P^{group}. The time between two consecutive arrivals is determined by a time variable $T^{arrival}$ which represents the hourly arrival rate of patients inside the clinic. This parameter follows a statistical distribution as all the time variables of the developed simulation model. The module 2 queues all the patients who are waiting outside the clinic as all the places in queue in phase A are occupied. The number of these places can change according to the space available inside the clinic. Once inside the clinic, phase A is performed thanks to modules 3 and 4. The former represents the queue, where the maximum number of waiting patients acceptable is valued in variable $X_{hand-out}$. The latter module is adopted to perform the hand-out service itself, measured with a time variable $T_{hand-out}$. Here, if all the available locations to fill in the form are busy, the patient waits in front of the hand-out operator, keeping him occupied even if his activity is finished until a location frees. Module 5 represents the phase B and is characterized by the time $T_{fill-in}$ needed to fill-in the given form, and by $X_{fill-in}$ which manages the maximum number of places available to complete the fill-in procedure. Modules 6 and 7 constitute the phase C. The former corresponds to the queue of the acceptance phase, with the maximum number of places available X_{acc}, while the latter carries out the service of patience acceptance through computers with a process time T_{acc}. Furthermore, Module 8 consists in the queue before the test execution, which comprises the maximum number of places available X_{test}, whereas module 9 represents the performance of the antigen swab test with a variable duration T_{test}. Together, these two modules implement the phase D of the testing process. Module 9 triggers the module for the registration of test results on the informatic system (module 10), which manages forms rather than entities with a processing time T_{reg}. Finally, the last module 11 just represents the exit of each patient to the clinic.

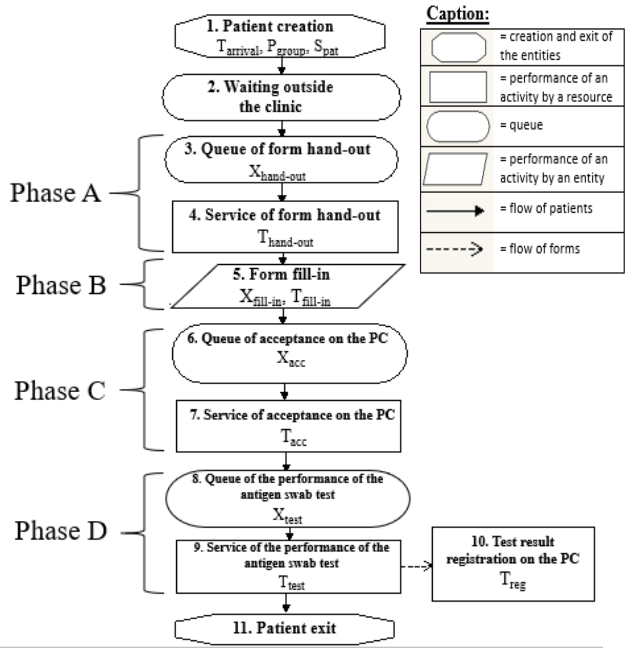

Figure 2: Structure of the simulation model

The modules which correspond to the process queues represent a single lane for each phase because all the resources of the same activity share the same queue (Figure 3). Once a resource frees, the first waiting patient occupies it. Indeed, this approach is adopted to improve the efficiency of the whole testing system.

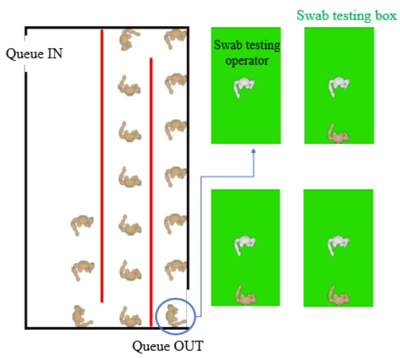

Figure 3: 2D visualization of queuing patients waiting the performance of antigen swab tests

The developed simulation model is distinguished by some main parameters which can be varied to find the best clinic configuration according to the desired targeted outputs. The first parameter is the number of resources (e.g., medical and paramedical personnel) allocated for each phase of the process (N_i, with i as a specific phase of the testing process). Indeed, the more resources available, the quicker the testing process but, on the other hand, some of these, as medical staff, are scarce and should be accurately leveraged. The second parameter to be considered as variable is the time between patient arrivals at the clinic ($T^{arrival}$), proposed in the first module. The more people arrive, the more the testing system is stressed but, if very few patients come, medical and paramedical resources will be very underutilized. The outcomes of the simulation model relevant for this research are, firstly, the number of people tested every day (N^{pat}), and, as a result, the number of people tested by each nurse (N^{eff}), which gives a representation of the testing system efficiency. In addition, resources utilization (U_i) would be measured in order to understand if their allocation should be improved by increasing or decreasing some units in specific phases. Lastly, also important is the average time in the clinic (T^{sys}) and in queue (T^{queue}) spent by patient, which are specific drivers for the healthcare service level and consequently citizens satisfaction. Therefore, the optimal layout of the testing clinic should focus to these goals. Finally, the following Table 1 presents the nomenclature of all the parameters aforedescribed in this Section along with their description.

Table 1: list of model parameters

Parameter	Description	Units of measurement
S^{pat}	N° of patients scheduled in each time window	patients
P^{group}	Probability of a specific size group	%
$T^{arrival}$	Time between two consecutive patient arrivals	sec
X_i	Max n° of places available in queue for phase i i = A, …, E	places
T_i	Processing time of phase i i = A, …, E	sec
N_i	N° of resources for phase i i = A, …, E	resources
N^{pat}	Total n° of patients vaccinated in a day	patients/day
N^{eff}	Average n° of patients vaccinated in a day by each nurse	patients/nurse
Ui	Resources utilization rate in phase i i = A, …, E	%
T^{sys}	Average patient time in testing clinic	min
T^{queue}	Average patient total time in queues of testing clinic	min

3. Case study:

The quantitative simulation model developed is used to support the design and organization of the mass testing campaign against COVID-19 performed in South Tyrol during November 2020. At the end of October 2020, the infections were rising dramatically and the RT, the average number of people who can be infected by a single positive person, was reaching the critical value of 2.0 (Italian Ministry of Health Report, 2020). For these reasons, South Tyrol administration decided to held a screening event for its entire population. The aim was to test around 350 thousand people in a weekend (from Friday morning to Sunday evening), which correspond to the 80% of the population excluding children under the age of six and elderly in the residential care homes. To test such huge number of people in few days it is necessary to detect several locations since it is not feasible to perform this activity inside a common hospital. Three different clinic types have been proposed with different properties, as well as strengths and weaknesses. The smallest one is a facility like the typical House of Culture present in the northern Italy. It has the peculiarity to be very numerous in South Tyrol region but it needs to be aerated frequently. The second type of clinic proposed is a school/sport gym, which has the same peculiarity of the aforementioned House of Culture, but it is distinguished by larger available spaces. The last possible clinic type is an outdoor place, like a football field, which is well aerated and guarantees wide areas for testing purposes. On the other hand, this clinic configuration is more difficult to be implemented because it needs tents for each phase of the screening process and it is prone to bad weather conditions which very often occur in this region in this time of the year (heavy snowfall). After a preliminary qualitative analysis shared with the directors of the healthcare agency, the clinic configuration selected for this mass testing campaign is the school/sport gym.

In order to create a reliable simulation model, this should be distinguished by process times and durations statistically distributed according to real dataset, rather than fixed average values. For this reason, in September and October 2020, during the screening campaign for touristic operators delivered in different locations of South Tyrol, a wide sampling campaign have been executed to collect on the field hundreds of data for each phase of the COVID-19 testing procedures. During this relevant activity, several values for the process times and durations have been collected and reported in order to obtain at least 80 measures of each swab testing phase. This activity is carried out ex-ante on a process similar to the one analysed in this case study in order to get real data to implement the simulation model. Through these data from September and October 2020, the model was able to support the design of the new target clinic that must be created within the half of November 2020. In addition, this campaign has been a good opportunity to talk with medical and paramedical operators as well as organizers to gather information regarding the characteristics and problems of such complex healthcare system, and to collect suggestions to further improve it. Once all the data were collected, they have been processed through proper data-fitting techniques to obtain the statistical distribution of each testing process phase which best fits with those values, including the most appropriate mathematical the function (Figure 4).

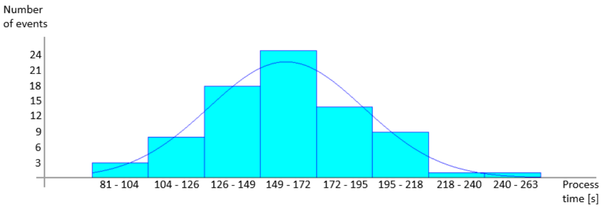

Figure 4: Distribution function of the duration of the swab test execution phase

This approach has been adopted for each model module distinguished by a time/duration parameter. The obtained distribution functions are listed in Table 2.

Table 2: distribution functions of each model module

Model block	Distribution function
4. Form hand-out	$T_{hand\text{-}out} = 6.5 + GAMM\ (6.27, 2.22)$
5. Form fill-in	$T_{fill\text{-}in} = TRIA\ (54, 65.1, 277)$
7. Acceptance	$T_{acc} = 23.5 + GAMM\ (10.6, 1.93)$
9. Performance	$T_{test} = NORM\ (160, 31.4)$
10. Results registration	$T_{reg} = TRIA\ (42.5, 75.5, 122)$

These distribution functions are adopted in the simulation model to increase its reliability and better represent the real healthcare system behaviour in the developed virtual environment. Beside time parameters, other parameters are set up to increase the accuracy of the proposed simulation model. The probability P^{group} that a specific number of people arrives at the clinic simultaneously is established according to real and sampled datasets. The group size is a percentage of S^{pat} which assumes the following values: 5%*S^{pat} with a probability P^{group} of 18.5%; 15%*S^{pat} with a probability P^{group} of 28.5%; 25%*S^{pat} with a probability P^{group} of 26.5%; 35%*S^{pat} with a probability P^{group} of 8.1%; 45%*S^{pat} with a probability P^{group} of 12.2%; 55%*S^{pat} with a probability P^{group} of 4.1%; and, finally, 65%*S^{pat} with a probability P^{group} of 2.0%.

4. Results and discussion:

After the development of the virtual simulation model, a sensitivity analysis is carried out to determine the best configuration of the mass testing clinic for the scenario presented in the case study section. The model is run through a commercial software for discrete-event simulation. The first constraint to consider is the available space to set up each testing clinic. In particular, according to the Ministerial Order of 18 December 1975 of Italian legislation, it is supposed a common gym with typical dimensions of 28m x 15m. The maximum number of personnel for each process phase is calculated considering the average working times of these phases. Thus, the average time needed is computed from Table 2 and divided by the time available (e.g., daily working hours), to determine the maximum number of resources deployable in each phase of the testing process (Table 4). In particular, phases A and E are performed in the same layout location and, thus, share a single desk. Indeed, the latter (test result registration) is an activity independent by the patients and it can consequently be joined to another phase to reduce the total occupied space. For this reason, the first row of Table 3 reports two numbers for the column “max N_i” of phases A+E.

Table 3: maximum number of resources and required area for each process phase

Process phase	max N_i	Area occupied by one resource
A+E. Form hand-out + test results registration on informatic system	2+2	5m x 2m
C. Acceptance on informatic system	3	3m x 2m
D. Performance of the antigen swab test	4	5m x 3m
	TOT: 11	

Starting from the maximum number of resources available for each process phase, these values are gradually decreased until a good solution is found. This one is evaluated according to a set of KPIs where the most relevant is N^{eff}, the average number of patients tested per nurse per day (10 hours), which is a proper indicator of the efficiency of the overall COVID-19 testing clinic. Furthermore, to be feasible, a simulation scenario must fulfil the layout boundaries represented by the maximum number of total places available for the sum of all the queues in the testing clinic ($\sum X_i$). This value consists in the remaining space after the determination of max N_i for each phase i, considering the social distancing requirements, and it is equal to 49 places. To determine the best clinic configuration, the simulation model was run multiple times obtaining varying different parameters and obtaining 48 scenarios. In particular, the first varying parameter is $T^{arrival}$, from TRIA (60, 141, 600) to TRIA (42, 99, 420) with an increment of its average of 14 sec for each step. A second set of varying parameters is the number of adopted resources for each phase: $N_{hand\text{-}out}$ from 2 to 1 operator, N_{acc} from 3 to 1 operator and N_{test} from 4 to 2 operators. Leveraging the aforedescribed multiple runs of the simulation model, the best configuration identified for the testing clinic in terms of N^{eff} is distinguished by the number of resources to be allotted for each process phase as proposed in Table 4, along with the number of places to be guaranteed for each queue as listed in Table 5. Figure 5 presents the clinic layout for its best configuration.

Table 4: number of resources for each phase for the proposed clinic layout

Process phase	N_i
A+E. Form hand-out + test results registration on informatic system	1+1
C. Acceptance on informatic system	2
D. Performance of the antigen swab test	4
TOT:	8

Table 5: number of queuing places to be guaranteed for each phase for the proposed clinic layout

Process phase	X_i
A+E. Form hand-out + test results registration on informatic system	3
B. Form fill-in	11
C. Acceptance on informatic system	10
D. Performance of the antigen swab test	22
TOT:	46

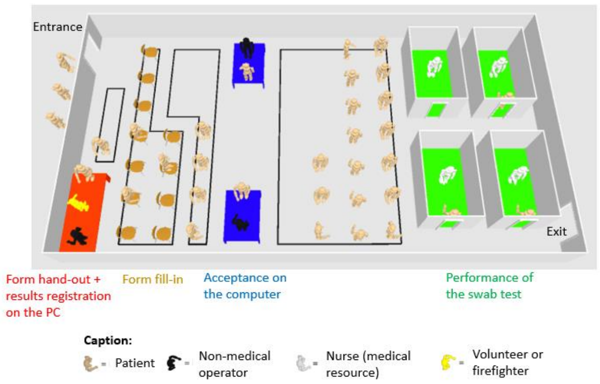

Figure 5: 3D layout of the proposed testing clinic

The proposed testing clinic provides an efficiency N^{eff} = 160 people/nurse per day, which means that every day (10 working hours) a single nurse can test 160 patients. It is an exceptional accomplishment considering that, in similar systems described in the literature, each nurse can test about 70 patients/day. This clinic configuration enables to obtain remarkable values also for the different parameters which distinguish the entire testing process (Table 6). The average time spent by each patient inside the clinic (T^{sys}) is equal to 8.8 minutes and just 2.5 minutes of them are not added-value time, since it represents the mean value of the total time spent in all the queues of the process by each patient. Moreover, it is important to notice that no resource is exploited for more than 80% of its available time to avoid any sort of worker burn-out phenomenon, considering the challenging goal to be faced. In particular, U_A is very low because the number of operators for the form hand-out phase are already the minimum possible (just 1 resource). U_C is equal to 42% since the clinic configuration with just one operator for the acceptance phase causes a dramatic model degrading distinguished by enormous waiting time in the queue of this phase. Nurses utilization (U_D) shows a high value (76%) even with the maximum number of resources available (4 nurses).

Table 6: output parameters value of the defined clinic configuration

Output parameter	Value
N^{eff}	160 patients/nurse x day
N^{pat}	640 patients/day
T^{sys}	8.8 min/patient
T^{queue}	2,5 min/patient
U_A	40%
U_C	42%
U_D	76%

The 20th of November 2020 the COVID-19 mass testing campaign started in South Tyrol region involving 184 clinics and about 1400 healthcare personnel. The event acquired media relevance because it was the first mass COVID-19 screening in Italy (Figure 6). This aimed at promptly isolating infected people and dramatically decrease the well-known RT value, the virus effective reproduction number. The campaign was implemented successfully. 362'050 citizens were tested in 3 days and 1.1% of them (3'695 people) was found positive and consequently isolated. Thanks to this mass screening campaign the RT value of Bozen province decreased from 1.22 to 0.74 in the following two weeks.

Figure 6: Example of media coverage for the case study COVID-19 mass testing campaign

5. Conclusions and further research

This paper proposes an original simulation model developed to support the design of testing clinics for the COVID-19 mass screening campaign organized and implemented in South Tyrol region (Italy) during November 2020. The entire patient testing process is distinguished by several sequential phases that are characterized by different parameters, such as service times and maximum places in queues available. Starting from the mapped process, an original discrete-event simulation model has been developed and implemented to replicate the real-world activities into a virtual environment. To increase the accuracy of the model compared to the actual environment, several measures of service times of each phase have been collected and analysed through data-fitting to define the most appropriate statistical distributions to be adopted for simulation purpose, rather than average values. After 48 runs of the simulation model obtained varying several parameters, the best scenario is identified according to the most relevant KPI of the testing process efficiency N^{eff}, which represents the number of patients tested by each nurse per working day. This so designed testing clinic includes 1 operator for the form hand-out, 2 operators for the patient acceptance in the informatic system, 4 nurses for the swab test performance and 1 operator for the test results registration. This best solution provides a of 160 patients/nurse per day and an average patient time in the clinic of 8.8 minutes and just 2.5 of them spent in queues. By setting and installing 184 clinics and leveraging 1400 medical and non-medical resources, this massive campaign tested 362'050 people in 3 days (20-22 November 2020) and identified 3'695 infected people that were immediately isolated, which enabled to lower the RT value of Bozen province from 1.22 to 0.74 in the following two weeks.

Future studies could be performed to develop simulation models for drive-through COVID-19 massive screening campaigns which could test more people per day. In addition, a further possible improvement could be the consideration in the simulation model of patients categories according to their age, with different service times and probabilities related to the various age groups.

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