Resilience Metrics for Interdependent Infrastructure Systems: A Literature Review (Part 1)

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To ensure the continuity of the essential services, resilience must be built into the Critical Infrastructure system to help them cope with adverse events. In recent years, there was a considerable research effort focusing on measuring resilience, but still, there is no unique or widely accepted mathematical formulation of resilience. Instead, several different metrics have been proposed to capture different resilience properties of a CI system and suitable for specific problems. This paper aims at performing an in-depth review study and comparative analysis of the most relevant models and metrics for quantifying resilience in networked systems. We depart from a systematic review of the literature on resilience metrics. A rigorous process is then carried out to select a reduced set of suitable metrics. For each metric, we consider its properties, major strengths/weaknesses, the applicability and possibly past practical applications. We advance the state-of-the-art by defining few new metrics to partly cover knowledge gaps. In the Part 2 of the paper both the reviewed and the new proposed metrics are analysed and compared through a benchmarking process, looking at the behaviour of the resilience metrics when the properties of the system vary.

Keywords: Critical Infrastructure, Resilience, Metrics, Assessment, Literature review

1. Introduction

Critical Infrastructure (CI) can be defined as those assets or systems that are critical for the maintenance of vital societal functions, providing services that society and citizens rely on in their daily life (EC, 2008). To ensure continuity of these essential services, while considering that not all the disruptive events can be prevented, resilience must be built into modern complex socio-technical systems to help them quickly recover and adapt when adverse events do occur. In the context of networked CI systems, the concept of resilience can be defined (CNSS, 2015) as the ability of a system to:

(1) provide continuous operation;
(2) recover effectively if failure does occur; and
(3) scale to meet rapid or unpredictable demands.

Despite the considerable research effort focusing on measuring resilience, there is no unique or widely accepted mathematical representation of resilience. Instead, several different metrics were proposed able to capture different resilience properties of a CI system or suitable for specific problems (e.g. system design vs system operations). There are many challenges in defining or selecting appropriate measurement frameworks for different resilience domains, different systems and different levels of detail. Many metrics difficult to put into practice and at the same time insufficiently take into account resilience concepts and dimensions.

The main objective of the present study is to critically and systematically compare the quality and usability of different resilience metrics to analyze the resilience properties of interdependent networked infrastructure systems and support capability-building strategies. To this aim, a systematic literature review was carried out in order to identify, select, and compare the resilience metrics proposed by researchers and their current applications. In the Part 2 of the paper both the reviewed and the new proposed metrics are then analyzed and compared through a simulation-based benchmarking process, looking at the behavior of the resilience metrics when the properties of the system vary.

2. Study Methodology

The technique adopted for the systematic literature review aimed at providing reproducible and see-through processes of locating, selecting, analyzing, and reporting relevant research in the selected topic. The seven steps proposed by Cooper (2010) were followed:

(i) Planning;
(ii) Searching;
(iii) Data gathering;
(iv) Quality evaluation of primary research;
(v) Analysis;
(vi) Interpretation;
(vii) Reporting.

2.1 *Planning, Searching and Data gathering*

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In the process of search, we covered all the domains where in the last decades the resilience concept was embraced to design and manage complex systems.

To collect scientifically relevant papers, documents available online in the Scopus and Web of Science databases were targeted. Publications were firstly filtered by searching the following words in the title, abstract and keywords: (*resili** AND (*metric** OR *index** OR *indicator**)). The first requirement emphasizes the need to tackle the topic of resilience; the second one wants to remark the objective of identifying metrics useful for resilience assessment. By matching the papers gathered from different databases, a final list of 346 unique publications was set. The distribution of the collected papers respect to the application domain are reported in Table 1.

Table 1. Number of identified papers across scientific fields (top 10)

Field	# of papers
Engineering Electrical / Electronic	44
Civil Engineering	43
Environmental Sciences	41
Water resources	39
Environmental Engineering	29
Geosciences (multidisciplinary)	27
Computer Science	21
Information Technology and Telecommunication Systems	19
Management	20
Meteorology Atmospheric Sciences	19

2.2 *Quality evaluation of primary research, Analysis and Interpretation*

Once the searched material has been collected, we focused on scanning the identified papers in order to filter them and come out with the most relevant ones. Two criteria were used:

- year of publication: preference was given to the most recent papers proposing advancements to metrics already reported in prior literature;
- similarity between the focus of the paper (title and abstract) and the objective of the present study, i.e. identifying the best metrics to assess the resilience of interdependent networked infrastructure systems.

A final selection was performed focusing only on consequence-based quantitative resilience assessment approaches. In particular, the search excluded risk-based measures. The reason of this choice is that system's resilience assessment generally starts postulating the occurrence of a disruption event and does not take into consideration probabilistic estimates on the occurrences of different types of events/threats. In Table 2 the identified metrics are classified against relevant features.

Following the systematic literature review process, a funneling process was then completed to evaluate which of the pre-selected metrics were the most suitable for the objective of the study. Some metrics have been excluded for the following reasons:

- *similarities with other metrics.* A significant number of metrics are built following the resilience loss triangle approach. Among this set, we decided to keep only the most recent/complete ones or peculiar;
- *amount of required information to compare all the features of the metrics.* Some metrics require information about recovery actions or budgets, about economic impacts and characteristics of the disruption. These types of analysis go beyond the scope of the study and require a huge amount of additional information to compare the metrics.

We also gave priority to metrics that showed the ability to include all the dimensions of resilience (see Section 3.1), so giving preference to composite metrics. For what concerns non-composite metrics, the selection process was carried out taking into consideration the definition of a valid metric provided by Najarian and Lim (2019). A metric, is said to be valid if it is: i) an index that reveals if a system has the abilities suggested by the associated conceptual framework; ii) an index that is not biased toward any of these abilities, that is, it must not overemphasize or underemphasize the importance of any of these abilities.

3. Description of the selected metrics and application cases

This section briefly describes the final sample of selected metrics, distinguishing between Generic models and Structure-based models, since this classification is the most critical respect to their applicability.

3.1 *Generic models*

Bruneau et al. (2003) defined four dimensions of resilience (robustness, rapidity, resourcefulness and redundancy) while adopting the resilience triangle model on civil infrastructures. They proposed a deterministic static metric (Eq. 1) able to measure the loss of resilience of a community. Disruption occurs at t_0, while t_1 represents time at which the community returns to its normal state. $Q(t)$ is the quality of the infrastructure at time t.

$$RL = \int_{t_0}^{t_1} [100 - Q(t)]\, dt \qquad (1)$$

The main advantage of this metric is its general applicability to all the systems in which a general quality performance can be evaluated, but it is limited by the main assumption that quality without disruptions is always at maximum level.

The resilience triangle model has been also applied by Zobel (2011), whose proposed metric calculates the percentage of total loss over a time interval T^*, as shown in Eq. 2. X represents the percentage of functionality lost after a disruption, while time T can have values from *0* to T^* and is equal to the time needed for full recovery (Fig. 1).

$$R(X,T) = \frac{T^* - XT/2}{T^*} = 1 - \frac{XT}{2T^*} \qquad (2)$$

The advantage of this metric is its simplicity, but its linear recovery may not be realistic for many systems. Furthermore, the degradation of performance is assumed to be immediate after a disruption. It means that these approaches give less importance to resistance (considering the ability to reduce the loss of functionality only, disregarding the dynamics of the loss).

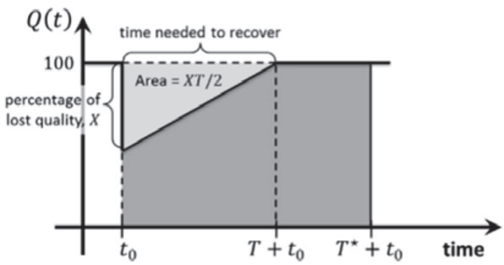

Fig. 1. A reinterpretation of the resilience triangle, adapted from Hosseini, Barker and Ramirez-Marquez (2016)

Rose (2007) concentrated its studies on the characteristic of resistance, defining resilience as "*the ability of an entity or system to maintain system' functionality when a disruption occurs*". The proposed metric, shown in Eq. 3, is a static and ex-post model where ΔY is the difference between non-disrupted and expected disrupted system performance, while ΔY^{max} represents the difference between the actual and the worst case of disrupted system performance. It is easy to realize that the main issue here is in the estimation of the expected degraded performance levels.

$$R = \frac{\%\Delta Y^{max} - \%\Delta Y}{\%\Delta Y^{max}} \qquad (3)$$

Cox, Prager, and Rose (2011) used a similar metric for London's transportation system. They use as worst case the maximum reduction of journeys for the attacked transportation modes. Rose (2007) also considered recovery, when defining dynamic resilience *DR*: in economics, it can be obtained by hastening repair. SO_{HR} in Eq. 4 is the output of the system under hastened recovery, while SO_{WR} is the output without hastened recovery. Parameters t_i and N are the i^{th} time step and the total number of time steps, respectively.

$$DR = \sum_{i=1}^{N} [SO_{HR}(t_i) - SO_{WR}(t_i)] \qquad (4)$$

The major concern about this metric is the range of *DR* values, that is not limited between 0 and 1, losing the possibility to compare different systems (or the same system in different conditions).

Henry and Ramirez-Marquez (2012) developed a time-dependent metric able to quantify resilience as a ratio between recovery and loss (Eq. 5). The metric also shows resilient behavior as a function of the disruptive event e^j.

$$R(t|e^j) = \frac{Q(t|e^j) - Q(t_d|e^j)}{Q(t_0) - Q(t_d|e^j)} T \qquad (5)$$

The numerator implies recovery up to time t, while the denominator refers to the total loss.

Wang, Gao and Ip (2010) proposed a metric measuring resilience in information systems characterized by m operations as shown by Eq. 6.

$$R = \max \sum_{i=1}^{m} z_i \frac{d_i}{c_i} \qquad (6)$$

d_i is the demand time for the recovery of the operation, c_i is the completion time and z_i is the weight given to its importance. The major limitation of the metric is that it assumes that the number of recovery actions and the number of operations are known.

Chen and Miller-Hooks (2012) studied a metric useful for transportation networks (Eq. 7). It returns the expected fraction of demand that can be satisfied after a disruption using a predetermined recovery budget. Parameter d_w quantifies the maximum demand that can be satisfied on a certain Origin-Destination connection w after the disruption, while D_w is relative to the scenario before the disruption. The biggest limitation of this metric is the absence of any analysis related to pre/post-disaster recovery activities and their impact on recovery time.

$$R = E\left(\frac{\sum_{w=1}^{W} d_w}{\sum_{w=1}^{W} D_w}\right) \qquad (7)$$

Orwin and Wardle (2004) linked resilience with instantaneous and maximum disturbance (Eq. 8). E_{max} is the maximum absorbable force without perturbing functions of the system, while

E_j refers to the effect of the disturbance on the safety of the system at time T_j. The major disadvantage is the lack of consideration for time to recover and so the possibility to obtain the same level of resilience with two different recovery times.

$$R = \left(\frac{2|E_{max}|}{|E_{max}| + |E_j|}\right) - 1 \tag{8}$$

Enjalbert et al. (2011) introduced the concepts of local and global resilience, applied to safety as performance indicator in public transportation. Global resilience is obtained by integrating local resilience over time, between t_d and t_f (Eq. 10).

$$Local\ resilience = \frac{dS(t)}{dt} \tag{9}$$

$$Global\ resilience = \int_{t_d}^{t_f} \frac{dS(t)}{dt} dt \tag{10}$$

Francis and Bekera (2014) proposed the dynamic resilience metric that is reported in Eq. 11. S_p is a variable representing speed of recovery and so related to recovery time, F_0 is the performance of the system before the disruption, F_r at the new stable state after the disruption, while F_d immediately after the disruption.

$$R = S_p \frac{F_r}{F_0}\frac{F_d}{F_0} \tag{11}$$

This is an ex-post metric which considers both absorptive and adaptive capacities in the same indicator. However, the relationship between them is not fully clear. A possible improvement could be the comparison of the recovered performance level with the difference ($F_0 - F_d$), as proposed by Hosseini, Barker, and Ramirez-Marquez (2016). Another weakness point is that this metric is not constrained on the interval between 0 and 1.

Cimellaro, Reinhorn, and Bruneau (2010) described resilience looking to the quality of service before and after the disruption (Q_1 and Q_2 respectively in Eq. 12), giving variable weights to the two entities according to the value of parameter α. For this reason, it is an ex-post metric. T_LC is the control time chosen for the system. The authors defined this metric keeping in mind the four characteristics of resilience mentioned before, but they did not include them in a direct way inside the indicator. In this case, the choice of the decision maker can obviously influence the results.

$$R = \propto \int_{T_{LC}} \frac{Q_1(t)}{T_{LC}} dt + (1{-}\propto) \int_{T_{LC}} \frac{Q_2(t)}{T_{LC}} dt \tag{12}$$

Ouyang and Wang (2015) assumed the main stages are to be (i) disaster prevention (ii) damage propagation (with the assumption of linear decrease of performance) (iii) assessment and recovery. These three stages can respectively reflect resistant, absorptive and restorative capacities. The final metric incorporates all the characteristics in Eq. 13. Resilience is quantified according to the curves of targeted performance $P_T(t)$ and the real one $P_R(t)$ over a time interval with length equal to T.

$$R(T) = \frac{\int_0^T P_R(t)\, dt}{\int_0^T P_r(t)\, dt} \tag{13}$$

It is important to notice that the time dependency of the metric gives the opportunity to analyze previous, current potential and future potential resilience according to the value of the period T (at each step metric).

Nan and Sansavini (2017) proposed a new metric able to integrate the measures of absorptive, adaptive and restorative capabilities in the four different phases (Eq. 14), as explained by Henry and Ramirez-Marquez (2012). The basic assumption is that its value must be constrained between 0 and 1.

$$R = f(RO, RAPI_{DP}, RAPI_{RP}, TAPL, RA) = $$
$$= RO \times \left(\frac{RAPI_{RP}}{RAPI_{DP}}\right) \times (TAPL^{-1}) \times RA \tag{14}$$

RO is a measure of robustness and is calculated as the minimum between t_d and t_f, where the former indicates the time when system starts to loose performance and the latter is the time in which the system reaches the new steady state (either lower, equal or higher then the original one). Finally, parameter t_a represents the time in which the system reaches the minimum performance level, i.e. $t_a = RO^{-1}(t)$. According to the authors, Robustness is not enough to reflect the absorptive ability; for this reason two additional measures are added to the model: Rapidity $RAPI_{DP}$ and Performance Loss PL_{DP}. Since there are no coefficients the same importance is given to all the characteristics analyzed with the metric. The big advantage of this indicator is the possibility to consider also possible improvements after a disruption: if the final performance level is higher than the initial one, the R value increases.

Li et al., 2017 proposed a metric similar to the one described by Bruneau et al., (2003), but limited between the beginning of the disruption and a chosen time delay T_a, as shown in Eq. 15. The idea of the authors was to make resilience measure comparable between different systems, considering the possibility that there is not a complete recovery in the chosen time period.

$$R = \frac{\int_{t_d}^{t_d + T_a} Q(t)\, dt}{T_a} \tag{15}$$

Najarian and Lim, 2019 developed a composite indicator that, according to them, is able to reflect absorption (r1), adaptation (r2) and time-to-recovery (r3) without being biased toward any of these components.

$$r_1 = \frac{\int_{t_d}^{t_a} P_R(t)\, dt}{\int_{t_d}^{t_a} P_r(t)\, dt};\ r_2 = \frac{\int_{t_d}^{T} P_R(t)\, dt}{\int_{t_d}^{t_a} P_r(t)\, dt} \quad (16)$$

where P_R and P_T have the same meaning of before, T is equal to t_f if the system recovers to a steady state level lower or equal to initial one, to the time in which the level is the same of the initial one if the steady state level reaches greater values during the recovery phase. Finally, it is possible to calculate *r3*.

$$r_3 = \begin{cases} 1 & t_f < T_0 \\ \dfrac{T_0}{t_f} & otherwise \end{cases} \quad (17)$$

where T_0 is defined as favorite time-to-recovery and can be determined in several ways, such as expert opinion.

The final metric is a combination of the three components:

$$R = \lambda_1 r_1 + \lambda_2 r_2 + \lambda_3 r_3$$
$$with \sum \lambda_i = 1,\ \lambda_i \geq 0 \quad (18)$$

Goldbeck, Angeloudis, and Ochieng (2019) proposed a performance measure that can be applied to all types of infrastructure systems. By estimating the total value of demand (*VoD*) and value of supply (*VoS*), and considering in a different way single and multi-commodity nodes, it is possible to evaluate three resilience indicators.

$$RLT = \sum_{t=0}^{t_{max}} (1 - \frac{VoS_t}{VoD_t}) \quad (19)$$

$$MSP = min\ \frac{VoS_t}{VoD_t} \quad (20)$$

$$TLD = \sum_{t=0}^{t_{max}} k_t\ with\ \ k_t = 1\ if\ \frac{VoS_t}{VoD_t} < 1 \quad (21)$$

The same ratio is used in each indicator: for the calculation of the resilience loss triangle *RLT*; for the minimum system performance *MSP* as index of robustness; and total length of disruption *TLD* as index of rapidity of recovery.

3.2 *Case-specific models*

With respect to structure-based models, the review focused on papers analyzing infrastructure networks. Adjetey-Bahun et al. (2014) used a time-dependent simulation model to measure the resilience indicators of a railway system. Several disruptive events are modelled, and simulations try to understand the consequences in terms of travel time and reduction of train capacity. Barker, Ramirez-Marquez, and Rocco (2013) exploited the metric described in Eq. (5) proposed by Henry and Ramirez-Marquez (2012) to evaluate the importance of each node of the network through a parameter CI defined as:

$$CI_i(t_r|e^j) = \frac{Q(t_0) - Q(t_{a,i})}{max_k\{Q(t_0) - Q(t_{a,k})\}} T \quad (22)$$

where $Q(t_{a,i})$ reflects the performance level of the disrupted system, with the disruption coming from a performance loss on node *i.* This equation gives importance to the effect that both disruption magnitude and recovery speed at component level have on the time to full network service recovery *T*. The metric named "resilience worth" (of link *i*), quantifies how the time total network resilience is improved for the scenario under analysis if link *i* is invulnerable (Eq. 23).

$$WR_i(t_r|e^j) = \frac{T - T_i}{T} \quad (23)$$

with T_i equal to the time total network resilience if node *i* is invulnerable.

Similarly, Kilanitis and Sextos (2019) defined network functionality as the sum of the importance factors of the links that are functional during each phase of the disruption (Eq. 25). The importance factors are calculated, prior to the disruption, with a ratio between the initial traffic load and the sum of loads of all the network links (Eq. 24), where $f_j = \gamma_j$ if *j* link is functional in that phase, 0 if not.

$$\gamma_i = \frac{V_{j0}}{\sum V_{j0}} \quad (24)$$

$$f_p = 100 \times \sum f_j \quad (25)$$

Ganin et al. (2017) use network science perspective, analysing topological features of the city transportation networks. They estimate resilience as the change in efficiency (delay of peak period commuters) resulting from roadway disruptions.

3.3 *Application domains and cases*

The further steps of the analysis focused on reported applications of resilience metrics (practical cases). For this purpose, for each of the selected metrics, a new search was performed on the same databases. This time the search targeted articles containing in title, abstract and keywords: (*resilien** AND (*metric** OR *index** OR *indicator**) AND (*appl** OR *exampl** OR *case**)). Table two reports the application cases found in literature for each one of the selected resilience metrics. Due to limitation in pages, the full references were not reported in this paper, but they are made available by the authors upon request.

4. Discussion

The main features and properties of the selected metrics are critically discussed to highlight their strengths and weaknesses and to select the sample for a systematic quantitative comparison (Part 2). Three main groups of resilience metrics were identified.

4.1 *Metrics built on the Resilience Loss Triangle*

The first group contains metrics that were developed from the definition of resilience proposed by Bruneau et al. (2003), i.e. based on the Resilience Loss Triangle – Eq. 2, Eq. 7, Eq. 13. In this first set of metrics, we decided to select and test the index given in Eq. 7 (Chen and Miller-Hooks, (2012)), but to apply it in a dynamic way, i.e. by evaluating the ratio between actual capacity of the system $c_w(T)$ and the theoretical one $C_w(T)$ at each time step. Then the metric has been slightly modified, as shown in Eq. (26).

$$R_c(T) = \frac{\sum_{w=1}^{W} c_w(T)}{\sum_{w=1}^{W} C_w(T)} \tag{26}$$

Moreover, a similar new metric was developed, which uses the ratio between demand successfully satisfied $d_w(T)$ and actual demand $D_w(T)$ (Eq. 27) at each node w at time t.

$$R_d(T) = \frac{\sum_{w=1}^{W} d_w(T)}{\sum_{w=1}^{W} D_w(T)} \tag{27}$$

This is a reinterpretation of the Eq. 13, applied to the framework of Eq. 7 adding the possibility of time-dependent instantaneous evaluations. Eq. 13 is a good measure of resilience according to performance, but the presence of the integral could increase too much the inertia of the measure (lowers the possibility to appreciate later time steps). The opposite approach could be followed too, i.e. applying the approach of Eq. 7 to the Eq. 13. It could be possible to obtain two measures of resilience, based on capacities and performance, not influenced by the specific situation characterizing the disruption, but taking into account also the past conditions of the system (Eq. 28, Eq. 29).

$$R_c(T) = \frac{\int_0^T c(t)\, dt}{\int_0^T C(t)\, dt} \tag{28}$$

The index given in Eq.2 was discarded because of its excessive approximation and because any application to relevant cases was found in literature.

$$R_d(T) = \frac{\int_0^T d(t)\, dt}{\int_0^T D(t)\, dt} \tag{29}$$

4.2 *Composite Resilience Metrics*

The second group of metrics includes all the composite indicators – Eq. 11, Eq. 14, Eq. 17.

The unclear relationship between the characteristics of resilience considered in Eq. 11 and its lack of normalization, were the main reasons for discarding this metrics. On the other side, very limited applications are reported for the metrics defined in Eq. 17. Thus the metric defined in Eq. 14 was finally chosen, because of the reduced need of data and its ability to cover possible improvements following a disruption. Another advantage of this metrics is the objectivity: according to Nan and Sansavini (2017) all the characteristics of resilience are included with the same weight.

4.3 *Composite Resilience Metrics with service segmentation*

The third group is composed by only one metric. Respect to the others, the metric proposed by Goldbeck, Angeloudis, and Ochieng (2019) is able to analyze an urban infrastructure system in which there is a differentiation between the flow of people and the flow of goods. This metric is made of three independent indexes (Eq. 19, Eq. 20, Eq. 21). Starting from them and following the same approach of Nan and Sansavini (2017), a new aggregate index can be developed to integrate all the resilience properties:

$$R = \frac{MSP}{RLT \times TLD} \tag{30}$$

4.4 *Case-specific Resilience Metrics*

This last group is made of the two selected case-specific metrics. The first one is the one proposed by Kilanitis and Sextos (2019) – Eq. 24, Eq. 25. It is a new metric, easy to apply, but able to give immediate response about resilience just looking to which nodes are functioning and which not, without focusing on the specific level of performance or amount of losses.

The second one follows the framework proposed by Barker, Ramirez-Marquez, and Rocco (2013) – Eq. 22, Eq. 23. This model exploits the metric which already found tens of applications, but looking to the importance of the single node in the network. It seems the best set of metrics to perform a Vital Node Analysis.

Table 2: Classification of reviewed literature for quantitative assessment of resilience

Reference	Metric Type	Dynamicity	Evaluation moment	Application domains IT – IT systems / networks; I – Infrastructure; O – Other	Completeness	Computational effort
Bruneau et al., 2003	Generic	Static	Ex-post			
Zobel, 2011	Generic	Static	Ex-post		*	***
Zobel and Khansa, 2014	Generic	Static	Ex-post			
Rose, 2007	Generic	Static	Ex-post			
Cox, Prager, and Rose, 2011	Generic	Static	Ex-post			
Henry and Ramirez-Marquez, 2012	Generic	Dynamic	At each step	Pant et al., 2014 (O); Baroud et al., 2014 (O,I); Ramirez-Marquez, Rocco, and Barker, 2017 (IT); Almoghathawi, Barker, and Albert, 2019 (I); Figueroa-Candia, Felder, and Coit, 2018 (I); Rocco, Hernández-Perdomo, and Barker, 2015 (IT); Rocco et al., 2018 (I)	**	***
Wang, Gao, and Ip, 2010	Generic	Static	Ex-post			
Chen and Miller-Hooks, 2012	Generic	Dynamic	Ex-post	Chen and Miller-Hooks, 2012 (I); Janic, 2015 (O,I); Janic, 2018 (O,I)	*	***
Orwin and Wardle, 2004	Generic	Static	Ex-post			
Enjalbert et al., 2011	Generic	Static	Ex-post			
Francis and Bekera, 2014	Generic		Ex-post	Huang and Ling, 2018 (I)	**	**
Cimellaro, Reinhorn, and Bruneau, 2010	Generic	Dynamic	Ex-post			
Ouyang and Wang, 2015	Generic	Dynamic	At each step	Ouyang and Wang, 2015 (I); Yodo,Wang, and Rafi, 2018 (I); Afrin and Yodo, 2019 (I); Kong and Simonovic, 2019 (I); Kong, Simonovic, and Zhang, 2018 (I)	*	***
Nan and Sansavini, 2017	Generic	Dynamic	Ex-post	Voropai, Kolosok, and Korkina, 2018 (IT)	***	***
Li et al., 2017	Generic	Static	Ex-post			
Najarian and Lim, 2019	Generic	Dynamic	Ex-post		**	*
Goldbeck, Angeloudis, and Ochieng, 2019	Generic	Dynamic	Ex-post		**	*
Adjetey-Bahun et al., 2014	Case-specific	Static	Ex-post			
Barker, Ramirez-Marquez, and Rocco, 2013	Case-specific	Static	Ex-post			
Kilanitis and Sextos, 2019	Case-specific	Dynamic	At each step			

5. Conclusions

In this paper a systematic literature review of the most relevant metrics for assessing the resilience properties of interdependent networked infrastructure systems was carried out. Their applicability, properties and limitations were highlighted and some proposals for modifications and enhancement were formulated as well.

In Part 2 both the selected and the newly proposed metrics will be put through a benchmarking process, made of experiments looking at the behaviour of the resilience metrics when the properties of the system vary. The benchmarking exercise will be completed in the context of a real and complex system of interdependent transportation infrastructures.

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