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Resilience-based optimal firefighting to prevent domino effects in process plants

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Abstract

In the recent years, fire domino effects have been involved in some extremely severe accidents in the chemical and process industries. In the need of a better understanding of the prevention of fire escalation scenarios, the present study focuses on emergency firefighting which compared to passive and active fire protection measures has received less attention. In the present study, we have introduced a resilience-based firefighting methodology to increase the absorptive capacity of process plants in withstanding fire escalation scenarios.

The area above the resilience curve (AARC), which is equal to the accumulation of loss of resiliency over time, has been considered as a metric to identify the optimal firefighting strategy, that is, the strategy leading to the lowest loss of resilience in the shortest time.

The modeling of fire escalation scenarios and the implementation of different firefighting strategies with regard to AARC have been conducted using a Bayesian network approach for an illustrative oil storage plant.

Keywords: Fire escalation; Optimal firefighting; Resilience; Bayesian network; Process plants.

1. Introduction

In the view of risk assessment in chemical plants, the identification of potential accidental scenarios is the first step to effectively prevent and mitigate the serious consequences that might occur. In particular, many of the most tragic industrial accidents that happened in history take roots in scenarios where a single mishap propagated to nearby units, leading to a chain of events with catastrophic results. This escalation mechanism, which is also known as domino effect, attains the most severe consequences in the ever-growing and complex industrial sites where several hazardous installations, involving high quantity of dangerous substances, operate in tight neighbourhoods. Heinrich[1] states that the occurrence of an accident results from the culmination of a sequence of events, the last one being the accident itself. In Europe, the basic guidelines for preventing major accidents are stipulated in the "Seveso-III" Directive[2]. The term domino effect is used in the context of industrial establishments or groups of establishments where the likelihood and the possibility or consequences of a major accident may be increased because of their location, their proximity, and their inventories of dangerous substances. The AIChE-CCPS[3] defines a domino effect as: “an incident which starts in one item, and may affect nearby items by thermal, blast or fragment impact, causing an increase in consequence severity or in failure frequencies”. Fire domino effects are amongst the most feared accidents in the chemical industry in terms of fatalities and damage to the assets[4][5]. Especially when pool fires are the primary events the consequences can easily escalate catastrophically, as they are responsible for triggering 44% of all domino effect related accidents[6]. A pool fire is an uncontrolled combustion provoked by the ignition of the vapours coming from an unconfined pool of flammable liquid. There’s a considerable and extended literature related to pool fires, including flames study and fire modelling to evaluate the emitting heat, but very few include domino effect assessment [7]. To reduce the rise of potential damaging scenarios, a number of preventing and protective measures can be implemented depending on the available resources, the type of installations, potential fire scenarios, and time evolving situations. Clearly enough, some of these measures can prove ineffective in preventing further escalations due to malfunction, exposure to severe heat, or inadequate capacity. In the case of fire triggered scenarios this probability depends on the primary accident but also on factors like the proximity of potential secondary units. As such, emergency firefighting plays a key role in control and delay of fire escalation in process plants. Effectiveness of firefighting strategies, however, is highly dependent on time. For instance, considering the cooling strategy of units exposed to the heat, time is needed for the shell temperature to drop under the failure threshold, which can delay but not completely exclude the failure of equipment. Also, time is needed for mobile resources to reach the endangered installations and start the intervention. Not all the possible scenarios can trigger a plausible escalation. Indeed, the severity of the secondary scenario should exceed the consequences of the primary event. Breaching the linearity of the events is the key factor to successfully enhance safety and prevent accidents. Nevertheless, this model fails at analysing accidents in complex sociotechnical systems caused by contemporary or concomitant factors in conjunction with the dynamicity of the working environment that are apparently unrelated or either unexpected to happen. These flaws can be easily overcome accepting a systemic view of safety deeply connected with the precepts of resilience engineering. The first analysis of the resilience engineering concepts was carried out by Hollnagel[8] where resilience is defined as “the ability that makes a system both safe and efficient, allowing it to maintain and recover a dynamic state of equilibrium while keeping functioning after a mishap or under permanent stress”. By accepting this natural variability, the focus shifts towards proactively finding which interdependent factors and mutual interactions can cause any escalation in the view of creating more flexible and thus resilient processes. Indeed, resilience engineering is interested in understanding how to enhance a system’s ability to recognise, adapt and absorb variations, disturbances and disruptions in order to effectively react and quickly return to a safe functioning state. In anticipating the potential upcoming mishaps, resilience is not only concerned with the ability of recomposing the damaged parts of the systems, but also with understanding the chances of adaptability they possess and the availability and range of sources to perform such behaviour. There have been some interesting works to take into account the concept of resilience in the safety of process facilities. Defining the resilience as the ability to properly recover quickly after an upset, Dinh et al.[9] demonstrated how to evaluate the resilience of a safe design of a process operation. In the trade-off between high productivity and resilience for safety in the chemical industry, Eguchi et al.[10] provided an analysis of the necessary managerial responsibilities to increase and improve the educational knowledge and training of the plant personnel in face of disruptions. Knegtering et al.[11] expressed the need of changing the process safety administrations including the resilience concepts, continuous learning from experience and proposing a holistic approach for new safety management. As argued by Hollnagel (2007), safety can successfully be generated in proactive resilient processes where foresight allows to anticipate the changing faces of risks rather than to build reactive barriers and defences from harms[12]. The inability of transitioning in tempo to the changing disturbances reveals important information about the absence of resilience in the system[13]. However, there has been no work to investigate the role of resilience in the emergency response of domino effects in the process industry. The present study is aimed at developing a methodology to identify the optimal firefighting intervention strategies to effectively suppress the propagation of fire across chemical plants. To this end, we first define a resilience metric to investigate the efficiency of firefighting strategies, and then employ a Bayesian Network approach to mode fire escalation, to implement firefighting strategies, and to calculate the resilience metric. Section 2 recapitulates the basic of BN and how it can be used to model fire domino effects. Section 3 is devoted to the definition of resiliency and the development of a metric in the context of emergency firefighting. In Section 4, the methodology is applied to a notional tank farm, while the work will be concluded in Section 5.

2. Fire escalation as a Bayesian Network model

2.1 Bayesian Network

A Bayesian Network (BN) is a graphical representation of uncertain knowledge that conveys the information on correlation between variables via conditional probabilities tables. BNs are acyclic direct graphs in which the variables that are the subject of inquiry are represented through nodes and their conditional probabilistic dependencies are represented with direct arcs that connect the nodes. Each node is associated with a probability function that takes, as input, a particular set of values for the node's parent variables, and gives as output the probability (or probability distribution, if applicable) of the variable represented by the node. This means that the information flows across the graph from the parent nodes down to the child nodes.

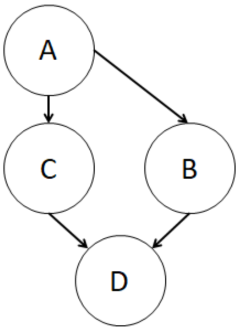

Fig. 1. A typical Bayesian Network

Quite often, the values that represent the possible states for a node are Boolean variables. Also in a BN, each node is conditionally independent of its non-descendants given the immediate parents.
As such, the joint probability distribution of a set of variables X ={x_1, x_2, …,x_n} can be written as:

$$p(x_1,..,x_n) = \prod_{i=1}^{n} p(x_i|\pi_i) \tag{1}$$

where π_i is the immediate parent sets of variable x_i.
In the specific case of **Fig.1** the joint probability distribution is equal to:

$$p(A,B,C,D,E) = p(A)p(B|A)p(C|A)p(E|B,C) \tag{2}$$

Another useful tool that can be used in BNs is marginalization. With this technique, the probability of an individual variable can be calculated from the global joint probability and considering conditional independencies[14]. BNs are increasingly used in the construction and simulation of complex systems where the presence of interdependent factors and hidden variables make the application of other probabilistic techniques very challenging if not impossible.

2.2 Fire domino effects

For fire domino effects, the procedural and normative measures are quite often aimed at limiting the dangerous effects by the installation of fireproofing coatings and automatic protection devices on the most critical units. In the reduction of fire escalation scenarios the works of Landucci et al.[15] and Tugnoli et al.[16] are of foremost importance. The former developed a new mathematical approach to evaluate the performance of passive and active safety barriers in preventing fire domino effect. The latter developed a risk-based methodology to identify the potentially critical units in the plant and to deploy the optimal fireproofing to prevent pool fire and jet fire domino scenarios.

In suppressing and confining the possible escalation of a pool fire, the intervention actions must act in order to break the vicious cycle that aliments the escalations.

The characterization of a domino effect includes the identification of possible primary events, escalation and subsequent propagation of primary events, and identification of secondary and higher order events.

Considering the risk assessment of domino effect accidents, Cozzani at al.[17-19] developed a systematic procedure, evaluating the most credible combination of events, their likelihood of occurrence and the minimum required safety distance among the potential targets.

In an industrial set up, the domino effect generates when an initiating accidental scenario spreads from an industrial unit or equipment to another resulting in the damage of one or more secondary targets within the same plant (internal domino) or in nearby plants (external domino).

The tactical decision for fire suppression, as reported by Svensson[20], differentiate mainly in confinement, ventilation and exposure protection. The approaches that are suggested in the studies of the aforementioned literature allow for straightforward estimation of indices or escalation vectors and thresholds that provide usual information on the estimation of potential hazards and the risk assessment. It is important to underline how the methodologies cover the aspects of fire prevention in the phase of process design and plant layout as proactive measures as well as fire protection of the critical units as reactive measures.

2.3 Domino effect modelling using Bayesian Network

BN has proved to be a reliable and robust technique in the risk analysis of process systems. From the early works of Khakzad et al.[21], BN has been used to predict the probabilities of unknown variables or to update the probabilities of known variables given certain states and preconditions. In their study a parallel comparison between fault tree and BN was carried out for accident analysis. More specifically, due to the easiness of probability updating, and the advantage of abductive reasoning, i.e., probability updating of the primary events given the accident occurrence, BN proved to be the most comprehensive method between the two. Khakzad et al.[22] developed a methodology based on BN to model domino effect propagation in process plants. In their approach, probit models[17] were used to calculate the conditional probabilities of the BN. Then through the comparison with threshold values, potential secondary events were selected and the domino probability assessed as the product of the primary event probability and the probability of escalation. This study was the main reference and guideline in the development and justification of the present work. In the optimization of risk-based strategies for allocation of chemical inventories, Khakzad et al.[23-25] extended the application of BN to reduce the escalation probabilities with preventive safety measures. In the dynamic approach, the synergic effect of contemporaneous damaging scenarios are considered comparing the time to burn of primary units to the time to failure of the potential targets. With the use of dynamic BN, the time sequence of events can be predicted, with the shrewdness of applying this method to small networks due to the inability of managing the exponential growth of probability tables for complex layouts. The complexity and abstractness of the resilience concepts are straightforwardly translated in a mathematical optimization model where the underlying variables and uncertain contributions of factors are effectively assessed. BNs are indeed able to analyse scenarios both in the disruptive and in the recovery phases as a result of flexibility in selection and modelling of different type of variables and in the ability to evaluate probability propagations among uncertainties. Inspired by the previous works, and in the awareness of the aforementioned reasons, the purpose of defining a new resilience engineering metric to apply to the emergency response in fire domino effect scenarios adopting the BN methodologies is of essential and unavoidable importance.

3. Resilience

3.1 Definition of Resilience and its components

Resilience can hardly be described univocally; it is rather a large group of related ides. The variability of the threatening situations offers different levels of challenge to which the system should respond. In general, resilience can be described as the intrinsic ability of a system to adjust its functioning prior to, during, or following changes and disturbances, so that it can sustain the performance of its own operations under both expected and unexpected conditions. The main point of the resilience based assessment methods is to define the resilience metrics, which are the parameters needed to evaluate the resilience performance of a system. They can be characterized as[26]:

- Deterministic vs. Probabilistic: the former excludes stochastic uncertainty, and
- Dynamic vs. Static: the former includes time-dependent behaviours.

The properties of resilience capacities that the metric should address include:

- Absorptive Capacity: that describes the extent to which the system can absorb the perturbations easily and thus minimize the impacts. Since it is a characteristic of the system, it roots in the original design phase and more specifically in the robustness (preventing measures) and redundancy (allowing different alternatives).
- Adaptive Capacity: describes the system ability to organize and readjust its functioning. It roots in the organizational phase and more specifically on how bypass operations (resourcefulness) are carried out at the sharp end dynamically and in the face of the mishap.
- Restorative Capacity: is the ability of a system to repair itself. This reparation must be effective and fast enough not to allow a further system decay. The new stable state might allow the system to enhance the absorptive capacity by learning from the experience.

A truly resilient system thus should be able to:

- Respond to regular and irregular threats in a robust yet elastic manner
- Monitor the on-going events while maintaining an acceptable performance level
- Anticipate risks, consequences and also opportunities, and
- Learn from past experience

Woods[27] defines resilience as the capability of a system to handle disruptions and variations that fall outside the adapting mechanisms defined during the design phase. When a system is conceptualized and the safety constraints are applied, the envelope of the accepted and sustained variability is also traced. A good resilience practice is then concerned with monitoring the operations that drift near to these boundaries and possibly help to expand them to better accommodate ever-changing events. A resilient system must be able to adjust the performance maintaining balance under control at all times without trying to resist and withstand the erosion of its global entirety.

3.2 Previous works on application of Resilience Engineering to Industrial Safety

An extensive review of the definitions and assessments of resilience engineering in literature was edited by Hosseini et al.[26] arranged by application domains and different proposed approaches. In the field of engineering the concept of resilience is relatively new and the definition of Resilience for a system or infrastructure strongly depends on the characteristics of the system.

In the process industry, the advancement of the resilience-based approaches is relatively limited and undeveloped, due to the tendency to rely on the well-assessed methodologies and the lack of clarity of the conceptual links between the resilience engineering concepts and the practical procedures. One of the first attempts to fill the gap in assessing resilience by quantitative methods was carried out by Shirali et al.[28] who attempted to assess resilience from a safety culture perspective in a chemical plant. The tools used to perform such task were in the form of questionnaires filled in by employees in the front-line of production and allowed to find a number of resilience indicators to identify the most critical process units. A similar approach was utilized to improve the resilience in an oil and distribution plant in Brazil[29]. The combination of a four-month observation and the interviews revealed that the main gaps that hindered a resilient performance were located in the communication network and in the different changes introduced in the operations. Holistic approaches are also introduced in the study of resilience engineering to manage process safety risks[30]. The idea of extending resilience into safety science has also been proposed by Steen and Aven[31]. The new insight considers that the main component of risk is uncertainty, and probability is a knowledge based tool to express uncertainty in assessing threats and their consequences. A statistical based resilience evaluation framework was successfully obtained analysing accidents and near-misses in an existing process plant and quantifying the keys contributing resilience parameter[32]. A resilient engineering model was also adapted[33] to reduce occupational injuries in the oil and gas industry. The main question is how the high reputation on safety of such industries can match the increasing number of injuries, and if resilience engineering can be used to reduce this trend. Whitson et al.[34] related the network resilience to the time to restore the performance in the case of external damaging events due to components failure. Using reliability concepts and Monte Carlo simulations, the resilience metric is evaluated as a probability density function when in the set of potential external failures a specific scenario perturbs the network integrity. Summing over all the scenarios the system is proved to be resilient if the metric doesn't exceed a safety threshold. Reliability was also used in a recent work by Yodo and Wang[35]. They focused on analysing the resilience in the early stages of the design of complex engineering systems. In other words, resilience is measured as the ability to prevent and mitigate accidental scenarios that affect the safety integrity. Not only a lack of resilience arises in the inability to confront sudden and unforeseen disturbances, but organisation policy that doesn't support a constant improvement in safety is responsible for an erosive drift and higher complacency.

3.3 Definition of resilience based on relevant previous works

As mentioned before, the different views on what characteristics to highlight leads to different definitions of resilience. In the basic meaning resilience is the ratio of the recovery at generic time to the loss suffered from the system up to that point in time. Given a general system under study, in the first stages it dwells on the original state before a disruptive event triggers the transition to a disrupted state[36] (**Fig.2**). Subsequently the system can recover thanks to a resilient action and can bounce back to a recovered state that could be different from the original one. This means that after the disruptive action, identified with e^j, the system can act resiliently based on the effects that this event has on the formerly assumed perfect performance, on the time necessary to the effective recovery, and on the cost derived from the applications of the recovery measurements. Among the collection of events the system can interact with, the sub-system of the disruptive events is identified as those events whose action at a generic time leads to a decrease of the performance. The performance of the system is often described with a function called figure of merit (FOM), and its expression allows to mathematically evaluate resilience. Different scenarios and strategies need to be considered because a system can react differently and exhibit different resilience indices from one FOM to another.

Resilience describes, after recovery actions have started, the proportion of service restored due to the loss associated to the main disruption e^j.

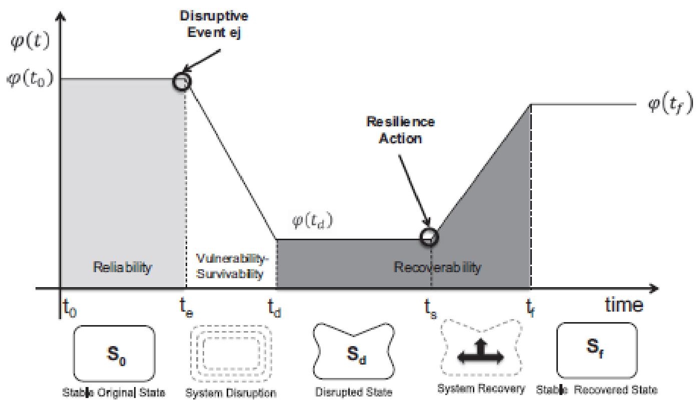

Fig. 2. System's states transition from Barker et al.[36]

Resilience is expressed as the ratio of the difference of the performance from the point of lowest resilience (t_d) to the generic time $t_r \in (t_d, t_f)$ and the maximum loss from to t_0 to t_d. In addition it is clear that Я with this definition is bounded between 0 and 1. (**Eq.3**)

$$Я_F(t_r|e^j) = \frac{\phi(t_r|e^j) - \phi(t_d|e^j)}{\phi(t_0) - \phi(t_{rd}|e^j)} \tag{3}$$

Henry et al[37] applied this definition in the case of parking network considering with three different FOMs. Each of them exploit a specific strategy of intervention for network-based problems: shortest path solution, maximum flow solution, and overall efficiency solution. That shows how a preferred action can severely influence the final results on the resilience value. Different scenarios and strategies need to be considered because a system can react differently and exhibit different resilience indices from one FOM to another. If the system is divided into smaller sub-systems that each can suffer from a disruptive event, the total time for recovery and cost occurred to implement the action is the sum of the sub-systems times but in the cost it's also subtracted the absolute value of the economic loss encountered during the disrupted phase. Following this description, Baroud et al.[38] made also use of this definition of resilience that, in the view of the authors, is the most exhaustive and suitable to describe domino effect scenarios in a chemical plant.

3.4 Resilience metric in the context of optimal firefighting

Considering the concepts earlier illustrated and bearing in mind the aspects of resilience engineering in chemical plants, the main focus in the present study is directed to the study of the vulnerability phase in the case of fire scenarios.

This means that, in the case of domino effect, the metric must consider possible subsequent degradations that with a certain probability can affect the network performance. Accordingly to the aforementioned reasons, the mathematical nature of the metric is to be stochastic, and needs to consider dynamic evolutions. A possible change in the performance function during fire escalation is shown in **Fig.3**.

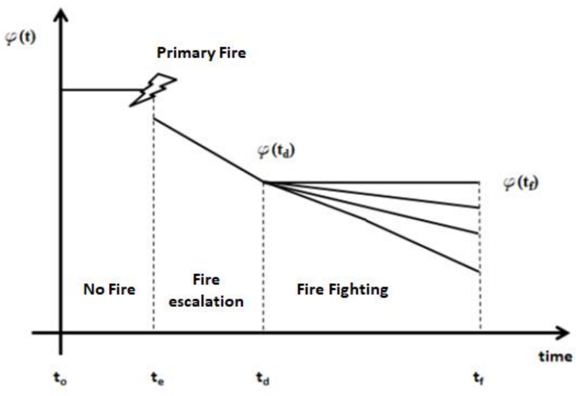

Fig. 3. Description of performance transition

The disrupting event, i.e., the primary fire, happens at t_e when the performance of the system is considered at its peak. The performance of the system drops accordingly and the system enters the so-called fire escalation phase. For a time span from t_e to t_d, the performance keeps dropping according to the uncertainty related to the escalation of fire to potential secondary units although the trend can be mitigated if effective protection actions are taken. The time t_d indicates the moment when the firefighting teams and resources intervene in the active suppression of the fire. If the resources are enough and the deployed intervention is able to suppress the spread of the fire, the performance of the system reaches a stable state. Otherwise, if the intervention is ineffective or allows the partial spread of fire to secondary units, the performance keeps dropping and eventually reaches a constant minimum value. The time indicated with t_f represents the furthest time for possible escalations. If the firefighters arrive in time, the fire escalation phase is not present and if the intervention action is immediately successful the performance drop is limited to that of the primary event. Phenomena such as late arrival of the firefighters can increase the downfall of the performance leading to states in which no action can prevent escalations and save the system. By doing so, the goal becomes identifying which intervention strategy is the best in reducing to the minimum the loss of performance of the system and preventing the further development of escalation scenarios. The Resilience metric scores differently according to which intervention strategy is considered in the analysis. Clearly, the optimal firefighting strategy is the one that prevents the spread of fire to the neighbouring units and limits the time of intervention. In the light of the definition of resilience and the nature of the application case, the metric expressed in **Eq.4** is adapted as follows:

$$R(t|PF) = \frac{\varphi(t|PF) - \varphi(t_d^*|PF)}{\varphi(t_0) - \varphi(t_d^*|PF)} \tag{4}$$

where PF stands for primary fire.

The time t_d* indicates the expected time of fire escalation to all the units in the absence of firefighting intervention. In that case, the performance reaches the minimum allowed value and the resilience score goes to zero. Given an intervention strategy, the numerator represents the difference between the instantaneous value of the performance at a generic time $t \in (t_0, t_f)$ and the performance in the case of ineffective firefighting intervention at t_d*. The imposed condition of t_d* derives from accepting that any possible deployed intervention strategy leads to a performance value higher than the worst case scenario. The denominator represents the maximum possible loss of performance, i.e., the difference between the original state and the final state with no firefighting intervention. The resilience metric scores zero, only in the case of ineffective intervention strategy, when t assumes the value t_d*. The metric scores one, when t coincides with t_o, i.e. when the value of expected resilience is the maximum. The resilience metric encompasses the dynamic development of the performance in time and the uncertainty in the efficacy of intervention strategies.

The definition for the performance function is considered as follows:

$$\varphi(t|PF) = \frac{No.of\ safe\ units(t)}{No.of\ total\ units} = \frac{No.of\ total\ units - \sum_{i=1}^{No.of\ total\ units} p(i|PF,t)}{No.of\ total\ units} \tag{5}$$

The performance index depends on the state of the system at the generic time t and is a function of the number of units that given the firefighting strategy can be kept safe. Indeed, the numerator represents, at a specific time t, the number of safe units as the difference between the total number of units of the plant and the sum of the conditional probabilities of fire escalation to secondary units by t. The denominator represents the total number of tanks. The performance assumes different values at different times as the escalation probabilities of units may change with time. The performance evaluation procedure is then a discrete process which allows to associate a numeric value to the resilience metric only for the times when an escalation scenario can take place. Slowly reacting systems in damage-enhancing environments perform worse in terms of resilience than the fast responsive counterparts. In the first case, the firefighters need to deploy the intervention strategy for a long time under dangerous conditions, increasing the probability of casualties; besides, the amount of water required for exposure protection can easily exceed that necessary for the extinction of fire. Moreover, the later the fire is completely suppressed and the recovery phase can take place, the higher the economic loss for the plant would be.

Thereby, if the performance and resilience loss are converted into continuous processes by means of the polynomial interpolation of the discrete points, the area above resilience curve (AARC) represents mathematically the loss of resilience for the corresponding time interval. The larger the area above each resilience curve, the larger the resilience loss over time and the worse the deployed strategy performs. The use of AARC is not new since it has already been practiced in earthquake restoration[39] and organizational and business management[40]. The comparison of the AARCs obtained for different intervention strategies allows to identify the optimal firefighting approach as the one that in the shortest time causes the least performance loss.

4. Application of methodology

4.1 Case study

The application concerns a tank farm comprising eight atmospheric storage tanks each containing 2500 metric tons of gasoline.

The modelling of the possible fire domino effect scenarios using the BN approach is conducted upon three main hypothesis:

- The storage tank D4 is considered as the primary unit from which the initial pool fire starts;
- Due to their limited resources, the firefighters can only cool two units at a time;
- For the units which are being cooled by the firefighters, the probability of failure due to adjacent heat radiation is considered to be zero.

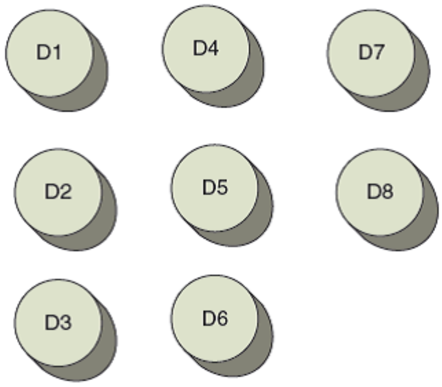

Fig. 4. An illustrative fuel storage plant

As mentioned in the assumptions, the protection measure under study is the active intervention of firefighters capable of cooling down only two exposed units in the vicinity of D4. Among all the target units, considering their geometrical arrangement, the possible secondary units are identified as those which may receive an amount of radiation from D4 higher than a defined threshold. As suggested by Cozzani et al.[17], the threshold value for atmospheric tanks is considered to be 15 kW/m^2. As noted previously, in such nearby clusters of units, in the case of secondary events, further potential targets can be exposed to several fires, which is also known as synergistic effect.

	D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**
D1	-	19.3	4.6	19.3	9.3	3.6	4.6	3.6
D2	19.3	-	19.3	9.3	19.3	9.3	3.6	4.6
D3	4.6	19.3	-	3.6	9.3	19.3	2.2	3.6
D4	19.3	9.3	3.6	-	19.3	4.6	19.3	9.3
D5	9.3	19.3	9.3	19.3	-	19.3	9.3	19.3
D6	3.6	9.3	19.3	4.6	19.3	-	3.6	9.3
D7	4.6	3.6	2.2	19.3	9.3	3.6	-	19.3
D8	3.6	4.6	3.6	9.3	19.3	9.3	19.3	-

Table 1. Heat Radiation Escalation Vectors kW/m^2

Therefore, to account for the synergic effect, the heat radiation values coming from nearby units are summed together. In the present study, ALOHA Software[41] is used to calculate heat radiation amounts as shown in **Table 1**, considering stability class F and wind speed of 2 m/s. As can be noted, there are several combinations of target units where the heat radiation may exceed the predefined threshold. Several scenarios can take place, each of which with a calculated probability of occurring.

Having the heat radiation amounts, probit functions can be used to calculate the escalation probabilities based on the time to failure and volume of the target units.

Equipment	Atmospheric	Pressurised
Volume range (m³)	25-17,500	5-250
Design pressure range (MPa)	0.1	1.5-2.5
Correlation	$\ln(ttf)=-1.13\ln(Q)-2.67\cdot10^{-5}\cdot V+9.9$	$\ln(ttf)=-0.95\ln(Q)+8.85\cdot V^{0.032}$

Table 2. Heat Radiation Escalation Vectors kW/m^2

In this case the probit functions developed by Landucci et al.[42] are used:

$$Y = 9.25 - 1.85\ln\left(\frac{ttf}{60}\right) \tag{6}$$

$$P = \Phi(Y-5) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{Y-5} e^{-\frac{u^2}{2}}du \tag{7}$$

with the following measuring units: ttf in s, Q in kW/m^2 and V in m^3. Also, Φ represents the cumulative density function of standards normal distribution, and u is the standardized variable of the Gaussian distribution. The values of the probabilities are calculated for each tank in the case of single or multiple influence of the heat radiation coming from adjacent units. They are then inserted into the BN model constructed in the proposed software[43] as showed in **Fig. 5**. The root node of the diagram is represented by the unit D4 which is the tank where the primary fire takes place. The arcs departing from D4 are only connected to those units which can be notably affected by the heat radiation, i.e., those units that receive a heat radiation higher than the predefined threshold. To follow, the potentially secondary units are connected only to their potential targets considering the synergic effects of multiple triggering units. An example of the conditional probability tables for node D2 is shown in **Table 3**.

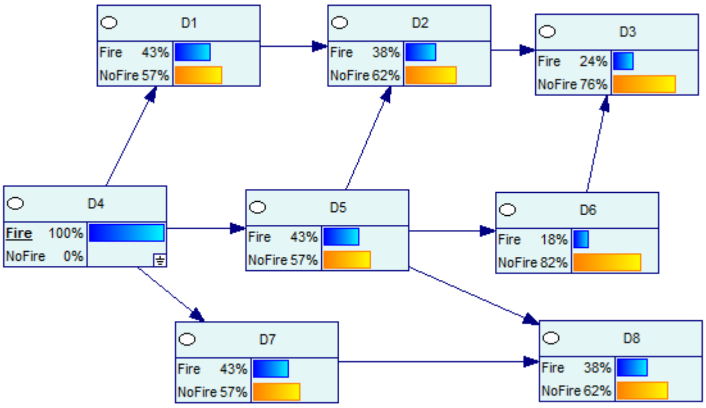

Fig. 5. Updated Bayesian Network given a fire at D4

D1	**Fire**		**No Fire**	
D5	Fire	No Fire	Fire	No Fire
Fire	0.898	0.429	0.429	0
No Fire	0.102	0.571	0.571	1

Table 3. Conditional Probability Tables for D2

Given a fire at D4, the posteriori probabilities of the children nodes are calculated as shown in **Fig. 5**.
In all the cases when the interest is to study how a deployed strategy can avoid the spread of fire across the farm and shield some units from the radiation, the evidence of the "No Fire" state must be instantiated for all the cooled tanks.

4.2 Intervention scenarios

In considering different intervention conditions, it's important to underline how the efficacy of a firefighting strategy not only depends on the efficiency of fire suppression techniques but also on the time needed to handle and operate the intervention strategies. In the first intervention scenario, the firefighters are expected to intervene as soon as the primary event occurs. The intervention is instantaneous and in the progression of the performance deficiency (**Fig. 3**) there is no waiting time and thus no subsequent vulnerability phase during which the system can face further escalation.
Further, to take into account the delay condition of the firefighters different scenarios can be assessed. All these cases are important because they allow to understand how differently and how fast the performance of the system can change, facilitating the determination of the best time gap in which the optimal intervention lies.
The delay time of the firefighters τ is stochastically modelled as a normal distribution $\tau \sim$ Normal (μ = 10 min, σ = 2.5 min). By doing so, it's possible to define different arrival times of firefighters and the corresponding escalation scenarios (the longer the arrival time the more extensive the escalation of fire) and applicable strategies. Also, in this frame, the escalation of fire to secondary or tertiary units is probabilistically liable to occur or not. Indeed, since the fire escalation is defined as a probability, during the vulnerability phase before the intervention, different delay scenarios can occur, allowing the primary fire to escalate to other secondary units. For illustrative purposes, we consider two fire escalation cases:

- Case 1: Primary fire at D4 with no further escalation
- Case 2: Primary fire at D4 escalates to D1, D5 and D7

Having the probability distribution of the arrival time of the firefighters and the time needed for the primary fire to escalate to neighbouring tanks, it is possible to determine the probability of each case. For instance, since the heat radiation the tanks D1, D5, and D7 receive from the fire at D4 is 19.3 kW/m^2, using the relationships given in Table 2, the time needed for fire escalation from D4 to its neighbouring tanks (D1, D5, D7) can be calculated as the time to failure (ttf) of the target tanks, which is 10.95 m. As such, the probability of Case 1 can be calculated as P(Case 1) = P (τ < 10.95) = Φ (10.95-10/2.5) = 0.65.

4.2.1 Case 1: Primary fire at D4 with no escalation

The first case to study is when at the moment of the disruption (the primary fire), the firefighters arrive at the fire before t = 10.95 and start to control the fire escalation. In this regard, the firefighters' aim would be to identify the optimal pair of tanks to cool down to minimize the probability of fire spread and thus to minimize the resilience loss. If unit D4 is on fire, the firefighters can start cool only two of the three exposed tanks D1, D5, and D7. In order to evaluate the resilience metric for the strategies, the worst case scenario is here addressed and labelled as 'fireall', that is, the escalation of fire to all the other tanks without intervention of firefighters. The time evolution of the process is exemplified in **Table 4** where for each unit the number is equal to the escalation probability (calculated using the developed BN) whereas the number 0 stands for a safe state.

The time t_e, i.e. the time when the primary event occurs, in the axis of time is considered to be at zero. The secondary units (D1, D5 and D7) receive from D4 a heat radiation equal to 19.3 kW/m^2. The ttf calculated from the probit models lead to a value of 10.95 minutes. This means that after 10.95 minutes (t_1), with the assumption of no intervention, these three units can catch fire with a probability. Further, the units D2 and D8 are exposed to the heat radiation of the secondary units. From the probit model the ttf of D2 and D8 is equal to 5 minutes and therefore the fire spreads to them with a given probability 15.95 minutes (t_2) after t_e. As time passes more units get involved in the chain of fires, generating an escalation which would affect the entire plant in 26.9 minutes after t_e, with D6 as the last unit in the chain.

	t_0	t_e	t_1=10.95	t_2=15.95	t_3=21.9	t_4=td*=26.9
D4	0	1	1	1	1	1
D1	0	0	0.43	0.43	0.43	0.43
D5	0	0	0.43	0.43	0.43	0.43
D7	0	0	0.43	0.43	0.43	0.43
D2	0	0	0	0.38	0.38	0.38
D6	0	0	0	0	0.18	0.18
D8	0	0	0	0.38	0.38	0.38
D3	0	0	0	0	0	0.24

Table 4. Probability evolution in time for FireAll

For this case, the performance and the resilience metric have been shown in **Table 5**. For instance, the performance and resilience metric at t_1 can be calculated as:

	t_0	t_e	t_1=10.95	t_2=15.95	t_3=21.9	t_4=t_d*=26.9
φ	1	0.875	0.714	0.619	0.596	0.566
R	1	0.712	0.341	0.122	0.069	0

Table 5. Performance and Resilience metric for fireall case (no firefighters' intervention)

$$\varphi(t_1|PF) = \frac{No.of\ total\ units - \sum_{i=1}^{No.of\ total\ units} p(i|PF,t_1)}{No.of\ total\ units} = \frac{8-1-(3\times 0.43)}{8} = 0.714 \tag{8}$$

$$R(t_1|PF) = \frac{\varphi(t_1|PF) - \varphi(t_d^*|PF)}{\varphi(t_0) - \varphi(t_d^*|PF)} = \frac{0.714 - 0.566}{1 - 0.566} = 0.341 \tag{9}$$

The patterns of the performance and the resilience are shown in **Fig.6** and **Fig.7**, respectively. It can be noted that from time t_e= 0 both indices follow a downward pattern as predicted. The graphs have been extended until 45 minutes to be able to make a comparison among different strategies in some of which it would take about 45 minutes (43.8) for the fire to escalate across the entire plant (t_f). The area above the curve of resilience (AARC) is defined as the index that better describes how time and resilience loss are combined. As can be considered then, the case of ineffective intervention is the one to which the largest area belongs. The cases of different intervention strategies are subsequently analysed and each one is labelled with s_{ij} where i and j represent the number of the protected tanks. In these cases, as soon as the primary fire occurs, the intervention of firefighters is immediate, i.e. t_e is equal to t_d and there's no vulnerability phase. the resilience metrics for all the viable strategies, that is, s15, s57, s17, s12, s25, and s58 are shown in **Fig.8**, with s15 as the optimal strategy (corresponding to the smallest AARC). The results of Case 1 show how the number of fires and the plant topology play an important role in defining the optimal strategy capable of minimizing the fire escalation (failure probabilities). Also, it is possible to see that the strategy s36 leads to a smallest value of t_f. This is due to the fact the D6 and D3 are the latest nodes in the network that receive the heat radiation and subsequently fail. Protecting these two units, doesn't reduce the domino escalation probability since in practice only neighbouring tanks are cooled. In **Fig.9** the Area Above the Resilience Curve (AARC) is reported for the cases which are the most relevant in the analysis.

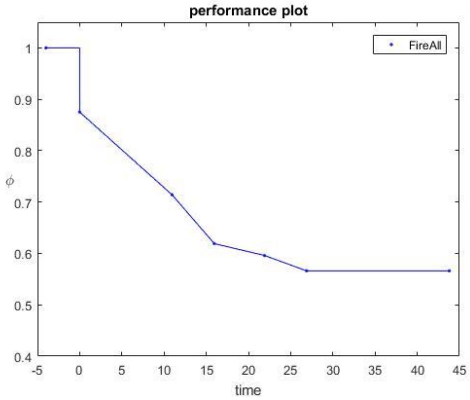

Fig. 6. Change of performance with time for FireAll

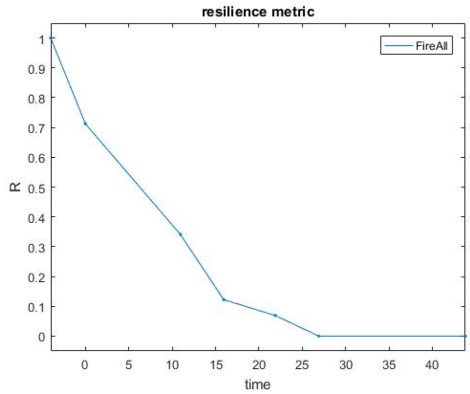

Fig. 7. Change of Resilience with time for FireAll

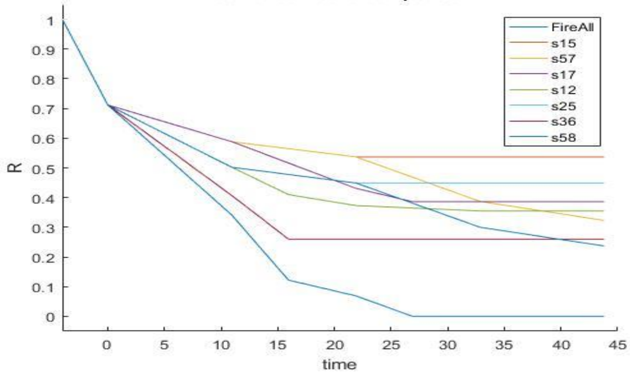

Fig. 8. Resilience with time comparison for strategies

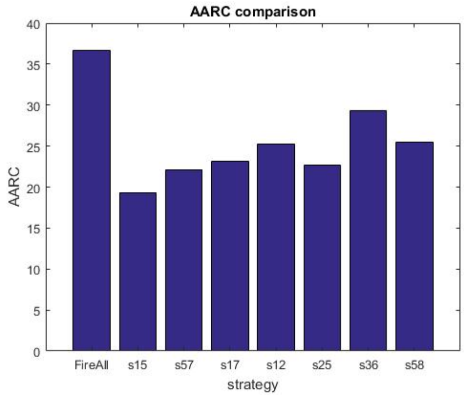

Fig. 9. AARC comparison for strategies

4.2.2. Case 2: Primary fire at D4 escalates to D1, D5 and D7

In this case, marked as D4-157, the analysis focuses on the condition when the firefighters arrive later than 10.95 minutes but still before 15.95 minutes. If the firefighters arrive in the aforementioned time interval, with the probability P(10.95 < τ < 15.95) the fire would have spread to the units D1, D5 and D7. This case is of major importance because it's the most critical amongst the one observed. If the firefighters arrive later than 15.95 minutes after the primary event, the fire would have spread, with a given probability to all the units but D3 and D6 (so the only strategy would have been to cool D3 and D6).

The firefighters can intervene only on the remaining four units, leading to six different intervention strategies. In this case, the probability of delay of the firefighters is calculated as the difference between the cumulative distribution function for 15.95 and the cumulative distribution function for 10.95: $P(\text{Case 2}) = P(10.95 < \tau < 15.95) = \Phi(15.95\text{-}10/2.5) - \Phi(10.95\text{-}10/2.5) = 0.34$.

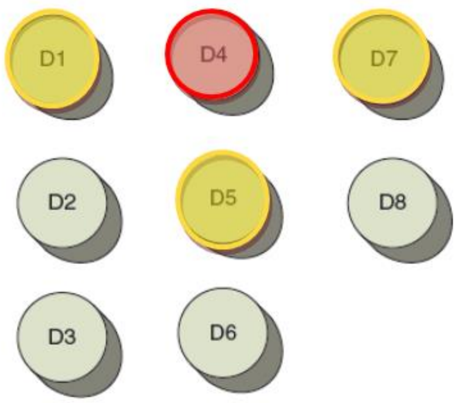

Fig. 10. A primary fire in D4 and escalation to D1, D5 and D7

Thus, the delay probability by which all the failure probabilities should be multiplied when calculating the resilience score is equal to 0.34. From results on the resilience metric and the values of AARC it is clear that unlike the case of no delay, the best strategy involves the cooling of D2 and D8.

	t_0	t_e	t_1=15.95	t_2=21.9	t_3=26.9
φ	1	0.748	0.671	0.653	0.628
R	1	0.323	0.116	0.067	0

Table 6. Performance and Resilience metric for fireall– delayed D4-157

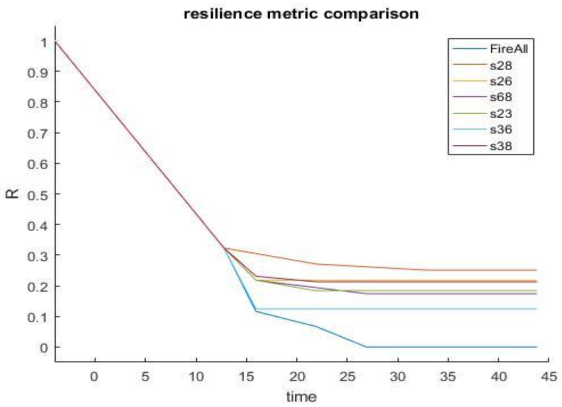

Fig. 11. Resilience with time comparison for strategies - delay D4-157

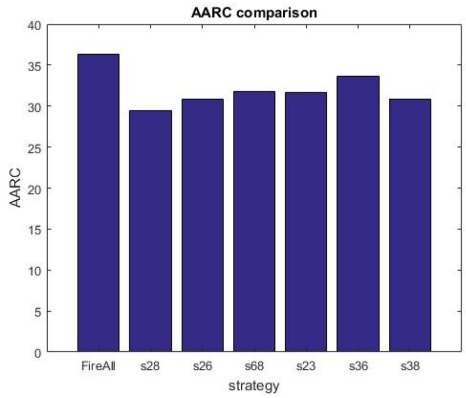

Fig. 12. AARC comparison for strategies - delay D4-157

5. Conclusions

In the present study we made an attempt to propose a new resilience-based approach for the identification of optimal firefighting strategies for control and suppression of fire domino effects in tank farms.

This study, up to the knowledge of the authors, is the first research in which the concept of resilience engineering is applied to the case of emergency response in fire domino effect scenarios in the chemical and process industries. The introduced methodology was shown to be able to increase the absorptive capacity of process plants in withstanding the expanding disruptions of fire escalation scenarios. We demonstrated that the concept of resilience engineering can effectively be coupled with the risk assessment and firefighting of fire domino effects especially that the impact of firefighting strategies on the plant's performance and resilience can nicely be reflected in the conditional probability tables. The use of the Area Above the Resilience Curve (AARC) was proposed in the present study as a resilience metric and discriminating factor to rank order the firefighting strategies due to its capability of combining the loss of resilience and the time needed for both the arrival of firefighters and the limitation of further escalation. By analysing the temporal changes of performances the analyst can evaluate the maximum acceptable amount of time after the primary event within which the plant can be restored to a stable state of functioning.

Further advancements of the resilience-based approach can be carried out by considering more factors such as the availability and reliability of passive and active fire protection systems, human resources, and the available budget for additional intervention. Extending the developed BN to a dynamic BN, the spatial-temporal changes can more explicitly been taken into account, making the analysis more in line with the dynamic nature of system's performance and resilience. Application of dynamic BN also seems to facilitate the modelling of simultaneous accidents and emergency actions such as the cooling of the exposed tanks and the extinguishment of the primary fire. This will be scope of our future studies. In this work, by combining resilience engineering and the support of the BN technique, we defined a new resilience-based metric which may open new paths for the evolution and improvement of risk assessment methodologies in process and chemical plants.

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