A Functional Resonance Analysis Method Driven Resilience Quantification for Socio-Technical Systems

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***Abstract*—Due to the continuous increment in complexity of the socio-technical systems, decision makers call for new methods which are able to support timely as well as accurate decision-making related to resilience management. The current methods tend to be polarized on: efficiency-thoroughness forcing decision makers in making decisions on the base of resource availability instead of the problem to be solved. This paper presents a new fast-forward, cost-effective, and thorough enough framework to quantify resilience of a complex socio-technical system. The approach extends the functional resonance analysis method (FRAM) with a numerical method for the quantification of the analysis (Q-FRAM). In particular, it has been extended and operationalized the qualitative concepts of functional variability and dumping capacities into a method in which key performance indicators are derived from the model and aggregated into four indicators representing the FRAM resilience cornerstones (anticipate, respond, monitor, learn) through a bottom-up hierarchical approach. Finally, the four indicators are composed in a unique system resilience index that expresses the total variability present in the system at instant *t*. A numerical example of the use of the framework is provided together with a validation based on a comparison of the proposed approach with the current landscape.**

***Index Terms*—Functional resonance analysis method (FRAM), resilience quantification, socio-technical systems, system resilience index (SRI), variability damping capacity.**

I. Introduction

RESILIENCE is not a new concept since it is already firmly based in the fields of engineering, biology, and psychiatry [12]–[16]. Resilience and its assessment for socio-technical systems, which have been recently broken into the political and social debate because of unpredictable social, economical, and infrastructural impact of recent natural, climate change and human made disasters, has surprised the experts for their unexpected dynamics, magnitude, and propagation, calling into question the decision-making based only on risk management. Because of its multifaceted nature [11], there is not a shared agreement about how resilience can be measured and quantified. On the other hand, the idea that one method fits all is no longer considered feasible [48].

Similar to what is stated in [33] for vulnerability, resilience is a theoretical concept, thus it could be more accurate to speak about making the concept operational instead of measuring it. Making a theoretical concept operational consists in providing a method (an operation) for mapping it to observable concepts. In fact, resilience cannot be measured by means of verifications such as the adherence to standards and rules. Thus, the quantification of resilience should be in relation with how a system performs. At least three relevant approaches for system resilience quantification based on performance seem to prevail in the literature, which are as follows:

1) direct based on indicators and characteristics [53];
2) direct based on the assessment of system component's functionality [25], [31];
3) indirect looking at the potential (capability) for resilience instead of a resilience itself [2], [3], [41].

According to [26], a number of tools and methods for system resilience assessments are currently available, and present very different formats [48], [49] and effort for their implementation [26]. In fact, decision makers are called to perform a continuous speed–accuracy tradeoff among data, time, and costs needed to reach the desired informative level for taking decisions. According to the literature analyses (see Section II), there is a general trend in which tools tend to position themselves at one of the speed–accuracy poles. In particular, indices and characteristics-based quantification methods are fast and cost effective but with a limited information capacity. On the contrary, the functionality-based approaches tend to be sophisticated and require a relevant amount of data, skills, and time for being put in practice. In between, there is a space unattended by any off the shelf solutions able to be cost effective and timely, while providing a valuable informative level to support timely informed decisions. In this respect, this paper proposes a novel, cost-effective, time-efficient, and accurate method for resilience quantification able to be more efficient of the functional-based approaches and more informative of indices-based methods. The proposed approach extends the functional resonance analysis method (FRAM) [36] theory with a quantification add-on (Q-FRAM) to define key performance indicators (KPIs) and calculate synthetic indicators at systemic level. The proposed extension (Q-FRAM) will serve as trusted guidance for practitioners who want to transfer the complexity of the findings obtained through the FRAM into

Manuscript received August 6, 2018; revised December 18, 2018; accepted February 12, 2019. Date of publication April 11, 2019; date of current version March 2, 2020. This work was supported in part by the RESOLUTE Project (www.RESOLUTE-eu.org) and in part by the European Commission's H2020 Programme under Contract 653460. *(Corresponding author: Paolo Nesi.)*

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Digital Object Identifier 10.1109/JSYST.2019.2905713

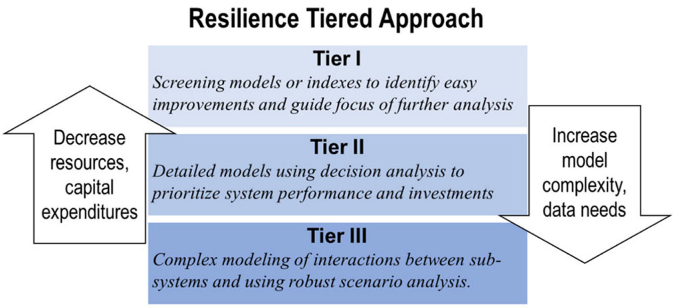

Fig. 1. Overview of tiered approach for resilience assessment [26].

tangible evidence, shifting from a pure qualitative to a quantitative approach.

This paper is organized as follows. In Section II, the related works and current limitations are discussed. Section III reports the resilience engineering perspective about resilience operationalization. In Section IV, the FRAM-driven assessment framework is defined including KPI definition, variability modeling, and indicator aggregations. Section V is dedicated to numerical examples and Section VI to discussion. Finally, conclusion is provided in Section VII.

II. Related Work

Currently, there are a number of approaches and methods to quantify system resilience. Such methods can be classified according to their outcome: scorecard, index, models, and toolkit [52], [55]. In particular, scorecard-based approaches are used to assess performance against each defined criterion in the tool. These values could be in a variety of forms, such as answers to dichotomous or multiple-choice questions calculated statistical values, or judgments. Indices use (weighted) aggregation function of scores obtained for all criteria in the assessment tool but without a model of the system behind. Therefore, indices are mainly relying on quantitative data for generating an aggregate index value [55]. Models are used to simplify the complexity of the reality and overcome uncertainties and limitations associated with predicting future events and their consequences. Model-based approaches require data utilized as input to mathematical algorithms and scenario analyses to approximate future conditions [52]. Probabilistic risk models and models for estimating losses and recovery time are examples of the model-based approach. Finally, toolkits may include [52], [55] procedures identifying assessment criteria, collecting data, assessing resilience, and support decisions. All these methods can be also classified according to a three-tiered model [26] considering costs, data, and time for their implementation and the related purpose (see Fig. 1).

Tier 1 represents the screening level to identify and prioritize critical components, capacities, or functions of the system. Tier 1 assessment helps decision makers identify "easy wins," or investments in some part of the system that can significantly improve overall resilience and that come at minimal cost or debate, for example, [50], [51], and [56]. Also, solutions based on a direct quantification using scorecards and indicators belong to this tier. Usually these approaches aim to measure wide-ranging concepts such as "*readiness for change*" [56]. The main differences among the various approaches in the tiers are related to the choice of indicators or characteristics and the ways in which they are weighted or combined. Most of the approaches use judgment, rather than empirical evidence, to choose the generic characteristics of resilience that they use [53]. In these approaches, resilience is considered to be composed of the same components in all situations. Thus, resilience is seen as modular, with any "module" (e.g., assets) able to substitute for deficiencies in any other. Moreover, the ability to cope is simply defined as the sum of the scores of all the different things present/used in the system. This approach is really cost effective, fast, and does not require any particular skills or data for being executed. However, it is obviously untenable for an in-depth analysis, setting policy, guiding programming, and determining resource allocation.

Tier 2 introduces descriptions of the structure (e.g., components, functions, interdependencies) of the system. These could be represented as formal diagrams (e.g., causal loop) or flowcharts that indicate some relationship between system components in time or space and describe major feedbacks within the system or connections to other systems. The models developed in this tier should reduce the use of conservative estimates and instead increase fidelity in terms of system representation. Of course, some observational data should be available at this stage for a simple validation of the model. To this tier belongs also the solution based on indirect system resilience quantification that combines modeling and observations calculation. For instance, in the field of resilience engineering, it is considered impossible to measure the resilience itself directly [2] because only the processes, the system develops toward resilience can be assessed in time. Moreover, if a system experiences a failure, it can still exhibit resilience in the form of survival and recovery from that failure. Conversely, if a system experiences success, it does not mean it will keep on doing so. Proactive indicators may check the (weak) "signs" of the system and identify areas for continuous improvement of the core business process. For instance, in [41], it is stated that resilience requires the presence of latent resources that can be activated or recombined as new situations and challenges arise. Therefore, measuring the amount of latent resources, whether this is time, financial, or technical resource, can be considered a proactive and indirect approach to measure resilience. However, resilience assessment should be able to capture a great diversity of system features [3]. In [3] and [4], a description for resilience characteristics based on recognizable system aspects of system performance has been provided. In particular, in [5] the characteristics for what a system could be considered resilient are summarized, and in [6] and [7], possible topics for measuring and auditing resilience are discussed.

Tier 3 aims to reach the highest fidelity in modeling a real-world system and thus observe/simulate the specific conditions under which system functional performance drops. The "functionality-based" approaches that belong to this tier are mostly related to the National Academy of Sciences resilience definition [30], which identifies four times-dependent phases (plan, absorb, recover, and adapt). The related literature tends

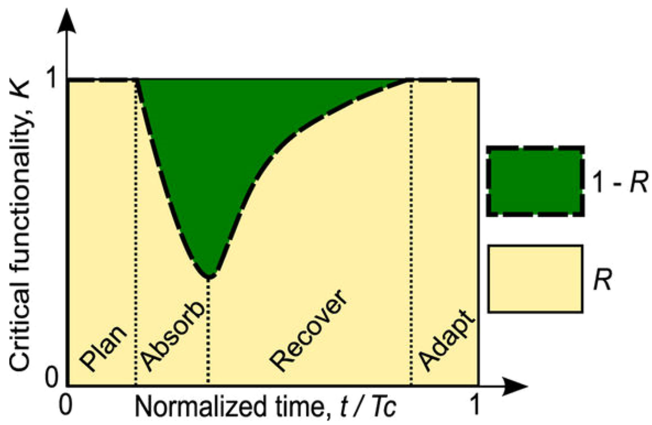

Fig. 2. System critical functionality from [31].

to assess the resilience through the quantification of system functionality considered as critical system performance components across the temporal stages [14], [19]–[25], [54]. In [8], for instance, the concept of functionality applied to a smart city is defined as a portfolio of single functionality elements (e.g., economic performance, material production performance, social and societal performance, etc.) whose performance assessment generates the classical curve as presented in Fig. 2. In fact, the normalized functionality level is considered maximum just before the occurrence of an event, which, in turn, triggers the resilience management process toward the absorb, recover, and adapt phases. The curve depicts the loss of functionality during the absorb phases; then, the level of functionality starts to be recovered bouncing back to the previous condition; as soon as the functionality reaches the target, the adaptation phase can start. According to this view, the area *R* below the curve is considered a quantification of the system resilience where the minimization of the loss of functionality after an event and the acceleration of the recovery phases represent the key drivers.

In [25], the functionality function of a system is defined as a nonstationary stochastic process and each ensemble is a piecewise continuous function where the functionality $Q(t)$ is measured as a dimensionless (percentage) function of time.

The strength point of the "functionality-based" approach to resilience quantification is related to the possibility to work with quantitative data. In addition, according to [53], further benefits are as follows:

1) the measurement of a functionality level, which has an unambiguous and uncontested definition;
2) the functionality can reasonably be reduced to a few clearly defined variables;
3) the system is clearly defined and managed for functionality optimization.

On the contrary, these approaches tend to avoid thresholds to define the necessary level of functionality, and consider any loss of function of a critical service or in a critical parameter to be equally avoided. Moreover, since these approaches are strongly dependent to the hazard/risks definition, less insights are provided about the actual capacity of the system to cope with emerging hazards and unexpected events: the so-called "unknown unknowns," before they occur. Finally, the approaches require high data availability (sensor data, satellite imagery, volunteered geographic information, insurance data, official publications and statistics, and so forth) that may be not available or incomplete (e.g., data from past events for training models); high level of system specification and knowledge for modeling; and a relevant amount of time and skills to translate system complexity into mathematical models and simulations. However, because of the underspecified nature of complex systems operations [18], even if a relevant effort is invested, the resulting quantification does not eliminate the existing gaps between how the operators think the system works ("as imagined") and how it actually works ("as done") [29], [40].

In order to overcome the limits of the presented approaches, we aimed at providing a new resilience assessment method at Tier 2, and able to integrate the property of systemic view, speed and cost-effective solution of Tier 1 with the need of accuracy that is usually obtained with relevant investment of resources as happens in Tier 3 [26], [47]. The objective has been to create a FRAM-driven fast-forward and robust toolkit able to quantify the current system capacity of coping to unwanted performance variability under unexpected/emerging changing conditions to support timely and accurate decision-making on system resilience management.

III. Resilience Engineering Perspective

Within resilience engineering field, resilience is more precisely defined as "the intrinsic ability of a system or organization to adjust its functioning prior to, during, or following changes, disturbances, and opportunities so that it can sustain required operations under both expected and unexpected conditions" [40].

In line with the resilience engineering approach, the potential for resilience to emerge from system performance is assessed based on the "four resilience cornerstones" [3], which are as follows:

1) knowing what to do (respond);
2) knowing what to look for (monitor);
3) knowing what to expect (anticipate);
4) knowing what has happened (learn).

This concept must encompass a certain timescale due to its focus on adjustment before, during, and after events. As such, resilience is an ability through which a balance between safety and efficiency is continuously achieved and maintained, rather than a quality or condition of a given socio-technical system. This realizes the shift from the efficiency of the function perspective toward the existence of the function presented in [29]. This balance must be built around efficiency as much as possible by maintaining operations close to the limits of system capacities and making the most of the resources available, all the while by still devoting enough attention and resources to safety as to avoid exceeding system capacities [5]. In this perspective assessing, resilience means to quantify such an ability to sustain required operations in both expected and unexpected conditions [1]. The large number of human, organizational, and technical aspects, together with their fast pace changing behavior, imposes serious

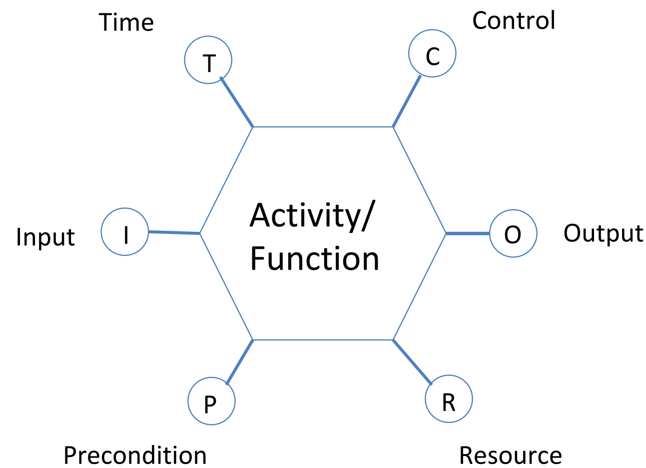

Fig. 3. FRAM function.

limitations to the ability to fully understand and monitor system operations. Thus, maintaining operational control must recognize high variability and uncertainty as constant challenges. As discussed in [3], one of the aims of resilience engineering is the ability to cope with variability of system operations and uncertainty about possible outcomes. To this end, the quantification of the potential of system resilience requires the understanding of the system performance variability, its buffer capacity, margin, and tolerance.

A. Functional Resonance Analysis Method

The FRAM [36], developed in the context of the resilience engineering, aims to capture the dynamics of complex socio-technical systems by modeling the nonlinear dependencies and variability that the functions experience. It supports the system analysis to identify potential variability of each function and the consequent emergent behaviors potentially relevant for resilience. In particular, according to the FRAM approach, a function is composed by six aspects: five inputs (input, time, control, precondition, resources) and one output (output) (see Fig. 3). A function refers to the activities—or set of activities—in the system under investigation that are required to produce an expected outcome.

A FRAM function describes the following:

1) what people—individually or collectively—have to do in order to achieve a specific aim;
2) what an organization does: for example, the function of an emergency room is to treat incoming patients;
3) what a technological system does either by itself (an automated function) or in collaboration with one or more humans (an interactive function or co-agency).

A function may refer to all the three assets at the same time, even if only one should be identified as prevalent. The variability of an output of a function is revealed by the variability occurred in its outputs, and is referred to the deviation of one or several of the following dimensions such as: timing, duration, magnitude, object, and so on, with respect to an expected value. Thus, the variability occurred in the upstream functions affects the performance of the downstream function. The subsequent propagation of the variability in the system may lead to nonlinear effect called resonance generating unexpected/uncontrolled consequences.

However, the impact of such variability over the system cannot be determined by observing the variability of the upstream function output only. In fact, it also depends on the variability acceptance capacity of the function receiving inputs (downstream). Thus, the functional resonance effect is triggered by the output variability of the upstream function exceeding the variability dumping capacity of the downstream function. In [10], the factors composing the functional dumping capacity are identified as: function buffer capacities, function flexibility, function margin, and function tolerance. Even if in the literature such concepts still have blurred definitions and further effort is required for their rigorous formalization, an operational definition of functional dumping capacity (FDC) can be provided. In particular, we define the minimum acceptance input performance threshold (MAIPT) of a downstream function, the limit of the input performance below which the function cannot be executed properly ending up to present a variability on its output (variability). Above the MAIPT, incoming variability does not affect the function performance directly because the variation is entirely absorbed by the function, and the subsequent output will be without any variation. If the variability exceeds the FDC in the link, the quantity not absorbed will be propagated by the downstream function toward its downstream functions, and so forth. The propagation has to be stopped as soon as the residual variability meets a function and is capable to absorb it and provides an output without variation. If the variability cannot be stopped, the system is going to experience the so-called "functional resonance" that leads to a disruption. Thus, the total deviation in a link needs to be calculated considering the FDC of the downstream function, so that the MAIPT should be defined for each downstream function in the FRAM model. However, if variability occurs, it should be attributable to internal factors of the function (common performance condition [43]) or to the variability occurred on the other aspects (resource, precondition, time, and control). In the sequent section, a comprehensive formalization of this theoretical approach for its use in a quantification method is provided.

IV. Q-FRAM Framework

The scope of Q-FRAM is to quantify the level of resilience in a system at a certain instant t through a unique expressive indicator: the system resilience index (SRI) as a proxy indicator for system resilience level. According to [27] and [28], implementing a measurement method to assess resilience of socio-technical system has implications at several levels, as at the political one because of its connection with the policies performance. Thus, the framework should be neutral, objective, and widely accepted in order to avoid its manipulation or misinterpretation in the political debate. To do so, it is necessary to define the following:

1) a semantic reconciliation of the most ambiguous concepts;
2) the development of sets of indicators and thresholds based on the agreed concepts;

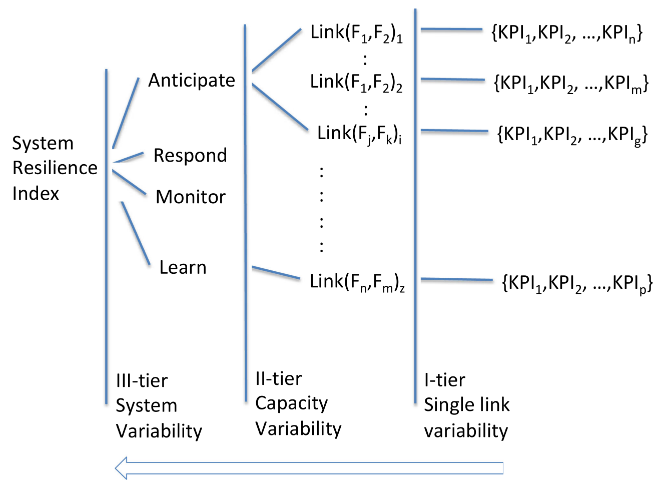

Fig. 4. Three-tier indicators composition pathway.

3) the identification of the sources to feed indicators with pertinent data.

Such an approach addresses the requirements of the so-called statistical information system to govern indicators development according to the transparency imperative [27], [28]. The principles adopted for indicator design are as follows:

1) easy to use/understand;
2) data availability;
3) measurement cost effective;
4) pertinence;
5) consensus driven.

In particular, a co-design approach during the indicators definition and weight assignments should be adopted involving relevant stakeholders.

A. Composition Method

The composition method is then organized on three tiers, as depicted in Fig. 4. In the first tier, the variability in each single link of the model is estimated. To quantify the variability of each link, a number of KPIs able to express the main components whose variation may determinate how the outputs vary are defined. In the second tier, the variability is aggregated according to the capacity of reference expressing a capacity variability index (xCVI). In the third tier, the four CVIs are aggregated in a unique indicator: the SRI as a synthetic indicator able to quantify the general system variability in a certain instant t.

B. System Resilience Index

The SRI is the result of a proper composition of indexes representing the variability occurred in the four resilience capacities: anticipate, respond, monitor, and learn. In fact, they might not have the same "importance" in a given system and are not perfectly independent. For instance, the respond (R) capacity might be considered more critical with respect to the learn by the practitioners, and in case of multiple options, it is necessary to rank these options accordingly to increase system resilience. In this respect, we propose to use the *Choquet integral* (Ch) [42], a method able to express the preference of difference configurations and it starts to be popular also in different applications [9]. Thus, the SRI is calculated as follows:

$$\mathrm{SRI} = \mathrm{Ch}([x_1, \ldots, x_n], \mu) = \sum_{i=1}^{n} \left(x_{(i)} - x_{(i-1)}\right) \cdot \mu\left(A_{(i)}\right) \tag{1}$$

where $x_{(0)} = 0$, and $x_{(i)}$ denotes a permutation of the x values such as $x_{(i)} \le x_{(i+1)}$ and μ is the weight function assigned to each subset of criteria, in our case $A = \{A, R, M, L\}$. According to [42], the weight assignment should be based on the interaction among criteria and express the configuration preferences.

C. Capacity Variability Quantification

The second step includes the definition of a synthetic indicator that represents the total variability (deviation) occurred in each of the four capacities and measured in the Link_i. The value obtained is the result of an aggregation of the deviation of the link grouped according to their classification. The links are classified according to the upstream function F_n contribution to one of the four adaptive capacities. In this case, the synthetic indicator should be noncompensatory. In fact, because of their independence, relevant deviations in a link belonging to a capacity should not be compensated with a good performance obtained in another one belonging to the same capacity. To this end, the weighted geometric mean, which represents a tradeoff between full compensation and not compensatory approaches with a lower information loss [34], [38], [39], has been selected. Thus, we define the xCVI as follows:

$$x\mathrm{CVI} = \sqrt[\left(\sum_{i=1}^{n} w_i\right)]{\prod_{i=1}^{n} \mathrm{Dev}_i^{\,w_i}} \tag{2}$$

where $x \in \{A: \text{Anticipate}, R: \text{Respond}, M: \text{Monitor}, L: \text{Learn}\}$; a represents the ath link in the model and r is the rth link in the model associated to a capacity x; Dev and w belong to the vector of the weighted deviations defined as follows:

$$x\text{Vector\_DEV} = \begin{pmatrix} w_{1\cdot a} * \mathrm{Dev}_{1\cdot \mathrm{Link}_a} \\ \vdots \\ w_{n\cdot r} * \mathrm{Dev}_{n\cdot \mathrm{Link}_r} \end{pmatrix} \tag{3}$$

where n is the cardiality of xVector_DEV. w is the weight derived from the degree prestige index (DPI) calculation of the upstream funtion of the link. In fact, not all the links have the same criticality in the model. This means that a deviation occurred in a critical link will have a relevant impact in the system with respect to a similar deviation magnitude in another but less important link. To model such a scenario, a weight to each link is assigned. In this case, the weighting methodology is inspired by the analysis carried out in [10], where the DPI calculation (the index of a node u as the sum of inbound edges to that node from all adjacent nodes) is applided to the FRAM model, to understand which are the most critical funtions in the system. Then, considering the FRAM model a node-weighted network, the DPI is associated to the nodes as weight. However, according to [46], a node transmits its relational influences through its outgoing links and result in the status change of its linked nodes.

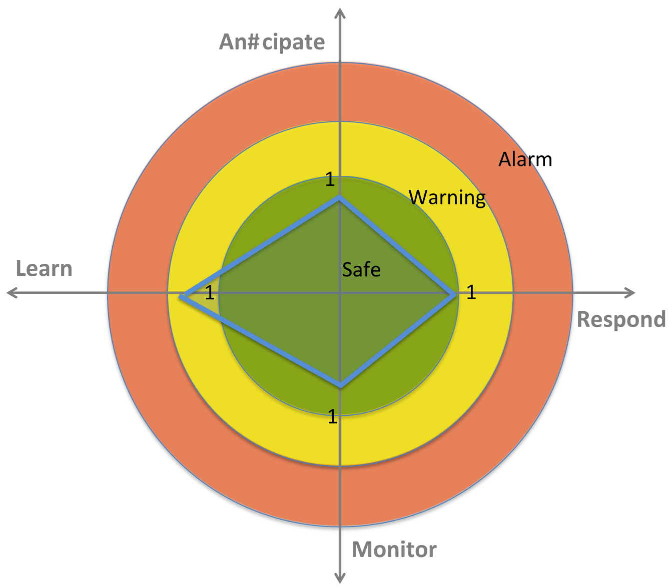

Fig. 5. Capacity variability representation inspired by the RAG.

This generates a principle in network analysis expressed as: “a node’s prominence in a characteristic depends on 1) the number of incoming links that transmitted the corresponding relational influences and 2) the prominence of this characteristic of the source nodes” [46]. According to this perspective, the weight of the origin node in the link is used as a source for assigning a weight to the link itself. In this way, we are able to transform the node-weighted network into a link-weighted network. Such a transformation can be applied partially following the approaches adopted in [45]. In particular, in this paper the link weight w_{Link_i} is defined as follows:

$$w_{\mathrm{Link}_i} = \mathrm{DPI}_{F_n}/\mathrm{MAX}\left(\mathrm{DPI}\right) \tag{4}$$

where DPI_{F_n} represents the degree prestige index of the origin node F_n in Link_i, and MAX(DPI) is the maximum DPI calculated in the FRAM model.

Hence, in addition to the amplitude of the deviation, the “importance” of the link becomes a parameter to be considered in decision-making (e.g., a small variability in a critical function might be more dangerous than a large variability in a less important function and might require a specific prioritization). Because the measurment might be performed several times (from periodical to close to real time), a dynamic index in order to assess increments/decrements is also defined

$$Dx\mathrm{CVI}_{t1/t0} = \left(\textstyle\sum_{i=1}^{n} w_i\right)\sqrt{\prod_{i=1}^{n} \frac{(\mathrm{Dev}_i{}^{w_i})_{t1}}{(\mathrm{Dev}_i{}^{wi})_{t0}}}. \tag{5}$$

Once the variability for each of the four resilience capacities is calculated, it is possible to visually represent the current level of the system (as represented in Fig. 5) inspired by the resilience analysis grid (RAG) [3], where the safer region of variation is within the green area (equal to 1).

D. Link Variability Quantification Modeling

Since the variability that affects the downstream functionality depends also to its dumping capacity, it is necessary to shift the focus of the analysis from the FRAM function to the FRAM relationships that include two functions of the FRAM model linked through an explicit interdependence. This has been formalized in [10], where the relationship $r \in R$ is represented by a quadruple $r = \{o.d.a.qn\}$, where $o \in F$ is the origin of the upstream function, $d \in F$ is the destination or downstream function, $a \in A$ refers to the aspects involved in the relationships (input, resource, precondition, time, and control), and $qn \in Q$Names is a qualified name of the relationship. An adjacent matrix *MX*, where in the element *MX*($x{\cdot}y$) the upstream function (e.g., F_n) with its output O_j and the downstream function (e.g., F_m) with its input I_k are represented, is used for its calculation. The link is then formalized as follows:

$$\mathrm{Link}_i = \ (F_n : O_j- > \ F_m : I_k) \tag{6}$$

where $n \neq m$ represents the index of the functions involved in the interdependence (link), *i* is the *i*th link in the model, *j* is the *j*th output (*O*) of the function F_n, and *k* is the *k*th input (*I*) of the function F_m. The evaluation of the variability in a link requires the definition of a number of KPIs able to characterize the source of this variability of the upstream function output first. The weighting method used here is based on expert judgment. In particular, the experts should estimate which of the identified KPIs are more representative in detecting/describing the output variability. Then, the total deviation in the *i*th link is defined as follows:

$$\mathrm{Dev}_{\mathrm{Link}_i} = \frac{\mathrm{Max}\left(\mathrm{WOP}_{F_n:O_j}\right) - \mathrm{WOP}_{F_n:O_j}}{\mathrm{FDC}_{\mathrm{Link}_i}} \tag{7}$$

where $\mathrm{Dev}_{\mathrm{Link}_i}$ is an index that expresses the deviation of the $\mathrm{WOP}_{F_n:O_j}$ from a targeted value—here defined as $\mathrm{Max}(\mathrm{WOP}_{F_n:O_j})$—with respect to $\mathrm{MAIPT}_{F_m:I_k}$ of the downstream function. The weighted observer performance (WOP) of $F_n : O_j$ is defined as

$$\mathrm{WOP}_{F_n:O_j} = \frac{\sum_{h=1}^{n} \mathrm{KPI}_h w_h}{\sum_{h=1}^{n} w_h} \tag{8}$$

where *n* is the cardinality of the $\mathrm{OP}_{\mathrm{Link}_i}$ vector. The observed performance (OP) associated to $F_n : O_j$ is described by a weighted vector of KPIs defined by the stakeholders (e.g., civil protection, infrastructure operators, first responders, etc.), where $w|0 \leq w \leq 10$ represents the weight associated with each KPI (not all the KPIs identified have the same impact in defining the output variability) and *y* is the cardinality of the vector and it is represented in (5)

$$\mathrm{OP}_{F_n:O_j} = \begin{pmatrix} w_1 * \mathrm{KPI}_1 \\ w_2 * \mathrm{KPI}_2 \\ \vdots \\ w_y * \mathrm{KPI}_y \end{pmatrix}. \tag{9}$$

There are a number of multiattribute aggregation methodologies to build composite indices [34], such as analytical hierarchical process, Mazziotta–Pareto index [35], (weighted) means,

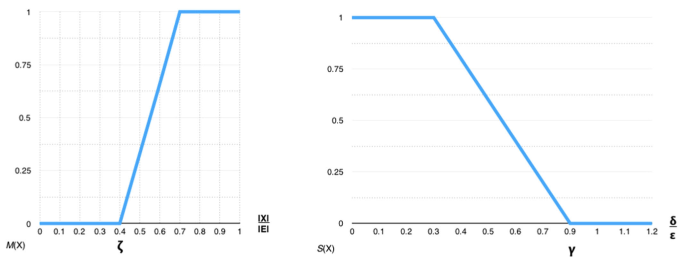

Fig. 6. Membership functions for *S*(*X*) and *M*(*X*) from [10].

multiple-criteria decision analysis (MDCA), and so on. In our case, the choice of an additive aggregation method to compute WOP is justified by the fact that a certain compensation among the KPIs in defining the variability is recognized by the experts.

Then, the FDC in Link_i can be defined as follows:

$$\text{FDC}_{\text{Link}_i} = \left|\text{Max}\left(\text{WOP}_{F_n:O_j}\right) - \text{MAIPT}_{F_m:I_k}\right| \quad (10)$$

where MAIPT is estimated using subjective reviews, through perception-based definitions as follows:

$$\text{MAIPT} = \text{MajOp}\,(E) = \sum_{X_i} W\,(X_i) \times \text{Op}\,(X_i) \quad (11)$$

where $\text{Op}(X_i)$ is the value averaging the opinions expressed by the majority, and $W(X_i)$ is a weight for each majority defined as follows:

$$W\,(X_i) = \frac{\text{Maj}\,(X_i)}{\sum_{X_j \subseteq E} \text{Maj}\,(X_j)}. \quad (12)$$

We adopted here a fuzzy logic approach to identify a representative majority, its strength, and the valuation reflecting the judgment of the majority. The approach is based on [44] where the calculation of a majority of opinion is considered an imprecise value. Thus, the assignment value passes through the definition of a fuzzy set instead of a single value. This fuzzy set includes all the possible subsets representative of a majority within the collection of values *E* expressing all the valuations. This requires the identification of both the strength of a majority and the synthesized value expressed by this majority. The observations from experts are gathered in a bag of valuation $V = \{v_1, \ldots, v_n\}$. Then, a characteristic function *S* (see Fig. 6) to define the intensity of similarities is defined (e.g., two values *vx* and *vy* are similar if their difference is not too much distant for the point of realization). Another function *M* (see Fig. 6) is defined to model the intensity of the majority. Thus, $X_i \subseteq E$ is a majority with degree defined by a function Maj, where

$$\text{Maj}\,(X_i) = \min\left(M\,(X_i)\,, S\,(X_i)\right). \quad (13)$$

The functions *M*(*X*) and *S*(*X*) are represented in Fig. 6.

Thus, for $\text{Dev}_{\text{Link}_i} < 1$, the variability is within a damping range, only micro adjustment is needed and the downstream function continue to perform as intended; for $\text{Dev}_{\text{Link}_i} > 1$, the deviation exceeds the FDC of the downstream function. In this second case, two scenarios may happen: a progressive degradation in output performance or a sudden disruption/interruption of the functionality (e.g., blackout for electricity overload). It is clear that as the FDC is wide in each function in the system, the system can be considered resilient, because most of the variability can be dampened through internal adaptation.

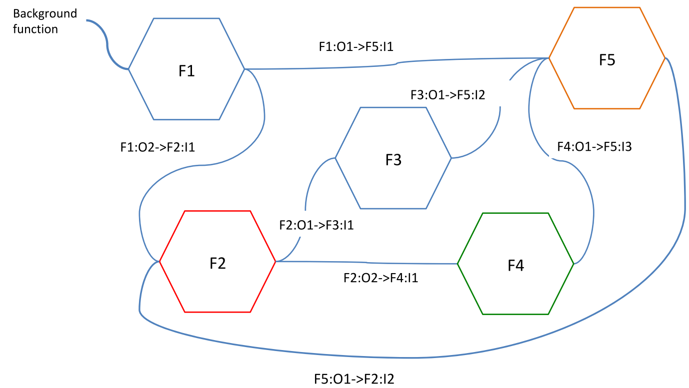

Fig. 7. FRAM model example.

V. Numerical Example

In order to show how the method works, we create a FRAM model of reference represented in Fig. 7, which may represent a part of a complex socio-technical system under investigation. The functions and dependencies identification is usually supported by a number of questions that guide the expert in the model design [17]. The model includes five functions that are grouped into four groups {Red: Response, Green: Learn, Blue: Anticipate, Orange: Monitor}, to the capacity they mainly contribute. In particular, the function F1 is the entry point of the system. The background functions[1] that represent the context of the system under investing are not represented here for the sake of simplicity and generate the input(s) for the entry point function.

Thus, for each output of the functions considered, it is necessary to identify a number of KPIs able to represent performance variability. In our example, we defined two KPIs for each output present in the model. The example of the checklist that should be defined is reported in Table I. In particular are defined: the capability contribution, the output, the KPI with its measurement method, the value obtained by the measurement, the weight associated to the KPI representing its contribution to the entire output variability, and the score calculated.

As explained above, *x*CVI represents an index of the variability within each of the four components. The safe range of variability is for *x*CVI < 1. With values of *x*CVI >1, the system is experiencing the so-called functional resonance, a phenomena in which the variability within the system exceed its buffer capacity leading to unpredictable consequences. The results of the calculation provided in Table II of *x*CVI here reported: LCVI = 0.83; ACVI = 1.8; MCVI = 0.59; and RCVI = 0.56. According to these figures, we can notice a critic value related to the anticipate capacity. This means that the system is experiencing some

[1] http://functionalresonance.com/a-fram-glossary.html

TABLE I
SYSTEM POTENTIAL VARIABILITY CHECKLIST

Main contributing capacity:	Output	KPI + measurement method	Value [0-10]	Weight [0-10]	(v*w)
Anticipate	F1:O1	KPI_1	3	4	12
		KPI_2	6	6	36
	F1:O2	KPI_1	5	3	15
		KPI_2	2	7	14
Respond	F2:O1	KPI_1	9	8	72
		KPI_2	1	2	2
	F2:O2	KPI_1	2	5	10
	F2:O2	KPI_2	3	5	15
Anticipate	F3:O1	KPI_1	7	4	28
		KPI_2	3	6	18
Learn	F4:O1	KPI_1	8	8	64
		KPI_2	1	2	2
Monitor	F5:O1	KPI_1	5	5	25
		KPI_2	7	5	30

TABLE II
LINK WEIGHTING AND DEVIATION

Link	Fuzzy bag	MajOp/MAIPT	WOP	FDC	DPI	W	DEV
F1:O1:F5:I1	{2.3.5.5.5}	4.61	4.8	5.39	0.2	0.33	0.96
F1:O2:F2:I1	{5.6.7.7.10}	6.34	2.9	3.66	0.2	0.33	1.93
F2:O1:F3:I1	{1.1.1.2.4}	1.2	7. 4	8.8	0.4	0.66	0.29
F2:O2:F4:I1	{3.3.3.4.6}	3.2	2.5	6.8	0.4	0.66	1.1
F3:O1:F5:I2	{3.7.8.9.10}	8.5	4.6	1.5	0.2	0.33	3.6
F4:O1:F5:I3	{3.4.6.6.7}	5.9	6.6	4.1	0.2	0.33	0.83
F5:O1:F2:I2	{1.2.2.3.4}	2.3	5.5	7.7	0.6	1	0.58

issues in those functions that are contributing on the anticipate component (see F1:O2 -> KPI2 value). Thus, an intervention to improve the performance on F1:O2-KPI2 may receive a high level of priority because of its impact on the system with respect to others. Finally, in order to provide a synthetic indicator able to inform users (e.g., decision makers) about the level of resilience of the system, the *Choquet integral* to evaluate SRI is calculated as follows.

1) Since the weight assignment should be based on the interaction among criteria, in our case the weight assignment expresses the configuration preferences as follows:

$$\mu_0(\emptyset) = 0$$
$$\mu_1(\{L\}) = 0.1$$
$$\mu_2(\{M\}) = 0.2$$
$$\mu_3(\{A\}) = 0.3$$
$$\mu_4(\{R\}) = 0.4$$
$$\mu_5(\{M, L\}) = 0.45$$
$$\mu_6(\{A, L\}) = 0.5$$
$$\mu_7(\{R, L\}) = 0.55$$
$$\mu_8(\{A, M\}) = 0.60$$
$$\mu_9(\{R, M\}) = 0.65$$
$$\mu_{10}(\{A, R\}) = 0.7$$
$$\mu_{11}(\{A, M, L\}) = 0.75$$
$$\mu_{12}(\{R, M, L\}) = 0.8$$
$$\mu_{13}(\{A, R, L\}) = 0.85$$
$$\mu_{14}(\{A, R, M\}) = 0.95$$
$$\mu_{15}(\{A, R, M, L\}) = 1.$$

2) The ordered subset criteria to be considered for the weight are: $\mu_{15}(\{A, R, M, L\}), \mu_{13}(\{A, R, L\})$, $\mu_7(\{R, L\}), \mu_1(\{L\})$.
3) The resulting equation is

$$\mathrm{SRI} = (\mathrm{MCVI} - 0) * \mu_{15} + (\mathrm{ACVI} - \mathrm{MCVI}) * \mu_{13} + (\mathrm{RCVI} - \mathrm{ACVI}) * \mu_7 + (\mathrm{LCVI} - \mathrm{RCVI}) * \mu_1. \tag{14}$$

In fact, the low scores in ACVI and RCVI representing a low variability within these components are considered preferable with respect to similar deviation in MCVI and LCVI

$$\mathrm{SRI} = (0.59 - 0) * 1 + (1.8 - 0.59) * 0.85 + (0.56 - 1.8) * 0.55 + (0.83 - 0.56) * 0.1 = 0.957.$$

Because of SRI is <1, we can claim that the system has a generic positive posture with respect to its capacity of adapting to unexpected condition. However, the proximity of the SRI score to safe boundary, which advices for a reduced buffer capacity of the system and a further investigation looking at what are the capacities that are most suffering, is required. Moreover, since the SRI is <1, the issue occurred in the anticipation component could not be classified as an emergence but an urgency. In this way, it is possible to better prioritize resources' allocation and intervention in order to maximize the impact at a system level.

VI. DISCUSSION

Q-FRAM was considered to be a fast-forward and cost-effective resilience assessment of socio-technical system while maximizing the level of rigor and information value to support strategic, tactical, and a certain degree of operational decisions. Q-FRAM provides guidance for a system-model-driven KPIs definition and a theory-driven method for indicators composition. Because of the diversity of the methods present in the literature, it is not possible to compare the simple computation results. In fact, all the methods are self-consistent and self-coherent. Thus, in order to evaluate the benefit of the proposed approach with respect to the existing landscape depicted in Section II, we identified some properties to represent an objective method of assessment, which are as follows.

1) *Nonregression Property*: The validity of the model developed should not be affected by the addition of new elements (e.g., a function, a KPI to be added to the assessment model).
2) *Rebound Effect [58]:* The increased efficiency in performing resilience assessment creates an additional demand of new assessments. It is a proxy indicator of the achieved efficiency.
3) *Computational Complexity:* The overall complexity of the assessment model.
4) *Accuracy:* It is related to the capacity of the framework of managing evidences/tangible assets (e.g., results of data

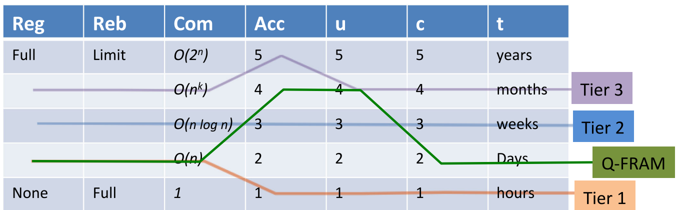

Fig. 8. Q-FRAM assessment (Reg: Regression, Reb: Rebound, Com: Complexity, Ac: Accuracy, Utl:Utility).

processing) in addition to the intangible (judgments) managed by Tier 1 solutions.

5) *Value of Information (VoI) [57]:* defined as VoI $= \mathcal{F}\{t, c, u\}$, where *t* is time needed for the info production; *c* is the costs to produce, buy, reconstruct, change, or compensate information; and *u* is the utility, the feature of information to produce required effects. The three dimensions are represented in Fig. 8.

According to these criteria, Q-FRAM is *not regressive*, because modifications in the system representation (FRAM model) or KPI definitions or weight definitions, etc., do not invalidate the rest of the framework and it is possible to test the model *a priori*. On the contrary, in Tier 3 method, changes may require the entire re-execution of the simulation and the results can be tested only in the aftermath (e.g., an agent-based system).

The Q-FRAM assessment produces a picture of the status of the system variability at time *t* that can be efficiently re-assessed from low (periodic) to high (close to real time) frequency simply increasing the sampling rate and the level of automation. In fact, the possibility to have results in a cost-effective, fast-forward and accurate way triggers the so-called *rebound effect* [58] that is expressed in an even more complex or higher rate assessment requests. Instead, for the Tier 3 methods, such a *rebound effec*t is difficult to trigger because of the complexly, the costs, and the purpose of the approaches that are usually focused on single aspect/component of a system. This means that a mix of tools is needed to gain a big picture view [47]. Moreover, Q-FRAM computational complexity is linear *O(n)* like the complexity upper bounds of Tier 1 methods. Tier 3 approaches have a higher computational complexity that is directly correlated to the time and costs needed to achieve the results. Moreover, Q-FRAM KPIs can be evaluated with different approaches simultaneously, from simple judgments to big data processing (e.g., traffic flow rate calculated in an urban transport system). The SRI can be also evaluated without waiting for an event to happen, and in the presence of incomplete data. This determinates a relevant VoI. On the contrary, the functionality-based approaches cannot preform this quantification until an event occurs and at least the recovery phase is not completed. The ex-ante analysis in Tier 3 applications is usually addressed by simulation techniques, considering the probability of functionality loss against some specific risk and scenarios. This kind of simulation requires skills, data of past events, and a detailed definition of the model or its sub-parts to provide a valuable outcome. Unfortunately, such data are often incomplete or not present and this affects the quality or the feasibility of the entire analysis (VoI). Finally, the time needed to perform Q-FRAM can be estimated in days according to the results of its application on Florence and Athens in the context of H2020-RESOLUTE project. The results of the comparison are depicted in Fig. 8.

A. Limitation of This Paper

At the movement, the possibility for Q-FRAM to be used for predictive assessment basically lies on the analysis of SRI and *x*CVI dynamics. This approach suffers from the well-known cold-start problem related to lack of indexes values at the Q-FRAM assessment cycle start-up. Moreover, to obtain a sufficient number of sampling for the analysis could take a relevant amount of time. On the other hand, most of the ingredients for a time-dependent simulation are now available (graph-based representation, variability differential quantification method defined, and so on). The possibility to model the variability propagation in time represents a further valuable improvement at hand. In fact, simulating how variability spreads in the model in time allows those predictive analysis that may further increase the accuracy and the VoI of the Q-FRAM.

Finally, a more precise evaluation of complexity of Q-FRAM with respect to the current resilience assessment landscape represents a desirable step ahead for a quantification of the effort required for its implementation. To do so, it is necessary to investigate more in depth the complexity of the different methods when they are put in practices. A practical approach for the complexity analysis as presented in [59] is recommended. Possible approaches are function point analysis [60], COCOMO [61], and activity-based costing model [62].

VII. Conclusion

The Q-FRAM aims to be considered a fast-forward and robust method to estimate the resilience level of a complex system in a certain instant *t*. The method has been applied in Florence and Athens in the context of the H2020-RESOLUTE pilot definition. The strength of the methodology proposed is related to its actual capacity of obtaining a result in a pragmatic manner, without getting lost into details or theoretical models that are difficult (in some case impossible) to validate. The resulting FRAM-driven variability quantification may represent a generic method to model and quantify many different kinds of (complex) systems that might be difficult to treat using dynamic and time-dependent analysis. The obtained indicators (SRI and *x*CVI) are able to provide 1) an immediate insight to the decision makers about the status of the system and 2) information about how to prioritize investments to dampen variability according to the desired systemic impact. The method can be further operationalized, defining KPIs that can be estimated through automatic processing on database or datastream/big data. This represents the next research step at hand.

Acknowledgment

This paper expresses the opinions of the authors and not necessarily those of the European Commission. The European Commission is not liable for any use that may be made of the information contained in this paper.

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