Artificial Intelligence and STOchasTic Simulation for the rEsiLience of Critical InfrastructurES (ARISTOTELES)

ARtificial Intelligence and STOchasTic simulation for the rEsiLience of critical infrastructurES (ARISTOTELES)

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***Abstract*—In this paper, we present the ambitions of the research project ARtificial Intelligence and STOchasTic simulation for the rEsiLience of critical infrastructurES (ARISTOTELES), funded by the Italian Ministry for Scientific Research (MIUR) under the PRIN 2022 program (grant 2022TAFXZ5) and by the European Union – Next Generation EU program. The aim is to share the objectives and preliminary results, for fostering further collaboration.**

Keywords—Critical Infrastructures, Resilience, Artificial Intelligence, Stochastic Simulation.

I. INTRODUCTION

Critical Infrastructures (CIs), like electric power and natural gas networks, telephone and other communication systems, water, wastewater and transportation systems (roads and highways, rail, ports, and airports) are exposed to different natural hazards (e.g., earthquakes, tusnamis, hurricanes and floods), whose intensity and severity has been increasing in the past years, possibly due to climate change. Resilience has, then, become a relevant attribute to consider in the design and operation for these infrastructures, for ensuring the capability of withstanding disruptive events and recovering from them (Figure 1). Resilience has been defined in different ways by different scholars and researchers (see for example [1]). In the context of CIs, resilience can be defined as the ability to resist (prevent and withstand) disruptive events, absorb the initial damage that they casuse and subsequently recover operation [2]. The Multidisciplinary Center for Earthquake Engineering Research (MCEER) has proposed a general framework to measure seismic resilience, which can also be applied for other hazard types (for example, hurricanes [3]). The UN Sendai framework for Disaster Risk Reduction sets the understanding of disaster risks as first priority and recommends complementing scientific knowledge in disaster risk and resilience assessment [4]. Many resilience metrics have been proposed, including (see also Figure 1) [5]: the area between the target performance curve and the real performance curve within the recovery phase period, the probability of meeting predefined system-level performance standards during an accidental scenario, the normalized area under the system performance curve for a single accidental scenario, a normalized and weighted sum of the disaster consequences and the recovery efforts. Quantification by these metrics relates to the resilience assessment of CIs under specific scenarios of disruption, postulated a-priori by the analyst. This neglects the variety of disruptive scenarios that might be generated by an initiating event and the variety of recovery strategies that might be considered by the decision maker [6].

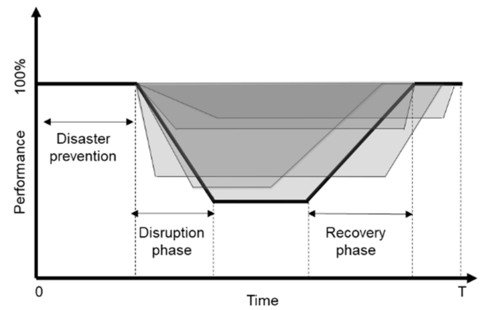

Figure 1. Performance curves

On the other hand, computational resilience assessment (CRA) enables analyzing resilience by scenario simulation and the outcomes can be used for informing on prevention, mitigation and recovery measures. However, computational cost can be demanding when considering large and complex CIs exposed to uncertain disruptive events. To cope with the computation burden, Artificial Intelligence (AI) and stochastic simulation can be combined for efficient simulation.

In this paper, we present the the ambitions of the research project ARtificial Intelligence and STOchasTic simulation for the rEsiLience of critical infrastructurES (ARISTOTELES), funded by the Italian Ministry for Scientific Research (MIUR) under the PRIN 2022 program (grant 2022TAFXZ5) and by the European Union – Next Generation EU program. The aim is to share the objectives and preliminary results, for fostering further collaboration. The project is aimed at developing an integrated framework and the corresponding computational platform for the resilience assessment of Cis. For the computation, AI and stochastic simulation methods are efficiently combined giving due account to the uncertainties inherent in the problem. In [7],

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[8], [9], and [10] the vulnerability of power grid, steam supply and natural gas systems under different hazard types has been investigated, whereas in [11] and [12] the recovery phase has been analysed for post-hazard recovery planning and optimization. However, the integrated modelling frameworks proposed in the previous studies have not considered the resilience of CIs under different hazards and climate change, duly considering the stochasticity of events and the uncertainties during both mitigation and recovery phases. As CIs modelling must reflect their interconnected and interdependent behaviour [13], the models are inevitably: 1) complex and nonlinear; 2) high-dimensional; 3) dynamic. This makes the solution of the integrated models computationally demanding, consider uncertainty in the hazards environmental conditions (e.g., climate change) [14]. To get practical solutions, then, advanced modelling and simulation techniques are required to reduce the computational burden.

The remainder of the paper is as follows: Section 2 presents the metodologies, Section 3 the project development phases, Section 4 the selected case studies and the preliminary results, and in Section 5 some conclusions are elaborated on the societal and scientific impacts of the project.

II. Methodologies

2.1. Modelling Natural Hazards

Natural hazards (such as earthquakes, tsunamis, hurricanes and floods) are modelled exploiting the knowledge gained in performing activities such as probabilistic hazard analysis for earthquakes and tsunamis [15], regional and local probabilistic flooding analysis [16], etc., also considering possible interactions among hazards.

2.2 Modelling Climate Change

Climate change is modelled with regards to its influence on the manifestation of undesirable operational conditions [17]. A pool of climate change models is available [18] and their outcomes will be combined [19] to account for the effects of climate change on CI resilience.

2.3 Modelling Vulnerability

The vulnerability of the infrastructures is assessed by the identification of relevant damage and failure states, which can lead to disfunctionality as quantified by proper performance measures. Fragility analyses based on specific models (for example [20]) are adopted, considering the natural hazards and their harshening due to climate change.

2.4 AI and stochastic simulation for modelling resilience

Uncertainties affecting the CI response to disruptive scenarios are characterized and represented in mathematical terms. Bayesian Inverse Uncertainty Quantification (IUQ) [21] can be used for building a robust uncertainty description, considering with the expert judgments and the experimental data available.

The following aspects are considered:

- multiple hazards of different nature and magnitude;
- vulnerability and robustness properties of the CI elements [22];
- residual performance after the disruptive event (i.e., absorptive capacity);
- restoration capability and recovery speed [13; 23].

The application of IUQ likely requires the reduction of the dimensionality of the CI model, by the identifying the variables, elements and environmental factors that affect most the CI response to the distruptive scenario: this is accomplished by advanced sensitivity analysis methods based on a limited number of model evaluations [24; 25]. The uncertainty (both aleatory and epistemic [26]) is propagated through the CI model to provide the full spectrum of system responses during the stochastic disruption and recovery phases, and to calculate the performance metrics of interest. The so-called system “limit surface(s)”, i.e., the quantitative limits of the physical variables discriminating the safe states of normal functioning, the disrupted states (“critical regions” of degraded performance) and the restored configurations (“recovery regions”) is identified by simulation. To cope with the computational demand for the simulation of the dynamic, nonlinear and high-dimensional models, efficient combinations of intelligent stochastic simulation strategies and AI methods are implemented for adaptively tracing the “limit surfaces” [25]. Finally, the system “critical and recovery region(s)” are characterized in detail, in order to understand which “type” of criticality and which “classes” of improved performance states they can represent: this information provides relevant insights for improving CI resilience [25].

Specifically:

- advanced stochastic simulation methods (e.g., affine invariant, interacting and multi-source Markov Chain Monte Carlo-MCMC samplers) are used for capturing the complex probabilistic, functional, and dynamic dependences involved [27], for deeply exploring the system state space and discovering those combinations of factors (i.e., of components failures, physical parameters variations, environmental conditions, repair strategies, spares allocations, …) leading to unexpected critical system configurations (disrupted performance states) [25] or to restored system configurations (recovered performance states).
- AI methods, such as Kriging surrogate models [28], are employed for emulating the computationally demanding model codes of the complex systems and CIs of interest. Kriging is used for two reasons: (i) its flexibility and capability of modeling local and global behaviors of the system response, and of diversifying the levels of accuracy of the same model within different regions; (ii) its capability of directly associating a confidence interval to each prediction, which can be used for building robustness and assessing the accuracy and precision of the meta-model.
- AI methods, such as deep learning, regression and clustering techniques, are employed for retrieving information and synthesizing the critical and recovery regions found, in terms of different classes of disrupted and recovered system states (e.g., different magnitudes and speeds of the system performance loss or recovery, respectively). The identification of “prototypes” of

disrupted and restored states is of paramount importance, since it may help the decision makers to select the best policy for infrastructure recovery [29].

2.5 Optimizing resilience

To date, most of the research on the optimization of the resilience of CIs has focused on post-event policies: see, e.g., [30] for power networks and [31] for gas pipelines. Only few works deal with pre-event resilience-based design [23] [32] [33].

Strategies and actions for the resilience of CIs subject to disruption consider:

- post-event (reactive) optimal strategies and actions that enable the most effective (full or partial) recovery of the performance of a CI, conditional on a set of "prototypical" stochastic disrupted states.
- a novel approach that jointly consider pre-disruption and during-disruption performance along with post-disruption functionality goals, to proactively incorporate (a priori) resilience in the optimization of the design and operation of a new CI [30].

Then, the project offers the following advancements with respect to previous works:

- in the modelling and simulation framework, all the uncertainties are characterized. Diverse (e.g., probabilistic and non-probabilistic) methods are used to handle both aleatory and epistemic uncertainties affecting: (i) the system responses during the disruption and recovery phases; (ii) the cost and impact of pre-event and post-event design strategies and recovery actions; and, (iii) the structural, functional and dynamic dependences of the CI to other systems;
- a novel IUQ method, combined with advanced sensitivity analysis, is proposed for dimensionality reduction of the CI model and for the characterization of uncertainty while addressing the computational burden posed;
- an approach based on global optimization is developed for the optimal design of CIs and their resilience management, in the presence of uncertainties. Kriging is adopted for: (i) emulating the long-running model codes, to reduce the computational burden due to the repeated model evaluations typically required by optimization problems in presence of uncertainties; and (ii) providing a direct assessment of the uncertainties in the estimates, which can be embedded in the design optimization task, thus producing robust results. Global population-based meta-heuristics (e.g., Genetic Algorithms, Sequential Cooperative Optimization), data-driven approaches (distributionally-robust optimization, Scenario Theory) and machine learning techniques (e.g., Reinforcement Learning) are employed to efficiently tackle the complex, nonlinear, multi-objective and multi-modal nature of the optimization problem;

III. Project development phases

A work program has been defined, structured in eight Work Packages (WPs) (see Figure 2). WP1 defines the boundary of the problem and presents concepts, definitions and methods for the quantitative characterization of the vulnerability, risk and resilience of CIs; WP2 introduces the efficient AI and stochastic simulation techniques that to implement for scenarios modelling and exploration during the disruption phase; WP3 does the same for scenarios modelling and exploration during the recovery phase; WP4 focuses on the methods for the optimization of the resilient design and management of CIs; WP5 presents the case studies to which the methodological development of WPs 2-4 are be applied.

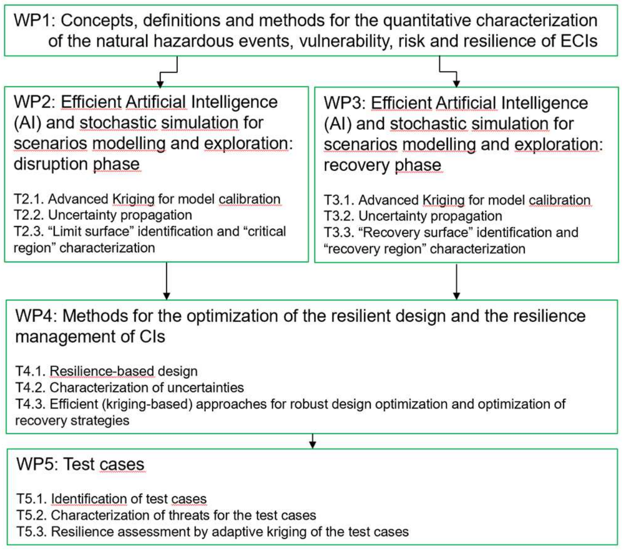

Figure 2. Pert chart of the research project

IV. Case Studies

The framework and computational platform will be tested on Energy Critical Infrastructures (ECIs), e.g., an Integrated Energy Systems (IES) exposed to earthquakes and tsunamis, and a chemical facility exposed to earthquakes.

The IES of interest (described in Section 4.1) is an energy system aimed at increasing the integration and coupling between different energy production plants (nuclear, gas, solar, wind, etc.) and vectors, such as electricity, natural gas, hydrogen, eventually coupled, also, with Energy Storage Systems (ESSs), such as accumulators and batteries, or hydrogen tanks.

The chemical facility of interest (described in Section 4.2) is composed of two atmospheric tanks (T1 and T2) that store liquid flammable substances, and one pressurized vessel (P1) that contains liquid petroleum gas [34] [35].

4.1 The IES

We consider an IES composed of different production technologies. The IES considered is plotted in Fig. 3, adapting it from previous works such as [36] and [37]. In particular, we assume that the IES mimics the positioning of a number of realistic plants based in central Sicily, that is exposed to both earthquakes and Tsunamis [38] [39]. In each node, energy can be either injected or absorbed into/from the grid: the six production plants (nodes 1 to 6) and the 8 user nodes (nodes 7 to 14) are connected in a ring with nominal voltage of 220 kV, where a radial grid (blue in Fig. 3) distributes gas and feeds the gas plants and gas customers. Notice that a virtual additional node (15) is added to the grid (not shown in Fig. 3) to account for the “import”, when the IES cannot provide enough energy to the customers.

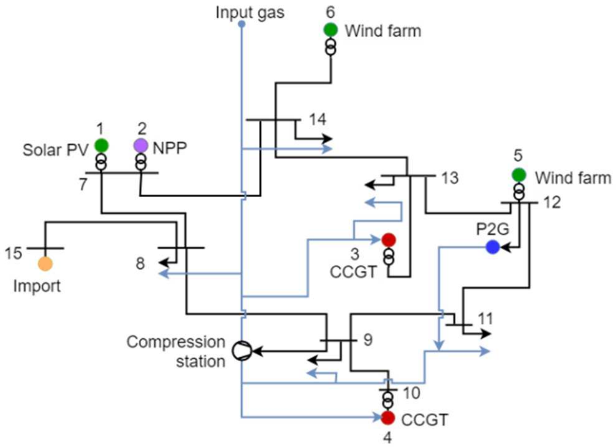

Figure 3. Sketch of the considered IES.

The IES must satisfy the demand while complying, at the same time, with the following technical constraints: minimum load for CCGT plants equal to 40% of the nominal power [40], maximum power for the CCGT equal to 110% of nominal power [41], NPP for baseload only, with constant power production at nominal power.

4.1.2 Hazard characterization

The Initiating Events (IEs) considered are:

1) the occurrence of an earthquake with Peak Ground Acceleration (PGA) in the range $[0, 9.81]\frac{m}{s^2}$, according to the seismic hazard curves for the Sicily region [39];
2) the occurrence of a Tsunami with Maximum Inundation Height (MIH) in the range [0,20]m, according to the tsunami hazard curves for the Sicilian coasts [38]. An example of these curves is shown in Fig. 4.

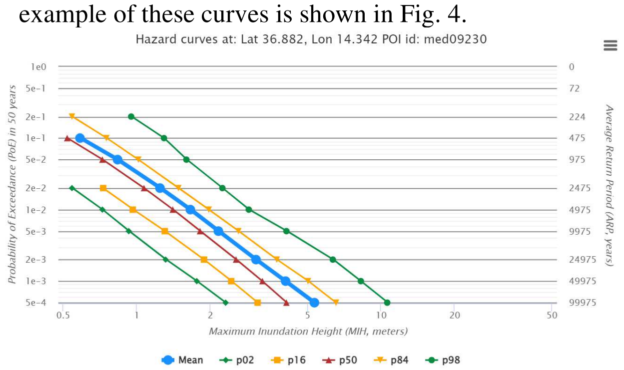

Figure 4. MIH hazard curve with associated uncertainties.

4.2 The chemical facility

The second case study regards a chemical facility of literature [35] composed of two atmospheric tanks (T1 and T2) that store liquid flammable substances and one pressurized vessel (P1) that contains liquid petroleum gas (Fig. 5). The design life is 50 years [42].

4.2.2 Hazard characterization

The Initiating Event (IE) considered is the occurrence of an earthquake with PGA in the range $[1, 9.81]\frac{m}{s^2}$. The PGA-frequency curve is taken from [43] and shown in Fig. 6.

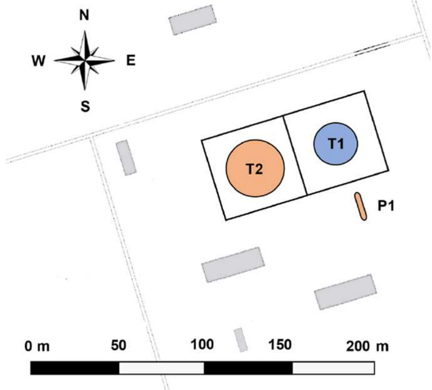

Figure 5. Layout of the chemical facility of the case study [42].

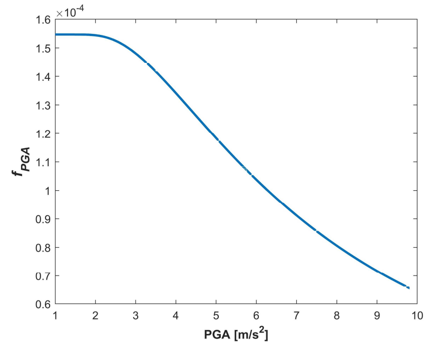

Figure 6. Earthquake PGA-frequency curve.

For illustrative purposes we assume that when one of the tanks fails it always leads to a pool fire (in case of T1 and T2) or to a jet fire (in case of P1), with a Time of Final Mitigation (TFM) of 150 min in both cases, which is the time needed for the accident to reach a safe state after implementing all the necessary mitigation actions.

A novel risk assessment framework based on Dynamic Bayesian Networks (DBN) for considering aging of safety barriers has been elaborated in [34]: Phisics of Failure (PoF)-based aging models are integrated into the safety barriers fragility models, to consider the time-dependency of the barriers fragility in relation to their aging processes, when exposed to natural hazards of different magitudes. The developed DBN also allows the update of the risk profile as knowledge on the components states and information on the hazards become available during the system life, allowing informed decisions to keep the risk at an acceptable level.

V. Conclusions

With this paper, we aimed at sharing the objectives and preliminary results of the research project ARISTOTELES, funded by the Italian Ministry for Scientific Research (MIUR) under the PRIN 2022 program (grant 2022TAFXZ5) and by the European Union – Next Generation EU program. The results of the research project will be particularly beneficial to first responders that will be called, during the pre- and post-disruption phases, to protect lives and minimize environmental and societal damage, should an accident occur. This entails facing uncertainty, due to the potential impact of the natural disaster on safety systems and safety barriers, and to the overload of the emergency system due to the possible multiple simultaneous scenarios triggered by the natural disaster, and their aging. ARISTOTELES is a step in the direction of a systematic exploration of solutions to these challenges.

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