Stress testing the transportation system subject to climate-induced hazards: A simulation approach

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ABSTRACT: This paper proposes a simulation-based approach to conduct stress tests on transportation systems subject to extreme scenarios of rainfall leading to flooding. Stress tests represent situations where at least one part of the system, e.g., hazard intensity, performance of assets, is significantly worse than expected. To conduct them, the proposed approach features a set of interacting models that capture the behavior of the system under the effect of the conditions imposed by the stress tests. These include models that capture the occurrence of hazard events, performance of infrastructure assets and network, and the societal impacts. The proposed approach was used to conduct stress tests on a road network in Switzerland and three types of stress tests were conducted, labeled climate change, which investigates performance with increases in rainfall intensity in the future; travel demand, which investigates increases in demand for travel due to societal developments; and restoration capacity, which investigates decreases in post-hazard restoration capacity. The results provide significant insight into the vulnerabilities of the system under the considered stress tests. This information can be used to better plan measures to improve the resilience of the system.

1. INTRODUCTION

The wellbeing of a society and the prosperity of its economy heavily depend on the functionality of transportation systems. However, they are subject to natural hazards, particularly climate-related hazards in some areas, which negatively impact their functionality. This, in turn, leads to direct and indirect consequences for their stakeholders, as well as the public. One of the main roles of transport infrastructure managers is to assess the resilience of their systems and ensure that they perform adequately against potentially disruptive events, i.e., the ensued consequences are within acceptable ranges and preferably minimal. Accordingly, and if needed, infrastructure managers will develop and plan measures for mitigating or adapting to those hazards.

The common state of practice to assess the resilience of transport systems is using qualitative methods, mainly exploiting experts' opinion (Kelly et al. 2015; Martani et al. 2021; Martins et al. 2019). In case of need for more detailed analysis, infrastructure managers can then employ quantitative methods (European Committee for Standardization 2021).

Quantitative methods are mainly composed of models that capture the behavior of individual parts of the system, e.g., the occurrence of a flood event or the incurred damages to a bridge due to scouring, and a higher-level approach that establishes relationships between those individual models in order to capture the behavior of the entire system, which is then used to assess its resilience (Lam et al. 2018). Simulation-based approaches have shown promise as an effective tool to model the behavior and assess the resilience of complex systems (Hackl et al. 2018; Heitzler et al. 2017; Nasrazadani and Mahsuli 2020).

The state-of-the-art in the use of simulation-based approaches for assessing the resilience of infrastructure systems is based on probabilistic risk assessment (PRA) methodologies (Linkov et al. 2022). That is, resilience is assessed through generating a host of stochastic scenarios, each representing a random realization of the system, estimating the risks, i.e., the incurred consequences, and lastly, evaluating the risks to check if acceptable, thus suggesting a resilient system (Hackl et al. 2018). Evaluation of risks involves three main tasks (Adey et al. 2021): 1) determining the measure of service and intervention costs to be estimated, e.g., costs of restoration interventions or reduction in ability to travel, 2) setting limits on the tolerable reductions in service and intervention costs, e.g., as a fraction of the gross domestic product of the region for costs of restoration and a percentage of normal service level for reduction in service, and 3) setting non-exceedance probability thresholds, e.g., 95% for restoration costs and 90% for service disruption. If the probability of the consequences not exceeding the defined limits is better than the acceptable threshold, the system is deemed resilient.

In this probabilistic simulation-based approach, uncertainties are modelled using probabilistic distributions to represent the values of key variables. Scenarios are then generated without imposing conditions on the values selected from the distributions. Resilience is, therefore, assessed considering all potential realizations of the modelled uncertainties, e.g., all potentially occurring disruptive events and all ranges of possible behavior of the infrastructure assets and networks. This probabilistic approach facilitates performing global sensitivity analyses as to find which parameters have, on average, a higher impact on the incurred risks. This approach, however, does not directly assess the resilience of the system under situations which are significantly worse than mean or median, e.g., occurrence of only low-probability high-intensity hazard events, or a situation where assets incur higher extent of damage when exposed to flooding.

A stress test is a simulation of the system where at least one variable in the model is considered to have a value considerably worse than its median or mean (Lam et al. 2018). Linkov et al. (2022) suggests that PRA approaches are not sufficient to fully capture the behavior of the system, including the cascading relationships between parts of the system, in order to assess its resilience. Additionally, one needs to define and conduct stress tests in order to ensure whether infrastructure systems would adequately perform when impacted by hazard events, and thus can be considered resilient (Adey et al. 2016; Linkov et al. 2022). Despite this importance, there are very few studies that focused on stress testing of infrastructure systems, particularly transportation systems subject climatic hazards.

Adey et al. (2016) proposed a conceptual framework for conducting stress tests to ensure acceptable performance of infrastructure systems. Lam et al. (2018) presented a simulation-based approach to conduct a specific type of stress test on road networks subject to extreme scenarios of rainfall leading to flooding. Their proposed stress tests represent a situation where roads and bridges have considerably worse performance when subjected to flooding, compared to their average [expected] performance. This was done by using 95th-percentile fragility functions and 95th-percentile functional capacity loss functions, leading to higher extents of damage under similar intensities of flooding than would normally be expected to occur. Aydin et al. (2018) proposed a graph theory-based approach to conduct a particular type of stress test on road networks under seismic hazard. Their stress tests are based on removing nodes from the network and evaluating the resulting performance of the network. Past studies mainly focused on asset-level stress tests, while other parts of the system, e.g., hazard occurrence, behavior of people after the hazard event, and management of restoration interventions, should also be stress tested to assess its resilience. In other words, comprehensive stress testing is very beneficial to have a good understanding of the system behavior when subjected to potentially disruptive events.

This paper presents a comprehensive simulation-based approach to conduct various types of stress tests on road networks subject to hydrometeorological hazards. The proposed approach is demonstrated by using it to conduct stress tests on road network in the eastern part of Switzerland subject to extreme scenarios of rainfall leading to flooding and landslide. Three types of stress tests were conducted.

2. APPROACH

The simulation-based stress testing approach is composed of a PRA part and a stress test development part, where the stress tests are done through model conditioning, as outlined in Adey et al. (2016) and Lam et al. (2018). The proposed approach implements the similar PRA methodology as adopted by Hackl et al. (2018) and Nasrazadani et al. (2023), and advances its use to conduct various types of stress tests.

The PRA part captures the spatial and temporal behavior of the system under scenarios of interest, based on which the risks are estimated. This is achieved by employing a set of interacting models each representing part of the system. These models are grouped into five types of events, namely, source, hazard, object, network, and societal. The models include those that capture the occurrence of extreme rainfall events (source events), the evolution of consequent flooding and landslide (hazard events), the physical damage and functionality of assets (object events), the performance of the network (network events), and lastly the impacts on the society in terms of costs of restoration interventions and losses to due to service disruption (societal events). Risk, in this approach, is estimated as a function of societal impacts, and then evaluated with respect to pre-defined thresholds set by stakeholders.

Figure 1 shows a schematic overview of the proposed approach, including the five sets of events (circles) and their corresponding models (rectangles). Hexagons represent stressors, which will be explained subsequently. The PRA part starts from the rainfall model, which generates a time-series of precipitation fields over the area of interest, followed by the runoff model, which generates hydrographs at various locations along the river. The flood model receives the predicted hydrographs and predicts the time-series of inundation maps. The mudflow model predicts the spatial distribution of mudflow induced by triggered landslides due to excessive rainfall. The object models predict the extent of physical damage to roads and bridges using fragility functions, and accordingly, predict the functionality of roads and bridges in terms of their speed limit and capacity. Additionally, object models predict the restoration needs, i.e., time and costs, based on their damage. The network model predicts the collective performance of individual roads and bridges as the transportation network in terms of functional routes that can hold traffic. The societal models predict the restoration of damaged components over time, and as well, the flow of the traffic within the network over time. These model interactions facilitate capturing the cascading effects between parts of the system, when estimating resilience and conducting stress tests. Please refer to Hackl et al. (2016) for a more detailed description of the models.

The PRA part ends with estimation of risks in terms of direct and indirect costs (cylinders in Figure 1). Direct costs include costs of restoration activities, e.g., repair of damaged assets and removal of mudflow from roads. Indirect costs include costs due increased travel time and missed trips due to connectivity loss, both during the hazard event and throughout the recovery period. These values are then compared to a predefined threshold by the stakeholders.

Following the PRA part, the stress tests are conducted. Each stress test is composed of one or multiple stressors, each imposing a condition on a model in the underlying PRA part. This model

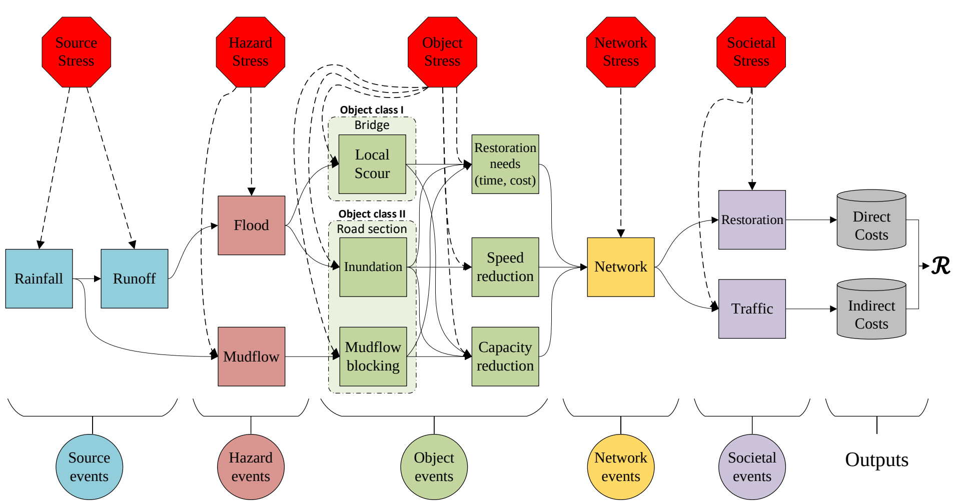

Figure 1. Schematic overview of the proposed simulation-based stress testing approach

conditioning is done such that at least one parameter in the model is represented with values considerably worse than its mean or median (Lam et al. 2018). Conducting a stress test starts with conditioning the appropriate models as defined per its stressors, e.g., hazard model is conditioned to only produce low-probability higher-intensity events. Therefore, in accordance with the PRA part, and as shown in Figure 1, there are five types of stressors, i.e., five types of models can be modified in stress tests, including source models where in e, e.g., occurrence of high-intensity low-probability rainfall events; hazard models, e.g., having significantly higher water levels due to flooding; object stress tests, e.g., bridges incurring higher extent of damage; network models, e.g., part of the network not being operational; and lastly, societal models, e.g., restoration interventions taking much longer than expected or significant increase in travel demand.

To conduct the stress test using simulation, the same stochastic scenario generation scheme is followed, with the modified models. A set of random scenarios are generated, and the probability distribution of the consequences are generated. For each stress test, a consequence limit and a non-exceedance probability are then decided, which determines the failure or pass of a stress test. Due to the conditions imposed on the system, the consequence limit might vary among stress tests (Lam et al. 2018).

There is a myriad of options to define stress tests. It is within the discretion of decision makers to decide which stress tests are more important and yield more insights about the behavior of the system and hence its resilience. Additionally, the ability to conduct each stress test depends on the level of detail of the corresponding model in the underlying PRA. For example, if the rainfall model does not capture the occurrence rate of the generated rainfall patterns, it is not possible to conduct stress tests that concern occurrence of low-probability high-intensity events. The overall goal, depending on the resources available, is to conduct as many stress tests as required to assess the resilience of the system in a reasonable amount of time. In the next section, the proposed approach is demonstrated.

3. EXAMPLE

The proposed approach was used to stress test the resilience of a road network in the region of Chur in south-eastern part of Switzerland. The area has a history of extreme events of rainfall causing flooding and landslides. The road network consists of 605 km of roadways and 121 bridges, 18 of which are located on the Rhine River. Two streams of the Rhine River, known as Anterior Rhine and Posterior Rhine, flow into the region from southwest, meeting at Reichenau to form the Rhine River, which then outflows the region in the northeast (Nasrazadani et al. 2022b). The precipitation measurement stations, as well as discharge gauging stations, whose historic data were used to calibrate the models can also be seen in Figure 2. For a more detailed description of the region, and the parameters and models used in the PRA, please refer to Hackl et al. (2016).

Three stress tests were conducted. In the first one, the amount of rainfall was increased due to climate change (source stressor). In the second, the travel demand was increased (societal stressor). In the third, the restoration capacity (societal stressor) was decreased. For each stress test, as well as the baseline situation, 700 random scenarios were simulated. These scenarios were distinguished by the return period of the generated flood event as 2, 10, 50, 100, 250, 500, 1000 years, i.e., 100 scenarios per return period. The description of each stress test is provided in the next subsections.

Figure 2. The studied road network in Chur, Switzerland (Hackl et al. 2018)

The resilience of the system was measured using the annual expected direct and indirect costs considering all potentially occurring events, i.e., with any return period, as follows:

$$\mathcal{R} = \sum_i \frac{1}{T_i} \cdot \left(\bar{\psi}_i - \bar{\psi}_{i-1} \right) \tag{1}$$

Where $\mathcal{R}$ = consequence, $\overline{\psi}$ = mean values of total costs (direct and indirect), T= return period, and i∈I= {simulated return periods in ascending order}. This equation, in essence, calculates the area under the risk curve, which shows the occurrence probabilities of events, i.e., $1/T$ assuming a Poisson process, vs. their induced (direct or indirect) costs. The equation uses a linear approximation approach to interpolate between the results of each pair of consecutive simulated return period to estimate the costs of all potentially occurring events (Deckers et al. 2010).

It should be remembered that the choice of consequence limit and non-exceedance probability is at the discretion of the decision makers and is influenced by multiple factors such as their risk attitude, their economic capacity to cope with the post-hazard consequences, the acceptable level of service provided to the public, among many others. The goal of this paper, however, is not to determine those quantities for the conducted stress tests, nor to provide guidelines on how they need to be determined. Instead, this study concerns how to conduct stress tests using simulation and discussing the results of the considered stress tests, without explicitly stating whether they pass or fail.

3.1. Climate change stress test

The intensity and frequency of extreme precipitation events are expected to significantly increase in many areas due to climate change. This, in turn, results in more extreme flood events and more disruptions in the transportation system. The Swiss National Centre for Climate Services (2018) provides projections for increases in the intensity of extreme rainfall scenarios under commonly accepted RCP scenarios, i.e., RCP2.6, RCP4.5, and RCP8.5. The corresponding projection data for Chur were adopted to define stressors, as introduced in Table 1. According to that, the rainfall intensity is projected to increase, on average, 6%, 14%, and 18% till 2060 under RCP2.6, RCP4.5, and RCP8.5, respectively. To model the stressors in this stress test, the rainfall intensity in the rainfall model per Figure 1 is adjusted accordingly.

Table 1: Climate change stress tests stressors

Parameter	*Rainfall intensity*
Scenarios	*RCP 2.6: +6%*
	RCP 4.6: +14%
	RCP 8.5: +18%

3.2. Travel demand stress test

The Federal Office for Spatial Development in Switzerland, considering the technological, societal and political trends, has devised scenarios for the development of traffic in Switzerland until year 2050 (Bundesamt für Raumentwicklung ARE 2022). The risk associated to these scenarios on the transport system can be quantified through conducting stress tests. The suggested stressors depict different directions of societal development. Table 2 introduces the three scenarios of stressors considered in this study. The EXP scenario describes the case where the federal strategies and policies regarding space and mobility will be implemented consistently, and thus an increase of 4.6% in the travel demand is expected. The WWB scenario represents the case where developments take place within the current regulative framework, also referred to as business as usual. This implies an 18.4% percent increase in the travel demand. The ITG assumes that transport is strongly impacted by technical innovations, such as automation of passenger vehicles, and thus a 22.7% increase in the travel demand is expected. To model this type of stress test, the input travel demand parameter in the traffic model per Figure 1, captured through the origin-destination (OD) matrix, needs to be modified in accordance with each scenario. It is also assumed that the increase in the travel demand is spatially uniform and thus, the entire OD matrix is modified uniformly.

Table 2: Travel demand stress test stressors

Parameter	*Travel demand (traffic model)*
Scenarios	*EXP: +4.6% (expected development)*
	WWB: +18.4% (business as usual)
	ITG: + 22.7 % (individualized society)

3.3. Restoration capacity stress test

A key contributing factor to the resilience of a system is how fast and efficient the system can be restored following a disruptive event. An influential factor to ensure efficient recovery is the available resources for restoration of damaged assets, e.g., repair crews, material and machinery. To facilitate an efficient recovery, infrastructure mangers plan to have enough resources after a hazard event to allocate to restoration interventions. However, due to several reasons, e.g., damage to the material or lack of available repair crew after the hazard event, the amount of available resources might be lower than what was expected or planned for. If this is the case, stress tests can be conducted to evaluate whether the system would still be able to limit the risks to an acceptable threshold even if the available recovery resources were significantly lower than expected. Lower available resources directly lead to lengthier recovery time and hence, more indirect costs due to service disruption after a hazard event. Two stress tests representing 20% (ARS_{20}) and 40% (ARS_{40}) lower available restoration resources were considered in this study, as introduced in Table 3. To model this stress test, the restoration capacity parameter in the restoration model per Figure 1 needs to be modified according to the defined stress tests.

Table 3: Restoration capacity stress test stressors

Parameter	Number of available restoration resources
Scenarios	ARS_{20}: -20% ARS_{40}: -40%

3.4. Results and Insights

Table 4 summarizes the results of the simulations for the eight conducted stress tests, as well as the baseline situation, i.e., total of 6300 simulations. Each cell represents the mean values of the 100 random scenarios in each stress test. The considered consequences ($\mathcal{R}$), i.e., the annual expected costs, is also provided for each stress test. Expectedly, an increasing trend in costs across higher-intensity events and stress tests are observed.

Table 4. Overview of simulation results

Stress test	ID	Mean total costs per return period*							$\mathcal{R}$
		2	**10**	**50**	**100**	**250**	**500**	**1000**	
baseline	**BASE**	34	57	81	90	102	115	129	22.5
Climate change	RCP2.6	38	64	87	95	107	118	131	24.9
	RCP4.5	44	71	93	99	116	125	137	28.2
	RCP8.5	47	75	96	102	115	127	141	29.7
Travel demand	EXP	36	60	86	95	107	121	136	23.8
	WWB	43	71	100	110	124	139	157	28.1
	ITG	45	75	105	115	130	145	164	29.5
Restor. capacity	ARS_{20}	36	61	87	96	110	124	141	24
	ARS_{40}	39	67	97	108	124	142	162	26.4

*values are in million Swiss Francs (CHF) adjusted for 2016

Figure 3 shows the relative increase in $\mathcal{R}$ vs. relative increase in rainfall intensity (black line) and their ratio (red line) across the three conducted climate change stress tests per Table 1. The dashed line is the 45° line, which represents equal increase in $\mathcal{R}$ vs. increase in rainfall intensity. An interesting observation here is that the increase in $\mathcal{R}$, i.e., consequences, is significantly higher with respect to the increase in rainfall intensity, around 1.81 times higher. This emphasizes the importance of climate change stress tests since the induced consequences could significantly increase by the imposed stressor. To improve the performance of the system against this stress test, climate adaptation measures such as flood protection walls, stormwater retention basins, and elevating road assets could be implemented (Nasrazadani et al. 2022a; b).

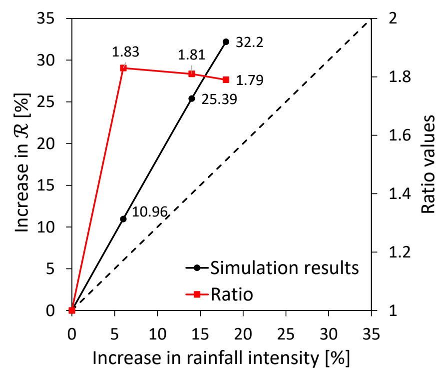

Figure 3. Relative increase in $\mathcal{R}$ under climate change stress tests

Figure 4 shows the relative increase in $\mathcal{R}$ vs. relative increase in travel demand (black line) and their ratio (red line) across the three conducted stress tests per Table 1. Even though this stress test only affects the tail of the chain of models per Figure 1, particularly having no impact on direct costs, still the increase in costs is relatively high, i.e., between 1.3 to 1.37 times. This underlines the importance of this stress test as the system seems to be sensitive to the imposed stressors. This information can help guide decision makers as to where action can be taken to improve resilience. For example, expansion interventions, e.g., building a new river-crossing bridge or a new road, can add redundancy to the network and hence improve its resilience against increase in demand for service.

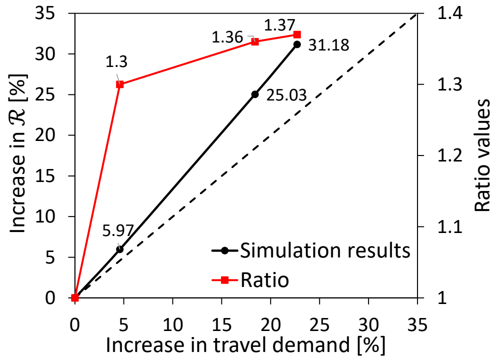

Figure 4. Relative increase in $\mathcal{R}$ under travel demand increase stress tests

Figure 5 displays the relative increase in $\mathcal{R}$ vs. relative decrease in restoration capacity (black line) and their ratio (red line) across the two conducted stress tests per Table 1. This stress test is also focused on the tail of the chain of models and only affects the indirect consequences due to inadequate service during an elongated recovery period. It has a significant impact on increasing the costs, i.e., 6.86% and 17.51% when ARS_{20} and ARS_{40} stress tests are conducted, respectively. To improve the resilience of the system in this situation, the reliability of access to and mobilizing restoration resources after the hazard events need to be enhanced, for example by planning additional contingency resources or making mutual aid agreements with neighbouring communities.

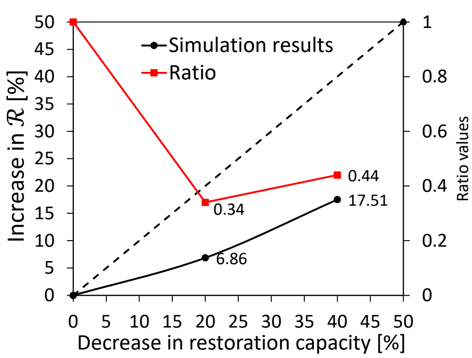

Figure 5. Relative increase in $\mathcal{R}$ under restoration capacity stress tests

4. CONCLUSION

A simulation-based approach to conduct stress tests on transportation systems subject to hydrometeorological hazards is proposed. Stress tests, in essence, are model conditioning approaches which realize a situation where at least one variable in the system is set at significantly worse values than its expected value, e.g., mean or median. Stress tests are then conducted by modifying the specific models and running simulations as to how the system will perform. Stress tests provide insights into the resilience of the system, e.g., local sensitivity analysis of influential parameters, beyond those that can be obtained using traditional probabilistic approaches, e.g., global sensitivity analysis using the entire range of possibilities for uncertainties.

The proposed approach was used to conduct eight stress tests of three types on a road network. The types of conducted stress tests are named as climate change, focused on increased rainfall intensity in the future; travel demand, focused on increased demand for travel due to societal developments; and restoration capacity, focused on decreases in post-hazard restoration capacity. The results showed significant increase in direct and indirect consequences due to the imposed conditions by stress tests and a deeper understanding of how the system may function in extenuating circumstances. Following the conduct of stress tests, decision makers need to evaluate whether or not the stress tests have been passed or failed, and if needed, plan for interventions to enhance the resilience of the system.

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