Approach to assess factors affecting laboratory workload during a pandemic situation

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Abstract

During the SARS-CoV-2 pandemic, various intervention strategies, including widespread testing, were deployed to contain the spread. Analytical laboratories in Germany conducted PCR tests, but they were unprepared for the surge in demand, leading to increased analysis times and workloads.

This work is based on the assumption that a delayed PCR test result has implications for the healthcare system. The reason for such an assumption is that infection chains are only identified with a delay, and intervention strategies depend on the number of reported infected individuals.

This research proposes a System Dynamics model integrating an SEIR model with a newly developed laboratory order processing model. This model elucidates the factors influencing analytical laboratory workloads and the total analysis time for PCR test orders, including machine and analyst availability. The applicability of the model is validated through the modeling of the pandemic situation in Germany at the beginning of 2022.

Introduction

The SARS-CoV-2 (severe acute respiratory syndrome coronavirus type 2) pandemic had global ramifications, impacting countries differently and prompting varied strategies to combat it. In Germany, among other measures, quarantines were imposed to reduce the risk of further transmission by diagnosed individuals. Quarantine was imposed for an infected person only upon receiving a positive PCR test result (polymerase chain reaction) confirming SARS-CoV-2 infection.

The analysis of PCR samples was carried out in analytical laboratories that were suddenly faced with a high and increasing demand for their services during the pandemic. Simultaneously, these laboratories were obligated by the German healthcare system to inform infected individuals of their test results within a maximum of three days after sample collection. Meeting this requirement was often challenging for laboratories during the pandemic. In Germany, the association ALM (Akkredierte Labore in der Medizin e.V.) monitored the workload of analytical laboratories during the pandemic and issued warnings when laboratory utilization exceeded 80%. (ALM e.V. b)

Insights from previous research on the workload of analytical laboratories, particularly in the context of a pandemic, were not found during the literature review. While studies on testing strategies exist in the scientific literature, they seldom focus on the operational level. Therefore, this study aims to determine the influence of selected factors on the workload of analytical laboratories and the resultant total analysis time (TAT) for PCR tests to facilitate compliance with legal requirements for these laboratories during future pandemics.

The core of this work involves developing a model to simulate the impact of factors on laboratory workload. System Dynamics (SD) methodology was chosen for its proven effectiveness in pandemic research and its suitability for analyzing individual factors and their associated effects.

State of the art

Research on optimizing and analyzing testing strategies in a pandemic situation exists. For instance, (Du et al. 2022) developed a mathematical framework for test allocation. Based on factors such as a limited budget and a pandemic scenario, test allocation scenarios can be derived.

(Lampariello and Sagratella 2021) created a mathematical model to determine the number of tests needed to maximize disease detection. Their study compared results with the actual number of tests for SARS-CoV-2 in Italy and demonstrated potential improvements to testing strategies.

In contrast, (Baker et al. 2021) demonstrated that the percentage of positive tests does not indicate the extent of disease transmission. Therefore, the influence of the testing rate on disease transmission is analyzed to establish a SARS-CoV-2 testing strategy. It is shown that the testing rate is directly related to test TAT and the percentage of positive tests. The study highlights that test TAT is the most crucial indicator for effective pandemic intervention strategies and that a lower testing rate can improve test system efficiency and reduce disease transmission.

The research conducted by (Lampariello and Sagratella 2021) as well as (Baker et al. 2021) regarding laboratory tests can thus be applied to PCR tests for the initial pandemic situation in Germany.

In research, pooling strategies are discussed at the operational level. Pooling refers to conducting collective tests from multiple swab samples in a single tube, i.e., in a single process. For instance, (Hapsari et al. 2022) explain the efficiency of pooling strategies for PCR mass testing in a pandemic situation, using the example of Indonesia. It is demonstrated that laboratory workload can be reduced by up to 50% with a test positivity rate of less than 22%, by reducing personnel and reagent costs. Additionally, there are studies on the environmental impact of PCR tests (Ji et al. 2022) analyze the life cycle of PCR tests, showing that mass testing burdens the environment, leading to recommendations. For example, efforts should be made to minimize logistical distances, and pooling strategies are recommended due to their cost efficiency.

Apart from determining testing strategies, there are also approaches for selecting optimal testing locations. For instance, (Liu et al. 2021) developed a method for determining locations for testing facilities. These testing facilities are rapid testing sites for the initial pandemic situation in Germany. They showed that it may be advantageous to close a facility rather than reduce the testing capacities of a facility.

(Buhat et al. 2021) developed a model for the allocation of test kits for SARS-CoV-2 in the Philippines. The model can be used to derive the optimal number of facilities based on resource constraints for test kits. The research findings can be applied to pandemic preparedness in Germany by interpreting defined testing facility locations as analytical laboratories.

Simulations, especially based on SD models, are also used to analyze the impacts and factors of testing strategies. For pandemic research, models such as SIR or SEIR are used, characterized by the development of a pandemic disease. Model elements include susceptible individuals (S),

infectious individuals (I), exposed individuals (E), recovered individuals (R), deceased individuals (D), and treated individuals (T).

For example, (Sy et al. 2021) developed an SD model to analyze the effects of public health interventions based on an SEIRD model. They provided a general model that can be used with minimal data and for multiple pandemic situations. (Paul und Venkateswaran 2018) developed a System Dynamics model to investigate inventory management strategy for a pandemic situation based on an SEITR model. The study showed that a simple SIR model is sufficient to model and analyze behavior during a pandemic. Moreover, it is shown that forecasting disease transmission, especially with shorter planning horizons, can reduce the need for frequent updates of inventory and therefore require more frequent updates in a pandemic situation (Van Oorschot et al. 2022) developed a System Dynamics model to analyze collaboration on test kits based on an SIR model. The study demonstrated the relevance of the modeled combination of disease transmission, policy measures, and test supply chain management. It is demonstrated that cooperation among these actors is possible. The most positive impact on overall disease transmission occurs in the scenario where individual countries act selfishly and claim the stock they need to reduce their disease transmission.

Research on analytical laboratories during a pandemic and testing strategies is limited. While the dependencies between testing strategy and test TAT are known, research on factors influencing workload or TAT, particularly those based on an SD model, could not be found.

Method

The developed System Dynamics (SD) model is described in detail below. The model employs days as the unit of time.

SEIR Model for describing laboratory demand for PCR tests in a pandemic situation

The spread of infection in a pandemic situation can be modeled and described using an SEIR model, as shown in Figure 1. Despite insights from research, an SEIR model was chosen over an SIR model due to the ability of the former to best represent key parameters such as the reproduction number and incubation period observed in past pandemics.

The underlying relationships of the model components are explained below. The stock of healthy individuals, *Susceptible (S)*, initially determined by the total population, is continuously reduced by a quantity of infected individuals, represented by the change rate (*Exposed Rate*). The *Exposed (E)* stock describes individuals within the incubation period who cannot transmit the disease. After the incubation period *(Infectious Rate*), these individuals can infect others and transition to

the stock of infected individuals, *Infectious (I)*. Infected individuals are considered recovered upon the expiration of a period of illness (*Recovery Rate Actual*), resulting in a stock of *Recovered (R)* individuals who can no longer transmit the disease.

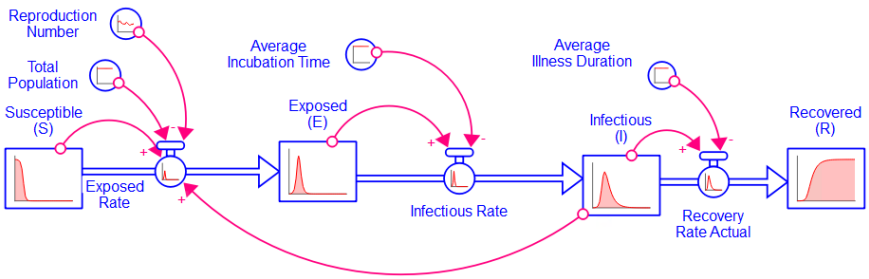

Figure 1: SEIR model in accordance in (Taghizadeh and Mohammad-Djafari 2022)

In this work, the SEIR model is expanded to determine the subset of individuals identified through the testing strategy. These individuals are described by the *Testing* stock and represent the expected workload for laboratories, as illustrated in Figure 2.

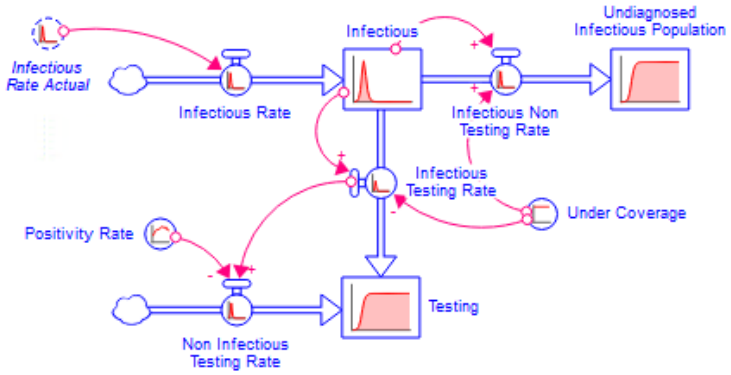

Figure 2: SEIR model extension to include undiagnosed (Undiagnosed Infectious Population), diagnosed (Testing by Infectious Testing Rate) and diagnosed non-infectious people (Testing by Non Infectious Testing Rate)

The expansion consists of the following three parts:

- Firstly, the constant *Under Coverage* is introduced to account for the fact that not all infectious individuals are willing to be tested (symptomatic) or are aware of a potential infection (asymptomatic). This constant influences the *Infectious Non Testing Rate* and is thus used to determine *Undiagnosed Infectious Population*, individuals who are infected but remain undiagnosed.
- Secondly, the constant *Under Coverage* affects the *Infectious Testing Rate*, which in turn determines the number of individuals yet to be tested in the *Testing* stock, thereby impacting the workload of laboratories.

- Thirdly, individuals who have been tested but are not infected are taken into account. This expansion is represented by the *Non Infectious Testing Rate*, which also affects the *Testing* stock and, consequently, the workload of laboratories.

In summary, the model divides the stock of infectious individuals (*Infectious*) into an *Undiagnosed Infectious Population* and a *Testing* stock of diagnosed infectious individuals. By directly partitioning the stock of *Infectious* in Figure 3, the stocks of *Actual Infectious* and *Recovered* are required subsequently, despite the expansion, to avoid distorting the corresponding stocks of *Undiagnosed Infectious Population* and *Testing*.

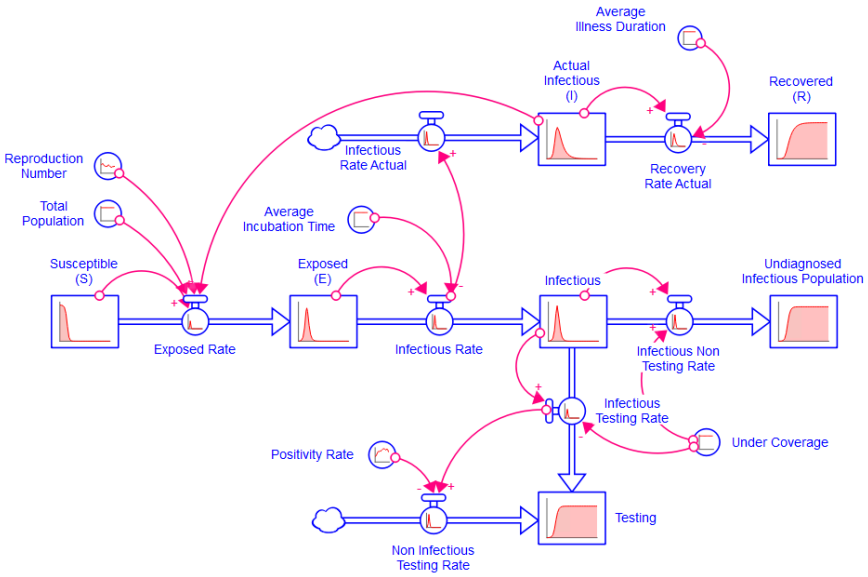

Figure 3: Expanded SEIR model

Laboratory order processing model for analytical laboratories regarding PCR Tests

In addition to expanding the SEIR model, a laboratory order processing model was developed. The general order processing of PCR tests in analytical laboratories, and thus the underlying structure of the model, is shown in Figure 4. Here, each individual to be diagnosed corresponds to a laboratory order or a PCR test.

PCR tests of individuals to be diagnosed, derived from the *Testing* stock, as provided by an SEIR model (e.g., Figure 2), are distributed to laboratories using the *Order Arrival Rate* and initially form the *Order Inventory* stock of laboratories. Therefore, the *Order Inventory* represents the workload of laboratories, which is continuously reduced according to the laboratory's performance represented by the *Order Analysis Rate*. The test results, *Order Analysed*, are

transmitted to the affected individuals, *Diagnosed Population*, with a time delay determined by the *Order Feedback Rate*.

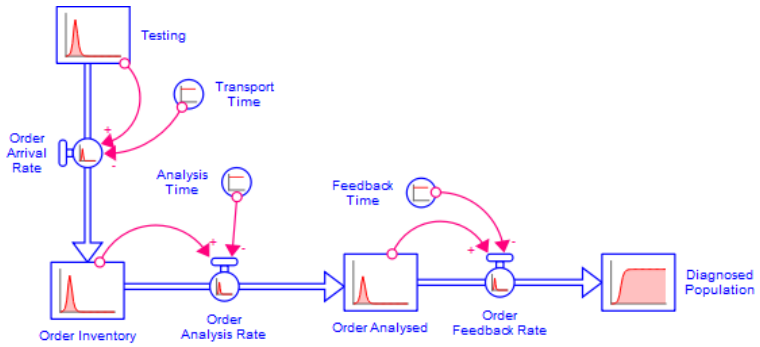

Figure 4: Simplified laboratory order model including PCR test delivery (Order Arrival Rate), PCR test analysis (Order Analysis Rate) and PCR test result submission (Order Feedback Rate)

The influencing factors of the *Order Arrival Rate* and *Order Analysis Rate* from Figure 4 are described in more detail below.

The *Order Arrival Rate* describes the number of transported PCR tests per day from the *Testing* stock. This rate, as depicted in Figure 5, is influenced by the constant *Transport Time* and the variable *Max Transport*. The *Max Transport* variable describes the maximum possible size of a transport, depending on the number of considered laboratories (*Number Labs*), the average number of transports per day (*Daily Transport*), and the available capacity of a transport (*Transport Capacity*).

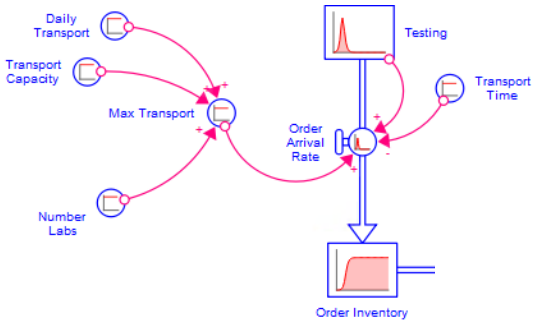

Figure 5: Detailed Order Arrival Rate of laboratory order model

The *Order Analysis Rate* in Figure 6 describes the amount of work performed per day, where the work of laboratories corresponds to the evaluation or analysis of PCR tests. This rate details the work that the considered number of laboratories (*Number Labs*) can perform in relation to the order inventory stock (*Order Inventory*) and takes into account fundamental factors influencing the average work performance of these laboratories.

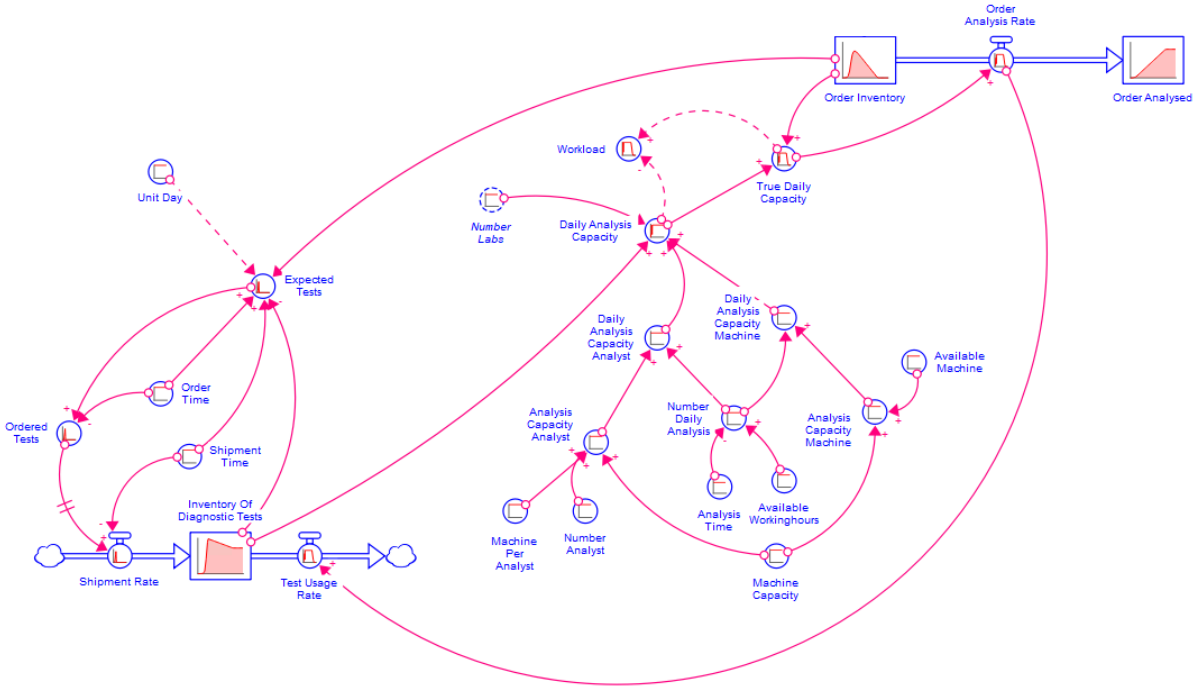

Figure 6: Detailed Order Analysis Rate of Laboratory order model

The *Order Analysis Rate* corresponds to *True Daily Capacity* and consequently depends on the *Daily Analysis Capacity* variable, which describes the actual laboratory capacity, and the *Order Inventory* stock, representing the amount of work present in a laboratory.-Therefore, the maximum number of PCR tests analyzed by a laboratory is determined by either the *Daily Analysis Capacity Analyst*, *Daily Analysis Capacity Machine*, or *Inventory Of Diagnostic Tests*, whichever is lower.

The *Daily Analysis Capacity Analyst* variable describes the maximum number of PCR tests that can be analyzed by the available analysts within a certain working time. This variable, in turn, depends on the *Analysis Capacity Analyst* and *Number Daily Analysis* variables. *Analysis Capacity Analyst* focuses on machine-related restrictions for the work of analysts and is determined by constants such as *Machine Per Analyst*, *Number Analyst*, and *Machine Capacity*. The *Machine Per Analyst* constant accounts for the restriction that an analyst can only be responsible for a maximum number of machines. The *Machine Capacity* constant allows for batch processing considerations, i.e., when analyzing multiple PCR tests in one process, and *Number Analyst* describes the amount of available personnel. *Number Daily Analysis* indicates how often an analysis run can be performed daily and depends on constants such as *Analysis Time*, representing the actual duration for conducting PCR process analysis, and *Available Working Hours*, determining the laboratory's working hours.

The maximum number of PCR tests that can be analyzed by the available machines within a certain working time is described by the *Daily Analysis Capacity Machine* variable. This variable

is influenced by the previously described *Number Daily Analysis* variable and the *Analysis Capacity Machine* variable. *Analysis Capacity Machine* depends on the number of PCR machines in a laboratory *(Available Machine)* and the dimension of each PCR machine *(Machine Capacity)*. The dimension represents the number of PCR samples that can be analyzed by the machine simultaneously.

Inventory Of Diagnostic Tests simplistically describes the available consumables, such as PCR test kits, which are used on a one-to-one basis in this case. For example, one unit of diagnostic test kits is used for one PCR test.

The availability of these materials depends on the delivery rate, *Shipment Rate*, described by the *Ordered Tests* variable and the constant *Shipment Time*. *Ordered Tests* corresponds to the value of the *Expected Tests* variable, delayed by the *Order Time* constant, which represents the duration of the ordering process. *Expected Tests* corresponds to the forecast of material demand based on the current workload *(Order Inventory)*. Due to the dynamic behavior of the *Inventory Of Diagnostic Tests* stock, the model assumes that no material inventory exists at the beginning of a pandemic situation and is replenished based on expected demand. Inventory management is considered in line with (Paul and Venkateswaran 2018).

Finally, the *Workload* variable is introduced for informational purposes, described by *True Daily Capacity* and *Daily Analysis Capacity*. It serves the direct evaluation of resulting laboratory workload in a single model run.

Consideration of the Developed System Dynamics Model

Both sub-models are linked through the *Testing* stock (see Figure 12 in the appendix). Thus, the developed extension of the SEIR model provides the demand for PCR tests and the resulting workload of laboratories in the event of a pandemic situation.

Results

In this chapter, the developed SD model is used to determine the influencing factors on the workload of laboratories. Following the classification of ALM e. V., four laboratory categories (see Table 1) are distinguished, each with different work capacities (test capacity per day). In optimal conditions, Category 1 small laboratories can analyze up to 350 tests per day, while Category 2 laboratories can handle up to 800 tests per day. Category 3 laboratories have a capacity for analyzing up to 3000 tests per day, and Category 4 describes large analysis centers capable of analyzing a minimum of 3000 tests per day. This differentiation is justified by the assumption that the same influencing factors may have different effects on the workload of each laboratory category.

Table 1: Characterization of laboratory categories by capacity distribution and laboratory (ALM e. V. a)

category	*capacity distribution*	*laboratory distribution*
1	0.05	0.344
2	0.15	0.328
3	0.28	0.24
4	0.52	0.088

Beforehand, in Chapter 4.1, the model will be validated based on data from an actual pandemic situation.

Simulation of the behavior of analytical laboratories in a pandemic situation

The evaluation of the developed model is based on data provided by ALM. These data represent the pandemic situation in Germany at the beginning of 2022 and are formatted in a 6-day week format. In accordance with the available data, the developed model focuses on calendar weeks 1 to 17 in the year 2022 and simulates a) technological availability (*Daily Analysis Capacity*), b) the number of diagnosed individuals (*Order Analysed*), and c) the workload of laboratories over a period of 102 days or 17 6-day weeks.

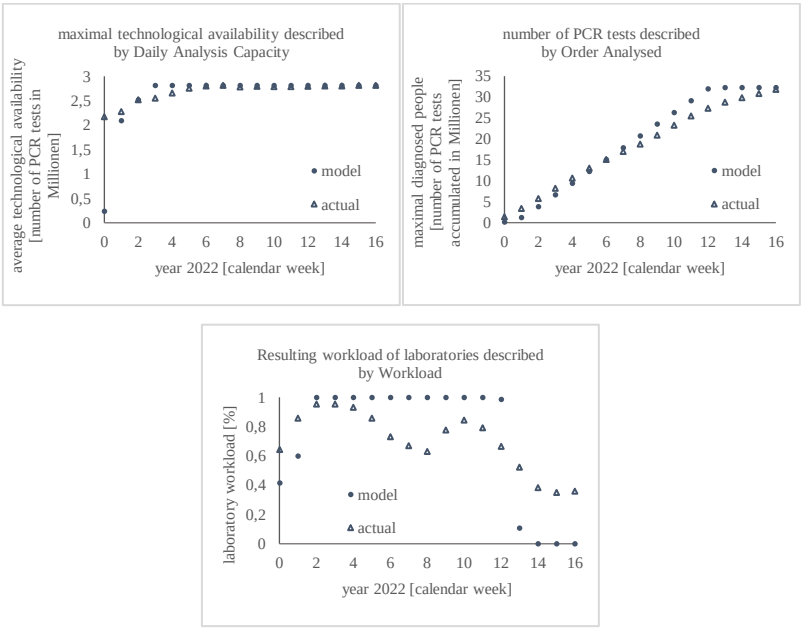

Figure 7: Model behavior regarding reproduction of pandemic situation early 2022 in Germany: (a) maximal technological availability described by Daily Analysis Capacity; (b) number of analysed PCR tests described by Order Analysed; (c) resulting workload of laboratories

In Figure 7, the results of the model can be compared with real data. It becomes evident that the developed model (*model*) approximately reproduces the maximum capacity (*actual*), as depicted in Figure 7 (a). However, a transition period is noticeable at the beginning. This is attributed to the dynamic behavior of the *Inventory Of Diagnostic Tests* stock and its initially empty state.

The cumulative trend of diagnosed individuals, illustrated in Figure 7 (b), is also comparable to the actual data. With the progression of the model time, the number of diagnosed individuals increases. However, there is a slight difference in reaching this quantity, as the model reaches the amount of diagnosed individuals earlier than the actual data. Initially, the model is also slower in diagnosing individuals compared to reality. These differences are attributed to the model's transition period at the beginning and the simplified representation of pandemic demand by the model itself.

Differences related to the model's definition are also evident at the beginning and end of the model time when evaluating workload in Figure 7 (c). The model is designed to simulate the pandemic situation of a single wave of infection, so without adjusting the model, a second wave or reinfection of the population is not possible. As a result, the model does not capture a second rise in laboratory workload, explaining the difference with the actual data.

Focusing on workload during the first wave, the model results show a comparable increase at the beginning. The modeled workloads are slightly higher than the actual real workloads. As shown in Figure 7 (a), this is attributed to the low technological availability of the model at the beginning.

It is worth noting that comparing workloads is inherently challenging. The *actual* workloads of laboratories in Germany correspond to an average workload and are provided by ALM as an average of the workloads of laboratories in individual states. A disaggregation of workload for each laboratory in detail could not be found in the research. Additionally, in reality, individual laboratory workloads could exceed 100%, whereas the model limits utilization to 100%. Lastly, the developed model assumes that each laboratory has the same characteristics, leading to equal technological availabilities. This assumption does not fully align with the actual situation in laboratories. Nonetheless, the model can be considered validated against this pandemic situation.

Analysis of effects concerning laboratories working to capacity

To assess the impact of factors such as *Shipment Time, Available Machines, Number Analyst, Available Workinghours,* and *Transport Time* on laboratory performance and consequently on TAT, the values of these factors in the SD model are varied, and their effects on changes in *True Daily Capacity* are evaluated. The simulation is conducted for each change in constant values following a full factorial experimental design.

The graphs in Figure 8, Figure 9, and Figure 10 illustrate how the number of weeks with maximum laboratory workload varies with changes in technological availability. These factors are varied accordingly. The different categories in the graphs represent various types of laboratories (see

Table 1 and Table 3). Additionally, results for a laboratory with an average performance characterization (average) are presented.

The laboratory *average* represents one with average performance, defined by factors such as *Available Machines*, *Number Analyst*, and *Available Workinghours*. The value of these factors is determined as the sum of the values of factors for individual laboratory categories [refer to Table 3], which were previously multiplied by their percentage share of the total number of laboratories (ALM e. V. c)

The target variable, the number of weeks with maximum workload, was chosen for two main reasons: firstly, because excessive workload at the operational level of laboratories poses challenges, and secondly, because it leads to an extension of the TAT. To comply with legal requirements, laboratories must operate in a state where they can efficiently handle demand to ensure a short time frame between sample acceptance and result communication. High workload and particularly long processing times significantly increase the likelihood of delayed results reaching patients. Consequently, delays can lead to delayed recognition of disease transmission and suboptimal pandemic response strategies. Prolonged processing times increase the risk of disruptions significantly impacting laboratory operations and result communication timelines.

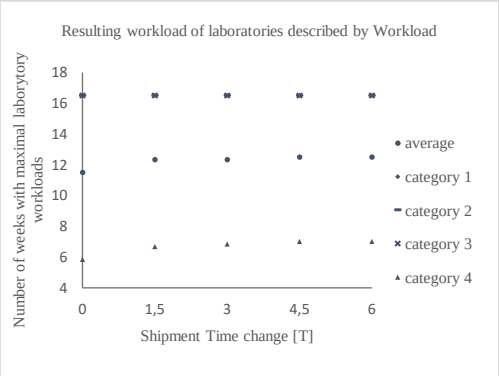

Figure 8: Diagram of Shipment Time for modelled laboratory behavior regarding maximal number of week's laboratories working to capacity

The variable *Shipment Time* is considered to analyze the effects of interruptions in material delivery to the laboratories. As can be seen from Figure 8, there is no increase in the number of weeks with maximum laboratory workload for laboratories in categories 1, 2, and 3 in the simulated scenario. The reason for this is the high workload in these laboratory categories, preventing them from accommodating an increase in sample analysis, which would require adjusted delivery of laboratory materials.

An increase in the number of weeks with maximum workload is observed for category 4 laboratories. The increase can be explained by the fact that these laboratory categories have a low workload buffer due to their high performance. Interruptions in material supply, with a constant delivery of samples, initially decrease the workload due to the lack of materials. Upon material delivery, the backlog is also processed, leading to an increase in workload and consequently explaining the slope of the number of weeks with maximum workload.

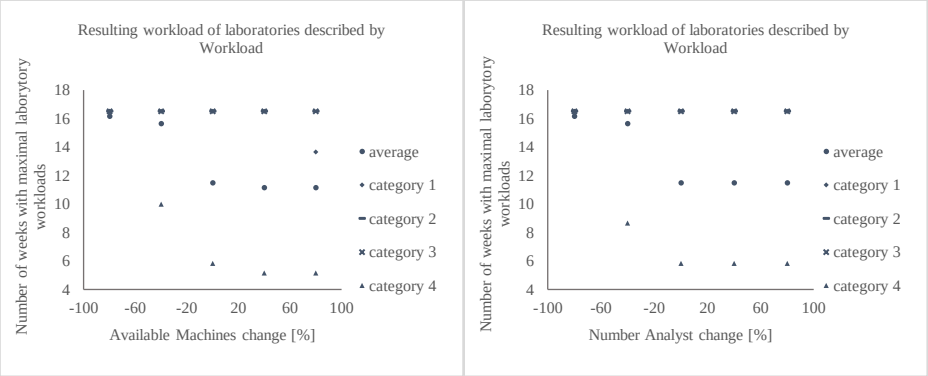

Figure 9: Diagram of Available Machine and Number Analyst for modelled laboratory behavior regarding maximal number of week's laboratories working to capacity

The variable *Available Machines* in Figure 9 is considered to analyze the effects of machine availability on the number of weeks with maximum workload. The results generally show that as machine availability decreases, the number of weeks where category 4 laboratories are fully utilized increases. It is important to note that categories 1, 2, and 3, where laboratories are almost fully utilized in all 17 weeks, can hardly be further utilized. The results indicate that laboratories in categories 1, 2, and 3 consistently have high utilization, even though about half of the PCR tests are analyzed by category 4 laboratories. Therefore, capacity reductions, such as machine failures, particularly exacerbate resource overload in small laboratories because they have little spare capacity.

As a result, capacity reductions, such as machine failures, particularly exacerbate resource overload in small laboratories because they have little spare capacity.

It can be inferred that reducing workload, especially in laboratories of categories 1, 2, and 3, increases flexibility or generates the ability to respond to unforeseen disruptions. This ability is essential for small laboratories to comply with legal TAT requirements.

Increasing machine availability does not lead to a reduction in weeks with maximum laboratory workload for laboratories in categories 1, 2, and 3. It can be concluded that machine availability is not the determining factor for *True Daily Capacity* in the simulation.

To analyze the effects of changing the number of available analysts while keeping the shift system or shift duration constant, the value of the variable *Number Analyst* is varied in Figure 9. The results show a similar trend in weeks with maximum laboratory workload as when reducing machine availability. A significant impact of reducing available analysts can be observed, especially in large category 4 laboratories, as this laboratory category has a higher number of machines compared to analysts in the model. Increasing the number of available analysts does not show an impact in any laboratory category.

In line with Figure 6 and Figure 9, it can be assumed that only arranging additional working hours, for example, in the form of overtime, can lead to relief for the laboratories.

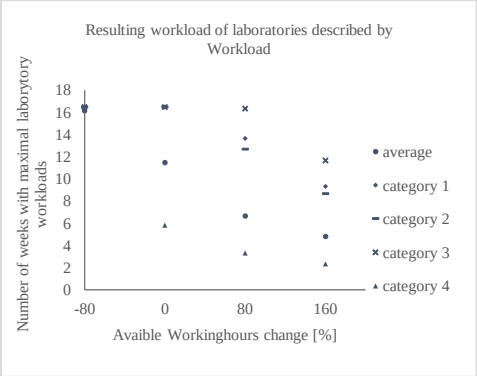

Figure 10: Diagram of Available Workinghours for modelled laboratory behavior regarding maximal number of week's laboratories working to capacity

Figure 10 illustrates the impact of reducing or increasing available working hours. It is evident that with an increasing number of available working hours per day, a significant reduction in weeks with maximum workload is achieved in all categories. Increasing working hours can involve measures such as introducing additional shifts or arranging overtime, significantly enhancing the responsiveness of laboratories in categories 1, 2, and 3 to unforeseen deviations.

Changes in *Transport Time* aim to determine the effects of both shortening and extending the required transport time between the sampling site and the laboratory on the performance of the laboratories. For instance, it can be assumed that a long transport time reduces the existing workload in laboratories. Consequently, temporary shutdowns may occur, increasing the number of days with maximum utilization while the workload remains constant. Shortening the transport time may lead to an excessive workload in the laboratories or increase the number of days with maximum workload if transport acts as a bottleneck for laboratory utilization.

As shown in Figure 12, there are hardly any changes in the workload of laboratories in categories 1, 2, and 3 when *Transport Time* is reduced or multiplied. The number of days where laboratories are maximally utilized remains unaffected by *Transport Time*.

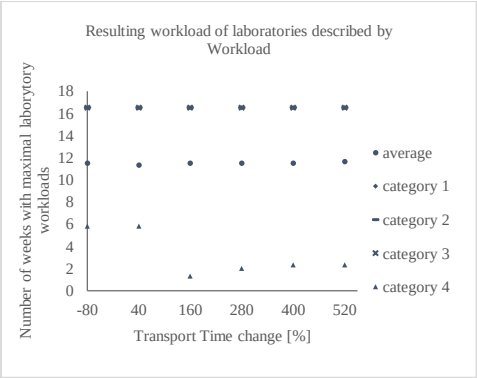

Figure 11: Diagram of Transport Time for modelled laboratory behavior regarding maximal number of week's laboratories working to capacity

The lack of effect of varying the duration of transport time on the utilization in categories 1, 2, and 3 is attributed to the quantity of PCR samples present in the laboratories. For instance, if PCR samples are delivered late, it has no impact on the workload because laboratories have a sufficient number of PCR samples for analysis, and the laboratory's resources remain utilized even with delayed delivery of PCR samples.

Only in the case of laboratories in category 4 does delayed delivery lead to a reduction in workload and a decrease in the number of weeks with maximum workload. This reduction can be explained by the high workload of category 4 laboratories compared to laboratories in categories 1, 2, and 3. A higher number of samples can be analyzed in the extended time span between the two deliveries, resulting in a smaller backlog and consequently inducing a more homogeneous resource utilization.

Restrictions and limitations

The developed model was only used for a specific use case and was not additionally tested or validated in another context. Therefore, the model can be enriched with additional details as part of further research activities. For example, the reinfection of individuals as well as the influence of the timing of the transmission of infectious positive PCR test results on the pandemic situation or on infection strategies could be included.

Furthermore, using an average laboratory represents a significant limitation of the modeling approach and leads to differences between the modeled and actual laboratory utilization. In addition, no size limitation is considered for *Inventory Of Diagnostic Tests*.

Another limitation is that the time between sampling and the notification of the result is not defined as a variable. Therefore, only the effects on influencing this time and the resulting workload are described and analyzed. It may be of interest in future research to analyze up to what pandemic demand, for example, determined by the reproduction number, a laboratory situation and characterization are feasible. Similarly, it could be interesting to analyze the impact of pooling strategies, for example, on laboratory utilization. This too has not been investigated and remains the subject of further research.

Summary

The present study proposes a System Dynamics model that illustrates the effects of changing various factors, such as the availability of analytical resources, on the workload of laboratories in a pandemic scenario. The model focuses on PCR tests due to their importance in selecting an intervention strategy in a pandemic situation.

Therefore, the developed model builds upon the SEIR model and the laboratory order processing model. The SEIR model describes the pandemic demand for PCR tests, and the laboratory order processing model describes the general PCR test order management in laboratories.

While research works on aspects of testing strategy could be identified, research works regarding the process of PCR sample analysis for the testing strategy and regarding the operational level of analytical laboratories could not be identified in the course of the research. This research aims to contribute to closing this gap. It is demonstrated that a simplified PCR sample analysis process can be described using an SD approach and compared with real data from a pandemic situation. While there are noticeable differences when comparing the modeled results with real data, these are attributable to the definition and limitations of the SD model. Therefore, possibilities to minimize them, for example, by considering the second wave of the pandemic, can be investigated in subsequent work.

It is evident that the results of the model significantly depend on the characteristics of the analysis laboratories used in the analysis. It is shown that the effects of a change in technological availability influence the workload of laboratories differently.

With the developed model, the authors show decision-makers in the healthcare system, based on Figure 10, that especially the availability of analysts during a pandemic is a crucial factor for small and medium-sized laboratories to comply with statutory requirements regarding TAT. Solely increasing machine availability proves not to be effective in this context. In Figure 8, decision-makers are shown that the supply of auxiliary materials, such as test kits, should also be considered as a decision factor. Therefore, PCR samples should not only be distributed to analysis

laboratories considering technological availability and workload, especially of large laboratories, but also ensuring the availability of auxiliary materials.

Limitations and boundaries of the approach exist and are discussed. However, the developed model represents the first System Dynamics model for investigating influencing factors in laboratories during a pandemic situation.

A Appendix

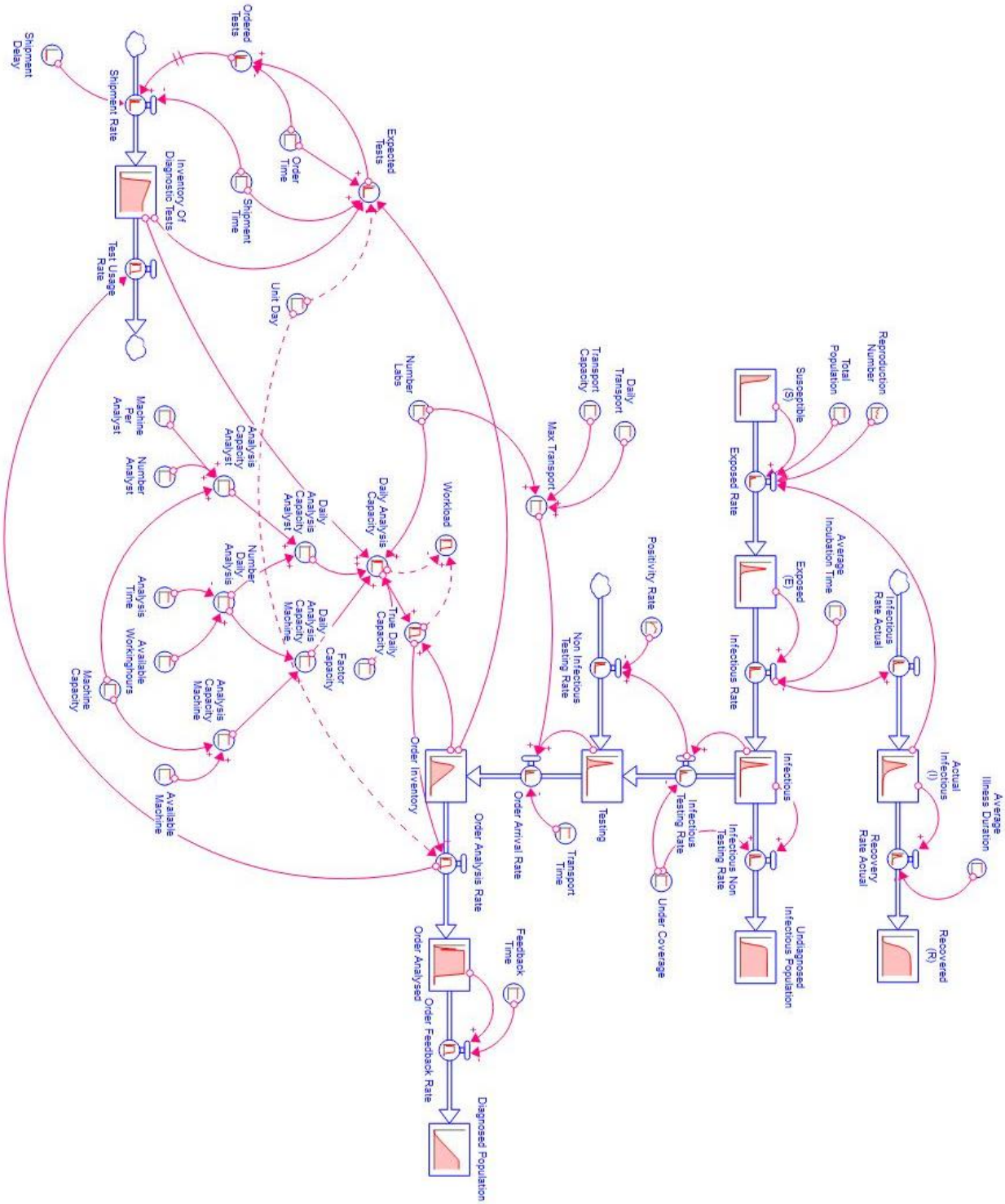

Figure 12: Developed SEIR – model

Table 2: Functions of rates and auxiliaries

Type	*Name*	*Function*
Rate	Exposed Rate	Actual Infectious * Reproduction Number * Susceptible / Total Population
Rate	Infectious Rate	Exposed / Average Incubation Time
Rate	Infectious Rate Actual	Infectious Rate
Rate	Infectious Testing Rate	Infectious * (1 - Under Coverage)
Rate	Infectious Non Testing Rate	Infectious * Under Coverage
Rate	Non Infectious Testing Rate	(Infectious Testing Rate / Positivity Rate) * (1 - Positivity Rate)
Rate	Recovery Rate Actual	Actual Infectious / Average Illness Duration
Rate	Order Arrival Rate	min (Testing, Max Transport) / Transport Time
Rate	Order Analysis Rate	True Daily Capacity * Unit Day
Rate	Order Feedback Rate	Order Analysed / Feedback Time
Rate	Shipment Rate	Ordered Tests / (Shipment Time + Shipment Delay)
Rate	Test Usage Rate	Order Analysis Rate
Auxiliary	Max Transport	Transport Capacity * Daily Transport * Number Labs
Auxiliary	True Daily Capacity	min (Daily Analysis Capacity, Order Inventory)
Auxiliary	Workload	True Daily Capacity / Daily Analysis Capacity
Auxiliary	Daily Analysis Capacity	min (Inventory Of Diagnostic Tests); min (Daily Analysis Capacity Analyst * Number Labs; Daily Analysis Capacity Machine * Number Labs)) * Factor Capacity
Auxiliary	Daily Analysis Capacity Analyst	Number Daily Analysis * Analysis Capacity Analyst
Auxiliary	Daily Analysis Capacity Machine	Analysis Capacity Machine * Number Daily Analysis
Auxiliary	Number Daily Analysis	Available Workinghours / Analysis Time
Auxiliary	Analysis Capacity Machine	Machine Capacity * Available Machines
Auxiliary	Analysis Capacity Analyst	Machine Capacity * Machine Per Analyst * Number Analyst
Auxiliary	Expected Tests	max (Order Inventory * (Order Time + Shipment Time) * Unit Day - Inventory Of Diagnostic Tests; 0)
Auxiliary	Ordered Tests	delay (Expected Tests, Order Time)

Table 3: Overview of model constants for categories

category	*Number Labs*	*Workinghours*	*Available Machines*
1	62.952	16	0.971
2	60.024	18	2.716
3	43.92	20	6.235
4	16.104	24	26.316

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