

# Applications of a rheological model analog to assess the resilience of socio-technical systems

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## ABSTRACT

Crises are ubiquitous in socio-technical systems. Upon tracking one or several performance parameters, a crisis commonly manifests by a breakdown of such performance parameters following singular events such as disasters or catastrophes. In (Stolz et al. 2024), a model has been proposed that describes the breakdown of one of the aforementioned performance parameters. In comparison to most previous models, this approach allows to capture not only full recovery, but also the permanent breakdown of the system, partial recovery, and improved performance above pre-crisis values. Previously, the model has been applied to several inherently different systems, and it could be shown for the number of flight departures at German airports following COVID-19 that model parameters can be correlated to real-world characteristics of these airports. In this Work in Progress, the model is applied to further systems, with the goal to unveil additional connections between model parameters and system characteristics.

## Keywords

Resilience engineering; quantitative assessment; single degree of freedom; interdependent socio-technical systems; crisis response

## INTRODUCTION

While the nature of socio-technical systems may vary wildly, associated crises in such systems share many characteristics. One way of characterizing the coping capacity of socio-technical systems subjected to crises is to track the system performance over time, in which a crisis manifests as a breakdown of this performance to an extent that exceeds usual fluctuations (Bruneau et al. 2003).

The resulting performance-over-time curve is used to measure resilience and can be approximated by models that feature a single degree of freedom (SDOF) (Cimellaro et al. 2010; Reed et al. 2016; Mahmoud und Chulahwat 2018; Tao und He 2020; Wang 2017). In some cases, simple linear models (*resilience triangle*) adequately capture the performance over time curve (Zobel 2011; Zobel und Khansa 2014; Xu et al. 2024). The approach, presented in (Weiss und Zobel 2025), characterizes performance by analyzing resilience, stability, and recovery modes depending on model characteristics. In (Stolz et al. 2024), a SDOF model has been proposed, that, in contrast to most previous approaches, allows to describe not only situations in which the socio-technical system under duress makes a full recovery to the performance level before the adverse event, but can also capture cases in which performance is not restored at all, recovery to performance levels lower than before the crisis, as well as recovery to performances that increase above pre-crisis levels.

This model has been applied to diverse socio-technical systems: the frequency stability of the continental Europe power grid, flight operations of German airports, and the revenue of the German gastronomic sector. In the case of the airports, the decline in departures following the onset of the COVID-19 pandemic has been investigated. It

could be shown that one of the model parameters is predicted from the ratio of cargo to passenger throughput, thus, from quantities not intrinsic to the model. This opens a path to predicting performance over time curves for systems for which the time evolution of the system performance has previously been unknown.

In this paper, crisis data of further socio-technical systems is considered with regard to the model of (Stolz et al. 2024). In (Podesta et al. 2021), population activities following a natural disaster are investigated. To this end, digital trace/location-intelligence data related to population activities is investigated. The crisis (in this case Hurricane Harvey) manifests in the frequency of visits to points of interest (POIs), which encodes changes in lifestyle, the built environment and the status of businesses. The goal is two-fold: First, the above-described SDOF-model is fitted to this dataset. From this fit, model parameters are extracted which quantify the resilience of the respective underlying system. Second, in analogy to the investigation of the airports in (Stolz et al. 2024), the aim is to identify characteristic, quantitative properties of these systems that show correlations with the model fit parameters, in order to eventually facilitate predictions of the latter without performing a fit. Once the model parameters for a specific system are determined, these parameters can systematically be linked to inherent characteristics of the system. Such correlations enable further investigations aimed at developing effective strategies to enhance the system's resilience against crises, including preparedness and prevention strategies, as well as recovery planning.

This paper is structured as follows: first, a recap of the model of (Stolz et al. 2024), its parameters and characteristics is provided, together with results for the German airports in the wake of the COVID-19 pandemic and the connection of model parameters to the quantities characteristic for the individual airports, as well as how the model reacts to parameter variations. Following the recap, the POI frequency-of-visit dataset is reviewed and cast into a format suitable for the investigation regarding the SDOF-model. Finally, the SDOF-fits of the data are performed, and the model parameters are extracted, followed by an assessment in view of making the connection to measurable quantities that characterize the respective POIs.

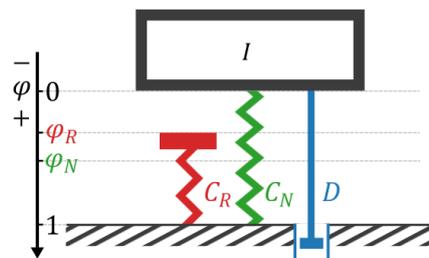
## RHEOLOGICAL MODEL ANALOG FOR THE RESILIENCE ASSESSMENT OF SOCIO-TECHNICAL SYSTEMS

The SDOF-model proposed by (Stolz et al. 2024) is depicted in Figure 1. The parameter  $\varphi$  measures the departure of the system from the steady-state performance ( $\varphi = 0$ ) up to complete breakdown ( $\varphi = 1$ ). Below  $\varphi = \varphi_N$  and  $\varphi = \varphi_R$ , the system operates in the regular regime, in which the dynamics corresponds to a harmonic oscillator governed by the differential equation

$$I \ddot{\varphi}(t) + D \dot{\varphi}(t) + C_N \varphi(t) = F(t), \quad (1)$$

in the overdamped parameter range, that is

$$D^2 - 4C_N I > 0. \quad (2)$$



**Figure 1 [from (Stolz et al. 2024)]: SDOF-model for the quantification of the resilience of socio-technical systems.**

In that regime, the dynamics depends on the system's inertia  $I$ , the damping constant  $D$ , and the regular operation spring constant  $C_N$ . Once  $\varphi$  surpasses the threshold  $\varphi_N$ , the regular operation spring breaks such that  $C_N = 0$ . If  $\varphi$  surpasses  $\varphi_R$  (note that not necessarily  $\varphi_N > \varphi_R$ ), restorative forces are activated. In this case, special conditions apply for the damper  $D$  and the restorative spring  $C_R$ , see Figure 2 and Figure 3, respectively. Here, the dynamics is stopped once  $\varphi$  reaches  $\varphi_{End}$  or when the performance loss  $\varphi$  turns from negative to positive values.  $F$  in Equation (1) denotes the force that causes the displacement as a consequence of the crisis.

With regard to the performance of critical infrastructure, the parameters in the SDOF model are directly linked to the characteristics of this performance. The inertia  $I$  represents the inertia properties of infrastructure. The sensitivity to changes  $C_N$ , along with the control resilience  $\varphi_N$ , significantly contribute to the robustness. Additionally, the damping  $D$  influences the ability to react to crises and mitigates performance degradation. Finally, recovery agility ( $\varphi_R, \varphi_{RE}$ ) and recovery strength ( $C_R$ ) reflect the recovery capability in response to crises.

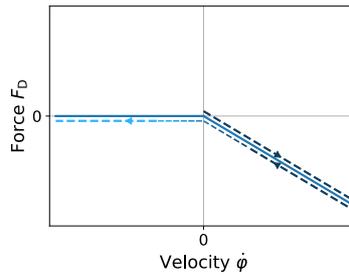


Figure 2 [from (Stolz et al. 2024)]: Once restoration forces are activated as  $\varphi$  exceeds  $\varphi_R$ , the damper  $D$  only acts against performance loss with the force  $F_D$ .

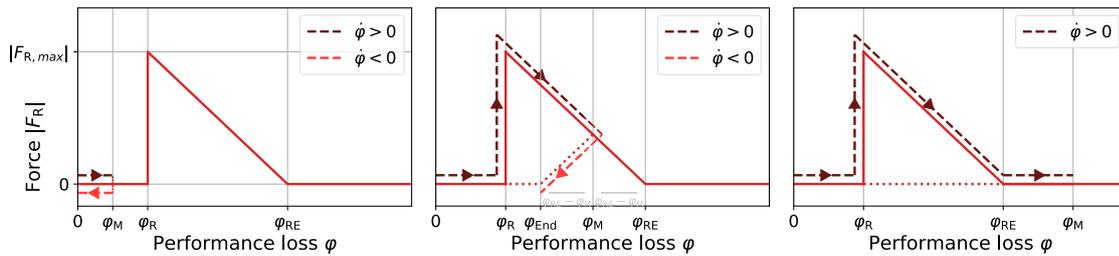


Figure 3 [from (Stolz et al. 2024)]: (Left) If the maximal performance loss  $\varphi_M$  remains below the activation threshold  $\varphi_R$  of restorative forces, these forces remain zero. (Center) Restorative forces act until they are depleted and restore the system’s performance to the value  $\varphi_{End}$ . (Right) If the performance loss exceeds  $\varphi_{RE}$ , the system collapses.

### APPLICATION AND INTERPRETATION

In (Stolz et al. 2024), the previously described SDOF-model is applied to describe flight departures at German airports in the wake of the COVID-19 pandemic and the associated travel restrictions (Statistisches Bundesamt). Figure 5 shows the data for the airports of Frankfurt (IATA-code FRA), Munich (MUC), Düsseldorf (DUS), , and Leipzig (LEJ) that have been corrected for annual variations, together with respective model fits and the ensuing parameter values. The time evolution of the performance at the airports of Frankfurt, Munich, and Düsseldorf in Figure 5 shows a qualitatively similar behavior. The airport of Leipzig stands out in that a much smaller fraction of the initial performance is lost in the course of the crisis, and the airport recovers performance that exceeds the level before the onset of the pandemic. The fact that the airport of Leipzig features a largely different ratio of freight to passenger flights evokes the hypothesis that this causes the qualitatively different behavior as compared to the other airports. This motivates the investigation of (Stolz et al. 2024) shown in **Figure 4** of the relation between this ratio and the inertia that results from the model fits. The double logarithmic plot shows that the inertia that results from the fit roughly follows a power-law relation as a function of the ratio of cargo-to-passenger volume. Thereby, the inertia of a given (especially, so far unknown) airport can be estimated just from the value of the aforementioned ratio. If similar relations can be uncovered for all model parameters, then the entire performance-over-time curve can be estimated from the model alone.

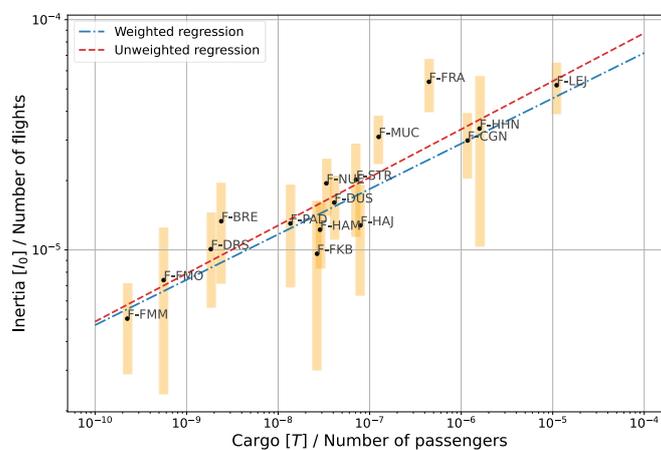
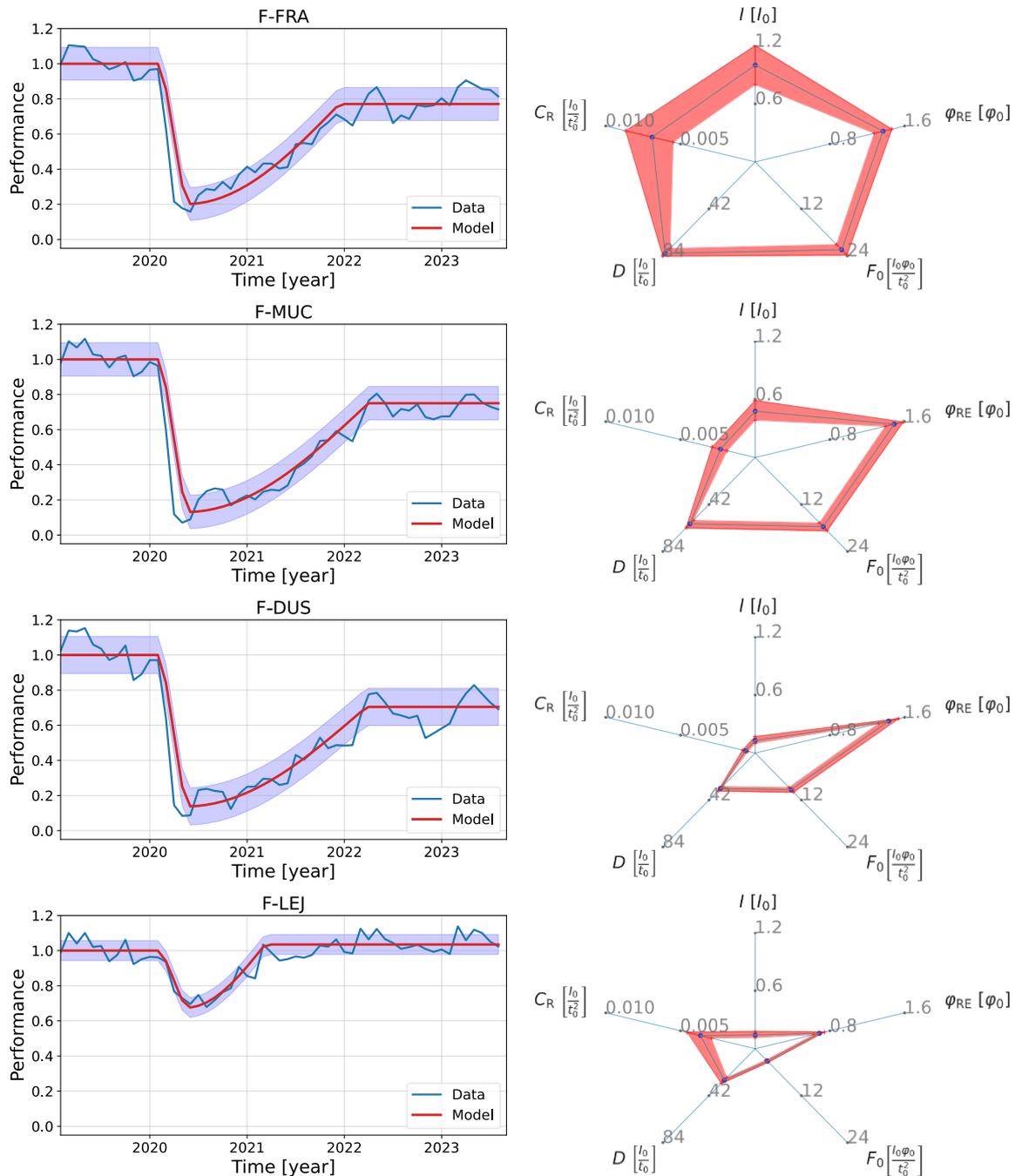


Figure 4 [from (Stolz et al. 2024)]: Plotting the inertia that results from a fit of the SDOF-model to flight departure data (Statistisches Bundesamt) against the cargo-to-passenger ratio for the respective airports reveals a power-law

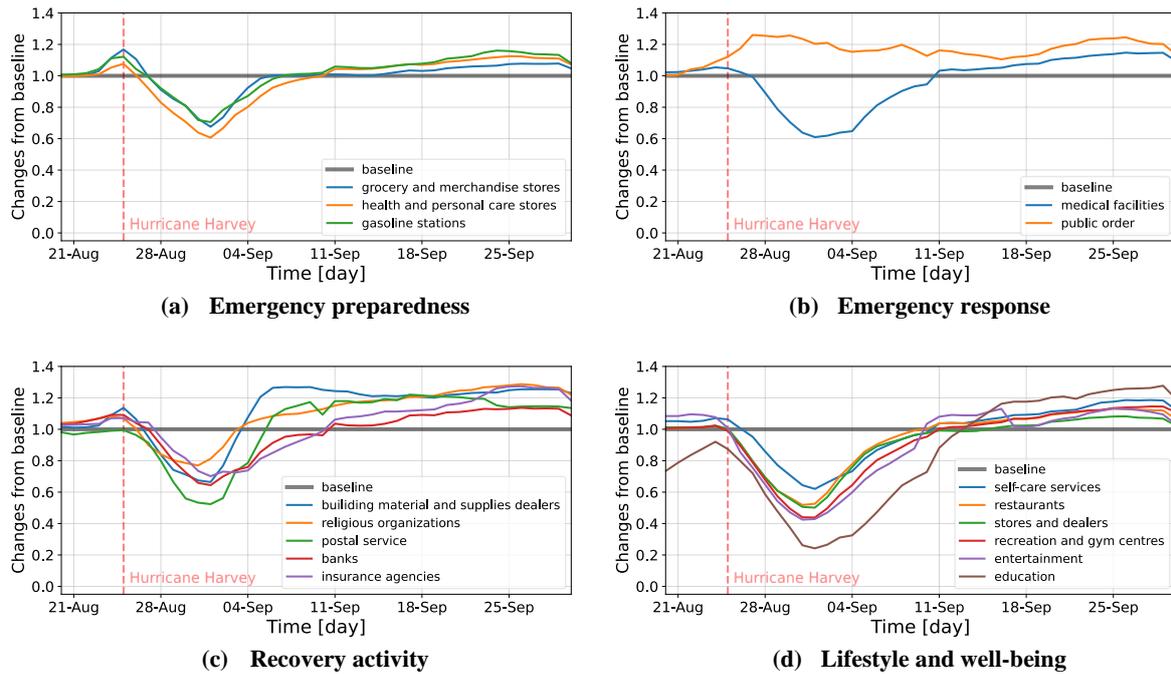
dependency.



**Figure 5** [from (Stolz et al. 2024)]: (Left) SDOF-model fits to the flight departure data of the airports of Frankfurt (IATA-code FRA), Munich (MUC), Düsseldorf (DUS), and Leipzig (LEJ), corrected for annual variations. The airport of Leipzig stands out in that fewer performance is lost in comparison to the other airports, and that the airport recovers operations to above pre-pandemic levels. (Right) Fit parameters expressed in terms of complete performance loss  $\varphi_0 = 1$ , the unit of time  $t_0 = 1$  month, and the inertia  $I_0$  of the airport of Frankfurt.

### POI VISIT DATA AND FITS

The study of (Podesta et al. 2021) examines communities as complex systems of interacting components, using point-of-interest (POI) visits as indicators to capture the dynamic state of communities affected by natural hazards. Utilizing data from the North American Industry Classification System (NAICS), the study quantifies community resilience by analyzing variations in POI visits before and after the landfall of Hurricane Harvey in Houston in 2017. This analysis focuses on resilience changes in four POI indicators suggested for community resilience by (Podesta et al. 2021): *emergency preparedness*, *emergency response*, *recovery activity*, and *lifestyle and well-being*, see Figure 6.



**Figure 6 [Data from (Podesta et al. 2021)]: Percentage performance changes  $Q = 1 - \varphi$  of the four groups of POI visits from baseline  $Q = 1$ , measured before and after Hurricane Harvey made landfall in Houston between August 20 and September 30, 2017. The four POI groups for community resilience are (a) emergency preparedness, (b) emergency response, (c) recovery activity, and (d) lifestyle and well-being.**

To demonstrate the applicability of the above-described SDOF model, a least-squares fit of the model is performed to the four POI indicators. The model computes the performance loss  $\varphi$  in relation to the baseline where no performance loss occurs ( $\varphi = 0$ ). The model is applied to the performance changes in POI indicators following the landfall of Hurricane Harvey on August 25, 2017. The initial performance for the SDOF-model corresponds to the day of the crisis. The performance loss is scaled by  $\varphi_0 = 1$  (full performance loss), and the time  $t_0$  is measured in days. The inertia of the system is scaled by  $I_0$ , corresponding to the inertia of each above-described POI group with the highest initial performance (see vertical dashed red line in Figure 6). All relevant parameters are expressed in terms of these basic units ( $\varphi_0, I_0, t_0$ ) as described in Section 2.3 of (Stolz et al. 2024).

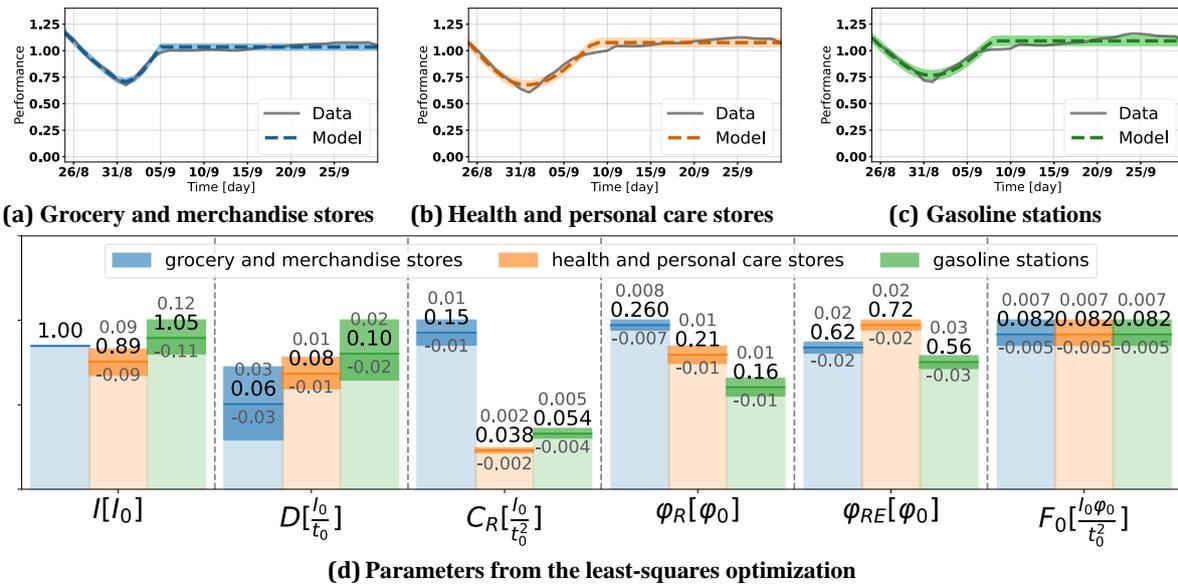
In the first step of modeling each group, all parameters ( $C_N, D, C_R, \varphi_N, \varphi_R, \varphi_{RE}, F_0$ ) are calibrated in a fit to the data from the category with the highest initial performance, while the inertia  $I$  is normalized to one. The resulting  $F_0$  is then applied to the remaining categories within the same group, allowing the model to align with the data by calibrating the remaining parameters ( $I, C_N, D, C_R, \varphi_N, \varphi_R, \varphi_{RE}$ ). The uncertainty bounds for each fitted parameter are estimated using the estimated deviation  $\sigma$ , which is computed based on the mismatch between the model and the data.

### Emergency Preparedness

The regular operating constant  $C_N$  and its threshold value  $\varphi_N$  are not shown due to the large uncertainties caused by the rapid performance drop at the beginning and the immediate cut-off associated with this performance drop [see Section 3 of (Stolz et al. 2024)]. The fitted parameters, including the uncertainty range, for different categories within the POI group *emergency preparedness* are comparable, except for recovery, see Figure 7 (d). Notably, the category of *grocery and merchandise stores* with the highest  $\varphi_R$  has a significantly higher recovery, which also corresponds to a higher magnitude of  $C_R$  than for the other categories, aligning with the earlier recovery date of approximately Sep. 5 of this category compared to Sep. 8 for the other categories, as shown in the performance over time curve in Figure 7 (a)-(c). The parameters *inertia*  $I$  and *damping*  $D$  reflect the system's robustness and its ability to mitigate crisis effects, which is evident in the observed maximal performance loss. *Gasoline stations* in particular, which had the highest inertia  $I$  and damping  $D$ , had the lowest total loss compared to other categories. All categories in this indicator emerge from the crisis in a close-to fully recovered state, with slight performance gains over the baseline. Selected statistical measures are an  $r^2$ -score (R2) ranging from 0.88 to 0.93, the root mean square error (RMSE) between 0.021 and 0.041, the standard error of the estimate (STD) ranging from 0.03 to 0.045, and the relative squared error (Rel. Error) between 2.7% and 4%. A summary of the statistical metrics for the model is presented in **Table I**.

**Table 1: Model evaluation metrics comparing the predicted and actual values for each sector in the POI group of emergency preparedness. The metrics are measured by the  $r^2$ -score (R2), the root mean square error (RMSE), the standard error of the estimate (STD), and the relative squared error (Rel. Error).**

	R2	RMSE	STD	Rel. Error
Grocery and merchandise stores	0.93	0.027	0.030	2.7%
Health and personal care stores	0.93	0.037	0.042	3.8%
Gasoline stations	0.88	0.041	0.045	4.0%



**Figure 7: (a)-(c) The SDOF model is fitted to the corresponding performance over time, showing the bounds (area) of the deviation  $\sigma$  between the model (dashed line) and the data (solid line). (d) The parameters of the corresponding model fit (solid line: fit parameters, area: parameter uncertainties) in (a)-(c) are expressed in terms of the basic units  $t_0 = 1$  day,  $\varphi_0 = 1$ , and  $I_0$ , referring to the inertia of the indicator of POI visits to grocery and merchandise stores.**

### Emergency Response

The *emergency response* group of POI visits consists of two categories: *medical facilities* and *public order*. The category *public order* did not show any performance loss during Hurricane Harvey (see Figure 8b), and thus has not directly been affected by the crisis, as mentioned in Section 4.2.2. in (Podesta et al. 2021). Therefore, *public order* is not investigated. The *medical facilities*, as illustrated by the performance curve over time in **Figure 8** (a), faced a crisis that resulted in a drop in performance. The model predicts the data with an  $r^2$ -score of 0.94, a mean square error of 0.042, a relative error of 4.3%, and an estimation error of 0.047.

The system ultimately recovered roughly around Sep. 12. The corresponding fit parameters, shown in **Figure 8** (b), are within comparable range of the parameters in the indicator of *emergency preparedness*, see **Figure 7** (b). The slightly larger performance loss is indicative of the damping parameter  $D$ . Furthermore, the extended recovery duration is associated with a delayed onset of recovery  $\varphi_R$  and a reduced recovery spring constant  $C_R$ .

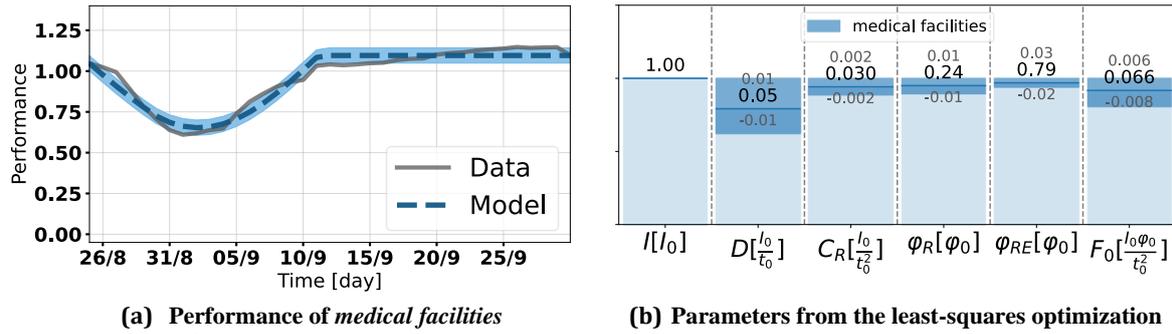


Figure 8: (a) The SDOF model is fitted to the corresponding performance over time, showing the bounds (area) of the deviation  $\sigma$  between the model (dashed line) and the data (solid line). (b) The parameters of the corresponding model fit (solid line: fit parameters, area: parameter uncertainties) in (a) are expressed in terms of the basic units  $t_0 = 1$  day,  $\varphi_0 = 1$ , and  $I_0$ , referring to the inertia of POI visits to medical facilities.

### Recovery Activity

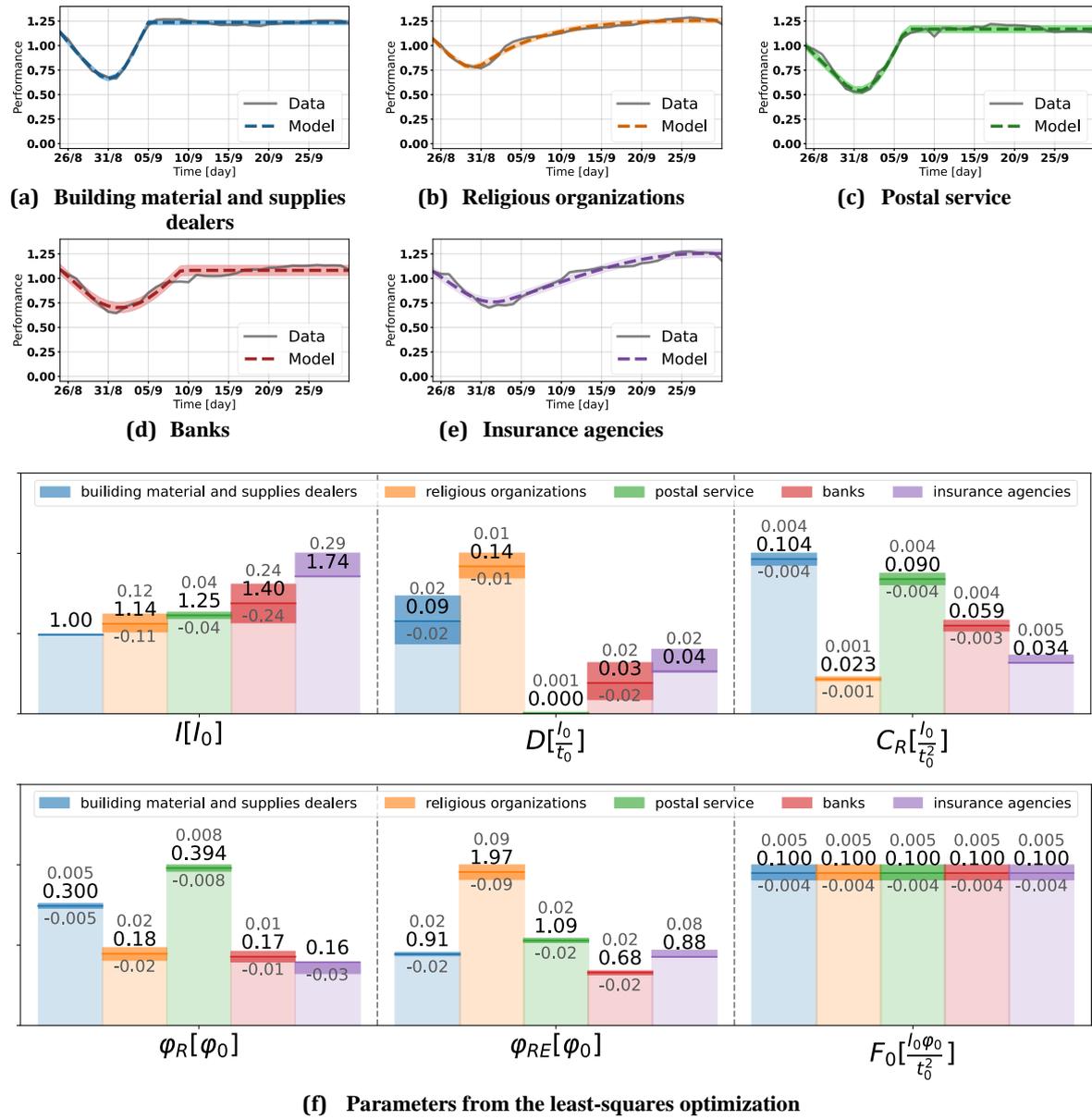
According to (Podesta et al. 2021), the indicator POI for the *recovery activity* group focuses on both short-term and long-term recovery from the crisis, including rebuilding homes and managing finances. This group consists of five categories: (a) *building material and supplies dealers*, (b) *religious organizations*, (c) *postal services*, (d) *banks*, and (e) *insurance agencies*. Each category undergoes full recovery, with improvements illustrated in the corresponding performance curves in **Figure 9** (a)-(e). The results indicate a high  $r^2$ -score ( $R^2$ : 0.95-0.99), reduced residual error (RMSE: 0.02-0.047 or Rel. Error: 1.8%-4.7%), and an estimation deviation (STD: 0.03-0.052), shown in Table 2.

In comparison to the three categories *building material and supplies dealers*, *postal services*, and *banks* which feature similar structures to those in *emergency preparedness and response*, the *religious organizations* and *insurance agencies* experienced significantly longer recovery times, as reflected in the smaller recovery spring constant  $C_R$  shown in Figure 9 (f). Additionally, the inertia  $I$  and damping  $D$  reflect the robustness of the recovery, with *postal services*, featuring a small magnitude of the damping  $D$ , and a large performance loss.

All categories in this indicator emerge in an improved state from the crisis. This comes with a comparatively high value of  $\varphi_{RE}$ , except for *banks*, which exhibits the smallest value.

**Table 2: Model evaluation metrics comparing the predicted and actual values for each sector in the POI group of recovery activity. The metrics are measured by the  $r^2$ -score (R2), the root mean square error (RMSE), the standard error of the estimate (STD), and the relative squared error (Rel. Error).**

	R2	RMSE	STD	Rel. Error
<b>Building material and supplies dealers</b>	0.99	0.020	0.023	1.8%
<b>Religious organizations</b>	0.98	0.023	0.026	2.1%
<b>Postal service</b>	0.98	0.033	0.037	3.2%
<b>Banks</b>	0.89	0.047	0.052	4.7%
<b>Insurance agencies</b>	0.95	0.037	0.041	3.5%



**Figure 9:** (a)-(e) The SDOF model is fitted to the corresponding performance over time, showing the bounds (area) of the deviation  $\sigma$  between the model (dashed line) and the data (solid line). (f) The parameters of the corresponding model fit (solid line: fit parameters, area: parameter uncertainties) in (a)-(e) are expressed in terms of the basic units  $t_0 = 1$  day,  $\varphi_0 = 1$ , and  $I_0$ , referring to the inertia of POI visits to *building material and supplies dealers*.

### Lifestyle and Well-being

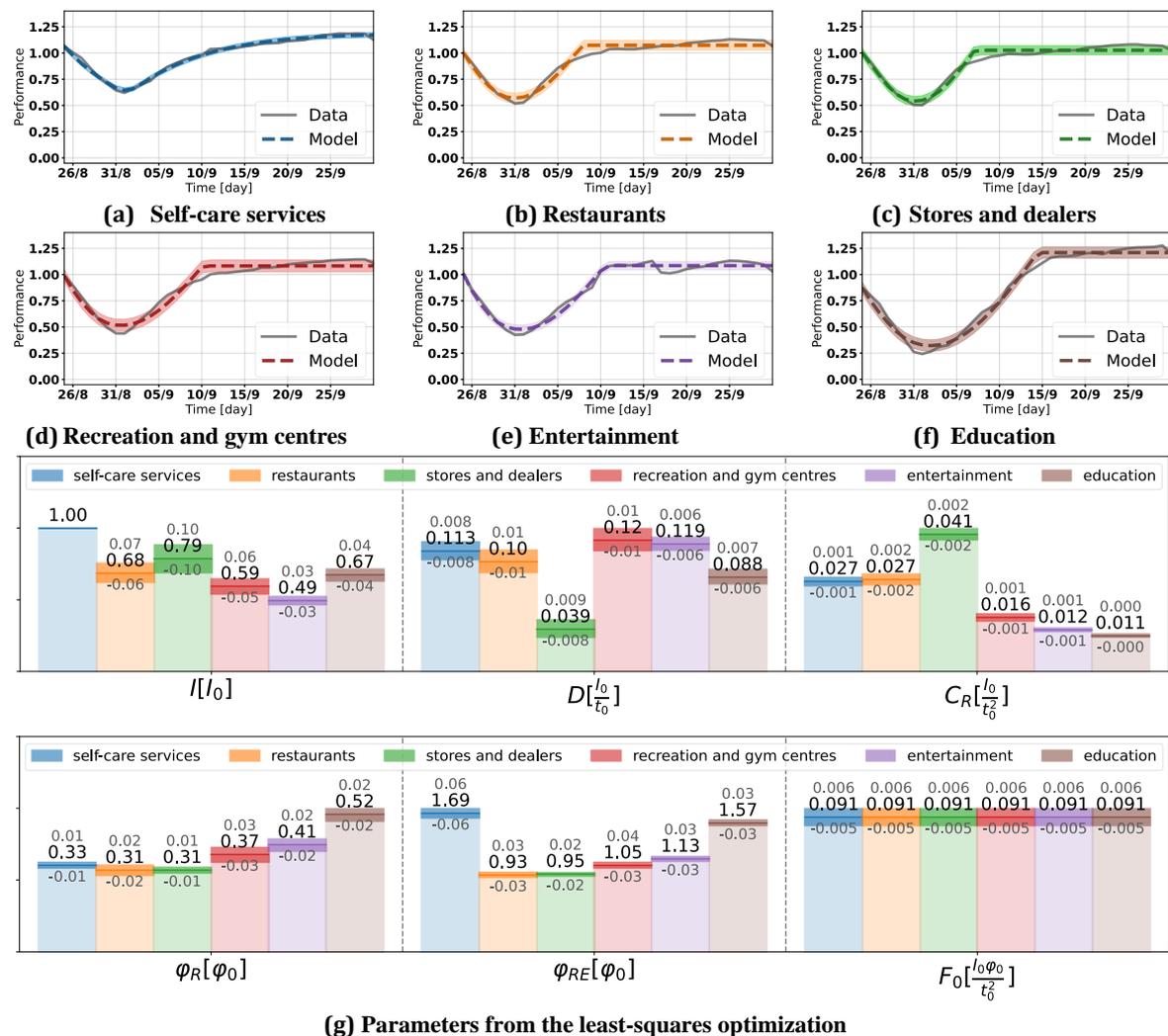
The group of POI visits related to *lifestyle and well-being* represents the economic, physical, and emotional well-being of residents (Podesta et al. 2021). This group includes (a) *self-care services*, (b) *stores and dealers*, (c) *restaurants*, (d) *recreation and gym centers*, (e) *entertainment*, and (f) *education*, as illustrated in **Figure 10**(a)-(f). With the exception of *self-care services*, which have a long recovery time, reflected by the small values of  $C_R$  and  $\varphi_R$  alongside a large magnitude of  $\varphi_{RE}$  [see **Figure 10** (g)], the fits for the remaining categories exhibit a similar pattern of performance loss and recovery as seen in other indicators. Only the two categories *self-care services* and *education* show significant improvement corresponding to a large value of  $\varphi_{RE}$ . Compared to the other groups of indicators, the present group features a large performance loss due to the combination of inertia  $I$  and damping  $D$ , particularly in *education*. Table 3 shows a highly correlated prediction from the model ( $R^2$ : 0.94-0.99) with a small relative error (2.1-5.4%).

In conclusion, self-care services with the highest inertia represent the largest sector in terms of POI visits related to *lifestyle and well-being* which can, consequently, in this regard be considered more resilient compared to the other sectors. Additionally, the recovery parameters emphasize the speed at which the respective sectors resumed their activities after the crisis. A high value indicates that *stores and dealers*, followed by *restaurants* and *self-*

care services, reopened quickly, enabling trade and shopping. Furthermore, analyzing census data (United States Census Bureau) can provide insights into and validate the size of each sector and their reopening strategies.

**Table 3: Model evaluation metrics comparing the predicted and actual values for each sector in the POI group of lifestyle and well-being. The metrics are measured by the r<sup>2</sup>-score (R2), the root mean square error (RMSE), the standard error of the estimate (STD), and the relative squared error (Rel. Error).**

	R2	RMSE	STD	Rel. Error
Self-care services	0.99	0.021	0.023	2.1%
Restaurants	0.95	0.043	0.047	4.4%
Stores and dealers	0.95	0.040	0.044	4.3%
Recreation and gym centres	0.94	0.051	0.057	5.4%
Entertainment	0.98	0.037	0.041	3.9%
Education	0.98	0.049	0.055	5.3%



**Figure 10: (a)-(f) The SDOF model is fitted to the corresponding performance over time, showing the bounds (area) of the deviation  $\sigma$  between the model (dashed line) and the data (solid line). (g) The parameters of the corresponding model fit (solid line; area: parameter uncertainties) in (a)-(f) are expressed in terms of the basic units  $t_0 = 1$  day,  $\varphi_0 = 1$ , and  $I_0$ , referring to the inertia of POI visits to self-care services.**

In summary, the robustness of POI visits is reflected in the magnitude of the parameters  $I$  and  $D$ , while the recovery properties are reflected by the parameters  $C_R$ ,  $\varphi_R$ , and  $\varphi_{RE}$ . The parameters of the SDOF model were obtained through least-squares fitting to the performance over time curve, observed through the performance changes.

## CONCLUSION

The SDOF model introduced by (Stolz et al. 2024) has been applied to POI data generated during hurricane Harvey (Podesta et al. 2021). The model adequately captures the performance-over-time data in all four considered sectors, *emergency preparedness*, *emergency response*, *recovery activity*, and *lifestyle and well-being*. The parameters obtained from the corresponding fits serve to quantify the resilience of the community in these sectors. Furthermore, the values of the fit parameters offer useful insights for emergency responders available at a glance, e.g., regarding the duration of the crisis in the different sectors. This might provide guidelines regarding the appropriate allocation of resources in view of disaster management strategies. At the same time, the fit parameters serve as a basis for further investigations: the goal is to uncover correlations between the obtained values and real-world data, such as quantities that represent the size of the respective sectors, which can be contained, e.g., in openly accessible census data (United States Census Bureau). In view of our analysis of the airports in connection with Figure 4, one example of possible correlations could be how the inertia of the sectors displayed in Figure 7 to Figure 10 is related to the size of the respective sector which can be inferred from the aforementioned census data. Unveiling such correlations has a large potential to identify important factors that can guide disaster management decisions. Useful insights are, e.g., expected in terms of which communal characteristics are significant in terms of the duration and magnitude of the crisis and in terms of measures that can shorten or mitigate adverse consequences of disasters. The goal of this Work in Progress is to uncover such correlations to the extent that the model allows predictions for the performance over time for sectors for which POI data is currently unavailable.

## ACKNOWLEDGMENTS

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