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Perspective

Advances in reliability analysis and risk assessment for enhanced safety

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Abstract
Reliability science and engineering are fundamental for guaranteeing the safe functioning of systems and products. Indeed, the risk of failure can be complex to assess and manage. Modes of failures and scenarios of accidents must be imagined and postulated, and evaluations of occurrence probabilities and consequences must be performed in the presence of uncertainties, possibly very deep. The outcomes of the evaluations inform decisions to prevent failures and undesired events and, were they to occur, mitigate and recover from their consequences. On the other hand in this world in continuous transition to meet the numerous and increasingly challenging objectives of reliability, efficiency, safety, sustainability etc, the innovations that are being developed for better-being and more benefits for all, also deepen the uncertainty related to new and unknown hazards and dangers. This calls for innovative methods of analysis, assessment and management of reliability and risk for enhanced safety. In this paper, directions of development are presented, including the use of simulation for accident scenario identification and exploration, the exploitation of monitoring data for the dynamic updating of reliability and risk assessment towards condition monitoring-based risk assessment, and the extension of the framework of risk assessment to resilience.

Keywords: reliability science and engineering, risk assessment and management, simulation, condition-based risk assessment, resilience

1. Introduction

No component or system is totally immune to failure and reliability science provides us with warranted statements as justified beliefs based on solid concepts, theories, principles, approaches, methods and models for understanding, assessing, characterizing, communicating and managing the degradation and failure processes of components and systems in various applications. It is a special case of risk science, with methodological and technical links to other sciences, like probability and statistics (Aven 2021, Aven *et al* 2024).

Reliability engineering is the engineering discipline that applies the know-how of reliability science to components and systems in order to ensure that it performs its intended function, without failure, for the required time duration in a specified environment. Functionally, reliability engineering is responsible for the development of reliability requirements for the system and supports the design of the system so as to meet such requirements. Reliability engineering then also establishes the reliability programs and analyzes to monitor the actual reliability of the component system throughout the life cycle. Reliability engineering is closely related to safety engineering and system safety. It deals with the estimation and management of high levels of 'lifetime' engineering uncertainty and risks of failure.

As reliability is related to risk and reliability science is related to risk science, reliability engineering is related to risk engineering. Within risk engineering, risk assessment is a mature discipline whose objective is to allow identifying the hazards/threats which the system of interest is exposed to, analyzing potential accident scenarios, their causes and consequences, and eventually describing risk, possibly quantitatively and with an adequate treatment of the uncertainties associated to the assessment. The risk assessment is based on the knowledge available on the failure mechanisms of the system of interest, wherein reliability science and engineering play a fundamental role.

On the other hand, the World we live in is rapidly changing in many ways. Digitalization is bringing new opportunities of connectivity, monitoring, knowledge and situational awareness increase. Advancements in technology are improving our production processes, products and services. A deep transformation is occurring in industry, for improved safety, reliability, quality and efficiency. The internet of things and big data, the industrial internet, artificial intelligence (AI), large language modeling and generative analytics will continue to change the way we design, manufacture, supply products and services.

In this exciting scenario of significant change and evolution, reliability and safety stand as a necessity to enable the benefits that could come and to address any new risk that may arise. Indeed, the increase in condition monitoring, information sharing, data availability and computational capabilities, and the advancements in methods and techniques, offer new opportunities for the improvement of the way we do reliability engineering and risk assessment (Zio 2018, Zio and Guarnieri 2024).

In this paper, I share some perspectives on directions for advancing and improving reliability engineering and risk assessment, in particular with regards to:

- exploiting computational power for simulation, within a computational reliability analysis and risk assessment;
- encompassing in the reliability and risk assessment all phases of the potential accident scenarios that may occur, including prevention, mitigation, emergency crisis management and restoration, thus moving towards a resilience view of safety management.
- using monitoring data recorded on components and systems, within a framework of condition-based reliability analysis and risk assessment;

2. Reliability and reliability engineering

Reliability relates to the ability of a system or component to function under stated conditions for a specified period of time. As such, it plays a key role in the functional performance of a system or component and, then, reliability engineering is concerned with the ability of a system or component to function without failure and is a sub-discipline of system engineering.

The reliability function of a system is theoretically defined as the probability of the system successfully providing its function at time t, which is denoted $R(t)$. In practice, it is calculated using different techniques and its value ranges between 0 and 1, where 0(1) indicates a sure failure (sure success). This probability is estimated from detailed (physics of failure) analysis, available data sets from the field or obtained through reliability testing and reliability modeling. Availability, testability, maintainability and maintenance are often considered as a part of reliability engineering in reliability programs.

Correspondingly, the mathematics of stochastic processes has given significant contribution to the development of mathematical models for reliability engineering. Specifically, stochastic processes are used for describing the evolution of degradation and the failure behavior of components and systems over time. Statistical inference for the parameters of the stochastic models has, then, been developed also from a Bayesian perspective for those cases where field data are scarce.

Inevitably, uncertainty is a fundamental element in the characterization of the reliability of a component or system (and of risk, as we shall see in the next Section). Uncertainty is related to incomplete knowledge of the phenomena and processes driving degradation and leading to failure, and to availability of only limited data and information related to them. Characterization and modeling of uncertainty are quite difficult tasks in practice, and various formulations and methods exist to address these tasks.

Reliability modeling, simulation, analysis are ultimately performed to make reliability estimations and predictions, which form the information base to support decision making on how to provide and maintain the requested reliability through design, maintenance, replacement etc An important outcome from the tasks of modeling and analysis in reliability engineering is the identification of the critical elements of a system, which deserve most attention and resources in design, operation and maintenance. For this, importance measures have been introduced to relate the failure and functioning states of a component to those of a system.

The outcomes of the activities of reliability engineering are used to define the system design, and decide on system operation and maintenance for providing and guaranteeing the expected system function for the requested time, under given operational conditions. This calls for decisions to be taken for reducing system failures and unplanned downtime, ultimately seeking for maximum reliability. Given the increasing complexity of modern engineering systems, the challenges of reliability optimization have significantly grown, and many efforts are being made for the development and application of new methods for reliability optimization.

Finally, AI and machine learning (ML) have arisen as a potential of improvement also of reliability engineering. AI and ML are seen as applied statistics and the developments for reliability engineering date back to the early introduction of neural networks (NNs) in the 1990s and develops to its recent burst for signal processing and data analysis, with uses that range from surrogate models in computationally demanding reliability assessments to degradation and failure prediction for system Prognostics and health management (PHM).

3. Risk and risk assessment

Risk assessment is a fundamental technical framework for the systemic analysis of the risk associated to an industrial activity. The objective of performing a risk assessment on a system is to develop a proper understanding of the hazardous issues involved in its operation, so as to properly manage them by taking confident risk-informed decisions.

The underlying principles of risk assessment are captured in the National Academy of Science 'Red Book', where the two activities of assessment and decision making are kept distinct: assessment of risk is treated as a scientific activity limited by the available knowledge and the uncertainty inherent in risk, and decision making based on risk is regarded as a political activity, with the outcomes of risk assessment being one type of input but never the sole basis for decision making (National Academy Press 1983). The risk concept and the qualification or quantification outcomes deriving from its assessment constitute, then, the input to rational decision making on risk prevention and mitigation measures, on risk regulation and risk liability transfer through insurance.

Risk assessment as a science has been developed in the past 50 years to help understanding and controlling the risk of accident events. The way it is done is to structure the information and knowledge available at the system element/component/basic event level, and elaborate this to assess the accident risk at system level. As knowledge and information are limited and assumptions are made on the system behavior, the assessment is affected by many uncertainties. The common framework used to describe these uncertainties is that of probability theory, and particularly the subjectivistic (Bayesian) theory of probability,which allows expert opinions to be combined with statistical data for the quantification of the risk metrics of interest (Kelly and Smith 2009, 2011). Then, the common term used for this is probabilistic risk assessment (PRA), although probabilistic safety assessment and quantitative risk assessment are also widely used. Actually, the purely PRA is somewhat challenged when dealing with highly unlikely industrial accident scenarios (with extreme consequences): for these rare events, only very limited knowledge exists in support to the risk assessment and a number of alternative frameworks for uncertainty representation and treatment have been proposed (Ahn and Yang 2003, Dubois 2010, Aven and Zio 2011, Aven *et al* 2014, Kang *et al* 2016).

For the purposes of quantitative assessment it is common to define risk in terms of the triplet description given in (Kaplan and Garrick 1981):

$$\mathrm{Risk} = \{\langle s_i, \mathscr{F}_i, c_i\rangle\}, i = 1, \ldots, N \tag{1}$$

where s_i represents the sequence of events of the ith of N accident scenarios, $\mathscr{F}_i$ represents the frequency of occurrence of such a sequence of events and c_i is the consequence that would result if that scenario were to occur. The corresponding risk assessment framework entails the identification of the complete set of accident scenarios that could occur, and the accurate estimation of their occurrence frequencies and consequences. For considering the uncertainties associated to the risk assessment, a second-level definition of risk needs to be introduced (Kaplan and Garrick 1981):

$$\mathrm{Risk} = \{\langle s_i, p_i(\mathscr{F}_i, c_i)\rangle\}, i = 1, \ldots, N+1 \tag{2}$$

where, $p_i(.,.)$ is a joint probability density function describing the uncertainties on the frequency of occurrence $\mathscr{F}_i$ and the consequences c_i of accident scenario s_i, and the $N + 1$ scenario is added to account for the incompleteness of the set of scenarios, i.e. for those scenarios that have not been considered because unknown at the time of the analysis (i.e. the so-called 'residual risk').

As risk assessment is based on the available knowledge, the definition of risk is extended to make it explicit (Aven 2010):

$$\mathrm{Risk} = (\mathcal{A}, \mathcal{C}, \mathcal{Q}; \mathcal{K}) \tag{3}$$

where $\mathcal{A}$ indicates the set of accident scenarios that may occur, $\mathcal{C}$ represents the set of consequences, $\mathcal{Q}$ is the metric used to quantify the associated uncertainties and $\mathcal{K}$ is the body of knowledge which the risk assessment (i.e. the identification of $\mathcal{A}$ and the quantification of $\mathcal{C}$ and $\mathcal{Q}$) is based on. This is coherent with the model of the world introduced in (Apostolakis 1990), conditional on the entire body of knowledge and beliefs of the modeler. Note that the formulation in (3) does not restrict the representation of the uncertainty to the classical probabilistic one and alternative representations can be employed (Dubois 2006, Aven 2011, Aven *et al* 2014, Flage *et al* 2014, Pedroni *et al* 2017).

Then, in simple words, risk assessment is a way of acquiring and organizing the knowledge about the elements of risk, to inform rational decision making. In this view, risk assessment must provide traceable information for arguing the decisions; the outcomes of the risk assessment must be communicated in a way that allow the decision makers to interpret them properly for their purposes and to understand the associated uncertainty related to the available knowledge used for the assessment.

4. Simulation for computational reliability engineering and risk assessment

Overall, failures, accidents and incidents can be considered as extreme states of behavior of the systems involved (Ale 2016), and their characterization implies knowledge mining for reliability engineering and risk assessment. This task is far from trivial in practice, given the complexity of the systems and processes: a large, combinatorial set of possible scenarios, events and conditioning factors needs to be considered, of which only few, rare ones lead to failures and critical, unsafe situations. This makes experimentation economically unsustainable in most industrial settings and physically infeasible, in most safety-critical cases.

This is why simulation has long been advocated as a way to explore and understand system behavior for knowledge retrieval (Simpson *et al* 2001, Santner *et al* 2003), and has been used for reliability engineering and safety assessment since the 1970s–80s. However, it is the continuous advancements in modeling techniques (including the fast-running AI -based surrogate/meta-modeling) and the impressive increase in computational power (including parallel computing, cloud computing, high power computing) that are pushing the use of simulation for exploring system behavior and its inclusion within frameworks of computational risk assessment.

Within a simulation-based degradation evolution, failure and accident scenarios exploration, a set of simulations is run with different initial configurations of the system design and operation parameters in input, and the system state is computed as output. Evaluation of the system state with respect to specified functional and safety conditions (critical thresholds) allows identifying the input configurations leading to system failure and critical states. These states form the so called 'critical regions' (CRs) or 'damage domains' (DDs) (Montero-Mayorga *et al* 2014). The CRs may be identified corresponding to prior knowledge and expectation of the analysts or be 'discovered', i.e. the analysts are not *a priori* aware of such critical configurations and simulation allows identifying them.

Concurrently, simulation can also be exploited to estimate the failure events and accident scenarios probabilities, or any other measure of uncertainty adopted to describe reliability and risk For this, Monte Carlo (MC) methods of stochastic discrete event simulation have been generally accepted as a gold standard (Labeau 1996, Marseguerra and Zio 1996, Kalos and Whitlock 2008, Dubi 2010, Zio 2013, Rubinstein and Kroese 2016). In practice, MC simulation consists in generating a large number of samples/trials/histories of system response and counting those that reach the state of interest, i.e. that end in the CRs DDs for reliability evaluation and risk assessment purposes. For example, for estimating the reliability of a system at a given time t, i.e. the probability that the system does not fail before t, a set of life histories of the system are run and the time at which the system fails (time to failure, TTF) in each history is recorded. Then, the reliability of the system at time t is estimated as the fraction of simulations whose TTF is larger than t. Likewise, estimating the probability of occurrence of an event leading the system into a given CR, defined by specific thresholds of system safety parameters (e.g. limit temperatures, pressures, heat fluxes etc), can be done by sampling realizations of the system life and counting the fraction of times that the system ends in the CR of interest (Robert and Casella 2004).

Then, the two key research questions in the practice of risk assessment that can be addressed with the use of simulation models are (Zio 2018):

- Identify hazardous conditions for the system, i.e. the pairs event-consequence $(\mathcal{A}, \mathcal{C}; \mathcal{K})$ in equation (3), which represent critical states of the system (i.e. identify the CRs of the system).
- Estimate the probability of occurrence of rare critical scenarios, i.e. $(\mathcal{Q}; \mathcal{K})$ in equation (3).

Yet in practice the use of simulation is actually quite challenging because the models of system behavior are:

- *high-dimensional,* i.e. with a large number of inputs and/or outputs;
- *black box,* i.e. without an explicit input/output (I/O) relation (because coded in a computer program or because implicit in an empirical surrogate or meta-model, e.g. based on data and AI);
- *dynamic,* because the system evolves in time;
- *computationally demanding*.

Indeed, although computational power is continuously increasing, in many practical situations computational cost still remains an issue for simulation-based computational risk assessment and prevents from running the model for many input configurations as would be necessary to characterize the CRs of highly reliable systems, i.e. systems characterized by very small probabilities of failure and whose CRs, thus, correspond to very small niches that are hard to explore and find in the large space of input configurations (Rubino and Tuffin 2009, Bucklew 2013). To overcome this issue, simulation by adaptive sampling is being proposed to intelligently guide the simulation towards the system states of interest (i.e. those belonging to the CRs). This entails that the simulation methods be capable of automatically understanding, during the simulation, which configurations are most promising to visit (Cérou and Guyader 2007, Kleijnen 2009, Echard *et al* 2011, Munoz Zuniga *et al* 2011, Cadini *et al* 2014, 2015, Turati *et al* 2017, Alibrandi *et al* 2022).

Using AI and ML, such frameworks can effectively combine model dimensionality reduction by feature selection/sensitivity analysis to screen important inputs, meta-modeling to reproduce the behavior of the computationally expensive model by a cheap-to-run one, efficient stochastic models for exploration of the system state space. AI and ML are essentially a form of applied statistics with increased emphasis on the use of computers to statistically estimate complicated, nonlinear functions. This form has been pervasive in a growing number of academic disciplines, in particular, including reliability engineering, safety analysis, risk assessment and management. This is due to the fact that AI and ML can help improving the way in which we address important challenges in reliability and safety applications (Zio 2009).

Early uses of AI and ML algorithms, like neural networks, in the areas of reliability and safety started in the 1990s and were directed towards the exploitation of their capabilities to serve as fast approximations of complex models and codes in computationally demanding calculations, such as those involved in dynamic reliability/safety analysis (Marseguerra *et al* 1994, 1995) and uncertainty/sensitivity analysis (Ricotti and Zio 1999, Marseguerra *et al* 2003). At the same time, the application of AI and ML was also developing in the areas of fault detection and diagnosis, as an extension of classical time series analysis and signal processing (Marseguerra *et al* 1992, Marseguerra and Zio 1994).

The field of AI and ML for signal processing and data analysis literally exploded with the paradigm of 'big data', grounded on the collection and storage of massive amount of data, and the development of data analytic models and algorithms to probe it. As a result, AI and ML have become one of the key drivers for the digital transition at the center of the fourth industrial revolution, Industry 4.0 (Farsi and Zio 2019, Compare *et al* 2019a, Pinciroli *et al* 2023).

AI and ML models and algorithms are used as surrogate models to enable computationally demanding reliability analyzes and risk assessments (Izquierdo *et al* 2019, Di Maio *et al* 2021), with the related uncertainty and sensitivity analyzes (Cervi *et al* 2022, Roma *et al* 2022). They are also at the core of PHM developments for a modern view of reliability and maintenance engineering, as regressors, classifiers and predictors (Zio 2013, Si *et al* 2015, Compare *et al* 2019b, Hu *et al* 2022, Zio 2022).

The application of AI and ML to PHM requires to process the monitoring data collected by sensors installed on the components and systems to produce an estimate and prediction of their degradation, and, on this basis, estimate the probability of continuing to provide the functions specified by design. The outcomes of PHM inform the decision making on future operation and maintenance (IEEE 2017).

Looking ahead, there are indeed numerous promising opportunities for the use of AI and ML in the reliability analysis and risk assessment fields. AI/ML-based PHM has been already proven successful at the component and sub-system levels. However, at system level it becomes a complicated task, because of the complexity of the system and the difficulties related to deciding what to monitor and which algorithms to use for processing the data. For deployment in practice, a number of challenges need to be tackled in relation to the AI/ML-based prognostic approach to reliability analysis and risk assessment, including the definition of adequate performance metrics for the AI and ML models and algorithms, and the development of a framework for linking these metrics to reliability (Compare *et al* 2017). Furthermore, accuracy of prediction and quantification of its uncertainty need to be carefully dealt with, for properly informed decision-making. Providing a single value of prediction of failure in the future is not sufficient and confidence (or credible) intervals must be provided. Also, unarguably, the practical application of AI and ML for reliability analysis and risk assessment is strongly connected to the availability of representative data and the extraction of informative content from it for reliability analysis and risk assessment. deep learning can contribute to the effective and efficient treatment of data by incorporating feature engineering in the process of learning of the predictive models, for extracting the information relevant to the reliability and risk application of interest. Finally, a quite relevant issue for trusting the use of AI and ML in reliability analysis and risk assessment relates to the fact that data-driven AI and ML models and algorithms are typically black boxes lacking interpretability, which reduces trust in their use particularly in critical applications. This calls for finding ways for improving transparency and interpretability so as to build trust on the use of AI and ML in reliability and risk applications.

5. Resilience assessment

As mentioned earlier, risk assessment is used to assess accident scenarios and enable informed decision making for risk-reducing measures. Differently from the concept of risk, resilience is focused also on the ability to prepare and recover quickly from an accident or disruptive event, which may be known or unknown. Designing and managing for resilience, then, require ensuring a system's ability to plan and prepare for the potential occurrence of accidents and disruptive events, and then absorb, recover, and adapt in case of occurrence.

The concept of resilience varies somewhat by discipline and application (Najjar and Gaudiot 1990, Henry and Ramirez-Marquez 2012, Ouyang *et al* 2012, Uday and Marais 2015), and different definitions exist such as 'the ability of the system to reduce the chances of shock, to absorb a shock if it occurs and to recover quickly after a shock (re-establish normal performance)' (Bruneau *et al* 2003), the 'ability of the system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable time and composite costs and risks' (Haimes 2009). From these definitions, it emerges that resilience is characterized in terms of four properties, i.e. robustness, redundancy, resourcefulness, rapidity and four interrelated dimensions, i.e. technical, organizational, social, economic. It can be considered a new paradigm for risk engineering, which proactively integrates the accident preventive tasks of anticipation (imagining what to expect) and monitoring (knowing what to look for), the in-accident tasks of responding (knowing what to do and being capable of doing it) and learning (knowing what has happened), the mitigative tasks of absorbing (damping the negative impact of the adverse effect) and the recovery tasks of adaptation (making intentional adjustment to come through a disruption), restoration (returning to the normal state) (Hollnagel 2016).

Various models, methods and frameworks for analyzing and quantifying resilience have been proposed in the literature (Carpenter *et al* 2001, Fiksel 2003, Wreathall 2006, Jackson 2007, Madni and Jackson 2009), with focus on diverse fields of application such as seismic engineering and structural systems (Cimellaro *et al* 2006, 2010, Dueñas-Osorio and Kwasinski 2012), ecological systems (Holling 1973), economics and financial systems (Starr *et al* 2003, Rose 2009, Amini *et al* 2013, Baroud *et al* 2015), service systems (Todini 2000, Rosenkrantz *et al* 2009, Wang *et al* 2022, Hao *et al* 2023), telecommunication systems (Omer *et al* 2009), urban infrastructures (Attoh-Okine *et al* 2009, Ouyang and Dueñas-Osorio 2012, Jin *et al* 2014), disaster analysis for avoidance and recovery (Bonanno *et al* 2007, Tierney and Bruneau 2007, Zobel 2011, Wang *et al* 2023), oil and gas pipeline systems (Yang *et al* 2023).

While resilience can be characterized by many system's features and attributes, recovery is a vital element of strategies to improve resilience. System recovery and its role in infrastructure system resilience have attracted quite some attention. Some studies have modeled the post-disaster restoration of various infrastructure systems in an effort to estimate the expected restoration time (Shinozuka *et al* 2004, Liu and Ji 2007, Ferrario and Zio 2014), and several others have compared the performance of different restoration strategies (Çağnan *et al* 2006, Buzna *et al* 2007). Other works have tackled the problem of post-disaster restoration strategy planning and optimization, for the purpose of restoring system service in a timely and efficient manner. A case of network restoration was addressed in (Lee *et al* 2007), involving the selection of the location of temporary arcs (e.g. shunts) needed to completely re-establish network services over a set of interdependent networks: a mixed-integer optimization model was proposed to minimize the operating costs involved in temporary emergency restoration. A genetic algorithm was applied in (Xu *et al* 2007) to optimize the restoration of electric power after an earthquake: the objective of the optimization was the minimization of the average time that each customer stays without power. An integer programming model was proposed in (Matisziw *et al* 2010) to restore networks where the connectivity between pairs of nodes is the driving performance metric associated with the network.

In more general terms, the resilience assessment requires to integrate a number of methods capable of viewing the problem from different perspectives (topological and functional, static and dynamic), under the existing uncertainties (Ouyang *et al* 2009, Reed *et al* 2009, Kröger and Zio 2011, Ouyang 2014):

- structural/topological methods based on system analysis, graph theory, statistical physics, etc; these methods are capable of describing the connectivity of a complex system and analyzing its effects on the system functionality, on the cascade propagation of a failure and on its recovery (resilience), as well as identifying the elements of the system which must be most robustly controlled because of their central role in the system connectivity (Newman and Dale 2005, Lee *et al* 2007, Zio and Sansavini 2011, Fang and Zio 2013, Khakzad and Reniers 2015, Praks *et al* 2015);
- logical methods based on system analysis, hierarchical logic trees, game theory, etc; these methods are capable of capturing the logic of the functioning/dysfunctioning of a complex system due to random effects and malicious attacks, and of identifying the combinations of failures of elements (hardware, software and human) which lead to the loss of the system function (Apostolakis and Lemon 2005, Bobbio *et al* 2010, Khakzad 2015, Zhang *et al* 2015);
- phenomenological/functional methods, based on transfer functions, state dynamic modeling, input-output modeling and control theory, agent-based modeling etc; these methods are capable of capturing the dynamics of interrelated operation between elements (hardware, software and human) of a complex system and with the environment, from which the dynamic operation of the system itself emerges (Trucco and Leva 2012, Alessandri and Filippini 2013);
- flow methods, based on detailed, mechanistic models (and computer codes) of the processes occurring in the system; these methods are capable of describing the physics of system operation, its monitoring and control (Sansavini *et al* 2014).

For electric power grids, for example, comparisons between structural/topological and power flow methods have been made. Some studies (Sun and Han 2005, Baldick *et al* 2008, Correa and Yusta 2013) have provided qualitative comparisons between complex network theory models and power flow models, identifying similarities and differences, and evaluating advantages and disadvantages. Also, by extensive comparative simulation, (Cupac *et al* 2013) has shown that a network-centric model exhibits ensemble properties which are consistent with the more realistic optimal power flow model. (Fang *et al* 2014) analyzed the problem of searching for the most favorable pattern of link capacities allocation that makes a power transmission network resilient to cascading failures with limited investment costs. The problem is formulated within a combinatorial multi-objective optimization framework and tackled by evolutionary algorithms. Two different models of increasing complexity are used to simulate cascading failures and to quantify resilience: a complex network model, and a more detailed and computationally demanding power flow model. Both models are tested and compared on a case study involving the 400 kV French power transmission network. The results show that the optimal solutions obtained using the two different models exhibit consistent characteristics in terms of phase transitions in the Pareto fronts and link capacity allocation patterns.

6. Condition-based risk assessment (CB-RA)

Condition-monitoring data collected by sensors (Zio 2018) contain information useful for risk assessment. Accident initiating events and safety barriers failures occur as a result of degradation mechanisms, e.g. wear (Zeng *et al* 2016), corrosion (Zeng *et al* 2014), fatigue (Jiang *et al* 2016), crack growth (Baraldi *et al* 2012), oxidation (Compare *et al* 2016), etc The degradation processes can be monitored in real time and failures can be predicted and anticipated with reference to specific thresholds of the monitored variables. The condition-monitoring data measured by sensors installed on the components and systems give information on the degradation processes evolution and on the health conditions of the components and systems, which can be used to update the failure probability values used in the risk assessment (Di Maio *et al* 2018, 2022). Therefore, condition-monitoring data can complement statistical failure data within a CB-RA (Zadakbar *et al* 2013, 2015, Wang *et al* 2016, Zeng and Zio 2017). Statistical data refer to the count data of the accidents and consequences of accidents that occur during the operation of similar systems, thus providing 'population' information, whereas condition-monitoring data come from the online monitoring and inspection of the degradation of the specific components and systems, allowing to account for their current health state. Inspection and monitoring data related to the degradation states of components and systems can allow updating the risk measures quantified within a risk assessment framework that is called CB-RA (Di Maio *et al* 2018, Zio 2018). The dynamic supply of condition-based risk measures estimates enables ranking the contribution to risk of the different failure mechanisms affecting the different components and systems and allows, on this basis, the conditioned-informed prioritization of the maintenance activities for asset management (Hoseyni *et al* 2019).

Digital Twins (DTs) can enable real-time system performance monitoring with feedbacks to improve system reliability, and perform real-time risk assessment and management (Kochunas and Huan 2021, You *et al* 2022, Zio and Miqueles 2024). DTs have been successfully implemented for several purposes in different contexts, including critical infrastructures monitoring, smart cities, smart grids, power plants control, and manufacturing process optimization (Fuller *et al* 2020, Gong *et al* 2022). Nevertheless, DTs application for real-time risk assessment and management is challenged by the need of modeling the complex nonlinear system dynamics by combining information derived from stochastic and deterministic simulation models with the data gathered from component and system condition-monitoring sensors. This results in a computational burden that may affect the real-time state prediction of the components and systems states, and consequently the real-time risk monitoring (Khaoula *et al* 2016, Gong *et al* 2022).

7. Conclusions

Reliability science and engineering are mature disciplines, widely applied in practice for the design and operation of safe systems. The reliability analysis and risk assessment involve a structured analysis of the system of interest to qualitatively and quantitatively describe reliability and risk, based on the available knowledge. The quantitative analysis is often criticized in view of the difficulty of assigning probabilities, the difficulty of verifying the assumptions behind the models at the basis of the assessment, the inherent uncertainty involved in the phenomena of interest. By engaging in quantifying the uncertainties and identifying the failure and risk contributors, reliability analysis and risk assessment contribute to the understanding of the reliability and risk and provide information useful for regulation and management. The reliability analysis and risk assessment provide an argument for rational decision making and it must be possible to scrutinize them, as they stand on the knowledge available and the related modeling assumptions made to formalize the analysis and assessment.

In this view, the increasing modeling and computational capabilities and data availability provide a way forward to improving reliability analysis and risk assessment, as analyzed in this paper with particular regards to the use of simulation for accident scenario identification and exploration, and the reliance on condition monitoring data for reliability analysis and risk assessment.

To fully exploit the benefits of simulation, trust must be put in the fast-running AI -based techniques of surrogate/meta-modeling for their controlled and verified use in reliability analysis and risk assessment, with adequate treatment of the errors of approximation and additional uncertainties introduced.

Regarding sensors-monitored condition data, there is the opportunity to develop condition-based reliability analysis and risk assessment that takes into consideration the actual state of the components and systems.

As for resilience, concepts, definitions, models and techniques are emerging but still advancements are needed to enable managing resilience from a design, normative and operational viewpoint, setting resilience goals, regulating resilience within a defence-in-depth safety approach and maintaining resilience margins during operation.

In conclusion, the directions discussed in this paper are some relevant ones in which reliability science and engineering, and risk assessment must continue to evolve for addressing the existing and future challenges for the safety of systems and products.

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Enrico Zio received the MSc degree in nuclear engineering from Politecnico di Milano in 1991 and in mechanical engineering from UCLA in 1995, and the PhD degree in nuclear engineering from Politecnico di Milano and in probabilistic risk assessment at MIT in 1996 and 1998, respectively. He is currently full professor and President of the AlumniAssociation at Politecnico di Milano, Italy, where he also served as Director of the PhD School.

He is also full professor at the Centre for research on Risk and Crises (CRC) of Ecole de Mines, Paris, PSL University, France, adjoint professor at Tromso University in Norway, City University of Hong Kong and Harbin University in China.

He is IEEE and Sigma Xi Distinguished Lecturer.

In 2020, he has been awarded the prestigious Humboldt Research Award from the Alexander von Humboldt Foundation in Germany (www.humboldt-foundation.de/web/home.html), one the world's most prestigious research awards across all scientific disciplines. The Award is granted in recognition of a researcher's entire achievements to date, to academics whose fundamental discoveries, new theories, or insights have had a significant impact on their own discipline and who are expected to continue producing cutting-edge achievements in the future. Professor Zio has been selected for the Award in light of being a World leading scientist in Risk and Resilience Assessment, Safety Analysis and Reliability Engineering of complex systems and infrastructures, in particular for energy applications.

He is author and co-author of several books and more than 600 papers on international journals, Chairman and Co-Chairman of several international Conferences, associate editor of several international journals and referee of more than 20.

His Google Scholar H-index is 99 and he is in the top 2% of the World scientists, according to Stanford ranking.

In 2023, he has been appointed as Scientific Director of Research and Development of Datrix AI Solutions group, an AI company listed on Euronext Growth Milan, he has been elevated to the status of IEEE fellow 'for contributions to safety and reliability engineering', he has been elected fellow of Asia-Pacific Artificial Intelligence Association as 'the top scientist with outstanding achievements in the area of reliability engineering and risk assessment'.

In 2024 he has been recognized with the lifetime achievement award by the Society for Reliability and Safety for pioneering the application of AI and GA in support of Risk and Resilience Assessment for Complex Engineering Systems, elected Fellow of the Artificial Intelligence Industry Academy, awarded the Alan O. Plait 2024 Award for a tutorial on industrial applications of Artificial Intelligence at the Annual Reliability and Maintainability Symposium, RAMS 2024, presented the International System Safety Society (ISSS) 2024 Educator of the Year Award for outstanding achievement in, or contribution to, system safety education and the advancement of the state of knowledge in system safety, named Distinguished Research Fellow of the Institute of Nuclear Energy Safety Technology, in Hefei, China, elected in the Italian Association of Technology and Engineering.