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SEVENTH FRAMEWORK PROGRAMME

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Abstract

The performance of modern critical non-nuclear civil infrastructure systems (CIs) subjected to long-term degradation processes is predicted and monitored using life cycle management tools. These tools are also used to plan and justify maintenance interventions during the lifetime of CIs. However, in regions exposed to natural events, life cycle management of the CIs should also take into account the effects of extreme natural events that may increase the probability of failure or loss of functionality during the CI lifetimes. Stress tests for CI systems have been proposed in the STREST project with the aim of providing a multi-level systematic and harmonized approach for the evaluation of the performance of these systems against extreme and disastrous natural events. In this report, a framework to integrate the results of stress tests and the data collected after disastrous events into a unified life cycle management strategy for CIs is introduced. This framework will enable management of both long-term degradation and instantaneous natural hazard-induced stressors during the lifetime of a CI system. The proposed framework is demonstrated in an application study focused on the L'Aquila (Italy) gas network.

Keywords: Life cycle, critical infrastructures, stress test, post-event data

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1 Introduction

Through the life cycle of a critical non-nuclear civil infrastructure system (CI) the system operators have the objective to maintain the infrastructure system and mitigate the degradation of system components in order to insure its continuous function and economically profitable operation. In the field of civil infrastructures, the life-cycle cost (LCC) concepts and methods have had a remarkable impact in the last few decades enabling prediction of the performance of a CI subjected to long-term degradation process during its lifetime and planning and optimization of maintenance interventions.

Observed consequences of recent catastrophic earthquakes (e.g. the 2009 L'Aquila earthquake or the 2011 Christchurch earthquake sequence) showed the incapacity of critical infrastructures to recover their functionality to the original pre-disaster state. Such lack of CI resilience raises public concern about the future of their communities in regions where natural hazards are common. Therefore, in regions exposed to natural events, LCC analysis should also take into account the effects of extremely rare natural events that may increase the probability of failure or loss of functionality during the CI lifetime. However, very few studies have been focused on the possibility to include the risk associated to high-consequence low-probability natural events in LCC analysis frameworks.

Stress tests for CI systems have been proposed in the STREST project with the aim of providing a multi-level systematic and harmonized approach for the evaluation of the performance of these systems against extreme and disastrous natural events. The results obtained using this tool (such as results of risk analysis, identified mitigation strategies, etc.) should be included in a long-term maintenance plan in order to increase and optimize the long-term performance of CIs.

In this context, this report presents a possible framework to integrate stress test outcomes and data collected after disastrous events into a unified life cycle management strategy to help infrastructure operators and decision makers to optimize the life cycle performance and maintenance plans for CI systems.

In the following sections, the principles of life-cycle analysis and life-cycle cost optimization, and the models and tools to evaluate the structural performance of critical infrastructures in time are presented first. Second, a framework to integrate the outcomes of a stress test and data collected after disastrous events in life-cycle management of CIs is presented. Finally, this framework is demonstrated by means of a case study focused on the L'Aquila (Italy) gas network.

2 Life cycle management of CIs

Structures and civil infrastructure systems are subjected to time-varying environmental stressors. These stressors can be low-consequence persistent stressors such as aging, fatigue or corrosion, as well as high-consequence low-probability-of-occurrence stressors such as natural or man-made disastrous events. Both types of stressors may induce huge economic losses and result in significant environmental impacts on the community these CI systems serve. In order to increase the long-term performance of such systems against rare events and long-term degradation process, it is very important to implement adequate strategies for maintaining such systems during their lifetimes.

These activities may include periodic inspections, maintenance and retrofit actions, structural health monitoring, and performance and risk analysis (Frangopol and Soliman, 2016). However, the maintenance of the performance of these systems within acceptable limits imposes a significant cost, ultimately borne by the community these systems serve. Therefore, the maintenance actions must be rationally scheduled during the life-cycle of the systems using an integrated life-cycle management (LCM) procedure. The procedure should be able to consider simultaneously both the economic and the safety requirements.

In the following sections, different aspects of LCM are presented. These concepts include life cycle analysis and cost optimization, degradation processes and modelling as well as the role of structural health monitoring and inspection techniques in supporting life cycle management decisions. The review of the basic concepts of LCM is based mainly on the paper of Frangopol and Soliman (2016).

2.1 LIFE CYCLE ANALYSIS AND OPTIMIZATION

Nowadays, the maintenance of structures has become a key aspect of engineering of existing structures to extending their useful lifetime in the most sustainable way. By modelling the maintenance program of structures, an optimal timing and scope of interventions can be determined. The inspections and maintenance intervention are always constrained by available financial resources, so the problem of LCM is often formulated as an optimization under constraints (i.e. maximization of the efficiency of the interventions and/or minimization of the costs). So derived life cycle management program is based on the life cycle analysis (LCA) of the infrastructure, a single or multiple criteria life cycle optimization, and single or multiple criteria decision-making.

The life cycle analysis of a structure or an infrastructure system aims at evaluating the effects of time-varying environmental stressors, such as ageing, fatigue and corrosion, on its lifetime performance. It combines the deterioration models that describe the evolution of the failure probability, the loss of structural performance, or the loss of a certain structural characteristics in time with system performance indicators.

The term “performance” is generally used by engineers to describe certain characteristics of structures or system function. For example, structural performance is used to describe the response of a structure to certain loading scenario(s). The performance of structures and infrastructure systems deteriorates during its lifetime due to the effect of long-term mechanical and environmental stressors as well as due to the effects of rare but extreme events.

To evaluate the performance of a structure or a system, performance indicators (PIs) related to some structure or system properties or functions are usually adopted. Reliability, risk, robustness or redundancy have been widely used to formulate PIs within the last decades because PIs are usually based on identifying the probability of failure of the system. The reliability index, which is directly related to the probability of failure, quantifies the probability that the component, system or network will not fail. Risk is defined as the product between the probability of failure and the consequences of that failure. The redundancy of a structure, a system or a network describes the reserve capacity of the structure, the system or the network, that is, the capacity of the system to adapt or to continue to operate in a case of a failure of one of its components. An example of redundancy is the presence of electrical back-up generator in a gas regulation station or in a sewage treatment plant in order to continue to operate even if the electrical network fails. The robustness describes the capacity to withstand high stresses without significant damages or loss of performance.

The performance profile (performance indicator plotted against time) of a CI system resulting from the LCA allows planning the necessary interventions in order to maintain the structural performance at an acceptable level. Establishing the best maintenance, inspection and repairs schedules require a robust optimization process to integrate the damage occurrence and propagation models (i.e. the performance profile) and the previous knowledge on the safety and financial constraints (Frangopol and Soliman, 2016). Optimization represents the most important aspect of the LCM process. The complexity of this process depends on the scale of the problem (single structure or a system) and on the type of deterioration phenomena considered (long-term processes and/or extraordinary events).

The life-cycle cost (LCC) optimization is aimed at defining the most economical plan for inspection/repair to maintain the lifetime performance of a structure or a system subjected to multi-hazard excitations. The optimal intervention program may depend on several attributes such as monetary value, time factors, environmental measures and social impact (Ang and Tang, 1984).

The classic LCC optimization problem may be summarized by the following equation (Furuta et al. 2011):

$$Min\left(C_{ET}\right) \textit{ subjected to } P_{f,life} < P^{*}_{f,life} \tag{2.1}$$

where the aim is to minimize the total expected costs C_{ET} (which includes initial design and construction costs, preventive maintenance costs, inspection and repair costs), under the condition that the lifetime probability of failure $P_{f,life}$ (cumulative in time) is smaller than the maximum acceptable lifetime probability of failure $P^{*}_{f,life}$.

Many techniques have been already proposed in literature to devise an optimization process that enables finding the optimum inspection, monitoring, repair and retrofit schedule. Single or a multiple optimization procedure can be constructed to find the optimal intervention program. An example of a single objective procedure for a single structure is the procedure proposed by Kim and Frangopol (2011) where the optimal inspection times have been defined minimizing the damage detection delay. Multi-objective problems, such as the one proposed by Kim and Frangopol (2012), aim at defining the optimal number of inspections and inspection times minimizing the inspection costs.

The life-cycle costs may also vary according to the type of maintenance that is applied. There are two types of maintenance: the preventive maintenance (PM) that only has a small effect on the performance index; and the essential maintenance (EM) that restores the system performance to a level close to its initial condition. An EM may be very expensive to perform and may require the closure of the whole or a part of the CI system in order to full restore it, which generates further indirect costs. As a result, infrastructure managers may prefer to perform several PM actions along the life cycle of the structure. The effect of the two types of maintenance intervention are shown in Fig. 2.1. Whether to perform only the PM, the EM or both is a difficult question especially due to the presence of uncertainties associated to the performance prediction, deterioration rates, damage propagation, occurrence of extreme events and their effect, the effect of maintenance action on the performance (Frangopol and Soliman, 2016).

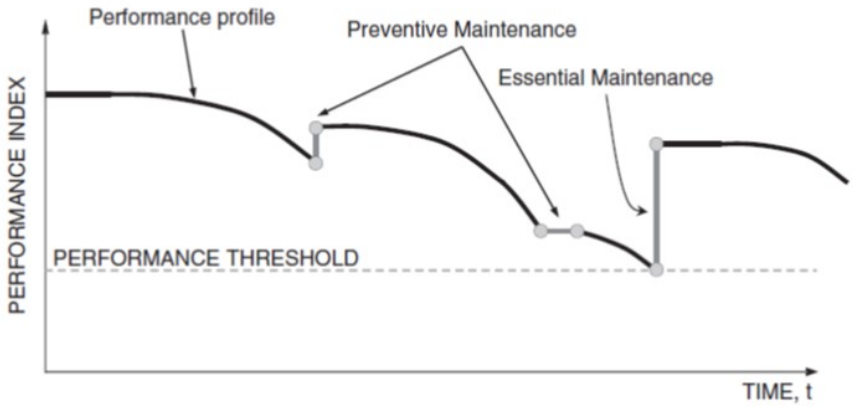

Fig. 2.1 Effect of different maintenance types on the system performance according to Frangopol and Soliman (2016).

2.1.1 Degradation processes and probabilistic models for life-cycle performance evaluation

The performance capacity of structures and infrastructure systems is not constant in time: several phenomena may contribute to reduce not only the capacity to perform but also the structural reliability and safety. A distinction is usually made between the persistent long-term degradation processes and extraordinary high-consequence low-probability (HC-LP) events (natural and man-made) that load the system only during a short period of time compared to its service life (Fig. 2.2).

The main three long-term effects, which may reduce the service life of systems, are:

1. Corrosion: it compromises the steel and steel-concrete structures through a chemical reaction with the oxygen in a humid environment. The steel transforms in oxide, which results in a section loss of the steel component and so in a weakening of the member.
2. Fatigue: it describes the cyclic loading that a structure or a structural member experienced. A cyclic load is typically induced by wind or traffic circulation.

3. Ageing: it describes all the other phenomena that influence the structural behavior such as the climate loads (freeze and thaw, daily temperature variations), shrinkage (volume reduction of the concrete through loss of water) and creep (deformation under constant loading).

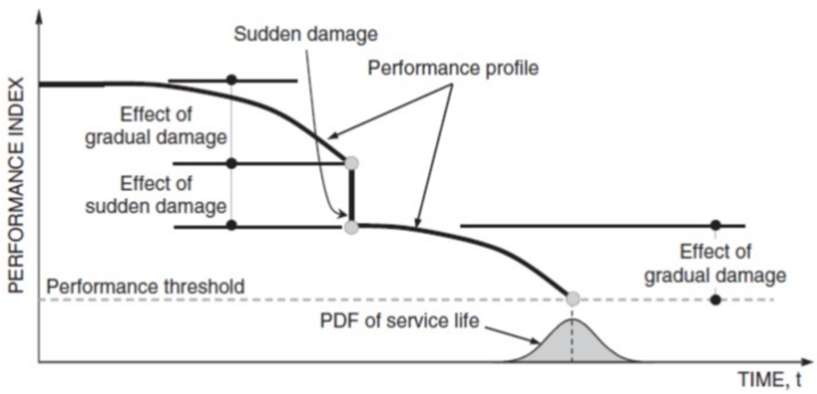

Fig. 2.2 Difference between long-term and extraordinary events on the performance of systems according to Frangopol and Soliman (2016).

Extraordinary events, such as natural hazards, usually load the system only during a short period of time. They can mostly be described as a shock or a shock series (e.g. earthquakes, tsunamis, mudslide, etc.).

Different models have been developed to characterize and predict the degradation process, especially to evaluate the effects of long-term processes[1]. Basically, the distinction is made between the random variables models, where the uncertainties related to the different characteristics (resistance and load) are modeled with random variables, and stochastic models that assume that deterioration over time is represented by a collection of random variables. Since the random-variable models consider the uncertainty at an evaluation time, these models are more static compared with the stochastic process model (Frangopol, et al. 2004).

The most widely used approaches in the random variable category are: the failure rate, the reliability index, and the time-dependent reliability models. In the failure rate model, the only random variable is the lifetime itself. This lifetime is represented by a cumulative distribution function $F(t)$ and an associated probability distribution function $f(t)$, and the failure rate can be expressed as:

$$r(t) = \frac{f(t)}{1 - F(t)} \tag{2.2}$$

In the reliability index model, the lifetime distribution follows from a limit state function *g* defined as the difference between the system or component's resistance R and the applied

[1] A detailed discussion of all the possible models is beyond the scope of this report. A more extensive description can be found in Frangopol, et al. (2004).

load or stress S in limit state space. The limit state function expresses the possible failure modes. It is evaluated for given values of stress and resistance. When the value of the state function is positive, the component or the system is considered to operate safely and it is unsafe when g<0. The points where g = 0 are limit states where failure is assumed to be imminent. The two variables are modeled as random variable and the state function can also be expressed as a function of time as the loads and the resistance can both vary in time. In the general case, the limit state function $g\left(X_1, X_2, ..., X_n\right)$ is considered, where the X_i; are *n* random variables.

The probability of failure is the total mass of the joint density for *g* in the failure region $\Omega = \left\{\mathbf{x} \mid g\left(\mathbf{x}\right) < 0\right\}$, as expressed in the following n-dimensional integral:

$$P\left(g\left(\mathbf{X}\right) < 0\right) = \int_{\mathbf{x} \in \Omega} f_{\mathbf{x}}\left(x_1, ..., x_n\right) dx_1 ... dx_n \qquad (2.3)$$

Since it is rarely possible to solve this integral analytically, simplified methods are usually adopted to approximate the probability of failure, such as the mean value first-order second-moment method (MVFOSM) or the first-order reliability method (FORM) that are based on the concept of the reliability index β. When the value of the reliability index is known, the probability of failure is approximated by calculating the value of the standard normal distribution at $-\beta$.

In the time-dependent reliability and condition index models, reliability and condition profiles are generated from random variables. The reliability profile is defined as the variation of the reliability index over time and it can account for different maintenance scenarios.

In case of lack of failure data, the deterioration process is usually modelled as a time-dependent stochastic processes $\left\{X\left(t\right), t \geq 0\right\}$ where $X\left(t\right)$ is a random quantity for all $t \geq 0$. Deterioration process is usually assumed to be a Markov Process. In a Markov Process, given the value of $X\left(t\right)$, the values of a time-dependent property at a time τ is independent of its value at the time *t,* where $\tau > t$. This means that the conditional distribution of future value of a given property given the present and the past, is independent of its past. The most useful classes for modelling stochastic deterioration are: discrete-time Markov processes having a countable state space called Markov chains, and continuous-time Markov processes with independent increments such as Brownian motion with drift and the gamma process.

2.1.2 Discussion

In the previous section some deterioration models were presented and their main aspects were discussed. A common observation to all the presented models is that high-consequence low-probability events have not been included. The models focus either on long-term degradation processes or on a certain type of natural hazard (earthquake or tsunami for example). The difficulty lies in the fact that the two mechanisms (slow degradation and sudden shocks) cannot be described with the same parameters as their nature and effect on systems are quite different, although some examples exists (Iervolino et al., 2013).

In fact, a solution to combine long-term degradation effects with earthquake shock through a gamma formulation has been prosed by Iervolino et al. (2013). The study is based on the damage accumulation process from ageing (continuous deterioration of material characteristics) and repeated overloading due to earthquake shocks. However, some of the model's assumptions bring limitations. First, it assumes that the occurrence of a seismic damage does not affect the progressive deterioration, which is not the case in practice: e.g. cracks induced by an earthquake tend to accelerate the corrosion in reinforced concrete structures. Second, the damage resulting from an earthquake is independent of both the age and deterioration amount of the system when the earthquake occurs. The effect of an earthquake hitting the structure twenty years after its construction will be the same as if the earthquake had occurred just after the end of the construction. As the relation between degradation and seismic performance of the structure may be nonlinear, this assumption is not conservative (the seismic performance will most likely decrease as the degradation processes progress).

2.2 LCC INCLUDING NATURAL HAZARD RISK

The main aim of a LCC is to predict the performance of a CI system subjected to all environmental stressors during its lifetime. However, it is noted that the seismic risk analysis, and natural hazard risk analysis in general, has not devoted enough attention to the structural maintenance optimization problem (Furuta et al., 2011), although some examples exist. In regions exposed to frequent catastrophic natural events, LCC optimization analysis should account for the effects of these hazards. The model proposed by Chang and Shinozuka (1996) represents one of the first attempts to include natural hazard (in particular seismic risk) in the LCA framework. The framework is shown in Fig. 2.4. It includes two innovative aspects:

i. First, in addition to the initial costs of construction and costs attributed to maintenance action, the costs due to service interruption are considered. The latter are called "user costs" that represent the societal costs that are imposed when the functionality of a system is reduced mostly during the routine maintenance work or the retrofit action. For example, during a maintenance intervention of a bridge, the serviceability of the road network (flow of goods and people) is reduced, imposing an increment of travel time for each user. The total extra travel cost due to the maintenance action represents the user cost.
ii. Second, the expected costs associated to seismic risk of a CI system (i.e. discount cost for seismic retrofit and damage/repair costs) during the lifecycle of a structure or a system are combined with the initial capital and discounted maintenance cost.

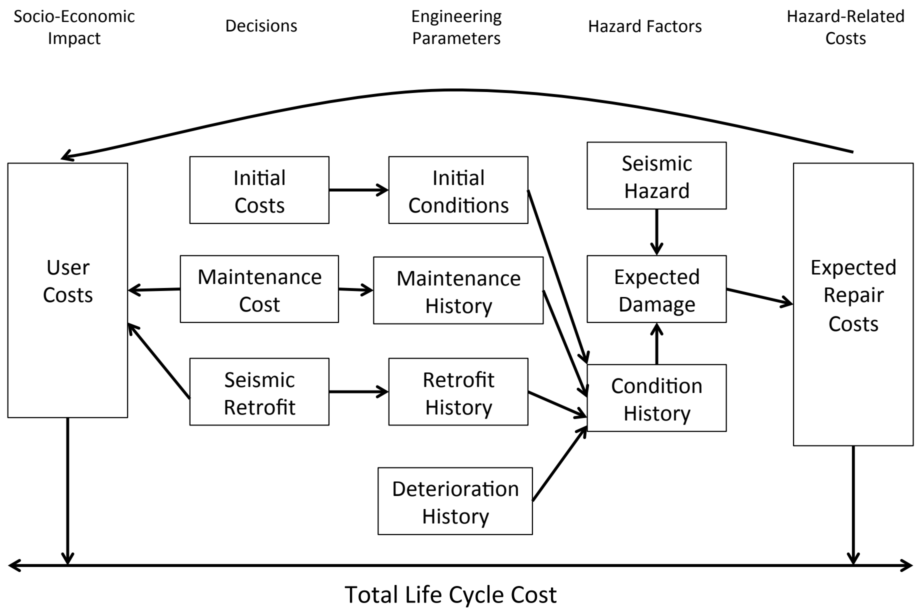

Fig. 2.3 Life-Cycle Cost framework including natural hazard risks adapted from Chang and Shinozuka (1996).

The life-cycle costs *C* is divided in four categories as expressed in the following equation:

$$C = C_1 + C_2 + C_3 + C_4 \qquad (2.4)$$

Where C_1 and C_2 represents the planned costs, C_3 and C_4 the unplanned costs.

Planned costs to owners (C_1) involves initial construction, subsequent expected discounted maintenance costs and discounted seismic retrofit costs, considering that a seismic retrofit is only applied once in the lifetime of a structure. In addition to planned costs paid by the owner of the structure/infrastructure system, maintenance and seismic retrofit actions may also impose user costs (C_2) due to the interruption of normal service (e.g. travel delay in a road network). This cost imposed to the society is function of the extent and the duration of the usage disruption during the maintenance activities and the retrofit action.

In addition to the costs associated to maintenance and design choices (planned costs), the framework includes unplanned life cycle costs related to the structural performance and associated repair costs due to a seismic event. Unplanned costs to owners (C_3) consist of expected discounted repair costs of earthquake damage over the life span of the structure. These costs are evaluated performing a probabilistic seismic risk/performance analysis of the system, conditional to its physical state at time t. The performance evaluation changes over time due to natural deterioration as well as mitigation actions. The unplanned hazard-related user costs (C_4) constitute the final category of this life-cycle cost framework and they are also based on a probabilistic condition/performance analysis of the system under study. These user costs are related to the service disruption due to earthquake damage and repairs and depend on the expected duration of repair/reconstruction activity over the life span of the structure.

2.3 ROLE OF STRUCTURAL HEALTH MONITORING (SHM) AND INSPECTION INFORMATION

The aim of Structural Health Monitoring (SHM) is to provide a diagnosis of the “state” of the constituent components and the entire system at every moment of the lifecycle of a structure or system, which helps to better understand the behavior and the state or the actual performance of the system. In addition to providing information about its performances, it can also provide a prognosis (e.g. evolution of damage, residual life, etc.) thanks to the continuous real-time monitoring of the state of the structure. SHM can be used to detect damage in structures or systems at an early stage, before an inspection. Many of the used approaches rely on vibration-based methods: the change in the dynamic response of the monitored structure represents a good indicator of damage occurrence (Frangopol and Soliman, 2016). SHM involves the integration of sensors, data transmission, computational power, and processing ability inside the structures. It makes it possible to reconsider the full management and maintenance plan of the structure itself by aiming to replace scheduled and periodic maintenance inspection with performance-based (or condition-based) short- and long-term maintenance.

Nowadays, SHM is especially used in railways steel bridges to evaluate the loss of performance due to fatigue or to determine their natural frequency. Sensors’ networks are also used in large dams to better understand the behavior of the dams that is largely dependent on the level of the reservoir and thus highly seasonal. In the case of complex CI systems and networks of systems, a variety of tools are adopted to evaluate in real time the network state, performance or level of service and safety.

Information gathered from SHM and non-destructive inspection on the current state of the structure can be also used to update performance prediction models adopted in the LCM to define the maintenance plan. This updated performance prediction will then result in an updated maintenance intervention schedule as shown in Fig. 2.3.

Because of unavoidable uncertainties related to the inspections and the SHM information, the updating is a crucial process. Several approaches for updating performance prediction models have been proposed in the last years. Most of them rely on Bayesian updating of model parameters. In this process, the information gathered is used to evaluate the posterior distribution of model parameters, combining the likelihood function with the prior information on these parameters (Ang and Tang, 2007).

The use of monitoring systems into the LCM of structure and infrastructures provides major benefits, such as automatic damage detections that can help to avoid significant losses to the monitored structure. However, its use of SHM brings additional costs (personal and material costs) to the life cycle management process. Therefore, an optimal economic balance between the potential amount of information that can be provided by the SHM and its associated cost should be sought.

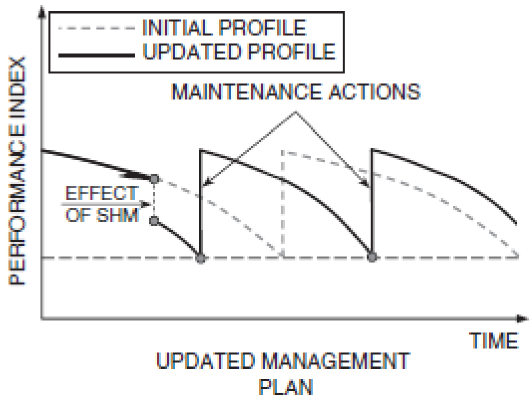

Fig. 2.4 Update management plan based on SHM or inspection information as introduced by Frangopol and Soliman (2016).

3 Unified life cycle management of CI

3.1 PROPOSED FRAMEWORK

Through the life cycle of the CI, systems operators have the objective to maintain the infrastructure systems and mitigate degradation of system components over time all the while achieving an economically justified operation of the system. To this aim, as illustrated in the previous chapter, LCC and optimization tools are usually adopted to predict the performance of an infrastructure subjected to long-term degradation process during its lifetime and planning maintenance interventions. However, in regions exposed to natural events, LCC analysis should also take into account the effects of extreme natural events that may increase the probability of failure or loss of functionality during their lifetime.

In the STREST project, a multi-level framework ST@STREST (Deliverable 5.1, Esposito et al., 2016) has been proposed with the aim of providing a multi-level systematic and harmonized approach for the evaluation of the performance of these systems against extreme and disastrous natural events. The framework is composed of four main phases and nine steps to be conducted sequentially (Fig. 3.1). In the Pre-Assessment phase (Phase 1) all the data available on the CI and on the phenomena of interest (hazard context) are collected. Then, the goal (i.e. the risk measures and objectives), the time frame, the total costs of the stress test and the most appropriate Stress Test Level to apply to test the CI are defined. In the Assessment phase (Phase 2), the stress test is performed at Component and System Levels. The performance of each component of the CI and of the whole system is checked according to the Stress Test Level selected in Phase 1. In the Decision Phase, the stress test outcomes are determined i.e. the results of risk assessment are compared with the risk objectives defined in Phase 1. In particular, a stress test grade is assigned and the global outcome is determined by employing a grading system. Further, a penalty system is also proposed to define how reliable the results of the stress test are, and in case it is needed, to penalize simplistic approaches that cannot guarantee an accurate analysis. Then, critical events, i.e. events that most likely cause a given level of loss value are identified through a disaggregation analysis. Finally, risk mitigation strategies and guidelines are formulated based on the identified critical events. In the Reporting Phase the results are presented to CI authorities and regulators.

In order to increase and optimize the long-term performance of CIs, the outcomes and findings of a stress test (e.g. results of risk analysis and identified risk mitigation strategies) should be included in the long-term maintenance plan of a CI. Results of the risk analysis (i.e. Assessment phase, Phase 2) in terms of system performance and expected costs of natural events may be incorporated in a LCC analysis and optimization problem. Furthermore, the evaluation of risk reduction strategies (Decision Phase) may make it possible to reconsider the full management and maintenance plan of the CI itself.

Therefore, the possibility to include the data on the current state of a CI in the aftermath of an actual disastrous event is another important aspect of the proposed framework. The state of civil infrastructures after the occurrence of a natural event is usually assessed through rapid visual inspection or automatic screening tools (e.g. close-circuit television). Through the use of standardized survey forms (e.g. EERI, 1996), data on the typology, location, component's features and the assessed physical damages are then collected to provide an estimate of the extent of the service disruption, costs and repair times and to define the repair/replacement strategy to apply. At the same time, the processing of these data can be useful to update the state condition history of the inspected components of the CI and for estimating and/or updating of the performance prediction models used in the risk analysis.

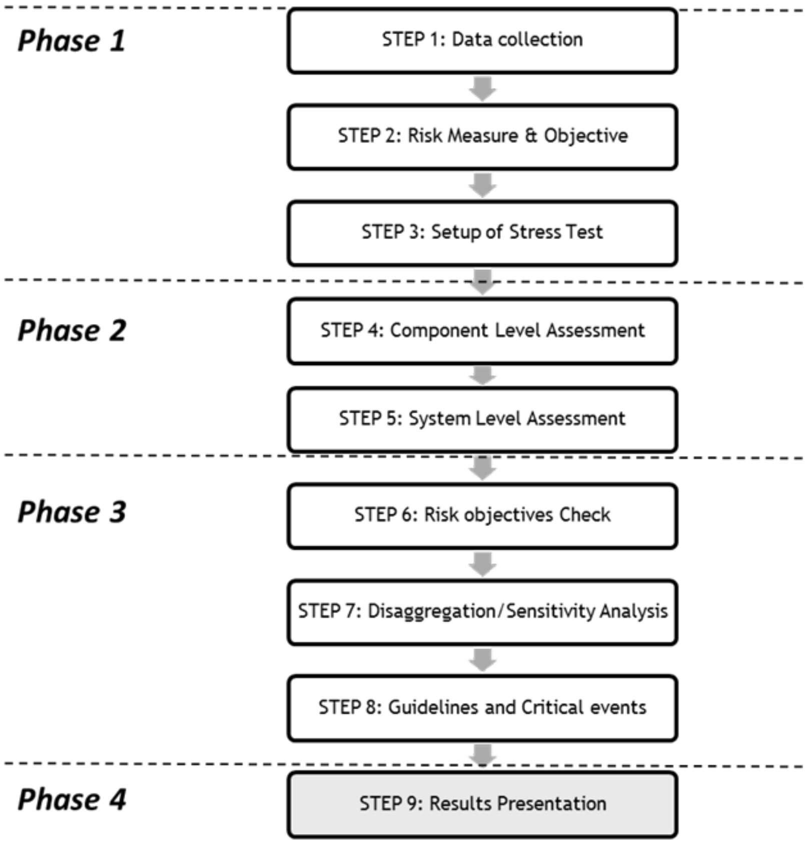

Fig. 3.1 Workflow of the ST@STREST methodology (from Deliverable 5.1, Esposito et al., 2016).

In this section, a framework to integrate stress test outcomes and findings and data gathered from post-event damage survey into a unified life-cycle management strategy is proposed and discussed. In particular, an extended version of the model proposed by Chang and Shinozuka (1996) (shown in Fig. 3.2), is herein is proposed. The proposed framework aims to include the stress test outcomes (i.e. loss curves, safety assessment and risk mitigation strategies) and information that can be retrieved from post-event damage survey into a life cycle cost evaluation and optimization procedure.

As an illustrative example, the case study of L'Aquila (Italy) gas network, is further presented to analyze and discuss in more details some aspects of the proposed framework.

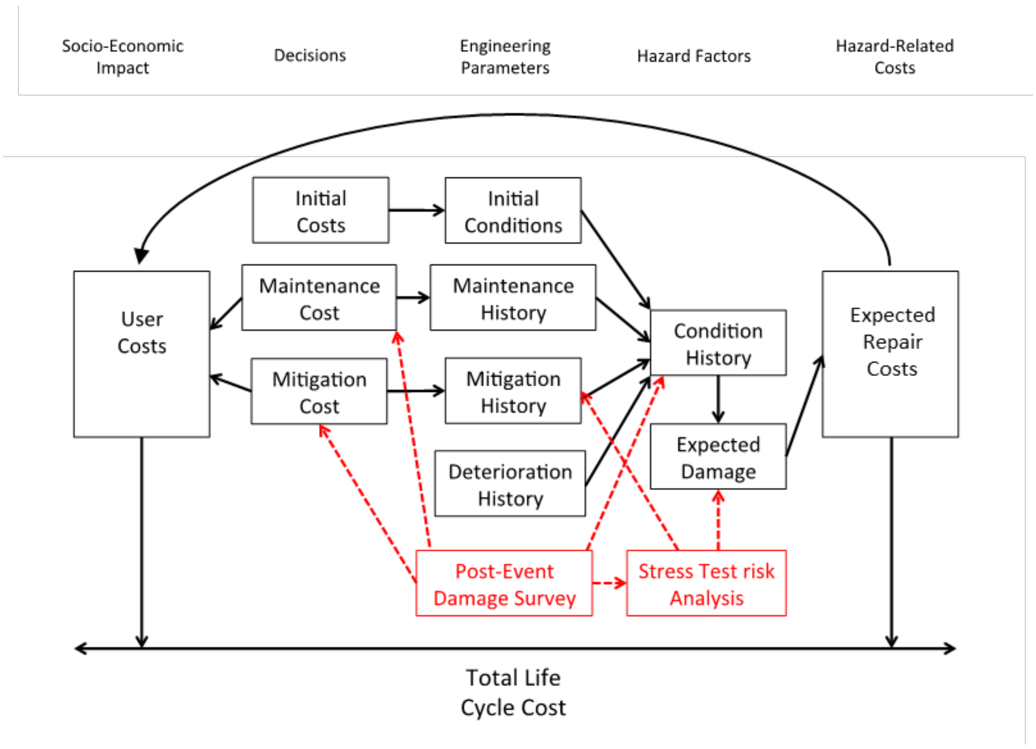

Fig. 3.2 Proposed framework for assimilating stress test and post-event data in a total life cycle cost analysis

3.2 LIFE CYCLE ANALYSIS INCLUDING STRESS TESTS

In order to optimize the life-cycle costs in a CI management strategy, the outputs of a stress test are going to be considered in the proposed framework.

As shown in Fig. 3.2, the outcomes of a Stress Test have an impact on:

- *Expected damages*: unplanned life cycle costs related to the structural performance and associated repair costs due to extreme natural events. A stress test allows to evaluate the performance of the CI against extreme natural events (according to the ST-Level adopted). In this way is possible to quantify the expected costs caused by extreme natural events and then evaluate the associated unplanned owner and user costs (C_3 and C_4 in equation 2.4) to be included in the LCC analysis and optimization.
- *Mitigation history*: another outcome of a stress test is represented by the evaluation of risk reduction strategies based on a disaggregation analysis (Decision Phase, Phase 3). A disaggregation analysis is aimed at obtaining the probability that a specific value of a variable involved in the risk assessment is causative for the exceedance of a loss value of interest. The loss may be disaggregated with respect to system’s response, which may help identifying the component the damage of which most likely causes the exceedance of the loss value of interest. Then, risk mitigation strategies are formulated based on the results of the disaggregation analysis with the aim of increasing the long-term performance of CIs.

3.2.1 Stress test and mitigation strategies

In order to analyze how the outputs of a stress test may be incorporated in the life cycle management of a CI, the proposed framework is applied to the case study of L'Aquila (Italy) gas network. First, a Stress Test Level 2a is performed on the L'Aquila network as it was before the 2009 earthquake event to assess the performance of the network due to earthquake hazard. Then, a disaggregation analysis is performed and possible risk mitigation strategies are identified. Finally, in order to evaluate the consequences of the risk reduction actions (e.g. seismic retrofit of some components of the gas network), the seismic performance of the gas network was assessed again, and results of the risk analysis were compared with the risk objectives identified at the beginning of the stress test.

3.2.1.1 Application to a gas network (case study)

STRESS TEST- Phase 1

Data collection

The L'Aquila gas network is 621-km long that supplies five municipalities. The network is divided into two pressure distributions: mid-pressure (234 km) and low-pressure (387 km). The pipelines are either made out of steel or high-density polyethylene (HDPE), and have nominal diameters varying from 25 to 400 mm. The network is connected to the high-pressure national gas distribution through 3 M/R Stations. The latter are one-story reinforced concrete buildings with steel roofs, which are equipped with not anchored internal regulators and mechanical equipment. The connection between the mid and low-pressure pipes is done via 300 buried reduction groups (RGs) and enables the supply of the end users.

For the purpose of the case study, the medium pressure (MP) portion of the system, shown in Fig. 3.3, has been selected. It includes the three M/R stations, 209 RGs, and pipelines at mid pressure (steel and HDPE pipes). All the physical and operational characteristics of the network have been collected and stored through a geographic information system. Detailed information on the database are available in Esposito (2011).

Risk Measures and Objectives

Risk is herein expressed in terms of annual probability of exceedance of service disruption levels, measured by a connectivity-based performance indicator (PI), i.e. the Connectivity Loss CL, (Poljansek et al. 2012). It measures the average reduction in the ability of demand nodes (i.e. RGs) to receive flow from source nodes (i.e. M/R stations):

$$CL = 1 - \left\langle \frac{N^i_{source,dam}}{N^i_{source,orig}} \right\rangle \tag{3.1}$$

where $N^i_{source,orig}$ is the number of source nodes connected to the *i*th demand node in the original (undamaged) network , $N^i_{source,dam}$ is the number of source nodes connected to the *i*th demand node in the damaged network and $\langle\ \rangle$ denotes averaging over all demand nodes.

Risk boundaries for the case study (Fig. 3.4) have been defined in terms of F-N limits, according to the equation reported in Deliverable 5.1 (Esposito et al. 2016), i.e.:

$$1 - F_N(x) < \frac{C}{x^n} \tag{3.2}$$

Since no regulatory boundaries (AA-A, A-B and B-C) exist for Italian gas systems, indicative *C* and *n* parameters for each of the three lines have been defined (Table 3.1)

Table 3.1 *C* and *n* parameters used for the case study (Eq. 3.1).

Boundary	*C*	*n*
AA-A	10^{-4}	1
A-B	$10^{-3.4}$	1
B-C	$10^{-3.1}$	1

Set-up of the Stress Test

Among the stress test levels proposed within STREST, the ST-Level 2 has been selected for the case study. In particular, a probabilistic single hazard (seismic hazard) analysis without epistemic uncertainty (ST-Level L2a) is undertaken at the system level.

STRESS TEST- Phase 2

Component Level Assessment

Not considered in this application study.

System Level Assessment

For the purposes of the System Level assessment, a simulation-based connectivity analysis was performed[2]. Analyses were carried out with a purpose-made object-oriented model of interconnected infrastructural systems (Franchin and Cavalieri, 2013), within which a prototype software for the seismic risk assessment of gas systems has been developed (Esposito et al., 2015). Considering that the function of the MP gas network is to deliver gas to RGs, the network performance was assessed evaluating the availability of end nodes (RGs) of the L'Aquila system.

Both transient ground deformation (TGD) and permanent ground deformation (PGD) hazards were evaluated. In particular, the Paganica fault was considered for the generation of characteristic earthquakes of (fixed) moment magnitude M_W equal to 6.3 and return period equal to 750 years (Pace et al., 2006). It is a normal fault type and is thought to have triggered the 2009 earthquake. Data on fault geometry (Fig. 3.2) are those of Chioccarelli and Iervolino (2010). Given the magnitude, the simulation of the event on the fault was in terms of the epicenter location, which was assumed as uniformly distributed.

The ground motion intensity for the primary intensity measure (peak ground acceleration, PGA) was evaluated using the Akkar and Bommer (2010) ground motion prediction equation (GMPE) on a regular grid of points discretizing the region covered by the network. The

[2] A more detailed description of the methodology adopted for the seismic risk analysis, corresponding to the initial state of the network, may be found in Esposito et al. (2015).

spatial correlation for intra-event residuals of PGA is that by Esposito and Iervolino (2011). Given the primary IM, the secondary IM (peak ground velocity, PGV) for each site of interest was obtained via the conditional hazard approach (Iervolino et al., 2010).

GMPE-based amplification factors were considered to account for local site conditions. To this aim a geological analysis of the region was performed and the average shear-wave velocity between 0 and 30-meters depth (Vs30) was associated to each site of the network. This makes it possible to compute the PGA_s and PGV_s values.

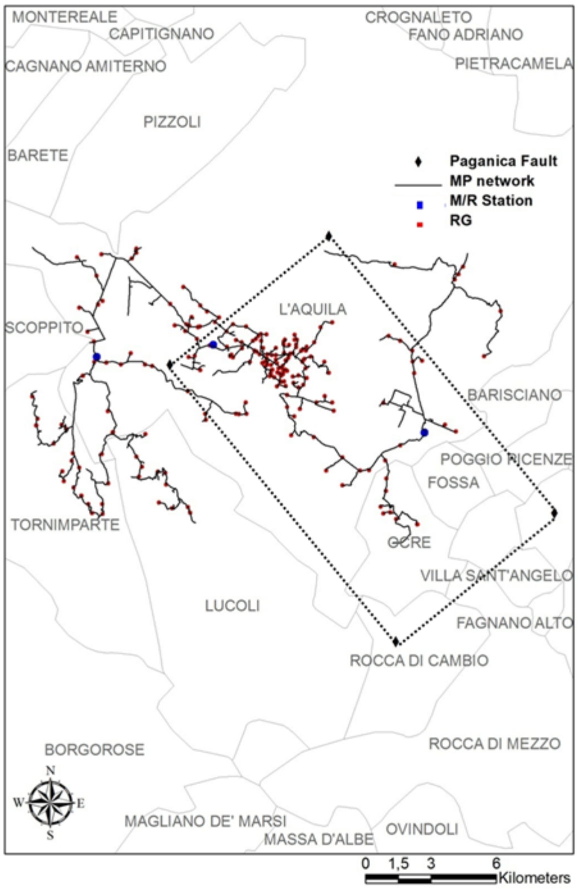

Fig. 3.3 L'Aquila gas network (from Esposito et al., 2015).

Regarding the permanent ground deformation hazard, the landslide potential of region where the network deployed was evaluated. In particular, overlying the slope angle, groundwater and lithology class maps, it was possible to draw a map of the landslide susceptibility, which was finally transformed, into the critical acceleration map according to the HAZUS methodology (FEMA, 2004). In each run the resulting displacement (PGD_{land}) is finally calculated via the Saygili and Rathje (2008) empirical model.

Pipelines and M/R stations were considered the vulnerable elements within the network. To estimate earthquake-induced damage, fragility models have been selected for typology of the two components. In particular, for buried pipelines, Poisson repair rates functions of PGV_s and PGD_{land} were selected in ALA (2001) for each pipe material (steel and HDPE) and diameter. For the M/R stations, a lognormal fragility curve for unanchored compressor stations was adopted (FEMA, 2004). These have median equal to 0.77g and 0.65 standard deviation (of the logarithms). Vulnerability to geotechnical hazards of the M/R stations was not considered since geotechnical analysis resulted in negligible susceptibility of the corresponding sites. The vulnerability of reduction groups was instead neglected.

Regarding the system performance, a connectivity analysis was performed; i.e., the system is considered functional if RGs remain accessible from at least one M/R station. To this aim, it was assumed that a pipe segment cannot deliver gas when the segment has at least one break, while for the supply node it was assumed that it loses its connectivity when it is in *extensive damage state*, according to the adopted fragility model.

Results indicate that the expected value of connectivity loss given the occurrence of an earthquake on the considered fault is 0.66, i.e. it is expected that the average reduction in the ability of demand nodes to be connected to M/R stations is 66% when a M_w 6.3 event occurs on the Paganica fault.

Results in terms of annual exceedance curve of the assessed performance loss are shown in Fig. 3.4 (yellow dashed line). The annual rate of exceedance of the CL has been obtained by multiplying the complementary cumulative density function (CCDF) shown in Esposito et al. (2015) by the rate of occurrence of the simulated earthquake, i.e. 1/750.

STRESS TEST- Phase 3

Risk objectives Check

According to the grading system proposed in ST@STREST (Deliverable 5.1, Esposito et al., 2016), the gas network obtains grade B, meaning that the risk is possibly unjustifiable and the CI partly passes the test. In fact, the point of the (yellow dashed) curve that is farthest from the F-N limits, is between the grade B and grade C boundaries. In particular the loss curve is in the B zone for moderate-high values of CL, i.e. for $0.32 \le CL \le 0.74$.

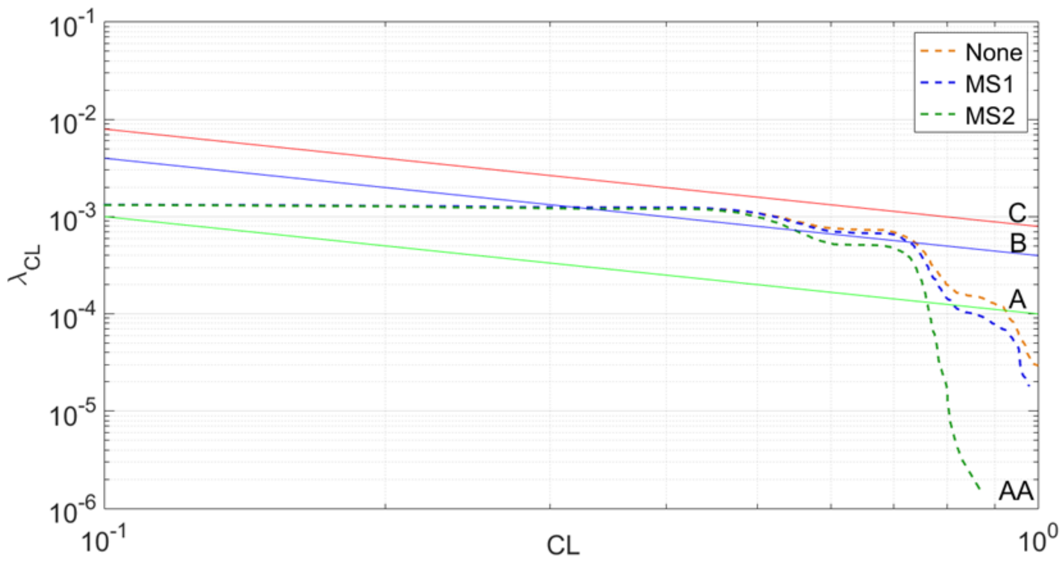

Fig. 3.4 Annual rate of exceedance of PI CL considering the initial state of the network (None), anchored components of the M/R stations (MS1), seismic retrofitting of the M/R building (MS2).

Disaggregation analysis

In order to evaluate the contribution of certain components on the overall performance of the network, a disaggregation analysis has been performed. In particular, the distribution of the number of broken pipes and damaged M/R stations conditional to the performance of the network (i.e. conditional to the occurrence of CL in 10 intervals CL) are shown in Fig. 3.5.

As already discussed in Esposito et al. (2015), the M/R stations conditional to large losses (high values of CL) results peaked toward a large number of damaged M/R stations. The distributions of number of broken pipes, conditional to the performance of the network, instead seems more flat, with several specific numbers of breaks with comparable contribution to the performance levels.

<u>*Guidelines and Critical events*</u>

In this case, the performance values that are farthest from the A-B boundary (blue line) are the moderate-high ones. Since the disaggregation analysis showed that the components that more contribute to the high values of the performance are the M/R stations, two strategies, based on the improvement of the seismic response of the stations, are suggested to mitigate the seismic risk to the network.

In particular, the risk mitigation strategies are:

- MS1: Anchoring of the equipment inside the M/R station
- MS2: Seismic retrofit of the housing of the M/R station (i.e. considered not vulnerable)

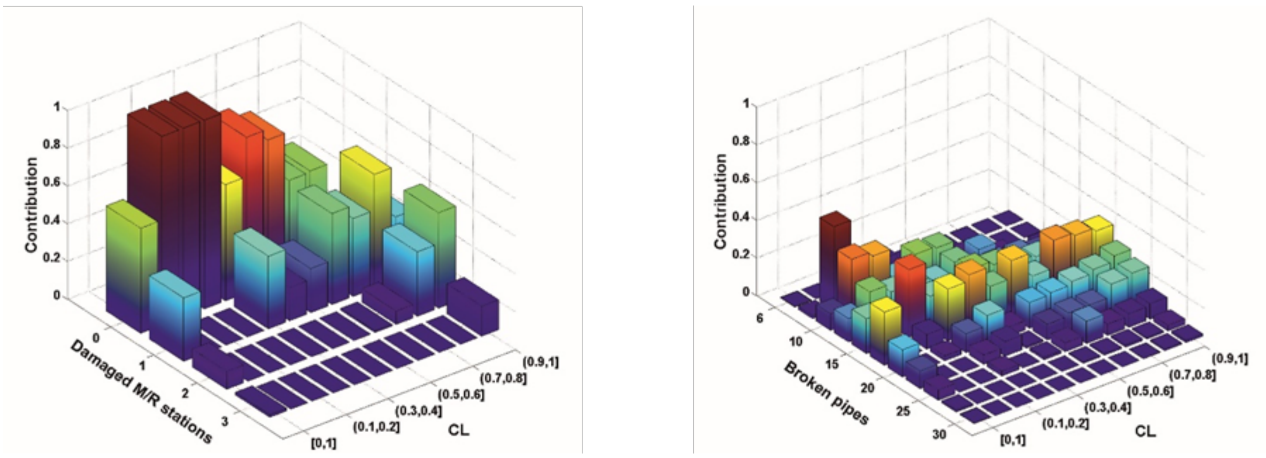

Fig. 3.5 Relative frequency of the number of damaged M/R stations and broken pipes conditional to CL (from Esposito et al., 2015).

3.2.1.1.1 Mitigation strategies and impact on the system performance

In order to evaluate the consequences of risk mitigation actions, the seismic risk of the gas network was re-assessed considering the upgraded condition of the M/R stations. In particular, the fragility curves of the three M/R station cabins were modified according to the new condition of the M/R stations.

For the MS1 option, lognormal fragility curves for the low-rise reinforced concrete structures with anchored components (Pitilakis et al., 2014) were adopted. These have median equal to

0.8 g and 0.5 standard deviation (of the logarithms) for the extensive damage state. For the MS2 option, the three stations were considered as not vulnerable.

Results of the two risk analysis indicate that the expected value of connectivity loss given the occurrence of an earthquake on the considered fault is 0.63 considering the MS1 strategy and 0.57 for the MS2, corresponding to an improvement of the system' performance of 3% and 11% respectively. The corresponding expected annual performance (EAP) respect to the initial state condition of the network (red point) and after the application of the two mitigation strategies (black points) is shown in Fig. 3.6. The EAP has been obtained multiplying the expected complementary value of CL given the occurrence of an earthquake, by the rate of occurrence of the simulated earthquake, i.e. 1/750[3].

In terms of annual exceedance rates of the network performance, the resulting loss curves for the two mitigation actions are shown in Fig. 3.4 (blue and green dashed lines, respectively). Both mitigation actions implied an improvement of the system's performance, especially for high connectivity losses. The MS2 had an impact on the decreasing of the annual exceedance curve for CL> 0.6, overcoming the grade A boundary at about CL= 0.72. The impact of the MS1 starts instead from CL=0.5 with the overcoming of the grade A boundary at about CL= 0.55.

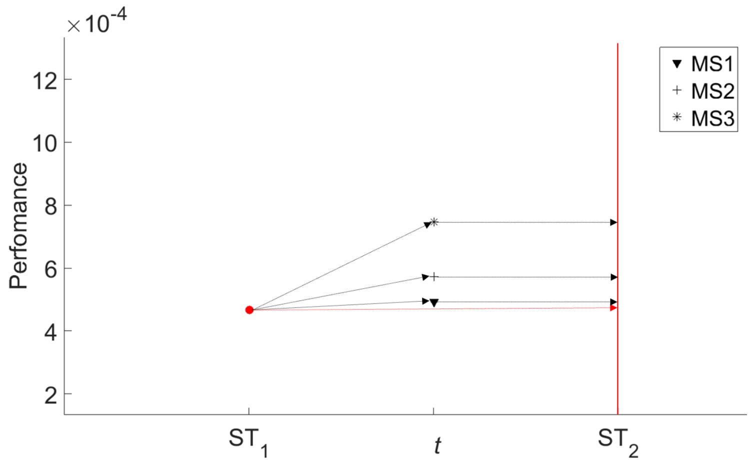

Fig. 3.6 Expected annual performance as result of a stress test at time T=1 (red point) and after the application of mitigation strategies (black points).

3.2.1.1.2 Discussions

Although the two mitigation actions implied an improvement of the system's performance, the resulting grade of the stress test is still B. This is because, according to the grading system proposed, the farthest point from the F-N limits is still between the B and C grade boundaries for both loss curves.

The B grade corresponds to a zone where the risk is considered "*tolerable only if risk reduction is impractical or if its cost is grossly disproportionate to the improvement gained*" (Helm, 1996). This means that the risk is tolerable as long as all reasonably practical steps are taken to reduce the risk further. Therefore, possible alternative mitigations actions aimed

[3] Under the hypothesis that the occurrence of earthquake events and the loss are independent.

at reaching the grade A, where the risk is considered "*tolerable if cost reduction would exceed the improvement gained*", should be investigated before the next stress test. At the same time, the costs associated to each mitigation strategy must be evaluated. In fact, the applicability of a risk reduction action depends both on the benefits (i.e. the improvement of system performance) and the associated investment costs.

For the specific case study, possible alternative mitigation actions should be more focused on the improvement of moderate values of the system's performance, i.e. CL between 0.3 and 0.7 rather than on the higher or lower values. To this aim, a mitigation strategy MS3 aimed at improving the seismic behavior of buried pipelines was investigated.

As an illustrative example, the extreme case of the improvement of the seismic behavior of all the pipes of the network is herein considered. In particular, the corrosion resistance of steel pipes was improved protecting them by coating while the resistance HDPE pipes subjected to slow crack growth was restored. As a consequence, the fragility functions of pipes were modified according to the new conditions. HDPE were considered not vulnerable while for steel pipes, the ALA (2001) fragility curves for buried pipes in non-corrosive soil conditions were adopted.

The expected value of connectivity loss given the occurrence of an earthquake on the considered fault is 0.44, corresponding to an improvement of the system' performance of 32%. The corresponding EAP is shown in Fig. 3.6.

Results of the risk analysis in terms of annual exceedance rates of the network performance are shown in Fig. 3.7 (grey dashed line). In this case, the resulting stress test grade is A since the farthest point from the F-N limits is between the grade A and grade B boundaries. In fact, although the annual exceedance rate of high losses has slightly increased with respect to MS2, the mitigation strategy applied to buried pipes implied a decrease of the annual rate of moderate performance values. This, according to the grading system proposed implies a "pass" result of the stress test.

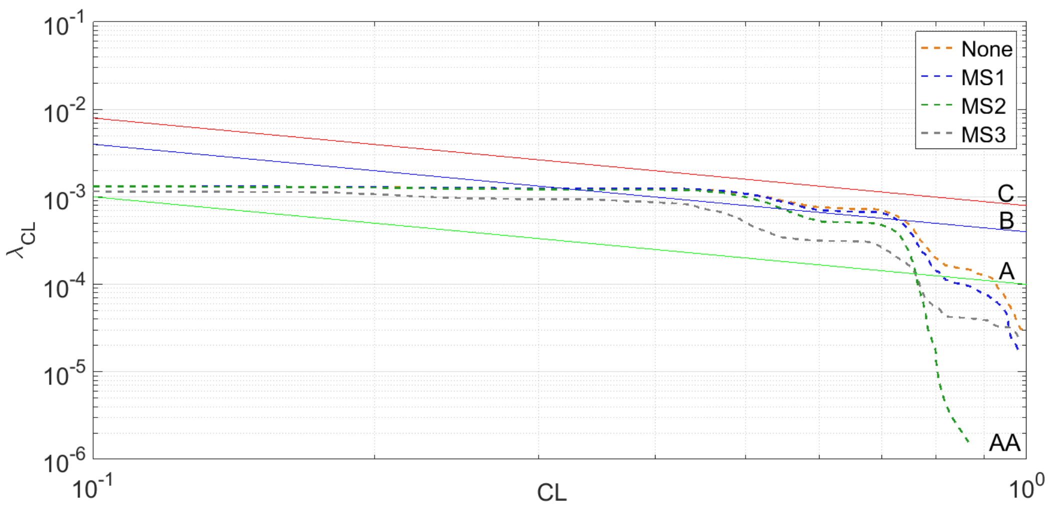

Fig. 3.7 Annual rate of exceedance of CL considering mitigation strategies applied to the M/R stations (MS1 and MS2) and to buried pipelines (MS3).

3.3 LIFE CYCLE ANALYSIS INCLUDING POST-EVENT DATA

Another important aspect of the proposed framework is represented by the use of collected data on the state of a CI in the aftermath of a disastrous event.

As shown in Fig. 3.2, the information gathered for post-event inspection and survey has an impact on:

- *Condition history:* after a disastrous even, new information about the CI is available. Through the collection and the processing of on-site data the state condition of the inspected components of the CI may be updated.
- *Risk analysis:* information gathered after the occurrence of a natural disaster can be used to estimate and/or update performance model parameters adopted in the risk analysis through the use of statistical regression methods or the more advanced Bayesian approaches.
- *Mitigation history:* the main purpose of post-event damage surveys is to assess the functionality of system's components and the repair/replacement strategy to apply.
- *Maintenance costs*: the updated state condition of the CI may be used to redefine the intervention maintenance schedule, i.e. to determine whether a maintenance action is needed or not.

3.3.1 Performance's Update using Post-Event Seismic Damage data

Information gathered after the occurrence of a natural disaster can be of extreme importance for the estimation and/or updating of performance prediction models adopted in the risk analysis. Through the gathering and the processing of the post event damage data, it is possible to derive empirical estimate of performance models (Basoz et al., 1999, Shinozuka et al., 2000; O'Rourke and So, 2000).

Statistical regression methods or more advanced Bayesian approaches can be used to estimate model parameters. In particular, Bayesian procedures are adopted to update model parameters estimates when new data becomes available, combining the likelihood function with the prior information on these parameters (Straub and Der Kiureghian, 2008). This approach has also the ability to handle all types of information and to include engineering expert opinion through a prior distribution.

In the following section, an example of empirical estimation and Bayesian updating of a fragility model for buried pipelines is provided.

3.3.1.1 Application to buried pipelines (L'Aquila case study)

Empirical fragility functions for buried pipelines are usually expressed in terms of average repair rate, R_R, evaluated as the number of pipeline repairs in an area divided by the length of the pipelines in the same area. Then, using a Poisson probability distribution and R_R as its parameter, one can assess the probability of having any number of damages in a pipe segment, given the local hazard intensity. Since buried pipelines are sensitive to both transient ground deformation (TGD) and permanent ground deformation (PGD) hazard

(Toprak and Taskin 2007), repair rates are usually expressed as a function of TGD and/or PGD ground motion intensity measures (or IM), such as PGV, PGA, PGD.

Data on pipeline failures collected in past earthquakes are usually processed to evaluate the empirical estimations of repair rates through regression analysis. An alternative way to fit fragility curves through the empirical data set is Bayesian Estimation. Bayesian methods provide an alternative to classic regression analysis of data that can be particularly effective for the assessment of seismic fragility based on field observations.

As an illustrative example, pipeline damage data retrieved after the 2009 L'Aquila earthquake have been herein used to estimate a fragility function for buried steel pipes caused by seismic ground shaking (TGD hazard).

A Bayesian estimation model along with the use of Importance sampling technique for numerical efficiency has been adopted to estimate the parameters of the fragility function considering as a-priori distribution of the model parameters a non-informative one (for more details see Appendix G in (ALA, 2001)).

Table 3.1 presents pipeline damage data for steel pipes from L'Aquila gas network for the 2009 earthquake (Esposito et al., 2013). Each data point is for a homogeneous length of pipeline *L* that experienced a range of peak ground velocity, PGV (cm/s) and *n* pipe repairs.

The available dataset does not allow a differentiation of the pipe sizes and joint type, therefore a two parameter model (Eq. 3.3) has been adopted as interpolation model:

$$R_R = a \cdot PGV^b \tag{3.3}$$

where *a* and *b* are the parameters to estimate.

To perform the Bayesian updating analysis, a prior distribution needs to be selected. In this case, since a prior information on the parameters is not available, a non-informative a-priori distribution has been used, which for the case of positive-valued parameters, is proportional to their reciprocals (Box and Tiao 1992).

Then, the likelihood function needs to be formulated by evaluating the conditional probability of the available data (listed in Table 3.2), given the set of parameters (*a* and *b*). The posterior distribution of the model parameters is then determined combining the information contained in the prior, with the information contained in the likelihood function.

Table 3.3 lists the posterior means, standard deviations and correlation coefficients of the model parameters estimated with an accuracy of 5%. In particular, the covariance of the mean values of both parameters reached a value of 5% after five set of runs.

Fig. 3.8 shows the results of the Bayesian estimation for all set of simulations. The results of the estimations are compared with a pipeline fragility relation considered suitable (in terms of pipe material and diameter) for the L'Aquila gas network, i.e. the ALA (2001) for steel arc welded pipes, expressed in the following equation:

$$R_R = K_1 \cdot 0.002416 \cdot PGV \tag{3.4}$$

where R_R is in 1/km, PGV in cm/s and K_1 represents the modification factor according to pipe material (for steel arc welded pipes, K_1 is 0.6).

Table 3.2 Pipeline damage data for steel pipes after the 2009 L'Aquila earthquake (Esposito et al., 2013).

PGV [cm/s]	L [km]	n
22	5.49	1
24	8.58	0
26	15.27	2
28	38.26	5
30	46.71	7
32	17.89	1
34	11.24	1

Table 3.3 Posterior statistics of parameters a, b for steel pipelines.

Parameter	μ	σ	ρ	
			a	b
a	0.0876	0.0380	1.0	-0.791
b	0.1164	0.1520	-0.791	1.0

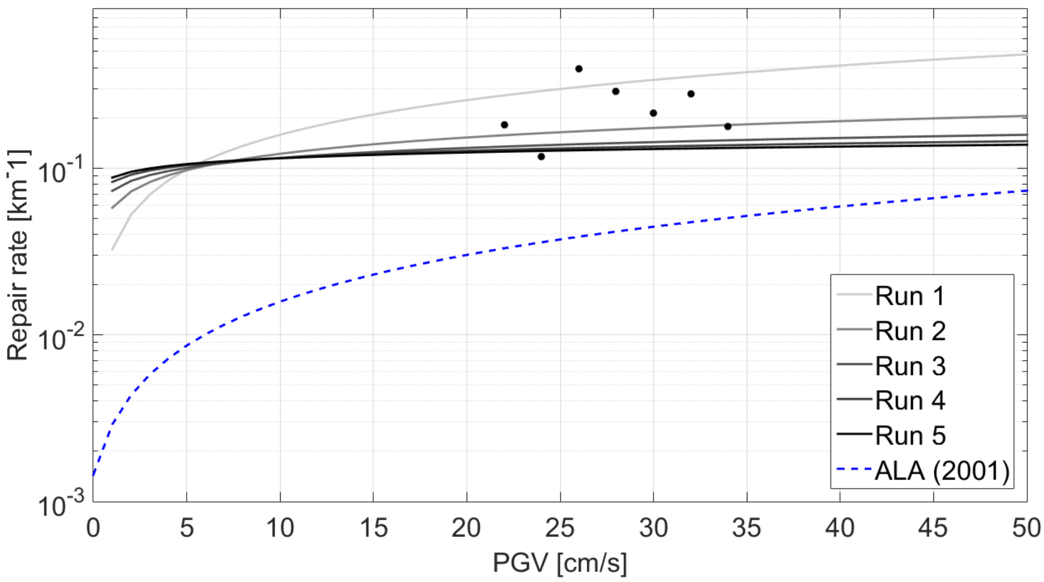

Fig. 3.8 Comparison of existing and updated fragility curves for L'Aquila gas steel pipes.

4 Conclusions

Critical civil infrastructure systems are subjected to time-varying environmental stressors, including low-consequence persistent degradation processes and high-consequence rare natural (and man-made) disasters. These processes may induce huge economic losses and cause significant environmental impact on the community these systems serve. In order to mitigate the degradation of system components over time, CI operators apply life-cycle management strategies during their lifetime of the CI. These actions are rationally scheduled along the life-cycle of the systems using a life-cycle management (LCM) procedure. Life cycle cost (LCC) and optimization tools are usually adopted to predict the performance of an infrastructure system subjected to long-term degradation process during its lifetime and to plan maintenance interventions. In particular, the performance profile (performance indicator graphed against time) resulting from the life cycle analysis allows planning the necessary interventions (maintenance, inspection and repair) in order to maintain the structural performance at an acceptable level. Establishing the best schedules require a robust optimization process. The complexity of this process depends on the scale of the problem and on the type of deterioration phenomena considered (long-term processes and/or extraordinary events).

In regions exposed to natural events, LCC analysis should also take into account the effects of extreme natural events that may increase the probability of failure or loss of functionality during their lifetime. However, very few studies have been focused on the possibility to include the risk associated to extreme natural events in a LCA framework.

Stress tests for civil infrastructure systems have been proposed in the STREST project with the aim of providing a multi-level systematic and harmonized approach for the evaluation of the performance of these systems against extreme and disastrous natural events. In particular, the ST@STERST multi-level framework has been proposed to verify the risk of CI systems respect to extreme natural events and to support decision makers in the evaluation of strategies to improve the performance of CIs along the life cycle. Each Stress Test Level is characterized by different objectives (component or system) and by different levels of risk analysis complexity (starting from design codes and ending with state-of-the-art risk analyses, such as modeling cascading failures). This makes the stress test adaptable to different hazard contexts and application to a broad range of civil infrastructure systems. Further, the level of complexity is tuned accordingly to types of critical infrastructures, the potential consequence of failure of the CIs, the types of hazards, and the available resources for conducting the stress tests.

A possible framework to integrate the results of stress tests and the data retrieved after disastrous events into a unified life-cycle management strategy of CIs has been introduced in order to manage both long degradation and instantaneous natural hazard-induced stresses during the lifetime of a civil infrastructure system.

In particular, results of the risk analysis conducted in the scope of a stress test in terms of system performance and expected costs of natural events, may be incorporated in a LCC analysis and optimization problem. Further, the evaluation of risk reduction strategies resulting from a loss disaggregation may make it possible to reconsider the full management and maintenance plan of the CI itself.

On the other hand, the evaluation of the state of civil infrastructures after the occurrence of a natural event, and the collection and processing of post-event data, such as typology, location, component's features and the assessed physical damages, can be useful to update the state condition history of the inspected components of the CI and to estimate and/or update performance prediction models used in the risk analysis.

As an application study, the proposed framework has been applied to L'Aquila (Italy) gas network in order to investigate some aspects of the proposed methodology. Detailed information about this system was available, including data on its performance in the 2009 earthquake. First, a Stress Test Level 2a was performed in order to assess the performance of the network due to earthquake hazard and identify possible risk mitigation strategies. Then, in order to evaluate the consequences of the identified risk reduction actions, the seismic performance of the upgraded gas network was assessed again, and results of the risk analysis were compared to the risk objectives identified at the beginning of the stress test. In addition, data retrieved after the 2009 L'Aquila earthquake on the damage occurred on the same case study, were used for the updating of vulnerability models adopted in the risk analysis.

The case study shows that valuable data from the model-based stress tests and actual post-event investigations can be inserted into a total life cycle cost analysis and that the effects of high-consequence low-probability events can be combined with the effects of low-consequence persistent degradation processes in a comprehensive model to better plan the life-cycle management of critical civil infrastructure systems.

References

Akkar, S., and J. J. Bommer. 2010. Empirical equations for the prediction of PGA, PGV and spectral accelerations in Europe, the Mediterranean region and the Middle East. *Seismological Research Letters*. 81(2): 195–206.

Ang, A.H.-S., and W.H. Tang. 1984. *Probability concepts in engineering planning and design: Decision, risk and reliability* (Vol. II). New York, NY: Wiley.

Ang, A.H.-S., and W.H. Tang. 2007. *Probability concepts in engineering: Emphasis on applications to civil and environmental engineering* (2nd ed.). Hoboken, NJ: John Wiley & Sons.

American Lifelines Alliance. 2001. *Seismic fragility formulations for water systems*. Part 2 – Appendices, ASCE-FEMA.

Basoz, N.I., A.S. Kiremidjian, S.A. King, and K.H. Law. 1999. Statistical analysis of bridge damage data from the 1994 Northridge, CA, earthquake. *Earthquake Spectra* 15(1):25–54.

Box, G. E. P., and C. Tiao. 1992. *Bayesian Inference in Statistical Ana*lysis. Wiley. ISBN: 978-0-471-57428-6.

Chang, S. E. and M. Shinozuka. 1996. Life-cycle cost analysis with natural hazard risk. *Journal of Infrastructure Systems,* 23: 118-126.

Chioccarelli, E. and I. Iervolino. 2010. Near-source seismic demand and pulse-like records: a discussion for L'Aquila earthquake. *Earthquake Engineering and Structural Dynamics*. 39(9): 1039–62.

Earthquake Engineering Research Institute. 1996. *Post-earthquake Investigation Field Guide*. https://www.eeri.org/projects/learning-from-earthquakes-lfe/post-earthquake-investigation-field-guide/.

Esposito, S. 2011. Systemic seismic risk analysis of gas distribution networks. Ph.D. thesis, University of Naples Federico II, Naples, Italy. Advisor: I. Iervolino, available at: wpage.unina.it/iuniervo.

Esposito, S., S. Giovinazzi, L. Elefante and I. Iervolino. 2013. Performance of the L'Aquila (central Italy) gas distribution network in the 2009 (M_w 6.3) earthquake. *Bulletin of Earthquake Engineering* 11:2447-2466.

Esposito, S. and I. Iervolino. 2011. PGA and PGV spatial correlation models based on European multievent datasets. *Bulletin of the Seismological Society of America,* 101(5): 2532-41.

Esposito, S., I. Iervolino, A. d'Onofrio, A. Santo, F. Cavalieri and P. Franchin. 2015. Simulation-Based Seismic Risk Assessment of Gas Distribution Networks. *Computer-Aided Civil and Infrastructure Engineering*, 30: 508–523.

Esposito et al. 2016. *Design stress test for CIs (non-nuclear).* Deliverable 5.1 STREST Project

Franchin, P. and F. Cavalieri. 2013. Seismic vulnerability analysis of a complex interconnected civil infrastructure. In S. Tesfamariam and K. Goda (eds.)*, Handbook of Seismic Risk Analysis and Management of Civil Infrastructure Systems.* Woodhead Publishing Limited, Cambridge, UK.

Frangopol, D.M., M.-J. Kallen, and J.M. van Noortwijk. 2004. Probabilistic models for life-cycle performance of deteriorating structures: review and future directions. *Progress in Structural Engineering and Material.* 6:197-212.

Frangopol, D.M. and M. Soliman. 2016. Life-cycle of structural systems: recent achievements and future directions. *Structure and Infrastructure Engineering*. 12:1: 1-20.

Furuta, H., D.M. Frangopol, and K. Nakatsu. 2011. Life-cycle cost of civil infrastructure with emphasis on balancing structural performance and seismic risk of road network. *Structure and Infrastructure Engineering.* 7*:* 65-74.

Helm, P. 1996. Integrated Risk Management for Natural and Technological Disasters. *Tephra*. 15(1): 4-13.

Iervolino, I., M. Giorgio, and E. Chioccarelli. 2013. Gamma degradation models for earthquake-resistant structures. *Structural Safety.* 45*:* 48-58.

Iervolino, I., M. Giorgio, C. Galasso, and G. Manfredi. 2010. Conditional hazard maps for secondary intensity measures. *Bulletin of the Seismological Society of America*. 100(6): 3312–19.

Kim, S. and D.M. Frangopol. 2011. Optimum inspection planning for minimizing fatigue damage detection delay of ship hull structures. *International Journal of Fatigue.* 33: 448-459.

Kim, S. and D.M. Frangopol. 2012. Probabilistic bicriterion optimum inspection/monitoring planning: Application to naval ships and bridges under fatigue. *Structure and Infrastructure Engineering*, 8: 912-927.

O'Rourke M.J., and P. So. 2000. Seismic fragility curves for on-grade steel tanks. *Earthquake Spectra*. 16(4):801–15.

Pace, B., L. Perruzza, G. La Vecchia, and P. Boncio. 2006. Layered seismogenic source model and probabilistic seismic-hazard analyses in central Italy. *Bulletin of the Seismological Society of America*. 96(1): 107–32.

Pitilakis, K., H. Crowley, and A.M. Kaynia, (eds). 2014. *SYNER-G: Typology Definition and Fragility Functions for Physical Elements at Seismic Risk*, vol 27, Geotechnical, geological and earthquake engineering, Springer, Netherlands.

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

Shinozuka, M., M.Q. Feng, J. Lee, and T. Naganuma. 2000. Statistical analysis of fragility curves. *Journal of Engineering Mechanics*. 126(12):1224–31.

Straub, D., and A. Der Kiureghian. 2008. Improved seismic fragility modeling from empirical data. *Structural Safe*ty. 30 (4): 320-336.

Toprak S., and F. Taskin. 2007. Estimation of earthquake damage to buried pipelines caused by ground shaking. *Natural Hazards.* 40:1–24.