ICONHIC2022
3rd International Conference on Natural Hazards & Infrastructure
5-7 July 2022, Athens, Greece

The HAPI sensor-aware framework for infrastructure risk and resilience assessment

Dimitrios Vamvatsikos, Akrivi Chatzidaki
National Technical University of Athens, Athens 15780, Greece

ABSTRACT

The (new) 20's have allowed us to dream big on protecting our infrastructure from natural hazards. Powerful computers, machine learning, terrestrial and airborne sensors are at our disposal to help us quantify the consequences of potential hazardous events that may come in the future, are already unfolding, or have already happened. Owing to its origins in four European projects, namely HYPERION, ARCHYTAS, PANOPTIS and INFRASTRESS, the HAPI framework has been formulated to perform pre/trans/post-event risk and resilience assessment of diverse infrastructure, comprising different layers of networked, loosely-connected or autonomous assets within a city, region or country. Building upon the well-worn basis of hazard-exposure-vulnerability that underpins practically all insurance risk estimates, HAPI enables assessment of cascading (e.g., mudflow/landslide after earthquake) and cotemporaneous (e.g., extreme precipitation, temperature, ice and wind scenario) hazards, while it offers sensor integration with near-real-time updating of predictions based on hazard/asset/consequence information input. Both "static" memoryless hazards (e.g., earthquake), as well as "dynamic" time-dependent hazards (e.g., climate projections) are incorporated in tandem with static/dynamic vulnerabilities, allowing the tracking of complex phenomena, such as climate change, and their effect on the aging/corrosion/fatigue of a diverse set of assets, including buildings, bridges, piping, powerlines, highways and cultural heritage monuments. At the very basis lies a vast database of hazard and asset realization scenarios, employing Total Probability Discrete Event Simulation to explicitly track network interdependencies and propagate uncertainty from our source information to the projected integrated-system functionality and eventual recovery.

Keywords: multi-hazard assessment, risk, climate, earthquake, nowcasting, forecasting

INTRODUCTION

Risk and resilience assessment under natural hazards has advanced in leaps and bounds over the past decade, moving from single assets (e.g. FEMA 2000) and groups of assets (Silva et al 2020) to lifelines and systems. These encompass transportation networks (Costa et al 2018; Kilanitis & Sextos 2019), gas distribution networks (Esposito et al 2015), and water supply networks (Romero et al 2010), as well as interdependent networks with cascading failures (Poljanšek et al 2012; Pitilakis et al 2014; Dueñas-Osorio et al 2007a,b; Dueñas-Osorio and Vemuru 2009). Furthermore, rather than capturing just one peril (or source of hazard), nowadays different perils are captured and multi-hazard assessment is slowly becoming the new standard (Argyroudis et al 2020).

Generally, the focus is on long-term pre-event assessment, targeting annualized long-term statistics of damage, loss and time-to-recover. Still, the advent of low-cost sensors has enabled a new era of multiple information sources that can be reliably used to update long-term statistics to develop short-term, trans/post-event estimates. Working in this direction, we offer a general framework that works through the well-known concepts of stochastic event sets, intensity measure fields and and asset realizations to help us provide near-real-time estimates of impact and recovery as an event unfolds or right after it has hit.

METHODOLOGY

The basic ingredients of the so-called HAPI framework are fundamentally the same employed in any practical risk assessment. As outlined in Figures 1 and 2, these include (i) the stochastic event set of potential event realizations together with (ii) the associated intensity measure (IM) fields that describe the correlated intensities of each event at each geographical location of interest. Next (iii) comes the exposure model of assets at risk, as well as their respective vulnerability functions that relate the metrics of interest given the intensity experienced by an asset. By employing a large-scale Monte Carlo analysis, at a minimum we expect to derive loss curves and loss maps, giving us overall statistics and detailed realizations of damage and loss (or any other metric of choice) for each asset and location of interest. Let us now take advantage of these well-known fundamental quantities and try to place them within a proper mathematical framework that will allow us to conduct both long-term and short-term assessments with ready fusion of sensor input.

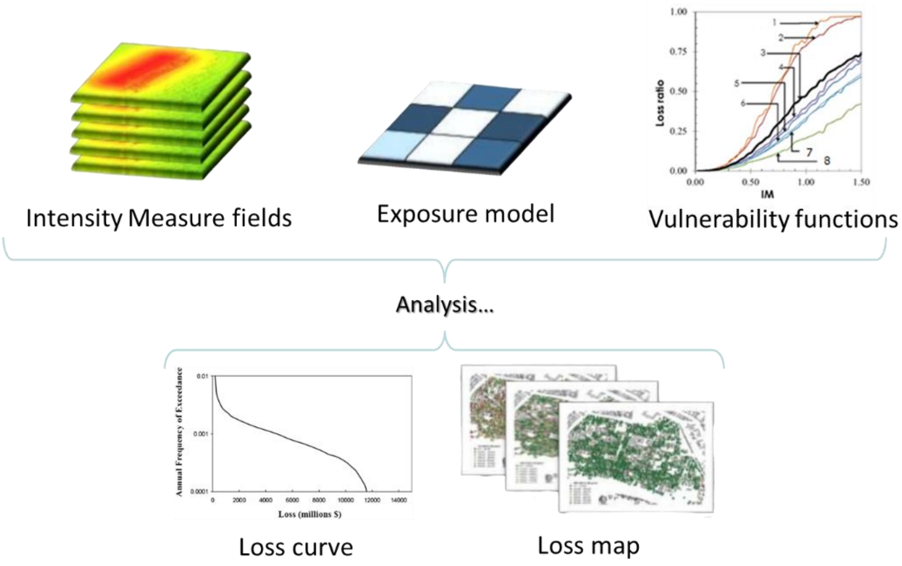

Figure 1. *The typical breakdown of risk into hazard, exposure, and vulnerability, forming the basis of the HAPI framework.*

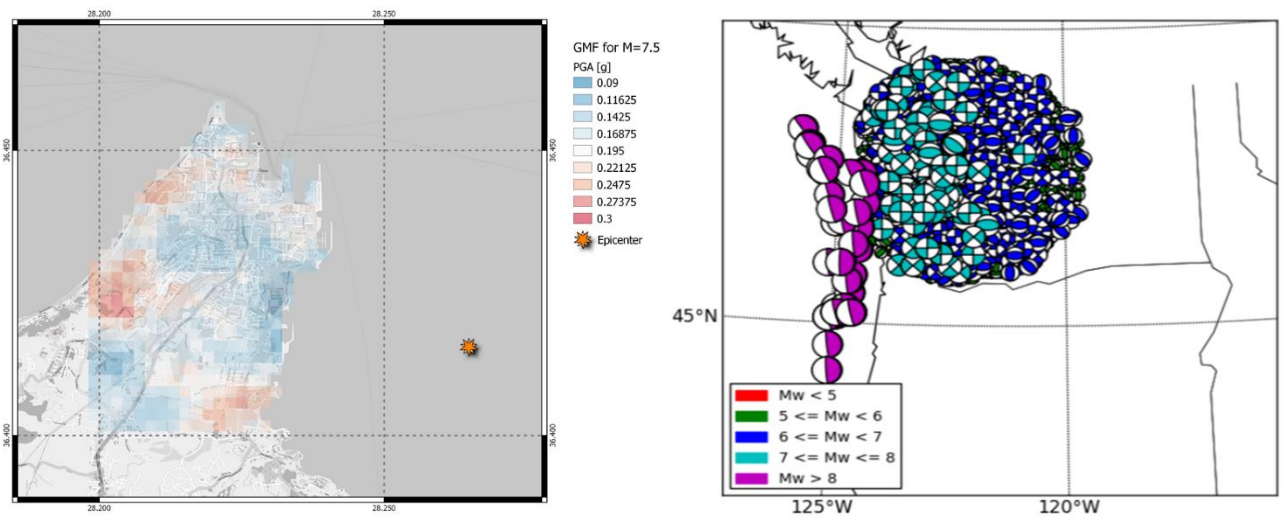

Figure 2. *An example of an IM field for seismic hazard (left), and a Stochastic Event Set of fault ruptures (right).*

Long-term pre-event assessment

Our long-term pre-event approach is largely based on the Cornell-Krawinkler framework (Cornell & Krawinkler 2000) originally adopted by the Pacific Earthquake Engineering Research Center for seismic risk assessment of single assets. Herein, a fairly straightforward extension to multiple assets and multiple hazards is undertaken. Whereas the original framework was written in terms of continuous variables and integrals, the HAPI extension acknowledges the practicality of the discrete formulation in a so-called Total Probability Discrete Event Simulation (TPDES), which is after all the standard for most (if not all) applications in practice:

$$\Delta\lambda(\mathbf{DV}) = \sum_{\mathbf{DS}}\sum_{\mathbf{EDP}}\sum_{\mathbf{IM}} \mathrm{p}(\mathbf{DV}\,|\,\mathbf{DS})\,\mathrm{p}(\mathbf{DS}\,|\,\mathbf{EDP})\,\mathrm{p}(\mathbf{EDP}\,|\,\mathbf{IM})\Delta\lambda(\mathbf{IM}) \tag{1}$$

where

$\lambda(\cdot)$ is the mean annual rate function of its argument

$\mathrm{p}(\cdot)$ is the probability mass function, or probability of occurrence of its argument

IM = ($IM_{i,j}$, $i = 1\ldots N_{\mathrm{peril}}$, $j = 1\ldots N_{\mathrm{site}}$) is the vector of intensity measures (IMs), which incorporates all intensity types employed to describe the N_{peril} perils of interest (e.g., wind, earthquake, flood, etc.), at all N_{site} sites where assets are located. Each realization of the vector represents a field of spatially and temporally correlated intensities that are consistent with a scenario event.

EDP = ($EDP_{i,j}$, $i = 1\ldots N_{\mathrm{asset}}$, $j = 1\ldots M_i$) is the vector of engineering demand parameters (EDPs), comprising the M_i structural response variables recorded from the N_{asset} assets. Obviously, different numbers and types of EDPs may be recorded for different assets depending on their characteristics and level of modelling detail employed. For example, a 5-story structure may be represented only by its roof drift for a 1D representation, 5 peak story drifts and 6 peak floor accelerations for 2D, or twice this number in a 3D model. Each realization of the **IM** vector typically corresponds to multiple **EDP** realizations, due to the inherent uncertainty in structural response given the hazard intensity for any single asset.

DS = ($DS_{i,j}$, $i = 1\ldots N_{\mathrm{asset}}$, $j = 1\ldots K_i$) is the vector of damage states (DSs), containing the K_i component damage states associated with each of N_{asset} assets. In general, one may choose to assign a single global damage state to a given asset (e.g. $DS_{i,1} = 0$ for no damage, 1 for light damage, etc.), or instead follow a component-by-component breakdown, assigning different damage states to different parts of the structure (Porter et al 2012; D'Ayala et al 2015). For example, in the latter case one may consider separately different stories of a multi-story building, or split a bridge to its abutments, piers, deck, and bearings. Note that originally the Cornell-Krawinkler framework (Cornell & Krawinkler 2000) specified a continuous Damage Measure rather than discrete DSs. Still, the latter is by far the norm in practice and naturally better fits our already discretized approach. In general, when considering unconnected assets, such as separate buildings that do not interact in any way which each other, one may reasonably assume that the EDPs corresponding to each asset will fully determine the corresponding DS distributions. For interconnected assets (e.g., transportation, power transmission or water supply networks) the state of an asset may be compromised by other adjacent ones. For example, an upstream pipe breakage will disrupt water supply for all downstream pipes, while failure of a power transmission tower will often overstress its adjacent ones, increasing their chance of collapse. In any case, each realization of **EDP** will invariably spawn a number of **DS** realizations, again due to the intrinsic uncertainty.

DV = (DS_i, $i = 1\ldots N_{\mathrm{DV}}$) is the vector of decision variables (DVs), incorporating both asset and system/ensemble-level quantities that can be used to assess the state of each individual asset and set/subset/system/subsystem of interest. Different metrics may be employed as DVs, ranging from the direct and indirect repair cost, time-to-repair, and casualties, for single assets per FEMA P-58 (FEMA 2012), or, at the system level, overall cost, time of recovery, traffic delays, number of customers without power, gas or water, etc. Similarly, each realization of **DS** can result to multiple **DV** values.

For simplicity, one may also write Equation 1 as follows:

$$\Delta\lambda(\mathbf{DV}) = \sum_{\mathbf{DS},\mathbf{EDP},\mathbf{IM}} \mathrm{p}(\mathbf{DV}\,|\,\mathbf{IM})\Delta\lambda(\mathbf{IM}) \tag{2}$$

where $\mathrm{p}(\mathbf{DV}\,|\,\mathbf{IM})$ can be broadly defined as the vulnerability function:

$$\mathrm{p}(\mathbf{DV}\,|\,\mathbf{IM})=\sum_{\mathbf{DS}}\sum_{\mathbf{EDP}}\mathrm{p}(\mathbf{DV}\,|\,\mathbf{DS})\,\mathrm{p}(\mathbf{DS}\,|\,\mathbf{EDP})\,\mathrm{p}(\mathbf{EDP}\,|\,\mathbf{IM}) \tag{3}$$

Conceptually, one may employ the concept of vulnerability functions to characterize each individual asset, similarly reducing the dimensionality of DV, DS, EDP and IM, to those elements that matter for the asset in question. In the case of unconnected assets, one may thus partition the cumbersome Equations 1 and 2 into the far more practical form of

$$\Delta\lambda(\mathbf{DV})=\sum_{i=1}^{N_{asset}}\sum_{\mathbf{DS}_i,\mathbf{EDP}_i,\mathbf{IM}_i}\mathrm{p}(\mathbf{DV}\,|\,\mathbf{IM}_i)\Delta\lambda(\mathbf{IM}_i) \tag{4}$$

where the subscript i is used to imply the parts of **DS**, **EDP** and **IM**, that pertain to the i^{th} asset. For interconnected assets, while one may still find good use for the single-asset vulnerability functions, their combination cannot be simplified to a simple sum per Equation 4, as network effects now come into play and the state of one asset can influence the others. The overall process is conceptually presented in Figure 3.

Short-term pre/trans-event risk

In the case of an event that has just occurred (e.g., an earthquake) or is presently unfolding (e.g., an on-going flood or storm), one can employ local sensor observations to improve her/his predictions. In order to achieve near-real-time assessment, the fastest approach is to take advantage of the vast scenario data pool that has already been generated for the long-term assessment. There are different types of sensors one may employ in this exercise:

− IM or Hazard sensors, such as seismographs, weather stations, or flood height meters can offer information on the actual values of the IM experienced at each site of interest
− EDP or (asset) Response sensors, such as accelerometers, strain gauges, etc. that offer information on the actual response of the asset.
− DS or Impact sensors, the simplest one of which is a camera, allowing us direct information on the damage state of an asset and/or its components.

Each of these sensors can reduce the uncertainty inherent in Equation 1, reducing the number of potential realizations that could match what has already occurred. Practically speaking, one may use said observations to screen the set of all available scenarios, essentially reducing it to (**DS**, **EDP**, **IM**) in C_{obs}, where C_{obs} is the subset of all DS, EDP, and IM scenarios that are compatible with the observations, as shown in Figure 4. Then the trans/post-event short-term risk is estimated as:

$$\mathrm{p}(\mathbf{DV}\,|\,\mathbf{obs})=\sum_{(\mathbf{DS},\mathbf{EDP},\mathbf{IM})\in C_{obs}}\mathrm{p}(\mathbf{DV}\,|\,\mathbf{DS},\mathbf{EDP},\mathbf{IM}) \tag{5}$$

where $\mathrm{p}(\mathbf{DV}\,|\,\mathbf{DS},\mathbf{EDP},\mathbf{IM})$ is the conditional probability mass function of achieving decision variable **DV** within C_{obs} scenarios, estimated by reweighting the original (long-term) probability of occurrence of the relevant scenario consistent with the values of **DV**, **DS**, **EDP** and **IM**, simply by dividing it by the sum of the probabilities of occurrence of all C_{obs} scenarios:

$$\mathrm{p}(\mathbf{DV}\,|\,\mathbf{DS},\mathbf{EDP},\mathbf{IM})=\frac{\mathrm{p}(\mathbf{DV}\cap\mathbf{DS},\mathbf{EDP},\mathbf{IM})}{\sum_{(\mathbf{DS},\mathbf{EDP},\mathbf{IM})\in C_{obs}}\mathrm{p}(\mathbf{DS},\mathbf{EDP},\mathbf{IM})} \tag{6}$$

There is no element of time in Equation 5, hence no mean annual rate to compute, as the event has or is occurring. Thus, no $\lambda(\cdot)$ term is needed. Compare also Equation 5 with Equation 2. Note how the consideration of “all” scenarios allowed us to simplify Equation 2, removing any conditioning on **DS** and **EDP**, and maintaining only **IM** as a summation variable. In the short-term assessment case this is no longer doable. The potential for having sensors of structural response, as well as damage state, do not allow us to perform a similar simplification on Equation 5. Now, we need to dig deep into all scenarios and keep only those that are compatible with the observations. Note also that, unless you believe in perfect models, unicorns and magic, there is a non-negligible chance that you may end up with observations that do not agree with any of your **IM** scenarios and **DS**, **EDP** realizations. In such cases, looking for the closest ones may be the best strategy. Otherwise, one can only calibrate, improve and recompute.

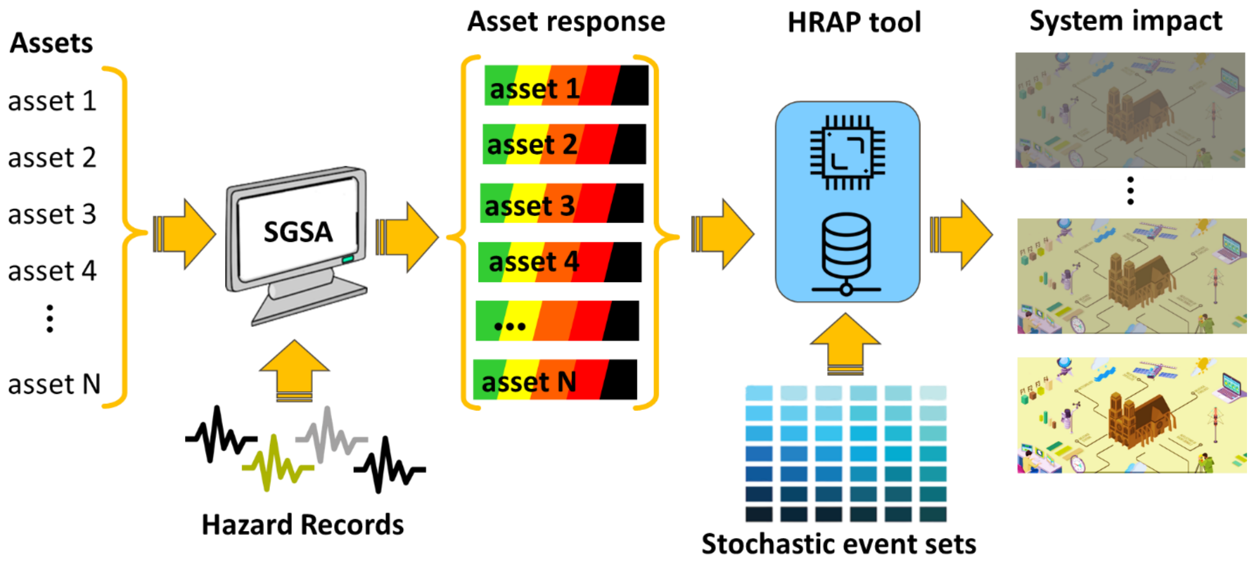

Figure 3. *Long-term pre-event risk assessment process.*

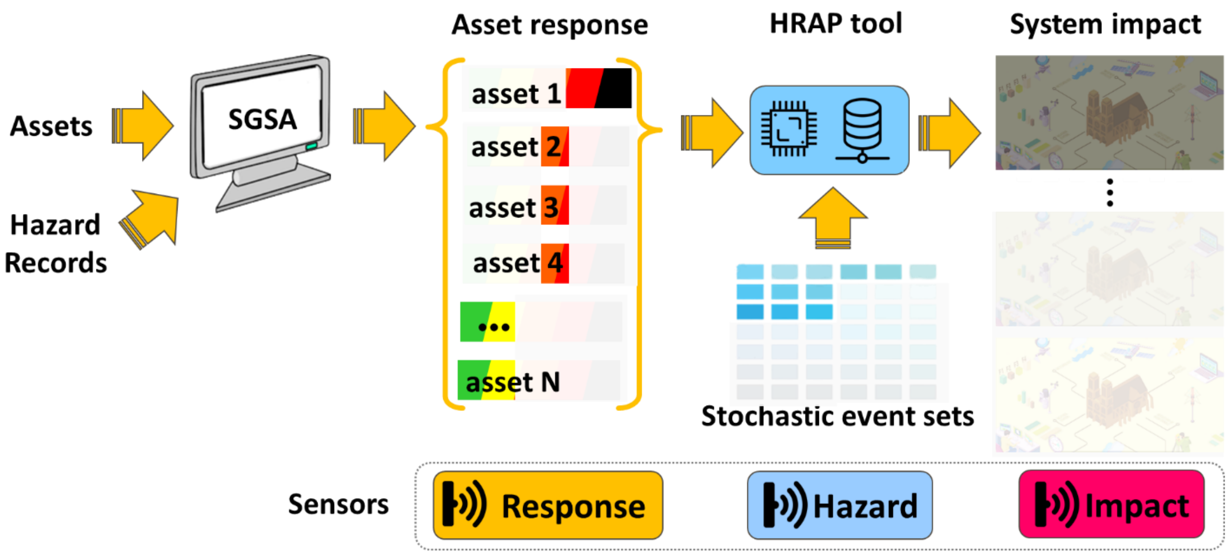

Figure 4. *Short-term trans/post-event scenario risk assessment process.*

EXAMPLES OF APPLICATION

The devil is in the details, and the mathematical simplicity of Equations 1 and 5 hides a lot of messy details underneath. Defining the elements needed to apply the HAPI framework to different case studies remains a difficult process that requires a lot of data and non-negligible analysis. The ARCHYTAS project (Archetypal telemetry and decision support system for the protection of monumental structures) explored application to an ensemble of cultural heritage monuments subject to seismic and flood hazards with no interdependence other than geographical proximity. They HYPERION project (Development of a decision support system for improved resilience & sustainable reconstruction of historic areas to cope with climate change & extreme events based on novel sensors and modelling tools) added a historical city core, utilities, socioeconomic aspects and aging hazards, as conceptualized in Figure 5. PANOPTIS (Development of a decision support system for increasing the resilience of transportation infrastructure based on combined use of terrestrial and airborne sensors and advanced modelling tools by means of an open testbed stress-testing system) explored application to highway networks under seismic and weather hazards, while INFRASTRESS (Improving resilience of sensitive industrial plants & infrastructures exposed to cyber-physical threats) addressed the risk of refineries in earthquake-prone locations (Figure 6). Each application carried its own challenges and allowed us to further refine the details. As each project nears its completion, further information and knowledge gained will be disseminated and the HAPI approach will be refined to ensure wide and general applicability.

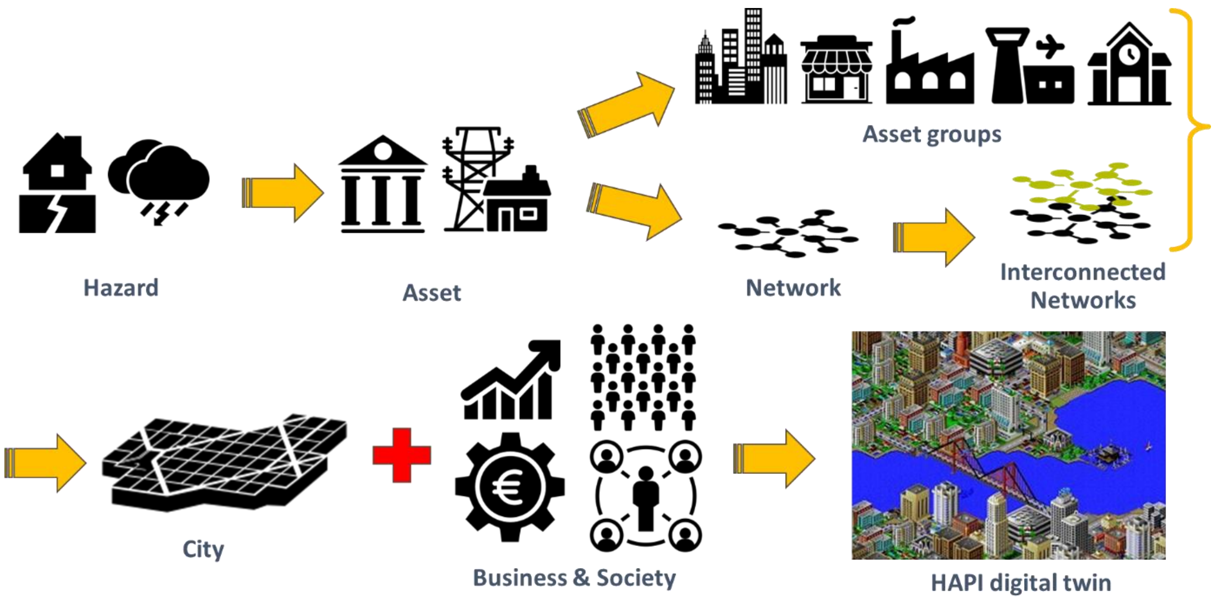

Figure 5. *Formulation of the HAPI digital twin for an urban area.*

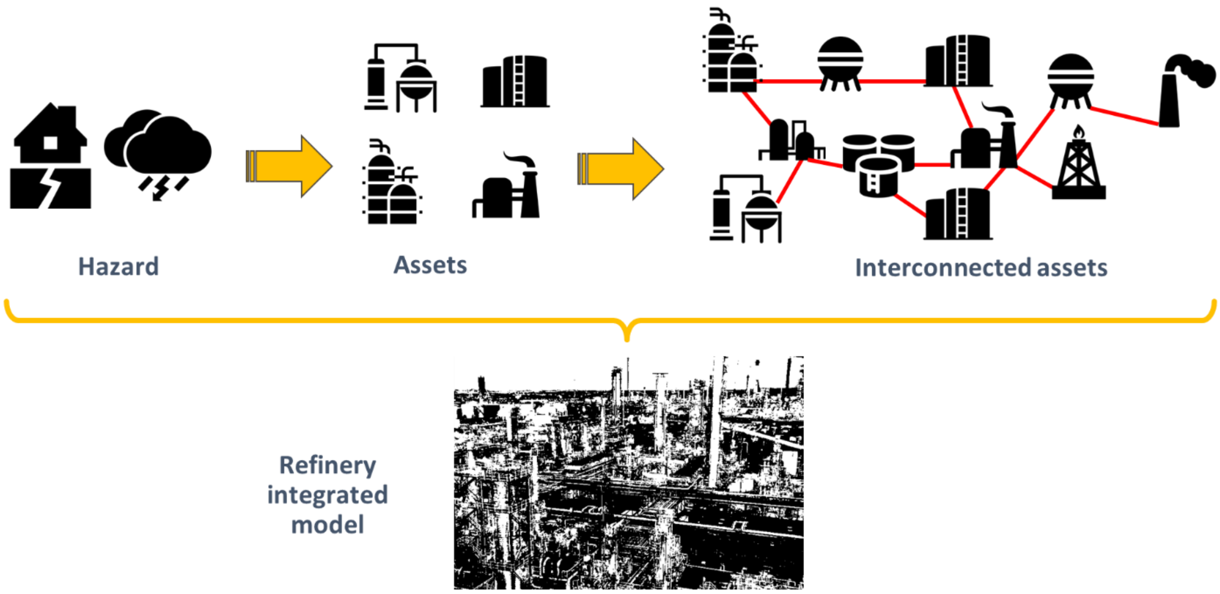

Figure 6. *Formulation of the HAPI integrated model for a refinery.*

CONCLUSIONS

The HAPI framework for risk and resilience assessment of assets and infrastructure networks has been presented. It carries a formalization of well-known concepts, further adding a general approach for sensor fusion to enable both long and short-term assessments. Efforts to enhance and formalize it are still on-going, and are targeting ever widening applications to different systems and hazards. Stay tuned for the forthcoming advances as our work moves forward!

ACKNOWLEDGEMENTS

Financial support has been provided by (i) the European Regional Development Fund of the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under the call RESEARCH – CREATE – INNOVATE (project code: T1EDK-00956), project: "ARCHYTAS: Archetypal telemetry and decision support system for the protection of monumental structures" and (ii) the European Commission via projects "PANOPTIS–Development of a decision support system for increasing the resilience of transportation infrastructure based on combined use of terrestrial and airborne sensors and advanced modelling tools by means of an open testbed stress-testing system" (Grant Agreement 769129), "HYPERION–Development of a decision support system for improved resilience & sustainable reconstruction of historic areas to cope with climate change & extreme events based on novel sensors and modelling tools" (Grant Agreement 821054), and "INFRASTRESS–Improving resilience of sensitive industrial plants & infrastructures exposed to cyber-physical threats" (Grant Agreement 833088).

REFERENCES

Argyroudis S.A., S.A. Mitoulis, L. Hofer, M.A. Zanini, E. Tubaldi, D.M. Frangopol. (2020). Resilience assessment framework for critical infrastructure in a multi-hazard environment: Case study on transport assets, Science of the Total Environment, 714, 136854.

Cornell C.A, H. Krawinkler (2000). Progress and challenges in seismic performance assessment. PEER Center News, 3, Pacific Earthquake Engineering Research Center, University of California, Berkeley, CA.

Costa C., V. Silva, P. Bazzurro. (2018). Assessing the impact of earthquake scenarios in transportation networks: the Portuguese mining factory case study, Bulletin of Earthquake Engineering, 16, pp. 1137-1163.

D'Ayala D., A. Meslem, D. Vamvatsikos, K. Porter, T. Rossetto. (2015). Guidelines for Analytical Vulnerability Assessment of Low/Mid-Rise Buildings. GEM Technical Report 2014-12. Global Earthquake Model Foundation, Pavia, Italy. DOI 10.13117/GEM.VULN-MOD.TR2014.12

Dueñas-Osorio L., J.I. Craig, B.J. Goodno. (2007a). Seismic response of critical interdependent networks. Earthquake engineering & structural dynamics, 36(2), pp.285-306.

Dueñas-Osorio L., J.I. Craig, B.J. Goodno, A. Bostrom. (2007b). Interdependent response of networked systems. Journal of Infrastructure Systems, 13(3), pp.185-194.

Dueñas-Osorio L., S.M. Vemuru. (2009). Cascading failures in complex infrastructure systems. Structural safety, 31(2), pp.157-167.

Esposito S., I. Iervolino, A. d'Onofrio, A. Santo, F. Cavalieri, P. Franchin. (2015). Simulation-based seismic risk assessment of gas distribution networks. Computer-Aided Civil and Infrastructure Engineering, 30(7), pp.508-523.

FEMA (2012). Seismic Performance Assessment of Buildings, Volume 1 – Methodology. Report FEMA P58-1, Federal Emergency Management Agency, Washington, DC.

Kilanitis I., A. Sextos (2019). Integrated seismic risk and resilience assessment of roadway networks in earthquake prone areas, Bulletin of Earthquake Engineering, 17(1), pp. 181-210.

Pitilakis K., P. Franchin, B. Khazai, H. Wenzel. (2014). SYNER-G: systemic seismic vulnerability and risk assessment of complex urban, utility, lifeline systems and critical facilities: methodology and applications (Vol. 31). ISBN 978-94-007-7872-6, Springer Science & Business Media, Dordrecht.

Poljanšek K., F. Bono, E. Gutiérrez. (2012). Seismic risk assessment of interdependent critical infrastructure systems: The case of European gas and electricity networks. Earthquake Engineering & Structural Dynamics, 41(1), pp.61-79.

Porter K., K. Farokhnia, D. Vamvatsikos, I.H. Cho. (2014). Guidelines for component-based analytical vulnerability assessment of buildings and nonstructural elements. GEM Technical Report 2014-13. Global Earthquake Model Foundation, Pavia, Italy. DOI: 10.13117/GEM.VULN-MOD.TR2014.13.

Romero N., T.D. O'Rourke, L.K. Nozick, C.A. Davis. (2010). Seismic hazards and water supply performance. Journal of Earthquake Engineering, 14(7), pp.1022-1043.

Silva V., D. Amo-Oduro, A. Calderon, C. Costa, J. Dabbeek, V. Despotaki, L. Martins, M. Pagani, A. Rao, M. Simionato, D. Viganò (2020). Development of a global seismic risk model. Earthquake Spectra, 36(1_suppl), pp.372-394.