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Improved model for continuous, real-time assessment and monitoring of the resilience of systems based on multiple data sources and stakeholders

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ABSTRACT

Faced with an increasing level of disruption from natural disasters, terrorist attacks or internal failures, organisations need to ensure their business continuity. Ensuring this continuity depends, among other things, on the continuous assessment, monitoring, and management of their resilience based on the variations of the functionalities. Resilience-assessment methodologies are nowadays used to (1) prepare stakeholders for future crisis management situations and (2) help stakeholders assess past levels of resilience in the aftermath of the crisis. However, continuous, real-time monitoring and assessment of resilience is generally either outside the scope of such methods or limited to raw data representation, lacking effective filtering, interpretation, or integration in the evolving context of the organisation's activities. This paper enhances previous works on resilience assessment. The result is a complementary methodology for continuous, real-time resilience assessment and monitoring based on multiple data-sources and stakeholders. The novelty is (1) in the context of use of the methodology, (2) in the way the functionality analysis model is obtained and (3) in the way the resilience is continuously assessed.

KEYWORDS

functionality; data; resilience; organisation; sensor; road; decision; simulation; monitoring

1. Introduction

The mutual exchange of services of various interconnected and interdependent organisations is essential to the functioning and well-being of modern societies. These services must be maintained to a satisfactory level even under threats and disruptive events. Failure to provide services can lead to domino and cascade effects that impact other organisations related to the one initially affected. By organisation, we mean by infrastructure in the generic sense such as railway stations, airports, shopping centers, factories etc. In this context, the definition of (Kamissoko et al., 2019) is adapted to consider the absorptive capability in the resilience definition as argued by (Reda Taha et al., 2021).

Hence, the resilience of the organisation is defined as its “ability to absorb the impacts of perturbations, and to recover, in a minimum time, with minimum costs (financial, human, workload, etc.), a certain functioning capacity on all dimensions of its performances”. From this definition, Resilience can be seen as a measure of how functionality is maintained after a disruption and how it is quickly gained. Then, Resilience can be assessed by analyzing how an organisation functions (Kamissoko et al., 2019). From this point of view, maintaining a satisfactory level of resilience ensures that an organisation's vital needs are protected and allows it to continue providing services.

To do so, first, organisations must keep track of the way they function in real time, by analyzing nonfunctional properties such as vulnerability, robustness, agility, performance,

quality, resilience etc. Secondly, organisations' stakeholders must make the right decisions at the right time based on indicators related to the functionalities, to guarantee the business continuity, the security, and the survival of the organisation. Note that an indicator can be used to estimate one or more functionalities. In addition, a functionality can integrate one or more indicators. Indicators can be heterogeneous and of different nature. However, within this context, decision-making is challenging due to the changing and uncertain nature of the context and the multiplicity of stakeholders, data sources, indicators, and functionalities. The literature highlights different resilience-based decision-making approaches. They can be divided into three categories: (1) approaches based on raw data extraction, (2) indicator-based approaches and (3) approaches based on functionality analysis.

Raw data extraction approaches: (Platt, Brown, & Hughes, 2016) have defined a list of data sources providing raw data for resilience assessment and decision-making. It includes satellite imagery analysis (both manual and semi-automatic), volunteered geographic information (VGI), ground survey and observation, social audits (key informant interviews, focus groups), household surveys, official publications and statistics, and insurance data. The goal is to use data to determine the state of a system before making any decision. For example, the raw data are used to determine the state of a power plant (Mehranbod, Soroush, Piovosio, & Ogunnaike, 2003), the quality control of an automobile assembly process (Li & Chen, 2009), etc. However, the main

limitation of such approaches is their non-exhaustiveness. This makes their implementation hard and challenging.

Indicator-based approaches: (Abdulkader, Bamhdi, Thayananthan, Jambi, & Alrasheedi, 2018) classify approaches in this category in four layers with reference to the assessment frameworks: sensors, network, middleware and application. (Laouira, Abdelli, Ben Othman, & Kim, 2021) identify three layers: detection, visualisation and identification, and a layer for decision making. In the proposal of (Abdulkader et al., 2018), the “sensors layer” identifies the sensors; the network layer is a sensor management architecture; the middle layer provides data exploitation models; and the application layer targets operational applications for the exploitation of results. Several of the proposed tools in this category are in the upper layer and are difficult to connect to the lower layers (i.e., the data and sensor layers). This lack of connection makes the proposals difficult to use in an operational situation.

There are also several studies for resilience assessment based on indicators. Some of them characterise the soil, lakes, vegetation, behavioural health, quality of life, critical infrastructures (Fisher & Norman, 2010), earthquakes (Bruneau & Reinhorn, 2007; Ishibashi et al., 2021), community (Renschler, Frazier, Arendt, & Cimellaro, 2010), or hospitals (Rodríguez & Aguirre, 2006). In (Cimellaro, Reinhorn, & Bruneau, 2010a), aggregated indicators are used to evaluate different system functionalities. (Brown et al., 2010) classify these indicators into six categories: *transport* (length of road, accessibility, reconstruction of bridges and transport facilities, presence of vehicles), *buildings/shelters* (removal and construction of buildings, changes in urban land use and morphology, quality of dwelling reconstruction), *transitional shelters and IDPs* (temporary dwellings and shelters, location of population), *services* (administration, education, healthcare and religious facilities, power, water and sanitation, (WATSAN facilities), *environment* (change in land cover and open public space), and *livelihoods* (recovery of livelihoods).

Functionality analysis approaches: several proposals address the problem of functionality evaluation. They are classified based on the evaluation of performance (Francis & Bekera, 2014; Ouyang & Wang, 2015; Reed, Kapur, & Christie, 2009), the measurement of the potential losses of a functionality (Henry & Emmanuel Ramirez-Marquez, 2012; Zobel, 2011), the measurement of service quality (Bruneau et al., 2003; Cimellaro, Reinhorn, & Bruneau, 2010b), the effectiveness of safety barriers (Enjalbert, Vanderhaegen, Pichon, Ouedraogo, & Millot, 2011), recovery activities (Cox, Prager, & Rose, 2011) or the evaluation of implemented processes (Hosseini, Barker, & Ramirez-Marquez, 2016). Another classification introduced in (Kamissoko et al., 2019) is based on the evolution of a functionality. There are several functionalities evaluation models presented in (Kussul et al., 2014; Nan & Sansavini, 2017; Tran, Balchanos, Domercant, & Mavris, 2017).

One of the difficulties in assessing functionality is that multiple indicators and stakeholders are involved in the decision process (Kamissoko et al., 2019). A similar problem

is encountered in life-cycle analysis (De Luca et al., 2017), project management (Olander, 2007; Yang, Wang, & Jin, 2014), sustainability evaluation (Campos-Guzmán, García-Cáscales, Espinosa, & Urbina, 2019), development planning and implementation (Thabrew, Wiek, & Ries, 2009). As for the evaluation of functionalities, the issue is addressed, for example, for resilience in (Cerreta & Panaro, 2017; Evers, Almoradie, & de Brito, 2018), or for performance in (Avkiran & Morita, 2010; Soltani, Hewage, Reza, & Sadiq, 2015).

In addition to the previous classification, resilience assessment approaches can be categorised based on the time horizon: (1) prospective, (2) retrospective and (3) perspective. Prospective resilience assessment approaches are used to assess a possible level of resilience based on approximated or simulated values of indicators. The proposal of (Kamissoko et al., 2019) is an example of the prospective approach. Retrospective resilience assessment approaches are used to assess resilience based on the values of indicators in the past. Perspective resilience assessment or resilience monitoring is used to assess the current level of resilience based on real-life and real-time raw data. The term real-time is here used to refer to the present instant with a possible short delay, to not be confused with the same term used in other domains. An evaluation can be one of these three modes or their combinations.

The drawback of most previously discussed approaches is the lack of a stakeholder-dedicated view for stakeholder needs, making implementation difficult in a real-life operational context. Another drawback is in the presentation and use of data. Data is presented in raw form and is not contextualised, limiting the understanding of data for any human operator (Jungert & Chang, 2015). For example, data can be properly structured based on models, as suggested in the domain of Model-Based Systems Engineering. In addition, data is often analyzed by a human operator; however, the limits of human operators are easily reached when there are great quantities of information to process. This makes implementation even more difficult. Moreover, evaluation models are generally based on a single indicator of a system, generally because data sources are not diversified and are primarily limited to a single source. The lack of genericity further limits the application to other types of organisations or other contexts. Finally, most models are designed to simulate the system and to provide an assessment retrospectively but not continuously with the simulation.

While the proposal of (Kamissoko et al., 2019) can be successfully used as a prospective approach by continuously assessing possible levels of resilience based on simulations, it lacks the ability for retrospective and perspective resilience assessment. This paper bridges that gap and introduces a complementary methodology for continuous, real-time assessment and monitoring of resilience, based on multiple data-sources and stakeholders. The new proposal can be used for prospective, retrospective, and perspective resilience assessment. The novelty is: (1) in the context of use of the methodology, (2) in the way the functionality analysis model

is obtained and (3) in the way the resilience is continuously assessed.

A data extraction mechanism is used to acquire data from any type of data source. Extracted data is processed, filtered, and interpreted into a value that represents either an indicator or a part of an indicator (i.e., the value of indicators can be based on multiple data-sources) at a given time. The resilience assessment model is based on multiple indicators. Both data extraction and resilience assessment processes are continuous and in real-time. Several redundancies have been removed and improvements are proposed to enhance existing proposal such as the proposal of (Kamissoko et al., 2019). For example, equations are presented according to the evaluation horizon. The need to evaluate at one instant, *a priori* and *posteriori* is also considered.

The term functionality refers to the ability of an organisation to function, i.e., to provide services. This is defined by a “functionality model” as a set of indicators. The value of these indicators is constantly changing as the organisation operates in its environment. The resilience level is then tied to the value of these indicators and based on the resilience assessment model, with each change in indicators’ values. The changes are in real time as data sources send data. Therefore, the resilience level also changes. The latter is referred to “resilience monitoring” in the context of this paper. The approach can also be used in the field of security and surveillance and for organisations’ business continuity planning, providing indicators that stakeholders can use to make the right decisions. This can lead to better cost control or allow organisations to be managed with serenity in particular situations. As Argued by (Achilopoulou, Mitoulis, Argyroudis, & Wang, 2020), monitoring is embraced as a vital component, providing expedient feedback for recovery measures, accelerating decision-making for adaptation of changing ecosystems and built environments, utilising emerging technologies, to continuously deliver safer and resilient infrastructure.

This paper is organised as follows: the following section introduces the contribution as a new methodology, detailing and comparing each point with existing methods. In the third section, two case studies are presented to demonstrate feasibility. They are analyzed in the fourth section, before concluding the paper in the last section.

2. Proposed methodology

The problem addressed by this paper can be formulated as follows: given several data sources, several type of indicators, several stakeholders, how can the resilience of an organisation be evaluated based on its functionalities in the present, in the past and in the future? To answer this question, a methodology for a continuous, real-time assessment and monitoring is proposed. This methodology is based on functionality analysis and the process is described in Figure 1.

The overall process is composed of two phases as show in Figure 1: a design and a runtime phase. The goal of the design phase is to identify all necessary elements from the assessment context. It consists of stakeholder hierarchization, concepts’ design, evaluation type identification,

determining the type of indicators, selection of data source and assessment of the evaluation frequency. The design phase involves stakeholders with different access and relevance levels in an organisation that collaborate in each sub-phase. This leads, first, to stakeholder hierarchization.

The goal of the runtime phase is the continuous and real-time design of a functionality model and the continuous and real-time assessment of resilience. Data provided by data sources is continuously processed and transformed into a functionality model as time advances. This is carried throughout six steps: Acquisition, Filtering, Quality Control, Interpretation, Integration and Storing. The resilience is assessed based on the values of indicators obtained from data.

2.1. Design phase

2.1.1. Stakeholder hierarchization

There can be multiple stakeholders involved in the assessment process. The analysis objectively qualifies them by indicators, as shown in Table 3. In this table, the evaluation of the relevance of a stakeholder h for an indicator m is denoted $I(h, m)$. From this set, the importance of a stakeholder is determined by using the AHP method if the indicators are independent, or the ANP method if they are dependent (Saaty, 2003, 2004). The result is a qualification of each stakeholder by a weight (or relative importance) in a hierarchy table. To be effective and without biases, this evaluation process must, however, be conducted by an analyst outside the decision-making process.

2.1.2. Concepts design

The conceptual model is based on the proposed concepts of (Kamissoko et al., 2019) and presented in Figure 2. It consists of structure and a behaviour. The structure is a set of Territory, System, Component and Criterion (indicator). The behaviour is a set of concepts Evolution, Influence and Aggregation Functions. In this proposal, the designed models are based on the conceptual framework and transformed into a simulation platform to obtain a functionality model. The functionality model is then evaluated based on several assertions to assess resilience values. Resilience values are tied to indicators. They are aggregated to obtain the overall resilience of a system.

Instead of simulating the value of an indicator as proposed by (Kamissoko et al., 2019), the idea in this proposal is to use data sources to obtain raw data and to transform them into an indicator value. This process is done continuously, as time advances. New values are returned by data sources, to form the functionality model. This type of functionality model is thus different from the one introduced in (Kamissoko et al., 2019).

2.1.3. Evaluation type identification

Two types of assessment are distinguished in this proposal: (1) continuous assessment, meaning that assertions are continuously applied with the design of the functionality model, (2) periodic assessment by extracting a sub-functionality

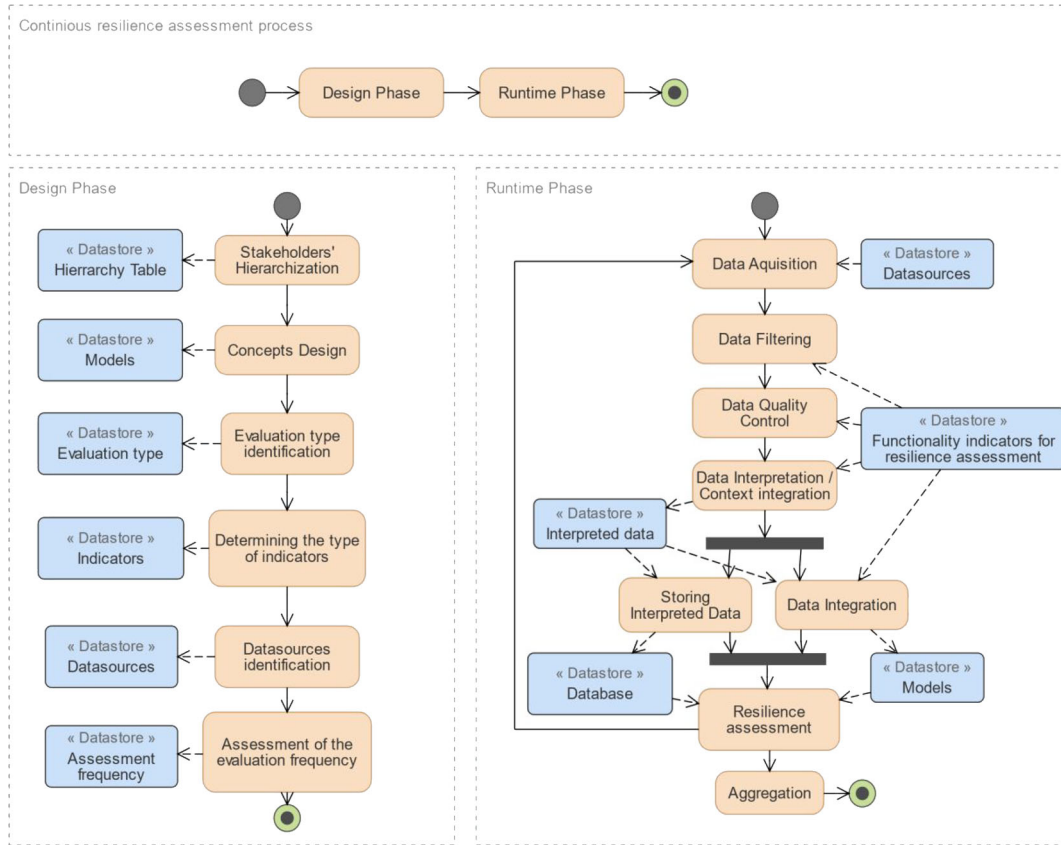


Figure 1. A process for continuous and real-time design of functionality model and resilience assessment.

model from the continuously designed functionality model based on a given period. The resilience can vary according to the type of assessment used.

Evaluation at a given instant: Given t the present instant, the evaluation can be made at t , at an instant $t - x$, i.e., in the past, or at an instant $t + x$, i.e., in the future ($x > 0$). The first focus of this proposal is the evaluation in the present.

Evaluation over a period: Given t the present instant, depending on the begin/end intervals of a period, a periodic evaluation concerns: (1) the past, if both begin and end intervals are in the past $[t - x_1; t - x_2]$, (2) the future, if both begin and end intervals are in the future $[t + x_1; t + x_2]$, (3) the past and the present, if the begin interval is in the past and the end interval is the present $[t - x; t]$, (4) the present and the future, if the begin interval is in the present and the end interval is in the future $[t; t + x]$, (5) the past and the future, if the begin interval is in the past and the end interval is in the future $[t - x; t + x]$. The work presented in (Kamissoko et al., 2019) focuses on the modes (2) and (4). The second and third focuses of this proposal are the modes (1) and (3). For this, traceability mechanisms are used. After evaluation at the present instant, results are stored in a database. As time advances, the database keeps track of all results. They are used later to obtain the results over a given period in the past.

2.1.4. Determining the type of indicators

The functionality model is designed based on several indicators. It is also multidimensional and linked to the following

dimensions: economic, regulatory, human, social, ecological/environmental, political, territorial, and operational/organisational. The goal of this step is to identify the relevant indicators based on the context, including the system of interest and the frontier systems. Identified indicators must be sufficient for the design of the functionality model.

2.1.5. Data source selection

In the context of this paper a data source is a material and/or human means capable of providing, at a defined frequency, by a reliable channel, raw and exploitable data necessary for the evaluation of at least one functionality. Data sources are classified into the following categories: (1) a physical sensor (e.g., video/audio camera, radar, floating car data, satellite, Bluetooth terminal, Wi-Fi terminal, mobile phone), (2) human expert, (3) data in the form of physical documents, (4) geographical information system (GIS), (5) building information modelling (BIM), (6) database (e.g., relational, NoSql, spreadsheet), (7) knowledge model and (8) simulation model.

The goal of this phase is to identify all available data sources that can provide the value of identified types of indicators at a given time. The challenges of this phase are in (1) quantifying the value of an indicator based on acquired raw data, (2) managing the inherent uncertainty in the acquired data to assure the quality of data and (3) managing redundancy if different data sources provide data about one indicator, as shown in Table 1.

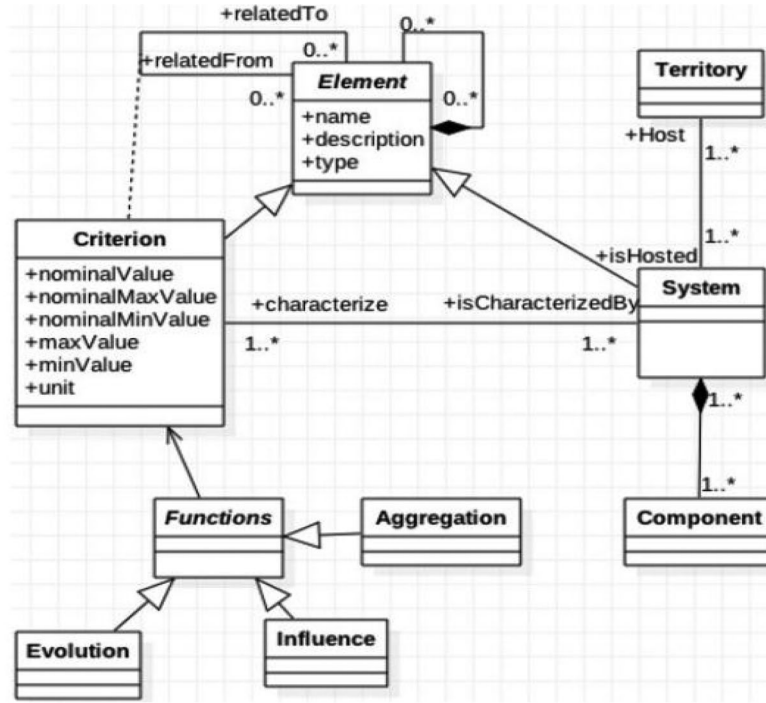


Figure 2. Conceptual model proposed by (Kamissoko et al., 2019). This model is generic enough to represent the context of any situation. The notion of criterion refers to an indicator.

Table 1 presents an example of different types of sources that can furthermore be interpreted to determine a given indicator. A value of 1 in a cell (s, i) indicates that the source s provides the indicator i . This situation can be illustrated on a highway. In such a case, the number of cars can be determined by a CCTV camera or by an electromagnetic loop on the ground. The problem is in choosing a single data source for a given indicator. For that, it is proposed to prioritise data sources, as shown in Table 2. This priority is an example. It depends on the context and the assessment type.

Table 3 illustrates a situation where multiple sources of different nature provide data about a given indicator I_i . The set of data sources to choose from is the initial set is denoted IS. To select the data source in this case, complementary information is needed. Obtaining this table assumes that there is an outside analyst who helps steer the decision-making process and who is responsible for collecting the information needed to model the decision-maker's preference. The data sources are then characterised by a set of complementary indicators (e.g., technical reliability, the value of uncertainty). Note that the indicators characterising the sources are different from those used for the design of a functionality model. The evaluation of the data source s for the indicator t is $DI(s, t)$. The complementary indicator set is noted CI. The point of view of the stakeholders, who are paramount in any choice issue, is considered through the attribution of a relative importance to the indicators and the proposal of a preference function for each indicator.

The relative importance is assessed in the form of a weighting. The preference function determines the results of pairwise comparison of the set IS. It is used to qualify the

Table 1. Data sources: a data source can provide multiple indicators. Likewise, an indicator can be provided by several sources.

	I_1	I_2	...	I_i
DS_1	1	0	...	0
DS_2	1	1	...	1
...
DS_s	1	0	...	1

indifference or the preference of a decision-maker when comparing two alternatives. For a given stakeholder, the preference is then composed of a set of weight (W) and a set of preference function (pf). Then, from Table 3, a multi-criteria decision-making methodology such as PROMETHEE is used to determine the compromise data source for all stakeholders. This approach to choosing data sources should limit errors and uncertainties in the indicators. However, it is possible that uncertainty remains in the indicators provided by the chosen source. This paper does not deal with such situations and assumes that the indicators provided by the source are deterministic, i.e., without uncertainty.

2.1.6. Assessment of the evaluation frequency

From the previous steps, a data source has been selected for a given indicator. Because there could be several indicators and that every data source has its emission frequency as shown in Table 4. The frequencies are given in multiples of a time unit period. The unit of the provided values depends on the type of the data source. There is the need to determine the overall assessment frequency. The resulting frequency is obtained by aggregation. Depending on the context, the aggregation function can be *min*, *max*, *mean*,

Table 2. Priority in data sources. Priority is given as an indication. The default table was determined through consultation with business experts.

	Past	Present	Future
Physical sensor	x	2	x
Human expert	2	1	1
GIS / BIM / DB / Form	1	3	2
Knowledge model / Simulation model	3	4	3

Table 3. Data source selection for an indicator by a stakeholder.

Indicator I_i , Stakeholder Sh	DSI_1	DSI_2	...	DSI_t
Decision maker set of preferences	w_1	w_2	...	w_t
Weight	pf_1	pf_2	...	pf_3
Preference function	DI_(1,1)	DI_(1,2)	...	DI_(1,t)
DS_1	DI_(2,1)	DI_(2,2)	...	DI_(2,t)
DS_2
...	DI_(s,1)	DI_(s,2)	...	DI_(s,t)
DS_s				

median, or one of the functions described in (Torra & Narukawa, 2007). The aggregate value of the frequency is (F).

2.2. Runtime phase

The goal of the runtime phase is the continuous and real-time design of a functionality model and assessment of resilience. This is carried out throughout the following processes: data acquisition, data filtering, data quality control, data interpretation, data integration, data storing and resilience assessment. Each phase is detailed hereafter. The goal of the data-acquisition process is to collect and transfer data, from data sources to the data-filtering process based on an emission frequency. This includes interfacing with data sources. The interface depends on the type of the data source and is done by an expert.

For example, interfacing with human sources can be done through interviews, based on surveys or through forms, whereas interfacing with technical resources requires dedicated technical expertise. The goal of the data-filtering process is to extract, from raw data, the information deemed important for the study and to send the latter to the data-quality engine. Note that, sometimes filtering is not necessary, and the raw data is equal to the filtered data. The goal of the quality-control phase is to limit errors and uncertainty in filtered data. It is assumed that at the end of this phase, there is no more uncertainty on data sources through the implemented decision-making process. Otherwise, these uncertainties can be handled by approaches such as Bayesian Networks (outside the scope of this paper). The goal of the data-interpretation process is to contextualise and link data to an indicator of the functionality model. Data interpretation involves contextualising one or more data values in a model. This contextualisation could result in creating, modifying, or deleting instances of indicators.

For instance, interpreting data from a camera could be formulated in these terms: “if a person is detected with a body temperature $>38^\circ\text{C}$, there is a COVID19-propagation risk”. Here again, the choice of the information to be contextualised is made by a business expert. Finally, the contextualised data is simultaneously integrated in the model (integration process) and saved in a database (storing

Table 4. Different frequencies and values for data sources.

	Frequency	Value
DS_1	F_1	V_1
DS_2	F_2	V_2
...
DS_s	F_s	V_s

interpreted data process). This allows us to synchronise the model with the real system based on the data sources that are internal or external to the system. Complete traceability is also provided by the storage database allowing for an evaluation over a period. Based on the resulting model, the resilience is assessed continuously and in real time. This methodology is presented below.

2.2.1. Context integration

The evaluation of the functionality model tied to a given indicator follows the rhythm of the variation of the context. The context is a set of objectives and constraints of the environment, defined through a set of four functions:

- The maximum limit f_{max} : beyond this limit, the functionality induced by the indicator is equal to zero.
- The minimum limit f_{min} : below this limit, the functionality induced by the indicator is equal to zero.
- The maximum nominal limit fn_{max} : below this limit the system is completely resilient.
- The nominal minimum limit fn_{min} : above this limit the system is completely resilient.

Thus, assuming that a system is characterised by a single indicator, it can be qualified as fully resilient if the value of this indicator is between fn_{min} and fn_{max} .

Figure 3 depicts the evolution of the value of an indicator characterising a system over the time. Before the disruptive event, the value of the indicator is assumed to be between fn_{min} and fn_{max} . If only this indicator characterises the system, the latter is in a good functioning state. The corresponding period to this state is G . At the occurrence of a disruptive event, the value of the indicator could drop and be lower than the minimum nominal value. The system is then in a bad functioning state. The period corresponding to this state is D or U if the value of the indicator is greater than maximum nominal value. In Figure 3, the periods $G1$, $G2$, $G3$ and $G4$ are the good functioning periods. $D1$, $U1$ and $U2$ are the bad functioning periods.

In such situations, S_1 , S_2 and S_3 are the area described by the shape of the indicator in bad functioning state, S'_1 , S'_2 , and S'_3 are the total surfaces for the period. The value of each

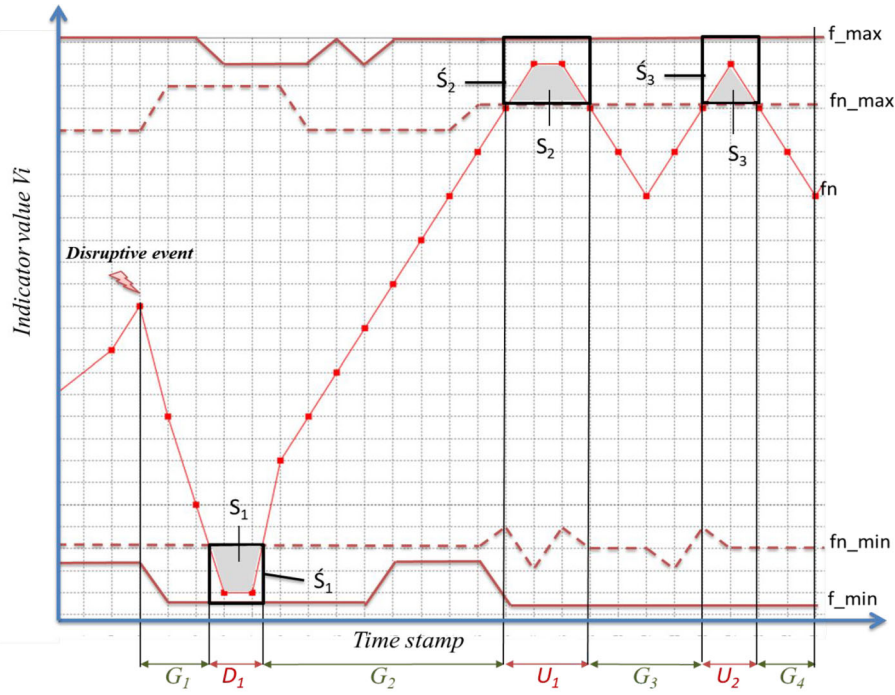


Figure 3. Evolution of the value of an indicator by (Kamissoko et al., 2019). The value of the indicator is obtained as described above. The existence of a disruptive event is not mandatory. This also makes it possible to assess resilience in a nominal situation.

limit is given by a data source which may be different depending on the stakeholder. Similarly, the data sources for quadruplet $\{f_{min}(i), f_{max}(i), fn_{min}(i), fn_{max}(i)\}$ are determined for the indicator Ii . In the same way, the final values of $\{f_{min}(i), f_{max}(i), fn_{min}(i), fn_{max}(i)\}$ and their frequencies are obtained by aggregation.

2.2.2. Functionality evaluation

The evaluation of the functionality is different depending on whether it is carried out at a given instant or over a period.

Evaluation for a given instant: For a component Cc , an indicator Ii that has a value Vi , at a given instant t , the evaluation of the induced functionality Fci is performed as follows:

If $f_{max}(i) \neq fn_{max}(i)$ and $f_{min}(i) \neq fn_{min}(i)$:

$$Fci = \begin{cases} 0, & \text{if } Vi \geq f_{max}(i) \text{ or } fn(i) \leq f_{min}(i) \\ 1, & \text{if } fn_{min}(i) \leq Vi \leq fn_{max}(i) \\ 1 - \frac{Vi - fn_{max}(i)}{f_{max}(i) - fn_{max}(i)}, & \text{if } fn_{max}(i) < Vi < f_{max}(i) \\ 1 - \frac{fn_{min}(i) - Vi}{fn_{min}(i) - f_{min}(i)}, & \text{if } f_{min}(i) < Vi < fn_{min}(i) \end{cases} \quad (1)$$

If $f_{max}(i) = fn_{max}(i)$ and $f_{min}(i) \neq fn_{min}(i)$:

$$Fci = \begin{cases} 0, & \text{if } Vi \geq f_{max}(i) = fn_{max}(i) \text{ or } fn(i) \leq f_{min}(i) \\ 1, & \text{if } fn_{min}(i) \leq Vi \leq fn_{max}(i) = f_{max}(i) \\ 1 - \frac{fn_{min}(i) - Vi}{fn_{min}(i) - f_{min}(i)}, & \text{if } f_{min}(i) < Vi < fn_{min}(i) \end{cases}$$

If $f_{max}(i) \neq fn_{max}(i)$ and $f_{min}(i) = fn_{min}(i)$:

$$Fci = \begin{cases} 0, & \text{if } Vi \geq f_{max}(i) \text{ or } fn(i) \leq f_{min}(i) = fn_{min}(i) \\ 1, & \text{if } f_{min}(i) = fn_{min}(i) \leq Vi \leq fn_{max}(i) \\ 1 - \frac{Vi - fn_{max}(i)}{f_{max}(i) - fn_{max}(i)}, & \text{if } fn_{max}(i) < Vi < f_{max}(i) \end{cases} \quad (3)$$

If $f_{max}(i) = fn_{max}(i)$ and $f_{min}(i) = fn_{min}(i)$:

$$Fci = \begin{cases} 0, & \text{if } Vi \geq f_{max}(i) = fn_{max}(i) \text{ or } fn(i) \leq f_{min}(i) = fn_{min}(i) \\ 1, & \text{if } fn_{min}(i) = f_{min}(i) \leq Vi \leq fn_{max}(i) = f_{max}(i) \end{cases} \quad (4)$$

Evaluation for a given period: The functionality calculated over a period depends on the points constituting this period. Points refer to the values of the indicators Vi , and the values of induced functionalities Fci at a given time-stamp in that period. By default, if for a point in the period, the induced functionality is zero, it is zero for the entire period (this condition can be null depending on the context). Otherwise, for a period where the values are external to the interval $[fn_{min}; fn_{max}]$, it is calculated according to two modes.

Mode 1: This mode is based on the calculation of the areas concerning the period of malfunction. The functionality for a single output outside the nominal zone (a single malfunction zone) is:

$$Zci = 1 - \frac{S}{S'} \quad (5)$$

(2) where S is the area of the profile in a bad functioning state and S' is the total area of bad functioning.

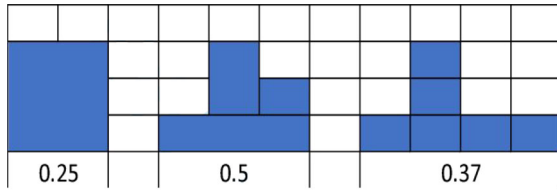


Figure 4. Influence of the indicator's profile on the functionality.

In a case with several zones in such a period, the value of the functionality is calculated for each interval j . The resulting value is then an aggregation of the different values:

$$Fci = g(Z^1(i), Z^2(i), \dots, Z^j(i)) \quad (6)$$

where g is an aggregation function.

Mode 2: This mode is based on the aggregation of the values of the Fci obtained for every point of the value V_i . The distinction between the two evaluation methods constitutes one of the original features of this paper. This distinction is not considered in (Kamissoko et al., 2019). Because the two modes are always computed, the value of the functionality is always very low. In addition, the assertion 8 of (Kamissoko et al., 2019) is corrected. In fact, this assertion states that “the closer the value of an indicator is to the limit f_{max} or f_{min} , the lower the value of assessed functionality.” But it turns out that the proximity of the value of the indicator to these limits influences the surfaces S and S' in Equation 5. This proximity is then considered. Assertion 8 of (Kamissoko et al., 2019) is therefore redundant.

2.2.3. Aggregation

It is now possible to assess the functionality of a component for a single indicator. The functionality of a component depends on the functionality tied to all the indicators related to the component. The induced functionality of a component C_c for an indicator I_i is Fci . The overall functionality of the component (Fc) is an aggregation of all induced functionalities Fci tied to the component. In the same way, given the fact that organisations and infrastructures can be composite, we argue that the functionality of a system depends on those of its components. System functionality is then an aggregation of the induced functionality of its components.

2.2.4. Complementary indicators

The area created by the value of indicators in a bad functioning state U or D has an influence on the final value of the functionality. Figure 4 displays three feature profiles having the same surface. According to Assertion 10 of (Kamissoko et al., 2019), “the more often the value of an indicator goes outside of f_{min} and f_{max} , the lower is the value of the assessed functionality.” Naively, one would tend to deduce that the three profiles have the same value of functionality. In fact, they have the same surface. However, the values of functionality induced by the three profiles are respectively 0.25, 0.5 and 0.37. Note that the value is

sensitive to the total cumulative duration, to the proximity of the maximum value, and to the number of times the value of the indicator is outside the interval $[f_{min}, f_{max}]$. These elements are already integrated in calculation mode 1 in Equation (5). Assertion 10 of (Kamissoko et al., 2019) is therefore redundant. However, the evolution of the value from one step to another is a calculated indicator that needs to be considered.

From this proposal, the approach's key features presented in this paper could be summarised as follows:

- *Continuous and real-time assessment of resilience based on all types of data:* Data is provided by various and varied sources. The type of data sources can vary. Raw data is transmitted at a given emission frequency, filtered, interpreted, and integrated in a functionality model that is later used for resilience assessment. This is a key contribution in comparison to related works;
- *Stakeholder integration.* Stakeholders are hierarchically integrated in the process in a unique way that allows them to make decisions based on their preferences. They collaborate in each of the stages of the process, i.e. from the data acquisition to its integration into models and databases. For example, stakeholders with technical expertise collaborate in the following processes: data acquisition, filtering, and quality control. Business stakeholders' knowledge is required in the processes of data-source selection and data filtering. Business knowledge is also required in the integration step: each indicator is linked to a model element, thus allowing the integration of indicator data into the models. Finally, the models can represent different views of the same infrastructure, allowing each stakeholder to visualise the infrastructure according to their own business vision.
- *Identification of multiple resilience-assessment strategies.* This includes the resilience assessment at a given instant or a given period, the assessment horizon (past, present and future) and the assessment modes. This approach can be effectively used in the preparation phase of a crisis management lifecycle. It can be also used in real-time monitoring and real-time evaluation.

3. Cases studies

The proposal of this paper is implemented in a prototype demonstrator. The prototype (under construction) is applied on two different case studies (Resiist Project, 2020, 2021) to demonstrate, the genericity one hand, and the claims of the paper on the other hand. The first case study aims to assess the resilience of a motorway section continuously and in real time. This refers to its capacity to provide fluid vehicle circulation, without traffic jams, despite given disruptive events. The second case study aims to evaluate – again in real time and continuously – the resilience of a shopping mall to a COVID-19 propagation, despite disturbing events such as people not wearing protective masks or not respecting social-distancing rules. Note that stakeholder hierarchization is out of the scope of this analysis because, both case

studies are toy examples for demonstration purposes. It is assumed that the stakeholders have equal weight in decision-making and for the sake of simplicity, stakeholder weight-related indicators are not shown.

3.1. Motorway section case study

3.1.1. Concept design and data-source selection

The conceptual model of a motorway section is shown in Figure 5. The motorway section component “Road sub-systems” contains components for monitoring purposes: air-temperature measurement component (“Air temperature measure system”), occupancy-rate component (“Occupancy rate measure system”) and a video-surveillance component (“Video Stream processing system”). The latter allows the extraction from a video stream of the number of people and vehicles and the detection and extinction of a fire. The emission frequency of all data sources is set to three seconds since all sensors send data every three seconds.

3.1.2. Determining the indicators

The assessment of motorway-section resilience is based on six indicators, represented by the “ResilistIndicator” tag, in Figure 5. Traffic fluidity is defined by two indicators: the occupancy rate of the section by vehicles (I1 - “OccupancyRate”) and the number of vehicles (I2 - “Detected Vehicules”). The occupancy rate of the motorway section measures the traffic flow in the motorway section, i.e., the rate at which vehicles circulate in an intersection. In addition, this case study focuses on the risk and impact of a fire accident, represented through four indicators: the air temperature (I3 - “MeasuredAirTemperature”), the presence of a fire (I4 - “DetectedFire”), that of pedestrians (I5 - “DetectedPerson”) and an indicator concerning the extinction of a fire (I6 - “DetectedFireExtinction”). These indicators are related to the three dimensions. The I2, I3 and I4 indicators are related to the environmental dimension, while the I1 and I5 indicators are linked to the technical dimension. Finally, the I6 indicator is related to the organizational dimension.

3.1.3. Context integration

The goal of this phase is to define the maximal and minimal limits (f_{max} , f_{min}) and the maximal and minimal nominal limits (fn_{max} and fn_{min}). For reasons of clarity and simplicity, the minimal limit and the minimal nominal limit are not considered (for example, the temperature may have a minimum threshold due to the risk of freezing). Table 5 shows the maximal limit and the maximal nominal limit for all indicators of this case study. The maximum limit above which the resilience to traffic jams is zero, is 90%. The maximum nominal limit (i.e., below which the resilience is greater than 0) is defined at 70%. Along with the occupancy rate, the number of vehicles on the section must not be greater than 5, with an acceptable rate set at 3.

Regarding a vehicle fire, the air temperature must not be greater than 5. It must not exceed 100 degrees Celsius (the

sensor not necessarily being at the location of the fire), with an acceptable threshold set at 80 degrees. This is accompanied by the detection of a fire or not. The maximum and acceptable rates for this indicator are then identical and equal to one. The presence of pedestrians on the section must not be more than four, otherwise there is no resilience to traffic jams. The acceptable level is equal to 2. Regarding fire interventions, the maximum and acceptable rates are identical: they must not be greater than 1. For all the indicators, the trend function is linked to the data sent by the sensors:

$$fn(t) = k(t) \quad (7)$$

where k is a function that gives the value provided by a data source at the time t .

3.2. Mall case study

3.2.1. Concepts design and data sources selection

The objective of this section is to present an ongoing assessment of the resilience of a shopping mall to a COVID propagation among customers. Figure 6 displays the 2D plan of the mall and the location of data sources (i.e., cameras). The mall is composed of 3 zones: (1) a common area (CA), (2) a grocery store (GS) and (3) a do-it-yourself (DIY) store. The common area is composed of an entrance (E) and a hallway (H). The hallway is composed of two zones HZ1 and HZ2. The grocery and DIY stores are each composed of two zones (GSZ1, GSZ2 and DSZ1, DSZ2).

A part of the conceptual model of the mall is illustrated in Figures 7 and 8. Figure 7 shows the context, composed of a system of interest, i.e., the mall (M), a frontier system, i.e., a Covid-information reception (CIR) and COVID-propagation indicators. The mall is equipped with: (1) a monitoring system composed of several cameras, each one providing a live feed of different zones, (2) an infrared monitoring system at the entrance hall, allowing for body temperature measurement of all people that enter the mall and (3) the means to connect to the health organisation for the regional COVID propagation rate. The monitoring system includes mechanisms for automatic detection of people that do not wear masks (i.e., mask-detection system) and people that do not respect social distancing (i.e., social-distance detection system), based on the live feed of each camera. For example, Figure 8 shows data sources as components of the mall entrance (E) and indicators for the COVID propagation risk, i.e., a system for body-temperature measurement (BTM), detecting mask wearing (EMD) and social distancing (ESDD).

3.2.2. Determining the indicators

The evaluation matrix for the COVID propagation, inspired by the COVID rules imposed by the French government in 2020, is composed of the following indicators: (1) mandatory mask wearing (MNW), (2) constant social distancing (SDD), i.e. a 1m distance between two people, (3) body temperature monitoring (BTM), i.e. entrance forbidden to people with 39+°C body temperature, and (4) the regional

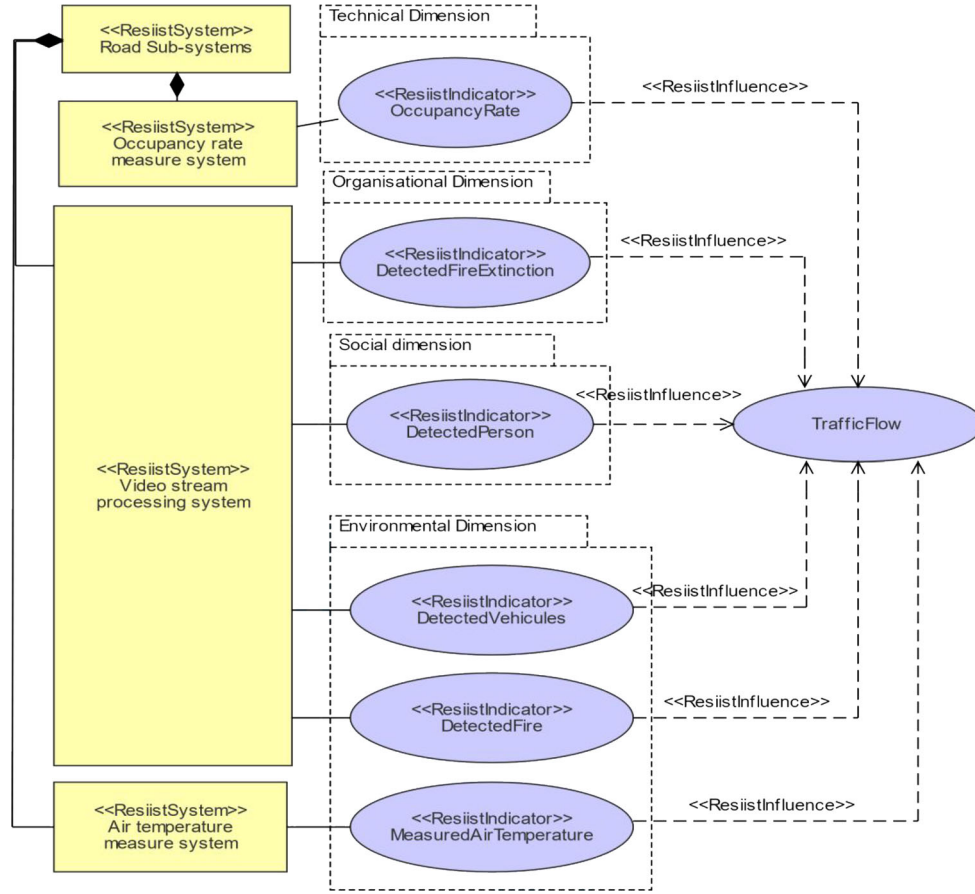


Figure 5. A conceptual model for the motorway section case study. The model is composed of components and indicators of a motorway section.

Table 5. Synthesis of context integration for the motorway-section case study: maximal limits and maximal nominal limits for all indicators.

	fn_{max}	f_{max}
Occupancy rate	70	90
Vehicle number	3	5
Air temperature	80	100
Fire extinction	1	1
Person number	2	4
Fire number	1	1

COVID propagation rate (CRR), which is, in France, translated by the national green, orange and red zones. The case study sets the measurement time (required frequency) to three seconds (the sensor sends data every two seconds). The mask-detection system provides information about the mandatory mask-wearing indicator for each zone, based on the camera live feed of a zone. The social-distancing detection system provides information about the social-distancing indicator for each zone. The mask-wearing indicator and the social-distancing indicators of a zone in the mall are combined (based on an aggregation function) and provide an aggregate indicator denoted “Protective Measure” for the zone in the mall.

Figure 7 depicts these indicators at a high level, i.e., without showing each one in each mall area. The MNW and SDD indicators are related to each of the 7 zones to indicate precisely where certain rules are not respected. The letter of the zone (e.g., E for mall entrance) is added as a prefix to the indicator. For instance, EMNW defines the number of

people that do not wear masks in the entrance of the mall, as shown in Figure 8, which is a low-level model in comparison to Figure 7. There is a total of 7 “mask not worn” indicators and 7 “no social distancing” indicators. The resilience based on these indicators is denoted by the letter R added as a prefix to the indicator (e.g., REMNW defines the resilience related to the indicator “people that do not wear masks in the entrance of the mall”). The PMR (protective-measure resilience) is also related to each of the 7 zones (e.g., EPMR to indicate the resilience based on protective measures in the mall entrance, as shown in Figure 8). This indicator is calculated by the aggregation function A1 that considers the RMNW and RNSD. Note that A1 is used in each zone to calculate the PMR based on the RMNW and RNSD related to the zone. The A1 aggregation function is defined as follows:

$$\begin{aligned}
 &A1(RMNW, RNSD) \\
 &= \begin{cases} 1, & \text{if } RMNW = 1 \text{ or } RNSD = 1 \\ 0, & \text{if } RMNW = 0 \text{ and } RNSD = 0 \\ n = \text{average}(RMNW, RNSD), & \text{elsewhere} \end{cases} \quad (8)
 \end{aligned}$$

This function is defined to consider different situations at a profound level. For example, to differentiate, in terms of resilience, a situation where an individual wears a mask and does not respect social distancing from a situation where the person does not wear a mask and does not respect social distancing. With, for example, an aggregation

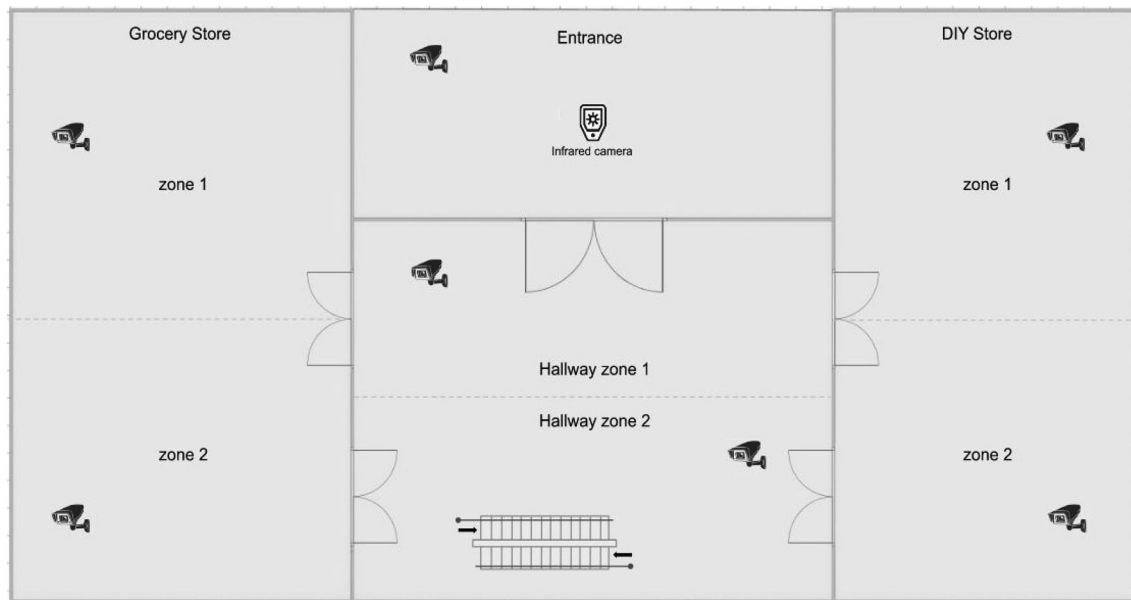


Figure 6. A 2D plan of a commercial mall with the position of data sources.

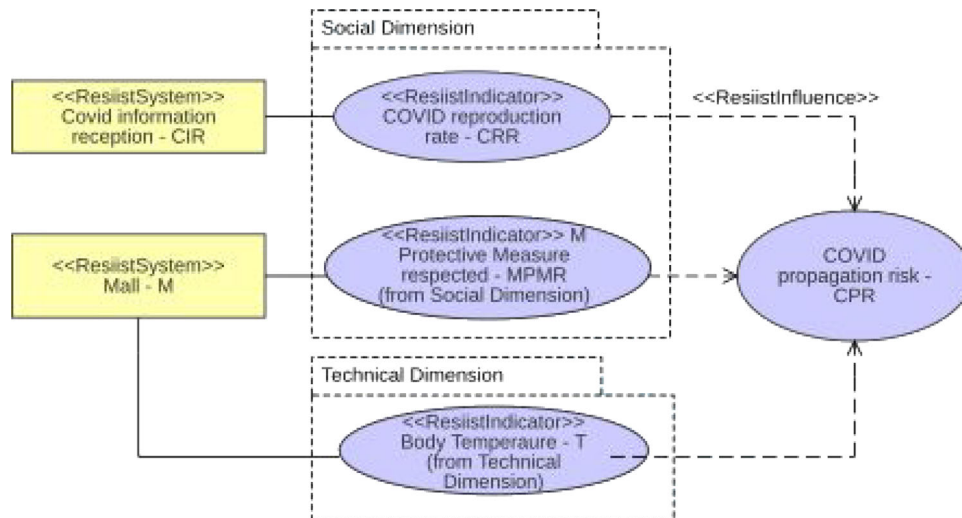


Figure 7. Conceptual model of the mall and a frontier system, i.e., Covid information (CIR), and indicators for the COVID-propagation risk (high-level representation).

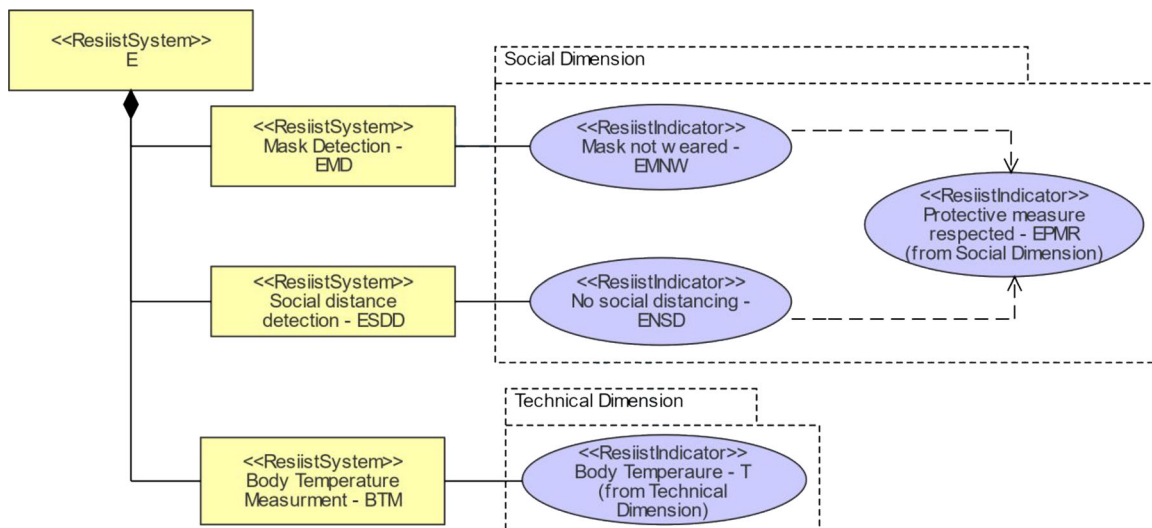


Figure 8. Case study - ArchiMate model: Entrance and indicators for the COVID propagation risk.

Table 6. Synthesis of context integration for the commercial mall case study: maximal limits and maximal nominal limits for all indicators.

	fn_{max}	f_{max}
MNW (mask not worn)	1	2
NSD (no social distancing)	2	4
PMR (protective measure resilience)	0,5	1
T (body temperature)	38	39
CRR (COVID reproduction rate)	1	1.5

by product, it would be impossible to differentiate the two situations since the result of the aggregation would be zero in both cases. Note that this aggregation function is only an example. Experts in the field could refine it or propose another. As indicated previously, it is the knowledge contribution of domain experts that allows the best configuration of the aggregation of indicators. Finally, the product of all resilience related to the protective measures of each zone (e.g., EPMR) gives the protective-measure resilience of the mall (MPMR). The overall resilience of the mall (CPR) is the product of MPMR, TR, and CRRR.

3.2.3. Context integration

The goal of this phase is to contextualise indicators by defining a set of objectives and constraints of the environment. This set consists of the maximal and minimal limits (f_{max} and f_{min}) and the maximal and minimal nominal limits (fn_{max} and fn_{min}). For reasons of clarity and simplicity, the minimal limit, and the minimal nominal limit (fn_{min} and f_{min}) are not considered. Table 6 presents the maximal limit and the maximal nominal limit for all indicators of this case study.

The acceptable limit for mask wearing (MNW) is one person, the maximum being two. For social distancing (NSD), several couples (disrespecting social distancing of 1 m) equal to two is considered acceptable, the maximum being four. These two indicators are aggregated, as explained above, in the protective-measure resilience (PMR). The acceptable limit for the body-temperature indicator (T) is 38°C, with a temperature not to be exceeded of 39°C. Finally, the COVID reproduction rate (CRR) must be between one and one-and-a-half at worst (meaning that a person theoretically contaminates between one and one-and-a-half people).

3.3. Results

The unfolding of both case studies and the continuous assessment of resilience via the implemented prototype are available at (Resiist Project, 2020) and (Resiist Project, 2021). Figure 9 depicts a screenshot from the video of the first case study. It shows the detection, from a video stream (simulation of a camera), of a vehicle fire (left) and the triggering of two alerts in the diagram (right). These alerts are represented by the red colour of the air temperature and vehicle-on-fire indicators.

In this figure, the value V at a given time instant t is defined in the input fn in the “Custom Properties” panel, visible on the left of the diagram. This is because V is the

result of fn in each time instant: $V = fn(t)$. The associated resilience value is defined in the input “resilience” in the same “Custom Properties” panel. For this case study, the results of the change in the value V and the continuous real-time assessment of resilience for each indicator results in the resilience of the motorway section, obtained by aggregating the resilience of each indicator. It should be noted that for reasons of clarity and simplicity, we have synchronised the time scales of the video and the charts. The integration of the interpreted data starts from 02:30 in the video. As for the charts, a default value is retained.

Figure 10 depicts a screenshot of the second case study video. It shows the detection of people not respecting social distance and not wearing masks (top and middle left) and the detection of their body temperature (bottom left). In the 2D map, one alert is visible and represented by the red colour of the detected “No social distancing” indicator. The online demonstration (Resiist Project, 2021) is split for each mall area.

There is a relationship between the value of an indicator V as a function of the limits and the value of the resilience linked to the latter. Indeed, resilience:

- is **maximum**, when the value of the indicator is nominal, that is to say, in a normal operating zone (less than $fn_{max}(i)$ and greater than $fn_{min}(i)$);
- is **zero**, when the value of the indicator reaches the maximum threshold $f_{max}(i)$ (or minimum $-f_{min}(i)$);
- **decreases**, when the value of the indicator changes from the acceptable limit $fn_{max}(i)/fn_{min}(i)$ to the unacceptable limit $f_{max}(i)/f_{min}(i)$;
- **increases**, when the value of the indicator changes from the unacceptable limit $f_{max}(i)/f_{min}(i)$ to the acceptable limit $fn_{max}(i)/fn_{min}(i)$;

For example, for the indicator *OCCUPANCY_RATE*, the resiliency is maximum until 03:03 because the value of the indicator V is less than the $fn_{max}(i)$ limit. From 03:04 to 03:40 the resilience decreases with the evolution of fn towards the threshold $f_{max}(i)$. The resilience is zero at 03:40 when the value reaches the threshold $f_{max}(i)$. Finally, between 03:44 to 04:20, the resilience increases with the evolution of the value V towards the limit $f_{max}(i)$.

Figure 11 displays the resilience of the motorway section. The result is obtained by aggregating the resilience linked to each indicator. For this, we used the product as an aggregation function. Indeed, in the analysis of resilience, it is commonly accepted that for a system made up of components and indicators, if the resilience of a component or that of an indicator is zero, then the resilience of the whole system becomes zero. Therefore, the product that is compatible with this point of view is chosen. In this case, if the resilience of one of the indicators is zero, the aggregate resilience is also zero (from 02:40 to 05:04 and from 05:10 to 06:49).

Figure 12 illustrates the resilience of each indicator, from 5:04 am to 5:10 am. During this period, the resilience of five indicators is maximal. Aggregated resilience (product based) depends on the sixth indicator, *OCCUPANCY_RATE* (see Figure 13).

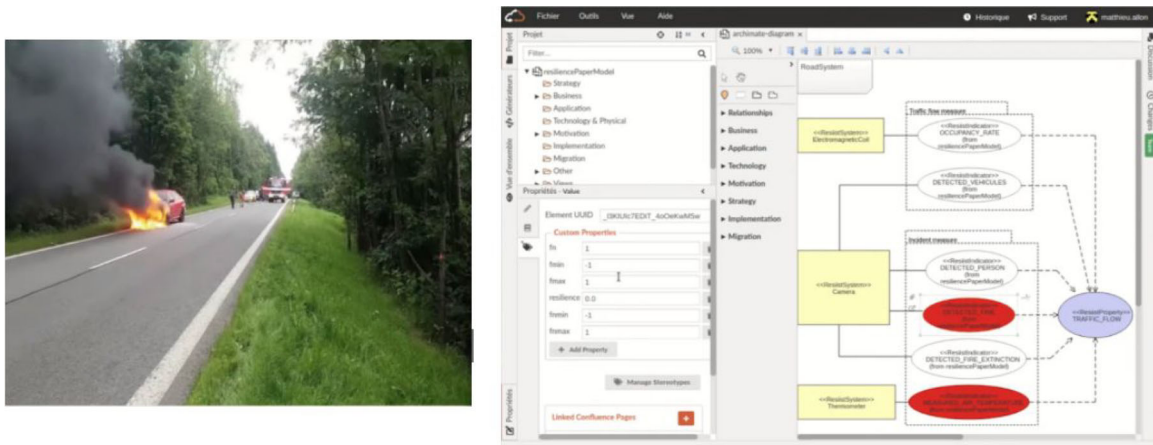


Figure 9. Excerpt from the video showing the detection of a vehicle on fire.

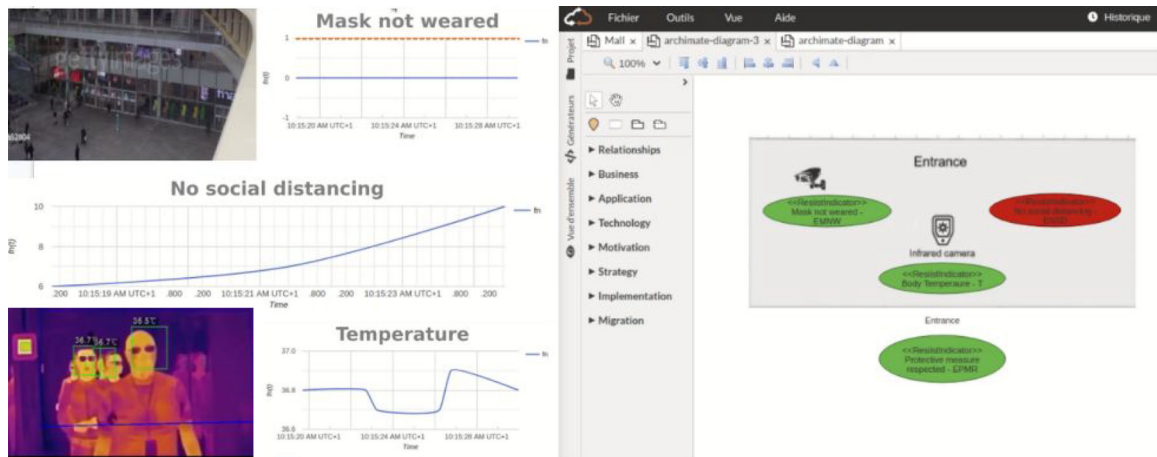


Figure 10. Extract from the video showing the COVID propagation risk evaluation in a mall via three indicators (body temperature, social distancing and mask wearing).

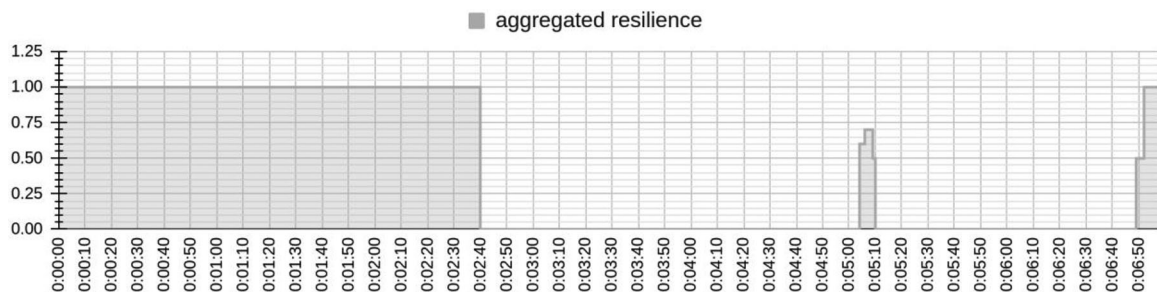


Figure 11. The resilience of the motorway section, obtained by aggregating the resilience of each indicator.

Periodic resilience can be used to compare the evolution of resilience over a period. For example, the periodic resilience (OCCUPANCY_RATE) graph shows the periodic resilience of OCCUPANCY_RATE. The idea is to be able to compare one level of resilience with another to determine the most advantageous level. For example, to compare OCCUPANCY_RATE in Figure 13 with OCCUPANCY_RATE in Figure 14.

In the first case the resilience increases by half a point and then decreases by one point (see the top right side of Figure 13). In the second case, the resilience does not change (see the top right side of Figure 14) because, as the functionality model is continuously constructed, the value of the indicator remains the same for the given period (see the

top left side of Figure 14). Based on the value of the indicator (equal to 78), the mode 2 resilience assessment method (discussed in Section 2.2) is used to assess the level of resilience (equal to 0.6) at each time stamp (each second). In comparison with the previous case, the value of the indicator does change (see the top left side of Figure 13), so consequently the value of the continuously assessed resilience also changes (see the top right side of Figure 13).

Considering the nature of the infrastructure (motorway intersection) and its resilience as the ability to provide a fluid movement of vehicles without a traffic jams traffic flow, for the periodic assessment of resilience based on the given period (from 00:05:04 to 00:05:10, i.e., a period of

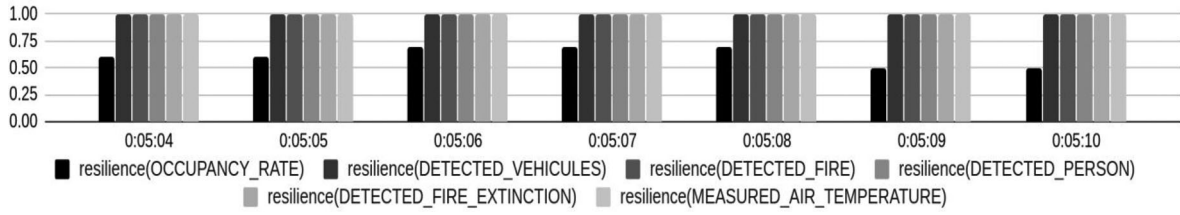


Figure 12. Resilience levels from 05:04 to 05:10.

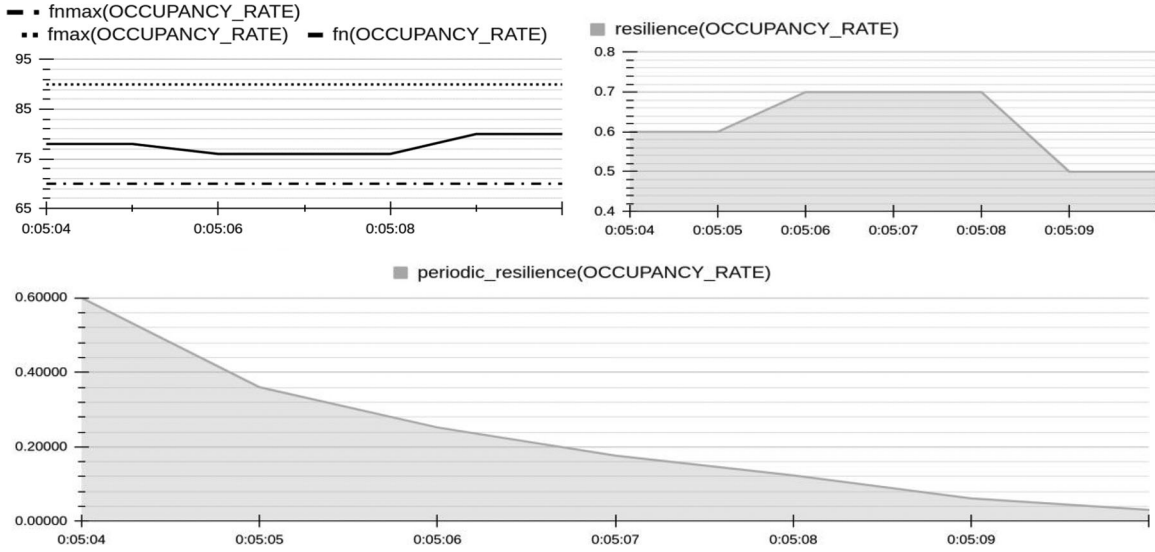


Figure 13. OCCUPANCY_RATE Resilience levels from 05:04 to 05:10.

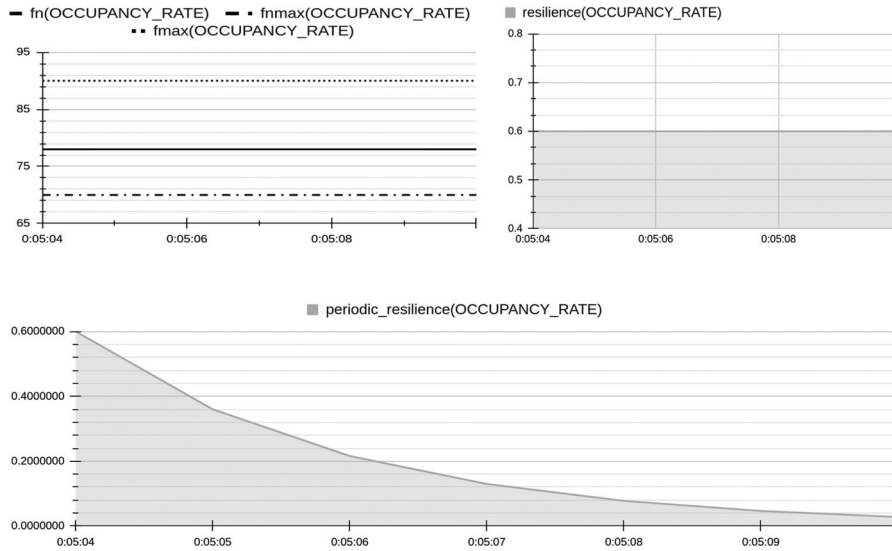


Figure 14. OCCUPANCY_RATE Resilience levels from 05:04 to 05:10 (alternative similar scenario).

5 seconds) the product is used as an aggregation function. This means that the infrastructure is less resilient the longer it stays in “traffic jam” state (occupancy_rate > 70 and <90), and the bigger the traffic jam is (as occupancy rate tends to 90). Determining the periodic resilience for the first study (Figure 13) and for the given period of 5 seconds, means that the continuously assessed resilience values need to be multiplied (0.6 at 00:05:04 and 00:05:05; 0.7 at 00:05:06, 00:05:07 and 00:05:08; and 0.5 at 00:05:09 and 00:05:10). The result, illustrated in the bottom right of Figure 13, is 0.03 ($0.6 \times 0.6 \times 0.7 \times 0.7 \times 0.7 \times 0.5 \times 0.5$). Similarly,

the value of 0.02 is obtained for the second case (the bottom right of Figure 14). Hence, the first case is more favourable: 0.03 against 0.02. The result is even more obvious in the context of scenarios with values that are far apart (positive or negative).

4. Conclusions

This paper proposes a methodology for continuous, real-time assessment and monitoring of the resilience of

organisations based on multiple data sources and stakeholders. Indeed, the mutual exchange of services of various interconnected and interdependent organisations is essential to the functioning and well-being of modern societies. These services must be maintained to a satisfactory level even under threats and disruptive events. To this end, the methodology introduced here can be used to assess resilience continuously and in real time by analyzing the functioning of organisations by means of indicators. Maintaining a satisfactory level of resilience ensures the vital needs of organisations and enables them to continue to provide services. The results of assessed resilience can be used by stakeholders to make the right decision, at the right time, and guarantee the resilience of organisations in terms of business continuity and security, thus ensuring the survival of the organisation.

This study improves a previous work on resilience assessment in three key areas: (1) in the context of use of the methodology, (2) in the way the functionality analysis model is obtained and (3) in the way the resilience is continuously assessed. The new approach is based on data-extraction mechanisms to acquire raw data from any type of data source that is further processed, filtered, and interpreted into a value of an indicator. Multiple indicators are tied into a functionality model, the latter being used to assess the resilience. Both data-extraction and resilience-assessment processes are continuous and in real-time. The resilience-assessment formulas are also improved: several redundancies are removed, an evaluation horizon is added, and the points of view of stakeholders are integrated in the process. In addition, the new approach is complementary and innovative in the time horizon of the resilience assessment. Indeed, the existing approach proposes a prospective resilience assessment. It lacks the ability for retrospective and perspective resilience assessment. The approach presented in this paper introduces a methodology for retrospective and perspective resilience assessment.

The results of this paper are applicable to any organisation. The applicability is demonstrated in two completely different case studies. The results of this paper can also be used to build security dashboards for organisation surveillance based on continuous, real-time resilience assessment and monitoring, leading to better cost control, or managing organisations in specific situations with serenity. The perimeter of this contribution is limited to assessing resilience continuously and in real time, and in making decisions to guarantee an acceptable level of resilience. Improving levels of resilience is out of the scope of this paper and is one of the key directions of future research. This includes the simulation of different non-functional properties and the integration of components that can help improve resilience, based on all the assessment horizons discussed in the paper. Managing data uncertainty and quality, for example, by using Bayesian Networks, is the second perspective of future works.

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References

- Abdulkader, O., Bamhdi, A. M., Thayanathan, V., Jambi, K., & Alrasheedi, M. (2018). A novel and secure smart parking management system (SPMS) based on integration of WSN, RFID, and IoT. In *2018 15th Learning and Technology Conference (L T)* (pp. 102–106). doi:10.1109/LT.2018.8368492
- Achillopoulou, D. V., Mitoulis, S. A., Argyroudis, S. A., & Wang, Y. (2020). Monitoring of transport infrastructure exposed to multiple hazards: A roadmap for building resilience. *The Science of the Total Environment*, 746, 141001. doi:10.1016/j.scitotenv.2020.141001
- Avkiran, N. K., & Morita, H. (2010). Benchmarking firm performance from a multiple-stakeholder perspective with an application to Chinese banking. *Omega*, 38(6), 501–508. doi:10.1016/j.omega.2009.12.007
- Brown, D., Platt, S., Bevington, J., Saito, K., Adams, B., Chenvidyakarn, T., ... Khan, A. (2010). Monitoring and evaluating post-disaster recovery using high-resolution satellite imagery -towards standardised indicators for post-disaster recovery.
- Bruneau, M., & Reinhorn, A. (2007). Exploring the Concept of Seismic Resilience for Acute Care Facilities. *Earthquake Spectra*, 23(1), 41–62. doi:10.1193/1.2431396
- Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., ... von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 19(4), 733–752. doi:10.1193/1.1623497
- Campos-Guzmán, V., García-Cáscales, M. S., Espinosa, N., & Urbina, A. (2019). Life Cycle Analysis with Multi-Criteria decision making: A review of approaches for the sustainability evaluation of renewable energy technologies. *Renewable and Sustainable Energy Reviews*, 104, 343–366. doi:10.1016/j.rser.2019.01.031
- Cerreta, M., & Panaro, S. (2017). From perceived values to shared values: a multi-stakeholder spatial decision analysis (M-SSDA) for resilient landscapes. *Sustainability*, 9(7), 1113. doi:10.3390/su9071113
- Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010a). Seismic resilience of a hospital system. *Structure and Infrastructure Engineering*, 6(1-2), 127–144. doi:10.1080/15732470802663847
- Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010b). Framework for analytical quantification of disaster resilience. *Engineering Structures*, 32(11), 3639–3649. doi:10.1016/j.engstruct.2010.08.008
- Cox, A., Prager, F., & Rose, A. (2011). Transportation security and the role of resilience: A foundation for operational metrics. *Transport Policy*, 18(2), 307–317. doi:10.1016/j.tranpol.2010.09.004
- De Luca, A. I., Iofrida, N., Leskinen, P., Stillitano, T., Falcone, G., Strano, A., & Gulisano, G. (2017). Life cycle tools combined with multi-criteria and participatory methods for agricultural sustainability: Insights from a systematic and critical review. *The Science of the Total Environment*, 595, 352–370. doi:10.1016/j.scitotenv.2017.03.284
- Enjalbert, S., Vanderhaegen, F., Pichon, M., Ouedraogo, K. A., & Millot, P. (2011). Assessment of transportation system resilience. In *Human modelling in assisted transportation* (pp. 335–341). Milano: Springer.
- Evers, M., Almoradie, A., & de Brito, M. M. (2018). Enhancing flood resilience through collaborative modelling and multi-criteria decision analysis (MCDA). In A. Fekete & F. Fiedrich (Eds.), *Urban disaster resilience and security: Addressing Risks in Societies* (pp. 221–236). Berlin/Heidelberg, Germany: Springer International Publishing. doi:10.1007/978-3-319-68606-6_14
- Fisher, R. E., & Norman, M. (2010). Developing measurement indices to enhance protection and resilience of critical infrastructure and

- key resources. *Journal of Business Continuity & Emergency Planning*, 4(3), 191–206.
- Francis, R., & Bekera, B. (2014). A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliability Engineering & System Safety*, 121, 90–103. doi:10.1016/j.res.2013.07.004
- Henry, D., & Emmanuel Ramirez-Marquez, J. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. *Reliability Engineering & System Safety*, 99, 114–122. doi:10.1016/j.res.2011.09.002
- Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. *Reliability Engineering & System Safety*, 145, 47–61. doi:10.1016/j.res.2015.08.006
- Ishibashi, H., Akiyama, M., Frangopol, D. M., Koshimura, S., Kojima, T., & Nanami, K. (2021). Framework for estimating the risk and resilience of road networks with bridges and embankments under both seismic and tsunami hazards. *Structure and Infrastructure Engineering*, 17(4), 494–514. doi:10.1080/15732479.2020.1843503
- Jungert, E., & Chang, S.-K. (2015). DMS2015-37: Surveillance system with SIS controller for incident handling using a situation-based recommendations handbook. *Journal of Visual Languages & Computing*, 31, 160–170. doi:10.1016/j.jvlc.2015.10.005
- Kamissoko, D., Nastov, B., Benaben, F., Chapurlat, V., Bony-Dandrieux, A., Tixier, J., ... Daclin, N. (2019). Continuous and multidimensional assessment of resilience based on functionality analysis for interconnected systems. *Structure and Infrastructure Engineering*, 15(4), 427–416. doi:10.1080/15732479.2018.1546327
- Kussul, N., Skakun, S., Shelestov, A., Yu, Kussul, O., & Yailymov, B. (2014). Resilience Aspects in the Sensor Web Infrastructure for Natural Disaster Monitoring and Risk Assessment Based on Earth Observation Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 7(9), 3826–3832. doi:10.1109/JSTARS.2014.2313573
- Laouira, M. L., Abdelli, A., Ben Othman, J., & Kim, H. (2021). An efficient WSN based solution for border surveillance. *IEEE Transactions on Sustainable Computing*, 6(1), 54–51. doi:10.1109/TSUSC.2019.2904855
- Li, S., & Chen, Y. (2009). Sensor fault detection for manufacturing quality control. *IIE Transactions*, 41(7), 605–614. doi:10.1080/07408170802389290
- Mehranbod, N., Soroush, M., Piovoso, M., & Ogunnaike, B. A. (2003). Probabilistic model for sensor fault detection and identification. *AIChE Journal*, 49(7), 1787–1802. doi:10.1002/aic.690490716
- Nan, C., & Sansavini, G. (2017). A quantitative method for assessing resilience of interdependent infrastructures. *Reliability Engineering & System Safety*, 157(C), 35–53. doi:10.1016/j.res.2016.08.013
- Olander, S. (2007). Stakeholder impact analysis in construction project management. *Construction Management and Economics*, 25(3), 277–287. doi:10.1080/01446190600879125
- Ouyang, M., & Wang, Z. (2015). Resilience assessment of interdependent infrastructure systems: With a focus on joint restoration modeling and analysis. *Reliability Engineering & System Safety*, 141, 74–82. doi:10.1016/j.res.2015.03.011
- Platt, S., Brown, D., & Hughes, M. (2016). Measuring resilience and recovery. *International Journal of Disaster Risk Reduction*, 19, 447–460. doi:10.1016/j.ijdrr.2016.05.006
- Reda Taha, M., Ayyub, B. M., Soga, K., Daghash, S., Heras Murcia, D., Moreu, F., & Soliman, E. (2021). Emerging Technologies for Resilient Infrastructure: Conspectus and Roadmap. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, 7(2), 03121002. doi:10.1061/AJRUA6.0001134
- Reed, D. A., Kapur, K. C., & Christie, R. D. (2009). Methodology for Assessing the Resilience of Networked Infrastructure. *IEEE Systems Journal*, 3(2), 174–180. doi:10.1109/JSYST.2009.2017396
- Renschler, C. S., Frazier, A. E., Arendt, L. A., & Cimellaro, G. P. (2010). A framework for defining and measuring resilience at the community scale: The PEOPLES resilience framework.
- Resiist Project. (2020, September 17). Real-time monitoring of the resilience of a road to traffic congestion during an accident. <https://youtu.be/zq-GPLnfiK8>.
- Resiist Project. (2021, March 14). COVID propagation risk—Mall resilience assessment. <https://youtu.be/XWVb6oU9JBc>.
- Rodríguez, H., & Aguirre, B. E. (2006). Hurricane Katrina and the healthcare infrastructure: A focus on disaster preparedness, response, and resiliency. *Frontiers of Health Services Management. Discussion* 25-30, 23(1), 13–23.
- Saaty, T. L. (2003). Decision-making with the AHP: Why is the principal eigenvector necessary. *European Journal of Operational Research*, 145(1), 85–91. doi:10.1016/S0377-2217(02)00227-8
- Saaty, T. L. (2004). Decision making—The analytic hierarchy and network processes (AHP/ANP). *Journal of Systems Science and Systems Engineering*, 13(1), 1–35. doi:10.1007/s11518-006-0151-5
- Soltani, A., Hewage, K., Reza, B., & Sadiq, R. (2015). Multiple stakeholders in multi-criteria decision-making in the context of municipal solid waste management: A review. *Waste Management (New York, N.Y.)*, 35, 318–328. doi:10.1016/j.wasman.2014.09.010
- Thabrew, L., Wiek, A., & Ries, R. (2009). Environmental decision making in multi-stakeholder contexts: Applicability of life cycle thinking in development planning and implementation. *Journal of Cleaner Production*, 17(1), 67–76. doi:10.1016/j.jclepro.2008.03.008
- Torra, V., & Narukawa, Y. (2007). *Modeling decisions: Information fusion and aggregation operators*. Berlin and Heidelberg: Springer Science & Business Media.
- Tran, H. T., Balchanos, M., Domercant, J. C., & Mavris, D. N. (2017). A framework for the quantitative assessment of performance-based system resilience. *Reliability Engineering & System Safety*, 158, 73–84. doi:10.1016/j.res.2016.10.014
- Yang, R. J., Wang, Y., & Jin, X.-H. (2014). Stakeholders' attributes, behaviors, and decision-making strategies in construction projects: Importance and correlations in practice. *Project Management Journal*, 45(3), 74–90. doi:10.1002/pmj.21412
- Zobel, C. (2011). Representing the multi-dimensional nature of disaster resilience. In *Proceedings of the 8th International ISCRAM Conference—Lisbon, Portugal*, 1–5.