Critical review of literature about industrial plants resilience computation

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Abstract: Resilience is a performance measure that represents both the ability of a system to resist disruptive events and the ability to quickly recover the operational state by restoring the initial capacity. The added value of resilience analysis, compared to established vulnerability and risk analyses, is to describe the temporal evolution of the consequences of the disruptive event, by analysing the time-phased path of capacity recovery as well as consider medium-long term effects. While resilience is a widely discussed topic in the fields of utilities networks and civil infrastructures, only recently the concept has been applied to industrial systems such as production plants. Referring to this latter domain, in order to assess the state of the art and identify research gaps and topics deserving further investigation, a critical review of literature is carried out in this paper. In particular, the different conceptual steps involved in resilience estimation are separately addressed, namely disruptive event characterization, damage states assessment, scenarios generation, initial capacity loss estimation, time trend of capacity recovery, economic loss analysis, resilience quantification. For each step the suggested approaches are critically compared, highlighting their strengths and weaknesses. A morphological matrix approach is then used to classify the existing models and identify opportunities for developing more effective resilience modelling tools and methods.

Keywords: Resilience, Process plants, Manufacturing plants

1.Introduction

The ability of a system to withstand unexpected disruptive events and quickly restore functionality can be defined as "Resilience". The concept of resilience was introduced in the field of ecology, where resilience represents the ability of an ecosystem to survive, adapt and grow in the presence of unexpected changes. Later, the concept spread to many other disciplines, including psychology, and indeed, engineering.

In this discipline there are already two tools to evaluate the behaviour of a system in the event of an unexpected disruptive event: vulnerability analysis and risk analysis. However, these tools are focused only on the first of the three characteristics described by resilience. Resilience is, in fact, characterized by three aspects, namely absorption capacity, adaptive capacity, and restorative capacity (Nan and Sansavini, 2016). The absorption capacity consists in the system's ability to reduce the impact and damage caused by disruptive events: this is also the goal of established vulnerability analysis and risk analysis. However, the added value of resilience analysis is that it also assesses the adaptive capacity, which consists in the ability of the system to adapt to the damage suffered, to reduce the negative consequences of the event on the functionality of the system, and the restorative capacity, which refers to system's capability of rapidly recovering functionality.

A schematic representation of temporal trend of system's capacity following a disruptive event (occurring at time t_0) is shown in fig. 1. One can observe the initial capacity loss $CL = C(t_d) - C(t_0)$ during time interval from t_0 to t_d caused by the disruptive event. The capacity loss is reduced by the absorption capacity of the system. From time t_d to time t_c a latency period occurs, in which the planning of recovery activities takes place. From time t_c to time t_r, recovery activities take place: in this phase both the adaptive capacity, and the restorative capacity play a role. Please note that final capacity may be less, equal or higher than initial capacity.

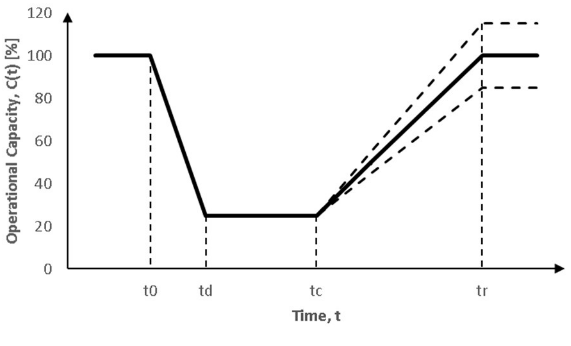

Figure 1: Diagram of capacity vs time

Of great importance in this last phase are the recovery duration and the trend of capacity during the recovery period. Given the above-described time trend of capacity some performance measure quantifying system resilience can be computed. In general, the lower the initial capacity loss, and the shorter the $(t_r - t_0)$ interval the higher is resilience. Therefore, in order to properly compute system resilience, it is critical to estimate in a precise manner the capacity recovery curve.

Research on resilience computation for process and manufacturing plants is scarce and an agreed methodology has not yet been established. In this paper the approaches developed in the literature to determine the capacity recovery curve and compute resilience, with special emphasis on industrial plants, will be reviewed and critically appraised, in order to show strengths and weaknesses of existing methods and point out research gaps justifying future research work. To better compare the existing approaches, it was decided to decompose the main problem of calculating resilience into different subproblems, since for each of them a specific solution tool is needed. Subsequently a morphological matrix was constructed, to provide a taxonomy of all the identified approaches.

The following work is structured as follows: section 2 describes the adopted analysis methodology, paying particular attention to the decomposition into subproblems and the resulting structure of the morphological matrix. Section 3 analyses, for each of the subproblems, the approaches proposed in the reviewed literature, highlighting any strengths and limitations. Finally, in section 4, all the gaps identified are summed up, proposing improvement opportunities and identifying topics deserving further research.

2.Methodology

2.1 Papers selection criteria

Research on industrial resilience literature was carried out mainly through scientific databases (Scopus, Web of Science and Science direct), and search engines such as ResearchGate and Google Scholar. More than 623 articles related to engineering resilience have been identified. Of these, only 43 have been selected and catalogued, as they are characterized by models applicable to the quantitative analysis of resilience of individual industrial plants. On the other hand, works focused on the resilience of networks, supply chains and infrastructures, which do not fit the case of industrial plants, due to their specificity, have been set aside. Focusing only on the issue of the calculation of resilience, 20 articles have been extracted from the set and used to build the morphological matrix (section 3.3). Among these, particular relevance is given to papers focusing specifically on industrial plants. However, papers not specifically focusing on industrial plants will also be included in the review in case the described approaches could be applied as well to industrial plants resilience estimation.

2.2 Decomposition into subproblems

Considering that, as described before, resilience calculation implies a sequence of conceptually distinct steps, and that the reviewed authors adopted widely different approaches and tools to carry out each step, it was decided to decompose the overall problem of resilience calculation into several "subproblems". This decomposition was identified as an effective and functional way to compare the various approaches, as it allows to highlight step by step the strengths and weaknesses of the strategies of each paper and allows generation of novel solution strategies by rearranging the subproblems solution methods in a combinatorial manner. The identified subproblems are listed in fig.2.

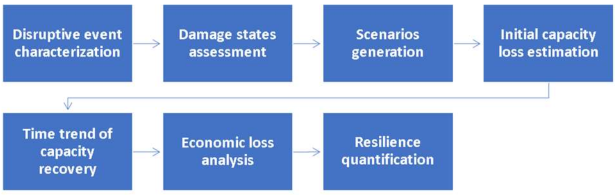

Figure 2: The subproblems of resilience calculation

2.3 Morphological matrix

For each of the subproblems identified, the models and conceptual approaches proposed in the selected literature were collected in a morphological matrix (Table 1). In engineering design and systems engineering a morphological matrix is a matrix showing all the alternatives available to perform a set of functions, so that the structure of a system can be determined by choosing a specific option for each single function. It should be noted that not all articles deal with every subproblem. This is a consequence of the scarcity of methods that address all phases of the calculation of resilience, while most of the time they focus only on partial aspects of the problem of calculation of resilience.

3.Approaches of solutions to subproblems

3.1 Disruptive event identification and characterization

The first subproblem concerns the identification of the disruptive event that generates the loss of capacity in the system. The choice of the considered disruptive event is relevant as it can completely change the manner that resilience computation is carried out. A first difference is between events generating physical loss of systems components (i.e. a physical failure caused by an external or internal event) or only interruption of operations (i.e. interruption in the delivery of materials caused by failure of a supplier). Another distinction is between events treated as deterministic or random. A further remark is that internal equipment failures usually affect one equipment at a time, although the functional failure consequence may affect the entire system, while external events (i.e. natural hazards) may act as common mode failure affecting simultaneously several system elements.

Some authors (Bristow and Hay, 2016; Caputo et al., 2019b) neglect the definition of a causal event or the specific failure type, as they focus directly on the subsequent phases, i.e., on the definition of capacity loss and its economic implications starting from a predetermined initial damage scenario specifying the loss of a set of systems components. For this reason, despite being suitable for any disruptive event, they do not provide any contribution to the resolution of this subproblem. As for specific events, on the other hand, some of the works (Matelli and Goebel, 2018; Patriarca et al., 2021; Xi et al., 2015), focus on the failure of a component. However, such approaches typically considered one failure at a time, which represents a strong limitation to the model.

The rest of the articles consider Na-Tech events, i.e. natural hazards triggering technological disaster. Usually this requires specifying a hazard curve representing the relationship between annual probability of occurrence of the event and its magnitude (i.e. annual probability of exceedance of a given intensity measure, such as Peak Ground Acceleration, PGA, in case of earthquakes). Some examples are hurricanes (Mahzarnia et al., 2020), floods (Argyroudis et al., 2020), earthquakes (Argyroudis et al., 2020; Caputo and Paolacci, 2017; Caputo et al., 2019a; Ferrario and Zio, 2013; Kalemi et al., 2020; Mussini et al., 2018; Singhal et al., 2020). The typical way of transforming Na-Tech events into damage to the system elements consists (see subsection 3.2) in tracing correlations between the magnitude of the harmful event, and the fragility of the elements. This approach is generalizable to any natural event (earthquakes, floods, hurricanes), maintaining the same structure based on the study of probability and magnitude of the disruptive event. The hazard curve approach can be even extended to events other than Na-Tech ones, for example those deriving from man-made hazards.

Table 1: Morphological matrix

Subproblems	**Approaches**				
Disruptive event characterization	Component failure (Matelli and Goebel, 2018; Patriarca et al., 2021; Xi et al., 2015)	Generic (Bristow and Hay, 2016; Caputo et al., 2019b)	Na-Tech (Argyroudis et al., 2020; Caputo and Paolacci, 2017; Caputo et al., 2019a; Ferrario and Zio, 2013; Kalemi et al., 2020 Mahzarnia et al., 2020; Mussini et al., 2018; Singhal et al., 2020)		
Damage states assessment	Fragility curves (Argyroudis et al., 2020; Caputo and Paolacci, 2017; Caputo et al., 2019a; Ferrario and Zio, 2013; Kalemi et al., 2020; Mahzarnia et al., 2020; Mussini et al., 2018)	Failure probability (Matelli and Goebel, 2018; Patriarca et al., 2021)	Arbitrarily assigned damage states (Bristow and Hay, 2016; Caputo et al., 2019b; Xi et al., 2015)		
Scenarios generation	Monte Carlo Simulation (Caputo et al., 2019a; Ferrario and Zio, 2013; Kalemi et al., 2020)	Systematic generation of all possible scenarios (Caputo and Paolacci, 2017; Caputo et al., 2019a)	Arbitrary user-defined scenarios (Caputo and Paolacci, 2017; Caputo et al., 2019a, 2019b; Patriarca et al., 2021; Xi et al., 2015)		
Initial capacity loss estimation	Fault tree (Ferrario and Zio, 2013)	Fixed capacity for each damage scenario (Matelli and Goebel, 2018; Patriarca et al., 2021)	Bernoulli reliability model (Xi et al., 2015)	Capacity Block Diagram (Caputo and Paolacci, 2017; Caputo et al., 2019a, 2019b; Kalemi et al., 2020; Mussini et al., 2018)	Discrete event simulation (Lohmer et al., 2020)
Time trend of capacity recovery	Activities network (Caputo and Paolacci, 2017; Caputo et al., 2019a, 2019b; Kalemi et al., 2020)	Scheduled activities (Mussini et al., 2018; Patriarca et al., 2021)	Fault tree (Ferrario and Zio, 2013)	Predefined shape (Cimellaro et al., 2006; Singhal et al. 2020)	
Economic loss analysis	Business interruption cost (Caputo and Paolacci, 2017; Caputo et al., 2019a, 2019b; Kalemi et al., 2020; Lohmer et al., 2020)	Repair cost (Caputo and Paolacci, 2017; Caputo et al., 2019a, 2019b; Kalemi et al., 2020; Singhal et al., 2020)	Expected annual loss (Kalemi et al., 2020; Mussini et al., 2018)		
Resilience quantification	Eq. (2) (Argyroudis et al., 2020; Caputo et al., 2019b; Singhal et al., 2020)	Eq. (3) (Zhao et al., 2016)	Eq. (4) (Kalemi et al., 2020)	Eq. (5) (Caputo et al., 2019a; Cincotta et al., 2019)	Eq. (6) (Patriarca et al., 2021)

3.2 Damage states assessment

The main objective of this subproblem consists in determining the type and number of damage states used to characterize the level of damage sustained by any equipment, and in assigning to each unit the proper damage state on the basis of the occurred disruptive event. This is relevant as the damage state can influence both system capacity and the type and duration of recovery activities to be performed. Consequently, diversification into multiple damage states allows for more realistic and reliable calculations of residual capacity and activities and recovery times, which represent the input data in the calculation of resilience.

A first classification is based on the assumption of a single damage state (usually implying total loss of the equipment, so that the unit can be either in undamaged or damaged states) or in the definition of multiple damage states implying different levels of loss of functionality.

The first family of damage state assignment approaches is "arbitrarily assigned damage states". It includes models where the damage state of the equipment is arbitrarily assigned by the user instead of being determined by the intensity of the disruptive event or by any other manner (Bristow and Hay, 2016; Caputo et al., 2019b; Xi et al., 2015). This often corresponds to models where the equipment state is binary (i.e. damaged or not) and the arbitrary assignment of the number of units being in damaged state corresponds to the definition of the initial damage scenario.

The second family, "Failure probability", addresses intrinsic failures of equipment which are not caused by any external events which is explicitly modelled. A simple probability of failure (Matelli and Goebel, 2018) or a reliability function (Patriarca et al., 2021), is then used. To compute failure probability the failure rates available in literature and data bases can be used. In this case a binary state of equipment (failed vs nonfailed) is only considered.

The third family of approaches uses fragility curves to determine the probability of sustaining a predefined level of damage or attaining a given damage state. This type of approach is typically used by works referring to Na-Tech disruptive events (subsection 3.1). The events proposed by the papers are hurricanes (Mahzarnia et al., 2020), floods (Argyroudis et al., 2020) or earthquakes (Caputo and Paolacci, 2017; Caputo et al., 2019a; Ferrario and Zio, 2013; Kalemi et al., 2020; Mussini et al., 2018), but the method can be extended to any other event from which to derive fragility curves. Fragility curves indicate the probability of reaching a specified damage state for each intensity value of the disruptive event. For example, in the event of earthquake, the magnitude level can be indicated by PGA. In this case the failure occurs when the intensity of the disruptive event is greater than the equipment capacity which is assumed to behave like a random variable with a lognormal distribution, so that the probability of equipment failure P_F (PGA) is:

$$P_F(PGA) = \Phi\left(\frac{1}{\beta}\ln\frac{PGA}{\mu}\right) \tag{1}$$

where Φ is the standard Gaussian cumulative distribution, μ and β are the mean value and the logarithmic standard deviation of the capacitance distribution respectively (Caputo et al., 2019a). The average annual frequency of occurrence of each given intensity level of the disruptive event in an assigned geographical area is defined by the hazard curves (see subsection 3.1). By multiplying the average annual frequency of an event magnitude by the probability of equipment damage at that magnitude level, the annual average frequency of equipment failures is computed.

Furthermore, fragility curves are well suited to random scenario generation methods (see subsection 3.3). For example, in Ferrario and Zio (2013), a random value is generated for each equipment (between 0 and 1): if the failure probability exceeds the random extracted value, it is considered failed. This approach fits well to including multiple levels of damage, each linked to a specific fragility curve (Caputo et al., 2019a; Kalemi et al., 2020). In this case the random number generated is compared with the probability of occurrence of the damage states of the element given by the appropriate fragility curves, and the damage state assigned will be the one of greater magnitude among those that have a greater probability than the number random extracted. In this way it becomes possible to diversify both the loss of capacity caused by the damage (Mussini et al., 2018), and the number and duration of the consequent restoration activities (Argyroudis et al., 2020; Caputo et al., 2019a; Kalemi et al., 2020). While generic fragility curves are available in the literature for a large number of equipment types, when a fragility curve cannot be found for the specific equipment or damage state of interest, it has to be built resorting to dedicated numerical computations performed by expert analysts.

3.3 Scenarios generation

The purpose of the various strategies is to generate damage scenarios that are as representative as possible of the general behaviour of the system in the event of a disruption. Specification of a scenario consists in defining a different combination of damaged and undamaged system elements. A single user-defined scenario can be used. Otherwise a procedure for generating multiple scenarios is adopted.

The "Arbitrary user-defined scenarios" is certainly the simplest method. Used both in the process industry (Caputo and Paolacci, 2017; Caputo et al., 2019a; Patriarca et al., 2021), and in the manufacturing industry (Caputo et al., 2019b; Xi et al., 2015), this approach allows to simulate scenarios, leaving the user to choose the elements of the system that are damaged or not. It can be very useful in case the goal is to evaluate the resilience of the system in specific situations (i.e. in the case of damage to critical equipment) and is easy to apply. However, due to its arbitrary nature it can hardly help to provide a general appraisal of the system resilience.

The second approach is "Systematic generation of all possible scenarios". This may require using combinatorial analysis to automatically and exhaustively list all conceivable scenarios, although in the real world the number of combinations to consider rapidly grows to become unmanageable (especially when multiple instead of binary damage states are allowed for each resource). In this case a procedure to identify more likely scenarios or, conversely, worst-case scenarios may be required. In the works adopting this approach (Caputo and Paolacci, 2017; Caputo et al., 2019a), the probability of occurrence of each generated scenario is computed and only the ones exceeding a predefined threshold are evaluated.

To solve this limitation, the "Monte Carlo Simulation" approach was introduced (Caputo et al., 2019a; Ferrario and Zio, 2013; Kalemi et al., 2020): in this case the damage scenarios are generated randomly over a suitably large number of replications. The latter strategy, provided that an adequate number of simulations are carried out, can combine the advantages of a lower computational complexity, with an adequate representativeness of the system behaviour. Furthermore, the computational complexity can be further reduced through K-means clustering (Mahzarnia et al., 2020): in this way only a reduced number of significant scenarios will be required to realistically represent a much larger number of actual possible scenarios, thus generating a computationally simpler problem.

3.4 Initial capacity loss estimation

The initial estimate of the loss of capacity consists in defining the residual capacity of system $C(t_d)$ (fig. 1) following the disruptive event. A function correlating the damage state of each single equipment to the overall system state and capacity is thus required. Such a correlation can be obtained either through analytical or numerical simulation models, with the former usually limited to binary states of the resources. The latter instead allow multiple states and complex dynamic interaction logic between components which cannot be captured in analytical models. It is important that the function considers the structure of the plant's process flows, as this can affect the overall residual capacity and business interruption loss. In fact, according to the process structure, a total or partial loss of some equipment can either determine partial or total loss in the capacity of one or more process flows and plant sections.

Some authors (Ferrario and Zio, 2013) use fault trees to compute the system state based on the binary state of its components. Other authors (Matelli and Goebel, 2018; Patriarca et al., 2021) addressing simple systems, assign a predefined capacity loss to any given damage scenario. This approach cannot be considered a real model, as its application on systems of greater complexity would be impractical. Another approach to calculating residual capacity is the Capacity Block Diagram (CBD) (Caputo and Paolacci, 2017; Caputo et al., 2019a; Kalemi et al., 2020; Mussini et al., 2018). In the CBD all equipment belonging to a process flow (PF) is grouped into sequential process stages (PS) connected in series. Each PS, in turn, is composed of several resources, connected in series, or in parallel, in a similar way to what happens in the reliability block diagram and in the function structure used in reliability analysis. In this way it is possible to: calculate residual capacity of the system taking into account the structure of process flows and a binary variable representing the state of each equipment, also distinguishing between the loss of capacity of distinct process flows, allowing a consequent more accurate calculation of the economic loss. CBD approach has been applied even in the manufacturing industry (Caputo et al., 2019b), where the change of process routings can allow to optimize the residual capacity of the system. Xi et al. (2015) refer to manufacturing plants employing a model for calculating the residual resilience of the system based on Bernoulli Reliability model and Markov Chain, through which the loss of production capacity in different configurations is computed. However, the model does not allow to distinguish between multiple process flows.

The last type of approach identified is discrete event simulation. Used in the calculation of Supply Chain resilience (Lohmer et al., 2020) it can be an interesting alternative to the models applied up to now in industrial plants, as it brings with it several advantages. In fact, in a simulator it is easier to analyse articulated systems than analytical methods, since the function that correlates the loss of capacity of a component with the capacity of the whole system is defined by the user-programmed logic. Furthermore, it is possible to represent the process flows in a more flexible way, allowing to study a model that is closer to reality. On the other hand, both the construction of the simulation model and its correct use can be a complex task.

3.5 Time trend of capacity recovery

The construction of the trajectory of capacity recovery over time consists in plotting the capacity value during the time interval t_c and t_r (Fig. 1) representing the period required to carry out recovery activities. A first approach (Cimellaro et al., 2006; Singhal et al., 2020) assumes a predefined mathematical function to represent the time trend of capacity recovery (linear, exponential, and cosine functions). This implies that actual recovery activities are not modelled in detail. In fact, a continuous recovery curve may not be realistic (Mussini et al., 2018), as discrete change of capacity may occur as soon as an equipment is brought back into operational state. Such "stepped" curves may be obtained from models in which recovery activities are scheduled over time, providing immediate capacity recovery correlated to each completed equipment recovery activity according to the functional role played by the equipment. Authors using such an approach have adopted simple scheduling (Mussini et al., 2018) or simulations (Patriarca et al., 2021). However, in both cases mutual interactions and logical constraints between recovery activities of the various equipment, which may delay the start of subsequent activities, are neglected. Ferrario and Zio (2013) adopt the fault tree to model the interactions between activities. Caputo and Paolacci (2017), on the other hand, addresses the problem by means of a recovery activity network similar to those used to schedule tasks in project management. At first a generic network is built for the entire plant, including all possible recovery tasks, then a zero duration task duration is assumed for all undamaged equipment. In this manner a generic network can be transformed into the actual activities network corresponding to a specific damage scenario. This allows both to derive a capacity curve correlated to the completion of the individual recovery activities and to consider the logical-temporal correlations between the activities themselves considering mutual interactions between the recovery activities of different equipment. Task duration can be either deterministic or randomly sampled from a probability density distribution. In both cases the task duration can be correlated to the damage level of the equipment.

3.6 Economic loss analysis

Economic loss analysis plays an essential role in calculating resilience by providing indicators of expected economic losses. Unlike the other subproblems, where each approach was alternative to the other, in this it is possible to make use of even more than one of the indicators identified. Initial damage and temporary operations interruption caused by the disruptive event, often determine an economic loss. Therefore, resilience computation can be integrated with the consequent economic loss estimation. The main cost items identified are the Business Interruption cost and the Repair cost. The first represents the contribution margin of the lost production caused by capacity loss. As a result, the more precise the method of calculating the loss of capacity and the recovery interval duration (subsections 3.4 and 3.5), the more accurate the calculation of the Business Interruption cost will be. The second item represents the expenditure generated by the recovery activities. The accuracy of its calculation depends on the rigor in correctly identifying the restoration activities to be carried out (subsection 3.5) and on the precision in the detailed definition of the damage states (subsection 3.2), based on which both the number of activities to be carried out and their importance, and therefore cost, can vary. Some authors only consider the Business Interruption cost (Lohmer et al., 2020), while other the Repair costs only (Singhal et al., 2020), but obviously both cost items may be significant. Therefore, some authors (Caputo and Paolacci, 2017; Caputo et al., 2019a, 2019b) consider both. Kalemi et al. (2020) consider an overall Expected Annual Loss computed as the average economic loss for each intensity value of the disruptive event times the probabilities of occurrence of each intensity level. Also Mussini et al. (2018) uses the EAL but expressed in days of shut down, considering only the Business Interruption cost and not the Repair costs.

3.7 Resilience quantification

A number of different formulations have been suggested to compute resilience based on the knowledge of the capacity recovery curve (Benczur et al., 2020). Table 2 lists the formulas more frequently used. They fall under two approaches, namely those aimed at computing resilience (i.e. the higher the better), and those aimed at computing the loss of resilience (the lower the better). Eq. 2 represents the typical resilience calculation formula: it consists of a dimensionless indicator referring to the percentage functionality maintained by the system with respect to full capacity, in the time span affected by the destructive event and by the recovery activities (the variables refer to Fig. 1) for a given damage scenario (Argyroudis et al., 2020; Caputo et al., 2019b; Singhal et al., 2020). In eq. 3 a weighted average resilience over a set Ω of different scenarios is computed, where each s-th scenario has an occurrence probability p(s), and C(t, s) and d(t) are respectively capacity and demand for capacity (Zhao et al., 2016). In eq. 4 the average resilience is calculated through an arithmetic mean of the resilience of the scenarios, as these are generated through Monte Carlo simulation (resilience of each scenario is calculated trough eq.2). In this case it is not necessary to use a weighted average, because the probability of occurrence of the scenarios has already been considered in the generation of the scenarios themselves (Kalemi et al., 2020). Patriarca et al. (2021), instead compute in Eq. 6 a conventional resilience by logic combination of three indicators. An Absorption metric (Ab), expressing the percent initial capacity loss. An adaptation metric (Ad), expressing the percent duration of the latency period. A recovery metric (Rec), expressing the rapidity of the capacity recovery. Unlike the first category of formulas, in eq. 5 the resilience loss is calculated, which corresponds to the area over the capacity curve, referred to fig. 1, which is lost due to the disruptive event (Caputo et al., 2019a; Cincotta et al., 2019). Instead of a capacity vs time plot, the resilient behaviour of a system can be also represented as a surface by adding a third dimension representing the intensity of the disruptive event, as done by Kalemi et al. (2020) when introducing the Operational Capacity Surface.

Table 2: Resilience calculation formulas

$R = \frac{1}{t_r - t_0} \times \int_{t_0}^{t_r} C(t)dt$ (2)	$R_T = \frac{1}{n} \times \sum_{s \in \Omega} R_s$ (4)
$R_T = \sum_{s \in \Omega} p(s) \sum_{t_0}^{t_r} \frac{C(t,s)}{d(t)}$ (3)	$RL = \int_{t_0}^{t_r} [100\% - C(t)]dt$ (5)
$R = Ab + Ad * Rec - Ab * Ad * Rec$ (6)	

3.8 Results discussion

Based on the above review, the following critical remarks can be pointed out. Although resilience of industrial plants received less attention by scholars as compared to civil infrastructure, supply chains and networked utilities, in recent time this topic is starting to become an active research stream, but an exhaustive solution to the issues related to resilience assessment of industrial plants is still missing. Many authors only focus on a few steps of the overall resilience computation. Therefore, only a few models are available for full resilience assessment over a range of scenarios and equipment damage levels accounting for full consequences quantifications (Caputo and Paolacci, 2017; Caputo et al., 2019a; Kalemi et al., 2020). In particular, the construction of capacity recovery curves is often carried out adopting rough-cut methods. Only few works consider the peculiarities of manufacturing plants, and in general few authors consider the actual structure of process flows to capture the interactions between process units either as far as capacity or recovery activities are concerned. A standardized method to account for scenarios generation and resilience computation is not yet agreed upon.

Apart from the conceptual differences in the adopted models, the following issues still need to be addressed, namely, the optimal planning of the capacity recovery process, the optimal cost-effective planning of protective and preventive actions required to enhance resilience, and the definition of proper sensitivity metrics to assess the criticality of each system component as far as the overall resilience is concerned. Solving the above mentioned issues, together with a precise methodology to compute resilience would allow plant managers and decision makers to optimally design industrial plants in order to maximize resilience or minimize loss in the face of expected disruptive scenarios.

4.Conclusion

The literature review carried out in this paper showed that resilience computation of industrial plant, even if neglected in the past is starting to gain academic attention. However, an exhaustive and standardized methodology to assess resilience has not yet been developed. The existing models apart from adopting different conceptual approaches, often focus on single issues while neglecting others. Therefore there is ample room for future research to fill the gaps identified in this critical review. The main contribution of this paper lies in the systematic classification of resilience computation steps and in comparison of existing approaches to identify strengths, weakness and gaps of the available mode. This conceptual map can guide researcher in developing more effective resilience computation methods for industrial plants.

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