Systems Approach to Localize Tipping Points for the Emergency Services in Face of the COVID-19 Pandemic

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Abstract — When it comes to the COVID-19 pandemic [1], various issues and problems arise for institutions and critical infrastructures. Institutions such as first responders can be affected by COVID-19 by temporary or permanent loss of their essential staff and resources and therefore loss of their carrying capacity. The gradual and partial loss of carrying capacity in combination with increased demand on first responder systems can potentially push these system towards their tipping point, and thus cause even more loss of capacity to respond to emergency situations. In addition to the increased mental and emotional pressure burdened on first responders due to the presence and dangers of the virus, emergency personnel such as police officers can experience increased workload and stress during the pandemic as well as exposure to symptomatic or asymptomatic individuals affected by COVID-19. By assessing the dynamic carrying capacity of the first responder systems and their interaction with the general population they provide service to, the resiliency of first responder systems can be assessed in face of various scenarios. The resiliency of first responder systems can be increased by designing extra capacity and preventing the system from coming into the proximity of its tipping point, which could result in partial or major collapse in performance of the system. Therefore, protecting the emergency personnel and these indispensable institutions as well as maintaining the capacity to respond to the majority of the emergency calls is paramount.

Since the police force, hospitals, fire departments, and other care institutions are structures consisting of a wide range of individuals and operate in an ever-changing environment, this paper attempts to assess the resilience and capacity of such institutions via simulations to find and localize their tipping points. To enable such simulations, the model developed by Vierlboeck, Nilchiani, and Edwards [2] was extended with further branches to allow for simulations of sub-systems and loads thereof. For this paper, the police force of New York City (NYC) was chosen as a case study. To assess the police force performance, the capabilities and capacities of the sub-system were evaluated by testing its function under different circumstances and with different influencing factors such as fatigue [3] and the influence of the Yerkes-Dodsen Law [4]. This way, it was possible to assess the performance of the emergency personnel and provide information that could potentially be used for regulatory measures and decisions.

The conducted evaluations and simulations studied the existing system's resiliency and its proximity to the system tipping point as the reduction of a number of emergency personnel is inevitable due to sickness caused by COVID-19. The baseline simulations showed performance drops under high loads which leaves the system in a more delicate state and vulnerable, with a higher tendency to collapse. Testing different scenarios, it was found that overall the system can tolerate a certain degree of changes in temporary demand. However, extended stress and increased demand on the emergency infrastructure systems can push them towards their tipping point and therefore cause irreversible damage.

Keywords — complex systems, dynamic simulation, System dynamics, tipping point, COVID-19, Coronavirus, SARS-CoV-2, pandemic, contact rate, infection, hospitalization, first responders, police force, health care infrastructure

I. Introduction, Situation, and Problem

Small changes in dynamic and complex systems can have effects and outcomes that are far disproportionate to their influence. When a system is pushed towards its operational limits, it is possible that the whole system experiences a change of state and transitions to another state in an irreversible fashion. The definition of such phenomena has been described as tipping point and in order to define this phenomenon in a general way, Milkoreit et al. [5] conducted an extensive and interdisciplinary literature review. The tipping point is defined as "… a threshold at which small quantitative changes in the system trigger a non-linear change process that is driven by system-internal feedback mechanisms and inevitably leads to a qualitatively different state of the system, which is often irreversible" [5]. Tipping points are phenomena that can have detrimental outcomes for a system or structure if, for example, the function of the system would be impaired or completely obliterated. In healthcare systems and emergency response systems such a loss of function could cost lives, cause medical supply shortages, or even health care systems collapses. Thus, it is essential to understand, assess, and where possible, anticipate such tipping points.

The pandemic caused by COVID-19 has been spreading continuously around the globe since it was discovered on December 31, 2019 [1][6][7]. Currently, over 27 million people globally have been confirmed infected and more than 889,000 deaths have been recorded. In the United States, over 6.2 million people have been confirmed infected with 189,000 fatalities [8]. With such high numbers, the management of the pandemic has been paramount. The situation created by COVID-19 is especially difficult for people who provide essential and emergency services. Due to the critical and essential nature of the emergency services, these systems have exposure to general population that are affected by COVID-19 by default. The police officers, fire fighters, and EMT are crucial and indispensable services for public and domestic order.

Unfortunately, the police, fire fighters, and EMT are also affected by the virus and over time, a number of them have contracted the virus. In New York City for example, at times, about 20% of the police force were out sick due to the pandemic [9]. Such circumstances can be detrimental if institutions such as the police, medical personnel, or EMT temporarily or permanently lose a considerable number of personnel and thus cannot cope with the dynamic demand anymore. In case of the police force, this could mean that not all service calls can be attended to. For nurses and doctors, such situations can lead to care shortages and lower nurse-to-patient ratios. This increases the workload for the remaining medical personnel and states waiving the limits and requirements of the nurse-to-patient ratios during the pandemic have already been reported [10].

The above described shortages and lack of personnel will increase the load of these systems and could induce their partial collapse. For example, with extreme shortages in personnel due to COVID-19, the police would only be able to respond to the most important calls, leaving smaller crimes unattended for the time being. This lack of attendance could cause a downward spiral and increase of those crimes if people notice that they are not being pursued. Such developments would put the entire social system under more stress as the effects are hard to predict and could quickly turn into a vicious cycle.

This predicament is what the research in this paper set out to address. The authors' previous paper described a simulation and system model for the spread of the COVID-19 pandemic in the general population. With this approach an increase in infections as a results of increased contacts over the celebratory events of Easter and Passover in NYC was predicted [2]. The prediction later was confirmed by the reported numbers, which showed a notable increase after the incubation period following Easter and Passover [11]. The paper at hand addresses the behavior of two connected systems/structures: the emergency personnel systems in dynamic interaction with general population. The authors expanded and modified the existing simulation to allow for the assessment of additional sub-systems besides the general public and were thus able to evaluate how the emergency personnel and forces react under load and pressure.

The current research studies the effects of the pandemic on the emergency personnel utilizing the example of the police force in NYC, as the data for this institution was publicly available and accessible. It has to be noted that this choice is by no means a definite restriction of the model as it can be easily adapted and fed with different numbers to fit various other locations, areas, and scenarios. The model and methodology are described in Section II, starting with a summary of previous work cited [2], followed by the extensions and modifications, and finally the methodology applied in this paper. Subsequently, the assumptions as well as the chosen parameter are discussed. Section IV and V outline and discuss various scenarios with different parameters and behaviors to show the possible outcomes also in relation to potential tipping points of the systems. Finally, Section VI summarizes the outcomes and observed phenomena, provides a discussion of the results, and describes an outlook regarding future research and possibilities.

II. Model and Methodology

The existing dynamic simulation model designed with the software Vensim [12] was derived from a standard SIR model. SIR stands for "susceptible–infective-removed" and was first proposed by Kermack and McKendrick in 1927 [13]. Instead of relying on a transmission factor presented by traditional SIR models though, the designed simulation uses the contact rate between individuals in conjunction with the infectivity of the virus to define the infection rate directly. This allows for mimicking and depiction of circumstances such as regulatory measures instead of relying merely on the virus transmission and its reproduction as a result. Furthermore, the model was designed to include various time delays due to incubation, recovery, and duration of hospital stays. The time steps and calculations were computed in one day intervals over a period of 180 days. A modified and simplified flowchart of the model and simulation from the previous publication is depicted in Figure 1.

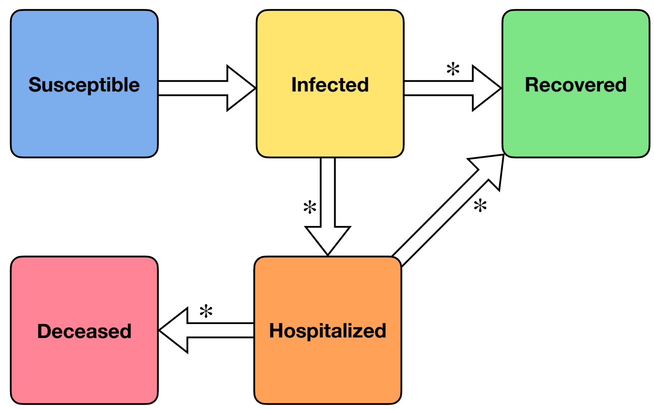

Fig. 1. Simulation Flowchart (* marks delay impacts) [2]

As part of the recent research, the existing model was extended to allow for the inclusion of sub-groups, such as the police or hospital personnel. To accomplish this, the sub-groups were given their own separate branch and therefore could be assessed separately in their own small sub-system. Since the two branches, the general population and the police force, are not isolated and share reciprocating influences, the interactions and causal links between the two systems were also included. This connection was modeled by splitting the police contact rate into two separate rates which eventually defines the police infection rate. The first contact rate was based on the contact rates between the police force and the general population during their services and duties at work, for example when an officer is dispatched. The other rate was based on the contacts that police officers have with each other while at work. These two rates, in addition to the already existing general contact rate, form the overall contact rate of the police force and therefore drive their infections. The sub-systems are depicted in Figure 2 and the equations are listed below.

The model is based on the same differential system that determines the behavior of the three levels S, I, and R for each of the two sub-systems with the additions described in the previous paper [2]. The infection/recovery of the two sub-systems is defined by similar equations separately. The equations were extended to fit the two sub-systems as described below [14].

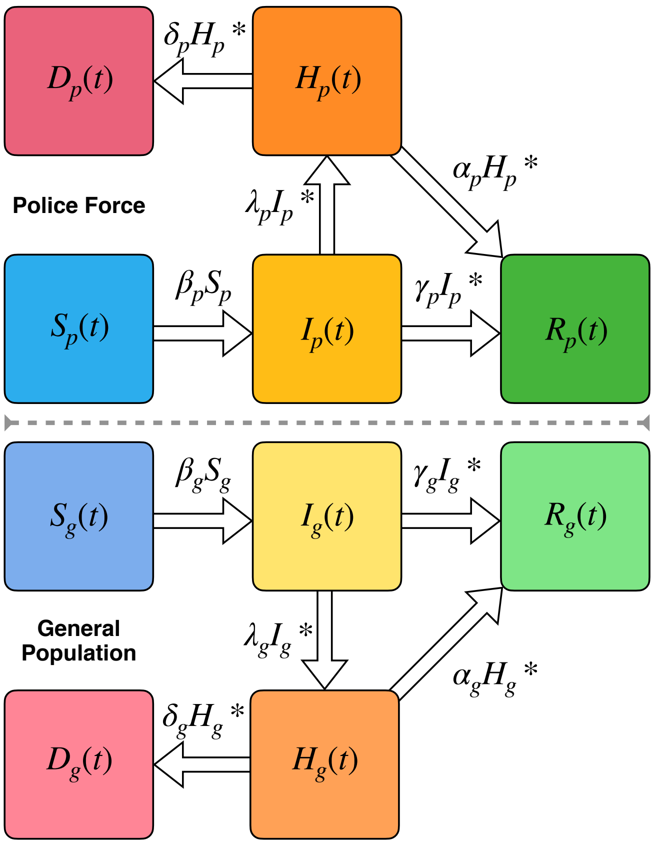

Fig. 2. Simulation Flowchart with police force sub-system (* marks delay impacts)

Equations for both sub-systems (x substitutes general population (g) and police force (p)):

(I) Susceptible General Population:

$\dot{S}_x = -\beta_x S_x$ with $S_x(0) = S_{xo} \geq 0$

(II) Infectious General Population:

$\dot{I}_z = \beta_z S_x - \gamma_x I_x - \lambda_x I_x$ with $I_x(0) = I_{xo} \geq 0$

(III) Removed General Population (delayed):

$\dot{R}_x = \gamma_x I_x + \alpha_x H_x$ with $R_x(0) = R_{xo} \geq 0$

(IV) Hospitalized General Population (delayed):

$\dot{H}_x = \lambda_x I_x - \delta_x H_x - \alpha_x H_x$ with $R_x(0) = R_{xo} \geq 0$

(V) Deceased General Population (delayed):

$\dot{D}_x = \delta_x H_x$ with $R_x(0) = R_{xo} \geq 0$

so that $S_x(t) + I_x(t) + R_x(t) + H_x(t) + D_x(t) = N_x$

and $\dot{S}_x + \dot{I}_x + \dot{R}_x + \dot{H}_x + \dot{D}_x = 0$

Table I below shows the definition of the variables used and depicted in Figure 3 above, which will also be explained further in the assumptions section starting on the next page.

TABLE I. VARIBALES FOR FIGURE 2

S_x	Susceptible Stock	β_x	Infection Rate
I_x	Infected Stock	γ_x	Recovery Rate (direct)
R_x	Recovered Stock	λ_x	Hospitalization Rate
H_x	Hospitalized Stock	α_x	Recovery Rate (Hospital)
D_x	Deceased Stock	δ_x	Death Rate

With these equations, it was possible to model the progress of the pandemic with the above mentioned contact rates. These rates define the parameters β_g and β_p. The assumptions behind these parameters will be outlined in the next section (III).

The last remaining part of the simulation was the performance of the police force. Simulating this factor was achieved by including the capacity of the police in the model. Herein, the number of available officers at a given time was calculated based on the susceptible and recovered individuals. With this number, the daily capacity for service calls was deduced. Combined with the amount of daily service calls, the capacity could be compared to the demand and thus, the actual completion of calls was simulated. In case calls were not completed, they were queued and a part of the queued calls were dropped due to expiration. Figure 3 shows the stocks:

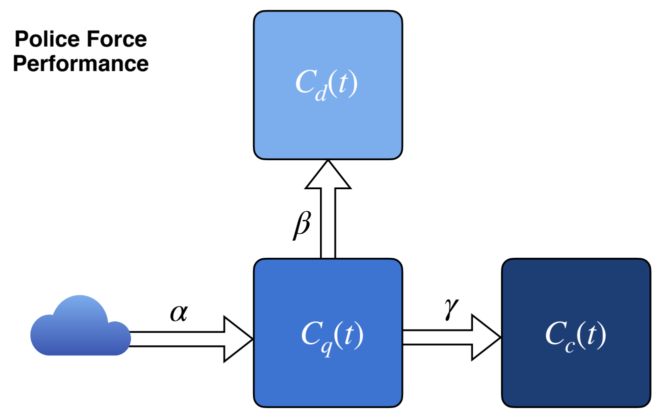

Fig. 3. Police Performance Flowchart

Table I below shows the definition of the variables used and depicted in Figure 3 above, which will also be explained further in the assumptions:

TABLE II. VARIBALES FOR FIGURE 3

C_q	Queued Demand/Calls	α	Incoming Demand Rate
C_c	Completed Calls	β	Drop Rate
C_d	Dropped Calls	γ	Compeletion Rate

As depicted in Figure 3 above, the calls for the police arrive at a constant rate α and are added to the queued calls C_q. From the queue then, the calls are either completed at the rate γ if the capacity is sufficient, or, if the capacity is insufficient, due to too many officers being out sick, are dropped at a rate β, which is defined as a percentage of the calls that were not attended to.

The performance of the police force is initially simulated over time. Then, based on the resulting performance and assumptions described in the next section (III), the load level was calculated, which allowed for the implementations of fatigue [3] and the Yerkes-Dodsen Law [4] (YD Law). These factors have a potential negative impact on the system and influence the completion rate γ. Therefore, the system develops another time dependent dynamic, which can possibly cause further complication. The exact assumptions behind the fatigue and the YD Law will be described below.

With this model setup, the research methodology outlined and described by Maria [15] for simulations was applied. Herein, after the definition and design of the model, the parameters were tested to yield an outcome that was verifiable. For the given case, the verification was conducted by comparing the results of the simulation with the real reported numbers regarding the pandemic. It has to be noted that, since the reported numbers might not include/represent a certain amount of unknown cases, that the fatality count was utilized to verify the model as this number is the only one tested comprehensively.

After verifying the model and setting parameters (see next section), various scenarios were simulated and assessed based on the chosen conditions. The scenarios and their results will be described in the fourth and fifth section. Regarding the results, the different scenarios were compared as well as analyzed separately, to determine their different behaviors and deduce potential anomalies or noteworthy behavior, such as system function failure. The main focus of the evaluation was the assessment of the behavior of the system under increased load and stress. The objective was to research how the police force, and thus in a transferable way the emergency services in general, can behave under load, and how, and to what extent the system can be pushed until it collapses. The results of these evaluations shed light on the system resilience and knowledge about potential threats and dangers.

The subsequent section will describe all assumptions included in the model in order to allow for simulation results as realistic as possible.

III. Assumptions and Parameter

Since the above described model was derived from a previously published paper [2], the factors of the core model and the underlying assumptions will only be summarized here, and afterwards, the new additions will be described in detail. The core model for the general population and situation of the model was not changed and the simulation was also based on New York City (NYC) in 2020, with a population of 8,398,748 people [16]. The data for the NYC police force was obtained from publicly available records [17] for the year 2018. These numbers allow for a verifiable and realistic application of the model.

The following sections outline the different parameters and additions/extension to the model. It has to be noted that, while some of the parameters were assumed, their impact is linear and correction later on would not change the system behavior nor the observed phenomena, only the data points at which the behavior emerges.

A. The Parameters β_g and β_p - the Infection Rates

The previously used infection rate (now β_g) of the model, which describes at what rate the susceptible general population is infected was unchanged. The added infection rate for the police was developed to fit the system and follows the following equation:

$$\beta_p \cdot S_p = S_p(t) \cdot \left(c_{g|p} \cdot \frac{I_g(t)}{N_g - D_g(t)} + c_{p|p} \cdot \frac{I_p(t)}{N_p - D_p(t)} \right) \cdot i$$

The infection rate of the police force depends on the contact rate of the police officers with the general population ($c_{p|g}$), and the contacts of the police personnel with each other during work hours ($c_{p|p}$). The contact rate of the police officers with the general population was assumed to be the contact rate of the general population plus the number of police operations each officer conducts per day multiplied by the number of contacts per service call.

The other parameters, namely the infectivity (i) and base contact rate (c) for NYC, were left unchanged [18, 19-21].

B. The Parameters γ and λ - Recovery & Hospitalization Rate

For the general population, the recovery and hospitalization rate (0.73 and 0.27 respectively) were kept unchanged based on the previous sources [22]. For the police force on the other hand, both rates were adjusted since the police personnel was assumed to not employ any field officers under the age of 20 nor over the age of 65. Therefore, based on the hospitalization/recovery fraction per age group, the parameters were adjusted, yielding a police recovery and hospitalization rate of 0.784 and 0.216.

C. The Parameters α and δ - Hospital Recovery & Mortality

As in the last sub-section, the parameters for the hospital recovery (0.777) and death rate (0.223) were unchanged for the general population, just adjusted for the group age difference, which yielded a Police Hospital Recovery Rate of 0.9710 and a Police Mortality Rate of 0.02899.

D. The police performance and capacity

The police performance flow shown in Figure 3 was assumed to have a steady inflow based on the report of the NYPD for the year 2018 [17]. According to this report, the NYPD responded to more than 6,100,000 service calls that year. This yields 16,712 calls per day as inflow α.

Also according to the report, the NYPD employed on average 36,484 uniformed members. Assuming a three shift routine, 24/7 availability of the police force, 5 workdays per officer, and 1.5 police officers on average per call, a permanent availability of 23.79% was calculated. With 1.5 officers per call, this would yield on average 2.88 service calls per officer per day at 100% completion rate and therefore a γ matching α. This is the base case. As for the capacity, it was assumed that each service call, with documentation and transportation, takes on average 2 hours. Therefore, one officer could complete 4 calls each day during an eight hour shift. This was not implemented as a hard limit, but as a possibility for expedition exists and thus, the maximum capacity of each officers was set to 6 calls per shift (emergency capacity). This limit increase comes at the cost of increasing fatigue nevertheless (see next sub-section).

E. Yerkes-Dodsen Influence and Fatigue

The two stress factors of the YD Law and fatigue were implemented as explained above as direct influences for the completion rate. The fatigue was implemented as a direct factor that starts accumulating when the capacity limit of the police is met as described in the last sub-section. Once the completion rate/demand falls under the capacity limit again, recuperation at the same rate as the fatigue increase before was enabled, allowing the police force to decrease the accumulated fatigue. As for the influencing factor, the performance changes measured by Arnedt et al. [23] were utilized and a factor of 0.00357 performance loss per fatigue point was applied.

As for the influence of the Yerkes-Dodsen Law, it was discovered that a flat curve had to be applied as otherwise the influence would have been disproportionately large and resulted in dropped calls at 30% load, for example. Thus, the curve was adjusted to negatively impact the performance in the higher load zones with a decline starting from 100% performance at 60% load down to 95% performance at 100% load (inverted for loads under 40%). Since the model could depict and simulate loads higher than 100% capacity, the Yerkes-Dodsen Law was implemented as a constant depreciation parameter (see Section V and VI) for loads over 100% in addition to the time-dependent factor above said threshold regulated by the implemented fatigue as described above.

With these parameters, the scenarios for the simulation could be run and assessed. In the first verification runs (Section IV), the model was validated and verified given the officially reported numbers [8] and the behavior observed. In the first scenario (Section V), the contact rate for the police force was increased to simulate a higher loss in capacity. In the second scenario and assessment (Section VI), the incoming calls were increased variably in order to test the resilience of the system and assess how far it can bounce back from such impacts under various conditions.

IV. BASELINE SCENARIOS AND GENERAL EFFECTS

With all the parameters described above, a base scenario was simulated with the average call rate unchanged and the core model of the general population verified as of May 13, 2020 for which the simulation showed 20,756 fatalities and the official numbers reported 20,406 deaths. Figure 4 below shows the fatalities of the simulation for the time from February 2nd through May 31st:

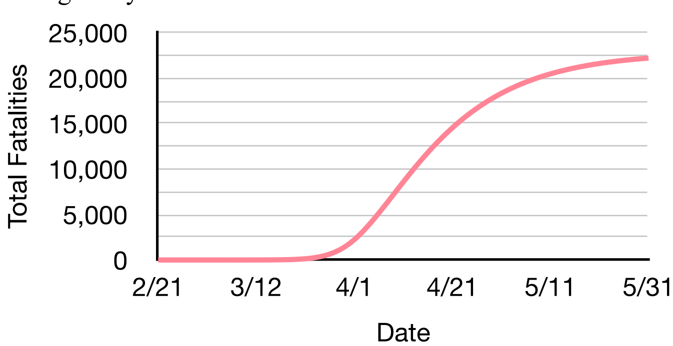

Fig. 4. Base Scenario General Population Fatalities NYC

As for the police force, with a contact rate of 2.8 contacts per service call, the fit for action personnel followed the graph depicted in Figure 5, which aligns with the official reports stating that at the worst time of the pandemic so far, up to 20% of the police force were out sick [9]. The below depicted graph shows a simulation for 180 days also starting February 2nd.

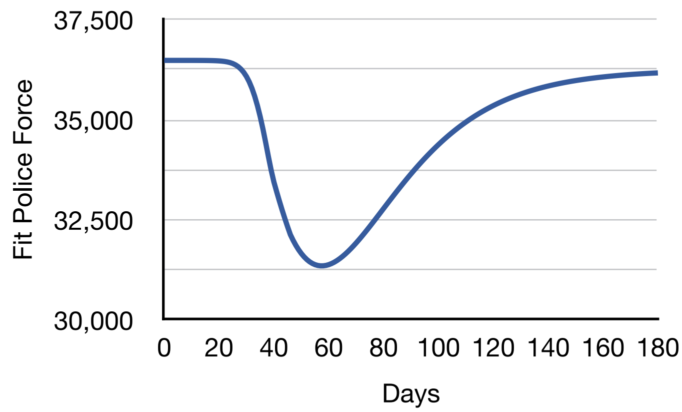

Fig. 5. Base Scenario Fit Police Force over time for the NYPD

The behavior and performance of the police force show that in this scenario, which closely mimics the real progress of the pandemic for those 180 days, the police force as operating within its capacity limits at all times. To measure this, the load, depicted in Figure 6, for each time step was calculated by dividing the number of received calls currently queued by the normal capacity of the police force depending on the number of currently fit and available officers.

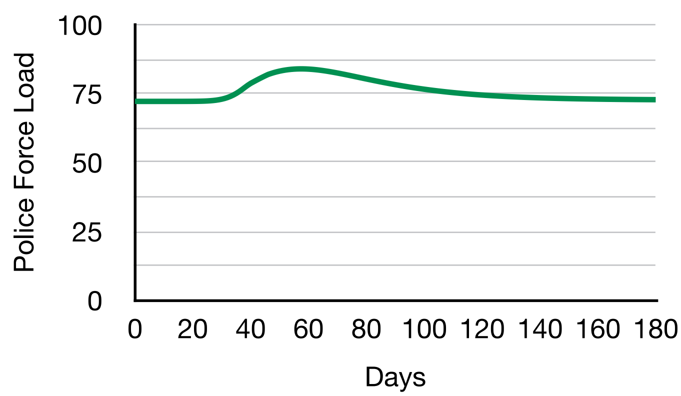

Fig. 6. Base Scenario Load based on capacity over time

Therefore, it can be concluded that during the pandemic until May 31st, the police force was at all times capable of dealing with the incoming calls. This has also been compared and verified by looking for reports that indicate the opposite during the current wave of the pandemic, which yielded no results as of May 31st and therefore no reports of capacity prolonged exceedance can be deduced.

The next section will describe the results from the simulations that pushed the system further and above its capacity limit to assess the possible behavior above those limits.

V. SCENARIO A AND B: MODULATED INFECTION NUMBERS

Since the baseline scenario showed that the police was operating within its capacity limits during the realistic case and the first wave, the system was pushed in order to observe its behavior under more load and stress. To achieve this, the contact rate of the police force with the population was increased. It was discovered that up to a contact rate of around 7, above which the system first hits the 100% load mark, it behaves as expected. Above this value, the behavior changes. It has to be considered that while the modulated parameter for this was the contact rate, this can also be caused by higher infection rates of the general population for example. The YD Law factor over 100% load was set to be declining by 0.0167% per load point.

Figure 7 shows the impact for the fit police force over time for the different contact rates and Figure 8 the respective load.

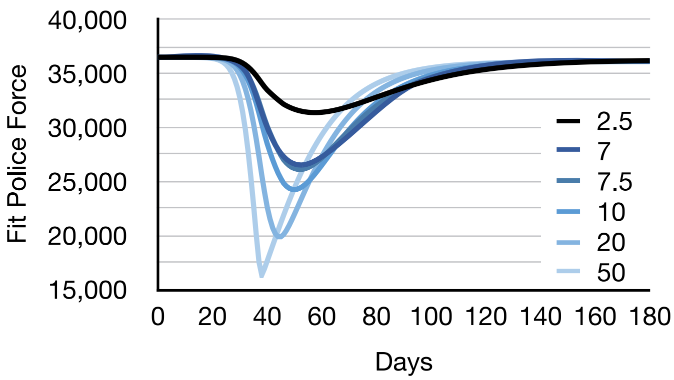

Fig. 7. Scenario A: Fit Police Force over time

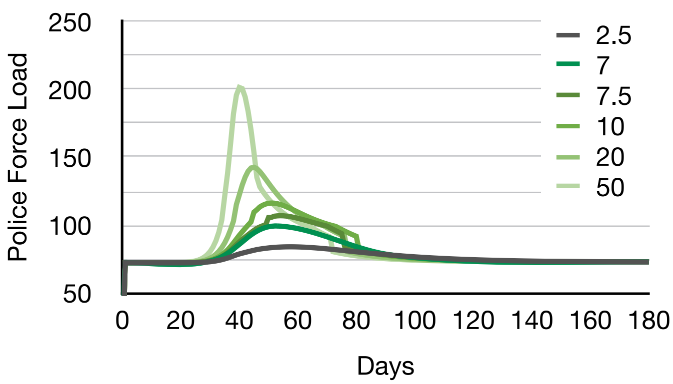

Fig. 8. Scenario A: Load over time

Once the system hits 100% load, it changes its behavior and the fatigue as well as the lower YD Law unfold their impact. Despite all these influences, the system still shows its capabilities to bounce back and always regain its full function, albeit with more losses for the higher scenarios. For example, the amount of dropped calls for the 50 scenario totaled at 19,628.7 calls. Moreover, the impact of fatigue was highest for the 20 and 10 scenarios. This is due to the fact that in the 50 scenario, an extreme amount of personnel left sick within a short time span before day 40, but the recovered portion of these infected people also returned early in the simulation, which resulted in less prolonged load for the system and therefore less fatigue in total.

For the second scenario (B), the same parameters were applied with a different Yerkes-Dodsen Factor above 100% load: this time a step down to 80% at 100% load and successively the previously stated constant depreciation. With these parameters, the system was not capable of bouncing back to its previous function after it hit 100% load. Even the scenarios that previously seemed like they could handle the impact without load spikes now turned into constant depreciation. Figure 9 and 10 show the load and completion rate over time. Once the system reaches its maximum capacity, the load increases at first before the available number of officers increases again, which spreads the demand and reduces the strain on the system. Unfortunately, despite the return to full personnel (minus the deceased staff), the effect of the fatigue cannot be mitigated and the capacity keeps declining over time. Once the emergency capacity per officer is reached, an even steeper decline can be observed and the system degradation increases even more.

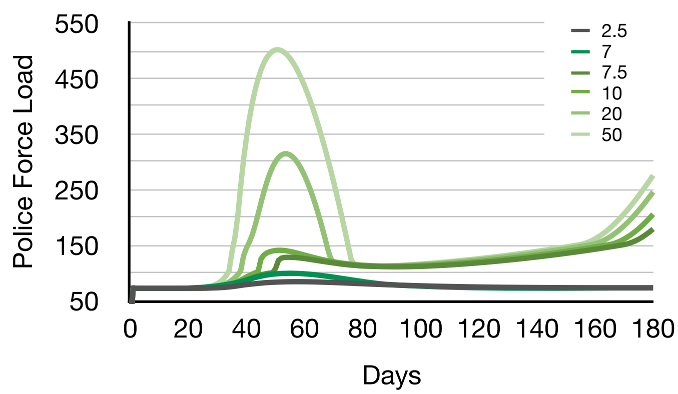

Fig. 9. Scenario B: Load over time

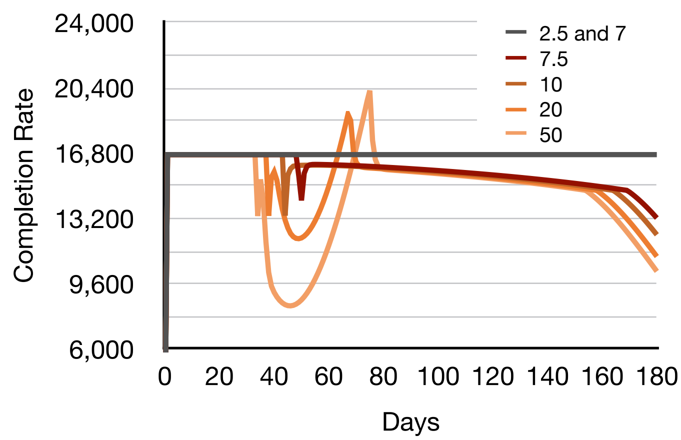

Fig. 10. Scenario B: Completion Rate over time

Figures 11 and 12 show that there are circumstances under which the model is not capable of dealing with and absorbing overload. This is a critical observation as it puts the resilience seen in Scenario A into perspective. A performance drop above 100% capacity/load has also been described by other researchers who examined this behavior [24]. Therefore, while such limits might be shaped by the parameters set in the model, they nevertheless pose a threshold that has to be accounted for.

VI. Sceanrio C and D: Modulated Inputs

Since the last scenarios showed that the system is resilient over time and has the capability to return to its function even after significant impacts, the last two scenarios were to evaluate the capability of the system to absorb varying input parameters. Therefore, the base scenario was utilized as a reference and the incoming calls were changed for each scenario.

First, Scenario C evaluated different constant increases in demand in percent compared to the baseline above. Scenario D evaluated changing increases in various forms, such as wave patterns for example. This allowed for the assessment of the system under changing and varying influences to see what behavior would emerge in a fluctuating environment.

Figure 11 and 12 show the results of Scenario C and will be evaluated hereinafter.

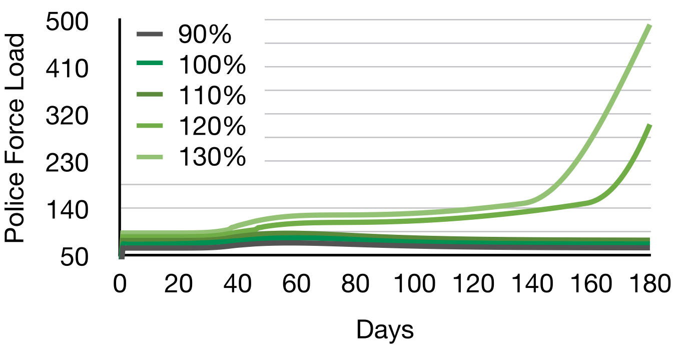

Fig. 11. Scenario C: Load over time

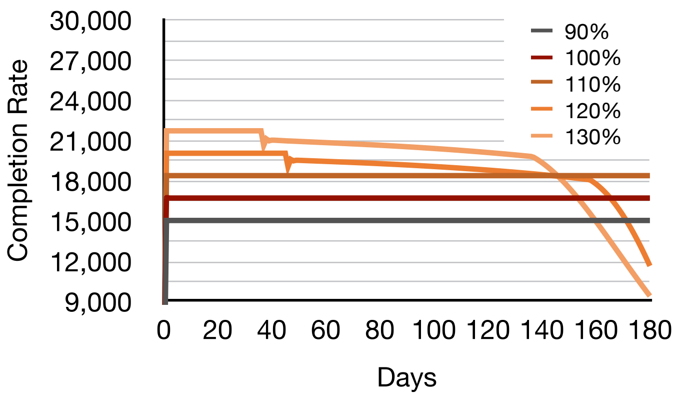

Fig. 12. Scenario C: Completion Rate over time

Figures 11 and 12 show that the system is capable of handling increased loads up to its capacity limits. Once the normal capacity limit is reached, the system has no means to absorb the increase and slowly degrades until it reaches its total emergency capacity limit. At this point, the system turns to a constant decline, which further worsens until the system reaches a steady rate of minimal performance.

Since such scenarios of constantly increased rates are extreme, the next, and last scenario looked at modulated and time dependent input increases/decreases. For the last scenario, inconsistent inputs such as spikes in intervals or wave form patterns were utilized. These patterns are described and discussed in the figures below. The results show that wave forms increase the resilience of the system by giving it room to recuperate during the spikes. For a utilized sinus wave in Figure 13 for example, the system maintains its function longer and the effect of the increases can be absorbed. This becomes more and more difficult once the waves get longer or increase their amplitude. As shown in Figure 13, doubling the wavelength leads to the obliteration of fatigue recovery and sent the system into a downward spiral. The depicted sinus waves describe an amplitude of 40% around the value stated in the legends.

With these influences, the system showed the capability to handle more temporary fluctuations as it would without the oscillating inputs. Yet, this only is true up until a certain point as well. Once the system enters a state at which the regeneration periods are not sufficient anymore, it again enters a degrading path and degenerates with the incoming waves. Herein, the length of the waves has a major impact as longer waves yield earlier consequences but cause a lower average slope in the long run. Thus, the system is better suited for short waves and can operate better under more predictable input deviations.

Figure 13 and 14 show the results of the different modulations for Scenario D.

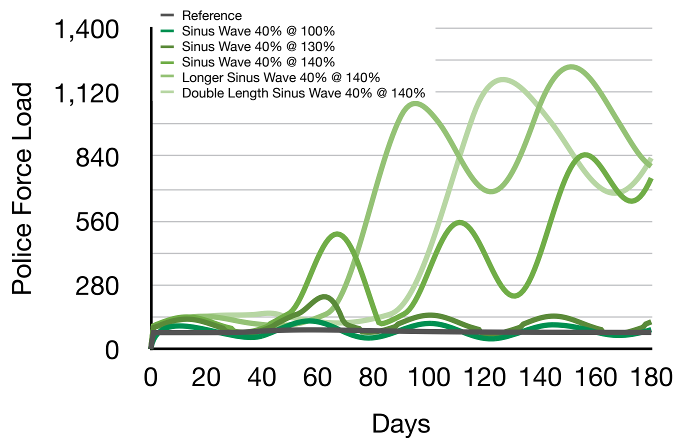

Fig. 13. Scenario D: Completion Rate over time

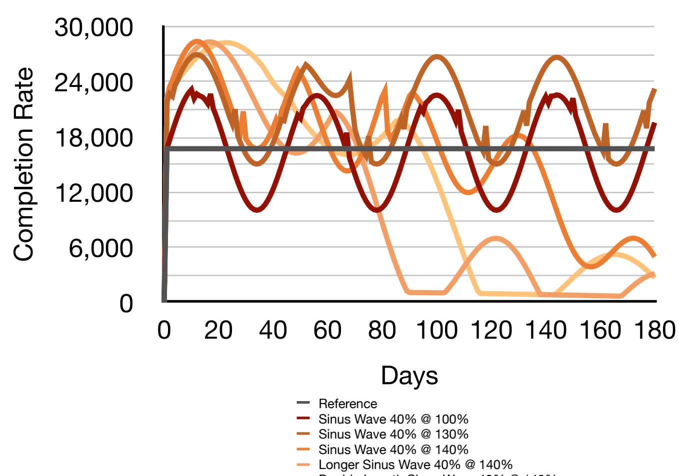

Fig. 14. Scenario D: Completion Rate over time

The final section will evaluate the results and discuss their meaning as a holistic assessment as well as comparison.

VII. Conclusion and Outlook

The previous sections explored four different scenarios that simulated various impacts and conditions for the police force as a representative system of the emergency services during the current pandemic. The first scenario simulated various degrees of temporary removal of officers due to sickness. The second scenario added a performance drop at the capacity maximum to the first scenario due to fatigue and performance under stress. The third and fourth scenario assessed increased inputs/demand in spikes or fluctuations. Herein, the third scenario simulated constant increases and the last scenario evaluated the effect of various fluctuating inputs.

Overall, the scenarios have shown different effects that the pandemic and other influencing factors can have on systems such as the emergency personnel, in this case the police force. In general, the system is resilient and stable when it comes to its capacities and it can even handle temporary small overloads, albeit with losses regarding its effectivity and efficiency.

The results from the first scenario show that the system is capable of absorbing temporary removal of officers effectively and is capable of regaining its function after the impact. These results were directly implemented into the second scenario, which showed that while resilient, the system can only handle performance drops above its maximum normal capacity to a certain limit. Once too many officers are removed from the system, it tips into a downward spiral and the accumulating fatigue, in combination with the YD performance impact, does not allow for the system to recover. It has to be noted that under certain circumstances, the system develops an overshooting phenomenon, which could be utilized to bring the system back to stability, if the adverse effects could be mitigated (see spikes above normal completion rate in Figure 10). Unfortunately, the system is not capable of utilizing these spikes as compensation just by itself without other influences..

The third scenario revealed that the system even possesses some resilience when it comes to constant demand increases. It showed that it can absorb/handle the missing officers even with increased demand up until a certain point. Once the demand was too high, the system steadily and slowly degrades until it reaches its emergency capacity, and finally collapses.

The fourth and last scenario demonstrated that erratic or inconsistent inputs can be beneficial as well as detrimental for the system. Short swings (close to square waves) allow the system enough time to recuperate and it thus showed the capability to deal with (on average) even higher demand as compared to its behavior with a continuous and increased input. Longer waves cause the opposite effect and send the system into degradation even earlier as it would have with a constant input of the same average. This is due to the fact that the increase brings the system to its threshold and then causes it to tip. At this point, the system is unable to handle the demand anymore even after the input subsides. The system completely collapses very quickly in two of the simulated runs. These insights can be very helpful and will be further pursued since the assumed call rate input was the calculated average and in reality fluctuates according to certain patterns as well.

Overall, the system has shown some thresholds that can be tipping points for the emergency response system during the current pandemic. In order to achieve quantification of the tipping points, the authors plan on extending this research and simulation to probe these phenomena in various systems.

Regarding current simulation for the real world application, some behaviors are observed that could be potentially helpful for regulatory decisions, such as the overshooting behavior in Scenario B. As aforementioned, this could be utilized to bring the system back to stability with the right inputs at the right time. The authors are planning to further investigate such singular behaviors in order to define a more general interpretation and derive suggestions for guidance.

Future plans also include the expansion of the research to add more details such as diversifying the Yerkes-Dodsen Influence based on studies and more substantial research as well as inclusion of fatigue.

In addition, the authors are modifying this model to mimic other branches of the emergency services, such as hospitals and fire fighters, in order to provide more institutions with the knowledge and power to increase the resilience of these complex systems as well as simulate some critical decisions in times of crisis. Lastly, the next steps include adding various factors, such as protective gear, their effects, and other regulatory measures to the simulation. This also entails the potential consideration and addition of re-infection, which would transfer individuals from the recovered stock back to the susceptible group. This could be possible due to the degeneration of anti-bodies, for example, and has not been considered in the initial simulation due to the parameters and time frame of less than one year and the fact that possible re-infections are more important for longer time spans.

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