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A Resilience Index for Process Safety Analysis

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Abstract
Qualitative risk analysis is focused on applying methods to prevent accidents in diverse process plants. The numerical number resulting in the QRA tells nothing about the ability for systems' recovery if an upset related to safety occurs in the process. Hence a resilience study is required to produce this additional information related to process safety. The resilience index is defined as the proportion of success in recovering the system compared to a number of safety-related upsets. The failure in recovering depends on type and quality of safety barriers, i.e. technology, but also on organizational principles. In this work, Monte Carlo simulation is carried out to estimate the resilience resulting in quantitative resilience estimations. These results provide means to compare processes from a more general safety point of view.

Introduction
Safety in the chemical industry is an important issue: it is directly related to saving lives and also to the global economy. Given the advances in process systems engineering, the complexity of current process operations and high demand of productivity become clear indicatives that risk should be reduced though it will never disappear. There are several techniques to estimate risk and its metrics to prevent a potentially high number of industry accidents (Prem *et al.*, 2010). Other techniques have been also developed to include dynamic risk estimations (Yang and Sam Mannan, 2010b; Yang and Sam Mannan, 2010a).

Inclusion of layers of protection are typically suggested to decrease the estimated risk value until it achieves an acceptable value for the law or the particular level established in the particular company. Risk units are eventually a product of frequency and severity such as affected individuals/year. It does not include the estimation of how often the implemented protections avoid that incidents become accidents, i.e. an estimation of performing their task successfully. Resilience is an appropriate term to provide measurements of this probability. Indeed, the concept of resilience has been applied in several directions such as, for instance, protecting chemical areas against terrorism attacks (Reniers *et al.*, 2014). Resilience in security is considered as the ability of systems to prevent or adapt to changing conditions in order to maintain (control over) a system property (Leveson *et al.*, 2006). It gives a clear inclusion of both re-active and pro-active resilience aspects.

In process systems engineering, an index for operational flexibility (also called static resiliency) was developed to describe the ability to operate a given process over a range of conditions while satisfying some performance specifications (Grossmann *et al.*, 1983; Swaney and Grossmann, 1985a; Swaney and Grossmann, 1985b). This flexibility index represents a systematic measure of the size of the feasible steady state operation region. Values between 0 and 1 for the flexibility index represent the fraction of the range of expected deviations which can be handled, while values of the index greater than 1 denote designs for which it is possible to exceed the expected deviations and yet have feasible operation; negative values are not valid. Eventually Morari and Grossmann agreed that flexibility and resilience are, in a way, similar concepts, see the historical evolution of pioneering work by these two workers in Grossmann *et al.* (2014). More recently, the concept of stability has been incorporated in flexibility analysis with the aim of detecting stable flexible regions for chemical processes (Jiang *et al.*, 2014). The flexibility index in process systems engineering is then used to describe the potential of a given process to extent but remaining feasible over potential deviations in variables relating inputs, operating conditions or model parameters. The behavior of the involved variables can be visualized as uncertain and the flexibility index represents the largest deviation in the uncertain parameters that the process can tolerate in terms of the parameter deviations (Rogers and Ierapetritou).

A concept of dynamic resilience has been also developed in control theory referring to the quality of the regulatory and the servo behavior which can be obtained for the plant by a feedback control (Morari, 1983). A procedure for analyzing the resilience to anticipate and predict how modifications in the design will change the resilience were then developed (Holt and Morari, 1985). As a result of that research, a dimensional dynamic resilience index was proposed to evaluate resilience in neat exchanger networks (Saboo *et al.*, 1985; Saboo *et al.*, 1987). Thus reliability can be seen as the probability that an item will survive without failure for a stated period of time under stated conditions of use (O'Connor, 1988). The definition implies that measurements or forecasts of reliability should be based on probability mathematics, and thus on statistics. Probability and statistics will then provide the basis for reliability theory though these disciplines cannot be applied with high credibility. Their improvements should be made early in the development cycle.

Thus the concept of resilience has been seen from different points of view. Barker *et al.* (2013) have described resilience as the ability of a given components network to “bounce back” to the desired performance state after a disruption. They consider resilience as a function of four interacting paradigms: reliability, vulnerability, survivability, and recoverability. For state transitions over time in any system service function, the first period is governed by reliability where no disruptions are detected; next is a period of vulnerability where a mitigation approach allows survivability; and the last period, named recoverability, refers to the speed at which an entity or system recovers from a severe shock to achieve a desired state. In this way, vulnerability and recoverability become important drivers for resilience. Dinh *et al.* (2012) have identified six principles (flexibility, controllability, early detection, minimization of failure, limitation of effects, and administrative controls/procedures) and five main factors (design, detection potential, emergency response plan, human factor, and safety management) to contribute in the resilience of a process. They also proposed a resilience design index by combining indices for sub-factors based on predefined weight factors.

In our opinion, it is clear that resilience is stochastic in nature. Design for reliability should include tolerance analysis due to the stochastic variability in production processes. An stochastic flexibility index has been already introduced to describe the probability that a particular design achieve feasible operation given process uncertainties incorporated through a joint probability distribution (Pistikopoulos and Mazzuchi, 1990; Straub and Grossmann, 1990; Straub and Grossmann, 1993). Safety systems should include resiliency in terms of avoiding failures (deliberately induced or not), pro-active, and losses, as well as responding appropriately after the fact, re-active. Any mathematical model used for reliability predictions must be subject to severe credibility limitations due to: a) the inappropriateness of mathematical models to the domain of reliability; b) the fact that the conditions do not necessarily remain constant over the period of prediction; c) sensitivity to variations of load and strength; d) human factors in management, manufacture, application and interpretation (O'Connor, 1988). Cai *et al.* (2015) have recently proposed a method to be used for fault propagation and control strategy analysis in petroleum refining system from the resilience engineering perspective.

In this work, a safety resilience index is proposed to provide an estimation of the probability of keeping a process safe during unexpected hazardous situation. The following section provides the definition of this index while the subsequent section provides an estimation strategy. Then the index is estimated by applying the strategy in a case study to end up with the conclusions.

A Safety Resilience Index (SRI)

M. Morari and I.E. Grossmann agreed that the terms resilience and flexibility have essentially the same meaning (Grossmann and Morari, 1984; Grossmann *et al.*, 2014). However, the term resilience has been preferred in control analysis whereas the term flexibility has been supported in overall process design. Thus a process is typically designed to operate at certain nominal conditions but, due to its flexibility, it could be operated for a certain range of uncertain conditions. Assuming a set of uncertain parameters **u**, e.g. inlet conditions; a set of control variables **z** to be adjusted during operation, e.g. flows; a set of state variables **x** defining the system, e.g. temperatures; and a set of design variables **d** related for instance to the structure and size of process units, then performance equations, e.g. conservation equations, and constraints such as physical constraints, define a model given by several equalities and inequalities constraints:

$$\boldsymbol{h}(\boldsymbol{u}, \boldsymbol{z}, \boldsymbol{x}, \boldsymbol{d}) = \boldsymbol{0} \tag{1a}$$

$$\boldsymbol{g}(\boldsymbol{u}, \boldsymbol{z}, \boldsymbol{x}, \boldsymbol{d}) \leq \mathbf{0} \qquad \text{(1b)}$$

The full mathematical formulation to estimate the flexibility index has been given elsewhere (Swaney and Grossmann, 1985a; Swaney and Grossmann, 1985b; Biegler *et al.*, 1997). This index becomes unity when the design has exactly the flexibility to satisfy the constraints on a given range of interest. A larger flexibility index implies that the design can go beyond this range whereas a lower value means that only a fraction of the range can be handled. A pictorial description of the flexibility analysis is given in Fig. 1 where two uncertain variables (u_1, u_2) are considered to design the system for a nominal state *NS*, and the feasible region is defined by four inequality constraints, (g_1, g_2, g_3, g_4). Assuming that the inner rectangle is based on possible uncertainties in the variables/parameters, then it indicates the design flexibility zone. In addition, the outer rectangle indicates that the flexibility index is greater than one since the design exceeds feasibility requirements.

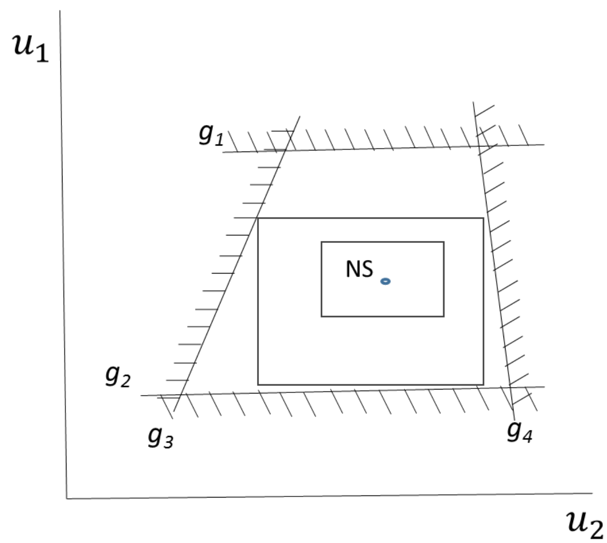

Figure 1: Geometrical representation of the flexibility index

In process safety, the term resilience has been preferred over the flexibility concept. It is then understood that a given safe and resilient process should remain safe after unwanted events perturb it. Risk assessment provides means to make a system more resilient than before. Dinh (2011) has suggested that several factors contribute to safe resilience of chemical processes, where design, detection potential, emergency response, human and safety management factors are considered top. At the end, safety resilience should be increased with the inclusion of safety devices in a process for minimizing failures, early failure detection, minimizing effects, administrative controls and procedures. It is thus clearly understood that resilience will prevent highly undesirable transitions to catastrophic states through several means such as protections, appropriate design, and even well planned emergency procedures. It should also prevent any potential escalation, e.g. domino effect.

While performing risk analysis such as QRA, a process is allocated in a certain risk level or category, see for instance Crowl and Louvar (2011), and each company may decide what is considered acceptable. For a given designed level of protection, the remaining question is related to its resilience. It is suggested here that unprotected processes should be considered to have nil resilience and denying the existence of absolute safety, then safety resilience index (SRI) definition should bound its values to the interval [0,1]. Any number in between would give the proportion of the number of incidents successfully prevented via safety devices or actions, i.e. the SRI represents the proportion of recovering from potential risk conditions. Considering that safety devices may become deteriorated with time, the SRI becomes dependent on time.

Safety indicators often depend on operating conditions in such a way that severity of incidents is typically higher when operating conditions are also severe, e.g. high pressure or temperature. However, SRI becomes independent of severity in this definition. This fact does not demerit its relevance since it could detect the need of other time dependent actions such as maintenance of safety devices. In addition, the resilience concept is not only uncertain but highly stochastic by nature. In terms of process safety resilience, incidents are considered as such whenever they enforce a safety device to perform its work. It would be expected that the SRI of a given process will be improved by incorporating protective factors. For instance, an expected release may be estimated for a QRA and the estimated risk will be higher according to the amount released and its associated severity. QRA is related to safeguard, mitigation measures, training and standard operations procedures for upset events but the resilience index will focus only to ensuring that the process remains under control.

Considering discrete events, the SRI can be considered as the proportion of incidents successfully avoided in a total amount of incidents where the use of any installed protective factor has been demanded. The estimation of the SRI is very difficult given its highly stochastic nature in the involved variables with complicated probability functions. However, the SRI ends up in a binomial distribution to indicate the probability of surviving an incident. This distribution should cover the whole operation possibilities for the system. Fig. 2 provides a graphical description of the SRI considering the system used in Fig. 1. The following section presents a strategy to estimate the SRI.

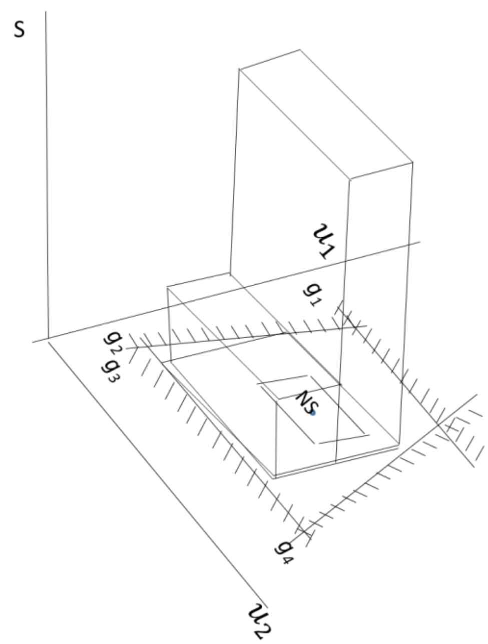

Figure 2: Geometrical representation of the safety resilience index

A Strategy to Estimate the SRI

The SRI is a stochastic variable but its distribution function becomes too complex since it is a function of several stochastic variables. A copula methodology has been applied to formulate the joint prior distributions of the failure probabilities of a safety system under different accident conditions, and of several safety systems, formulated using event-trees (Meel and Seider, 2006; Yu *et al.*, 2016)It gives an efficient alternative to traditional statistical methods. In this work, we proposed a Monte Carlo-based approach to generate a mapping of results in a binomial distribution function. Thus, a distribution function is associated to the failure of every safety protective item such as a valve. In fact, the resilience theory establishes the strategy to estimate system failures very often based on determining which system components are most influential on the performance of the system. Hence every safety protective measure can have an associated expression to calculate its failure probability. A safety protective system is meant to prevent that an incident becomes an accident and its probability of failure on demand depends on several factors such as maintenance. It is not the purpose of this work to review this material. Then we assume that these concepts are well known including the fact that there are means to estimate the probability of failure on demand. It is also clear that it is a function of time though we will assume that calculations are performed for a reduced time interval so that it can be seen as time independent.

In this work, it is assumed that the main cause of producing hazardous incidents in a chemical process is due to pipe ruptures. However, the methodology can be extended to other initial events. Thus the methodology is described as follows:

1. Identify all hazardous scenarios.
2. Identify the cause-consequence scenarios.

3. Apply the Monte Carlo approach. For each scenario:
    a) Solve all source models for dispersion, fire and explosion in for each stochastic variable.
    b) Identify if the scenario affects a surrounded populated sector.
4. The SRI is estimated by the relation of scenarios where safety devices are demanded to operate and its operation prevents affecting populated sectors divided by the total number of simulated scenarios.

Stochastic variables include initial event frequency, wind direction, wind speed, atmospheric stability and percent of pipe rupture. Their values in each scenario are randomly selected based on their respective probability distribution function. Safety protections could include alarms, automatic shutdown, interlocks, release systems, hydrocarbon detectors, fire protection systems and even safety procedures, see for instance Crowl and Louvar (2011) for details of description. The above procedure has been applied to a case study to estimate the SRI.

Case Study

The case given in the CCPS (AIChE/CCPS, 2000) a mixture is used here. Several scenarios with hazardous operations are simulated in Excel using the Risk Solver Platform (FrontlineSolvers, 2016). The process consists of a typical distillation column operating at 4barg where the feed, containing 58% wt hexane and 42% heptane, is separated. It involves the column, a reflux drum and a thermosiphon reboiler, as well as the piping system. Diameter pipe for vapor service is 0.5m and for water service is 0.15m. Figure 3 gives a schematically description of the whole system.

The plant is installed in a place such that 80m east there exist a warehouse and offices with 200 people present 24 hours a day, uniformly distributed on a 1ha square land. This zone is in the average wind direction with respect to the distillation column (directions SE, E, and NE). The rest of the surrounded area is in fact unpopulated and flat land.

The QRA approach suggests defining an initial list of incidents to consider all possible breaks or ruptures of items of equipment which would lead to a loss of containment. In this case, it is considered that pipes may break or rupture in several ways from a pinhole due to a full bore rupture at any position between the pipe ends. Possible reasons for ruptures includes corrosion or bad welding. At the end, the amount of material released depends on the rupture size and, in principle, it could be instantaneous or continuous. For simplicity, it was considered that all incidental releases contain pure hexane since it represents 2/3 part of the total inventory. Released material can be liquid, vapor, or a liquid-vapor mixture. Thus two scenarios are considered:
1. Continuous releases due to partial pipe ruptures in liquid/vapor pipes.
2. Instantaneous release where the column contents is released due to a rupture size larger than80% pipe diameters. The main cause is an overpressure in the process.

It is assumed that there is always an initial event (either instantaneous or continuous) and any ignition source can produce fire or explosion. For instantaneous releases, the potential consequences are BLEVE, UVCE and flash fire (FF) while for continuous releases Jet Fires (JF) and FF are more likely. These consequences depend on having immediate or delayed ignition with or without cloud formation.

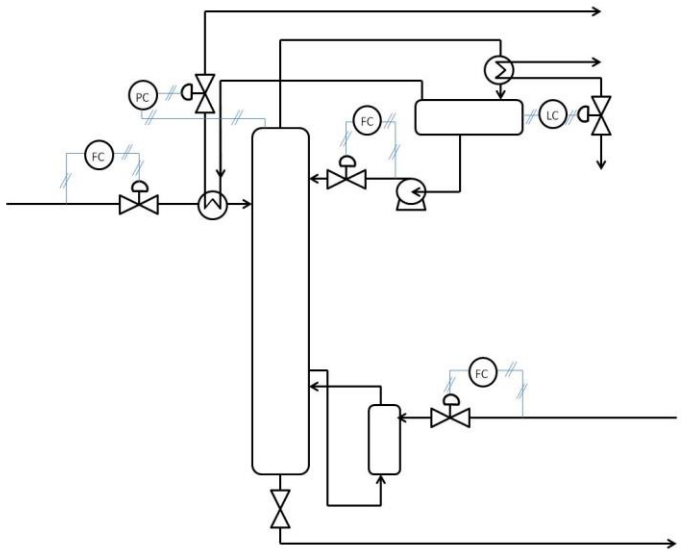

Figure 3: Control systems and alarms in a distillation column

Uncertain variables considered in this case are wind direction, wind speed, atmospheric stability, percent of rupture in pipes with liquid and percent of rupture in pipes with vapor. A probability distribution function is then assigned to each uncertain and highly stochastic variable. A uniform discrete probability function was applied for the following wind directions: 30°, 60°, 90°, 120°, 150°, 180°, 210°, 240°, 270°, 300°, 330° and 360°. For wind speed, the Weibull probability distribution function have been adopted and 4 stability conditions (A, B, C and D) were assumed feasible with different assigned probability. Table 1 gives Weibull parameters used in this work for each selected direction. Historical data (OGP, 2010) have been used for releasing failure probabilities in the distillation column, Tables 2 and 3. Rupture frequency in pipes with liquids are indicated in Table 2 and for the vapor case are given in Table 3. A discrete probability distribution function was used to model the probability of rupture in both types of pipe.

Table 1: Weibull parameters for wind speed distribution at each selected wind direction

Wind direction (°)	Weibull parameters for wind speed	
	Shape factor	Scaling factor
30	2.6533	4.5024
60	2.7053	5.2755
90	2.6186	6.8634
120	3.1254	8.6449
150	2.9283	7.1950
180	3.2550	6.6034
210	2.7645	6.1306
240	2.7597	6.5711
270	2.7790	6.7461
300	2.4984	7.3041
330	2.1698	6.0327

360	2.3463	4.5294

Table 2: Rupture frequencies in 0.15m diameter pipes

% rupture	Frequency, times/year
10	0.69
30	0.22
40	0.074
80	0.016

Table 3: Rupture frequencies in 0.5m diameter pipes

% rupture	Frequency, times/year
10	0.69
20	0.22
30	0.074
40	0.011
80	0.005

The amount pf released material in the case of instantaneous release have been 28,000kg of hexane, assuming that gas is released in atomized form. In this way, drops are so small than they remain suspended to eventually be vaporized rather than accumulated in a pool. Appropriate models were used to estimate mass speed of liquid and vapor for continuous releases as suggested in Crowl and Louvar (2011). Released liquid partially vaporizes and some drops remain suspended in air to eventually vaporize. In addition, liquid forming a pond will eventually vaporize. Therefore, all liquid releases will eventually become vapor releases so that they could be dealt with as a single event of vapor releases. Since hexane is a dense gas, the dispersion model by Britter y McQuaid as described in Crowl and Louvar (2011) was used to estimate the downwind distance, x, where the lower flammability limit concentration for hexane is achieved. It includes a cloud size estimation. Since the released material is mainly flammable, no toxic effect was included in this analysis.

Impact zones for BLEVE, UVCE, FF and JF were estimated using appropriate models in Crowl and Louvar (2011). An exposition time of 12sec and solar radiation to produce 50% fatality was used to estimate harms caused by BLEVEs. An overpressure of 3psi (causing minimal damage in buildings) was used to estimate damage due to UVCE. To calculate the area affected by the FF, the results of the dispersion model is used to define the area of fire where the LFL is reached from the releasing point. A simple step function is used where the likelihood of death is 1 for the area affected by the incident and 0 outside this area. Once affected areas for each incident are known, it was determined which of them had impact on the population close to the distillation column. It was defined as nefarious events those where the population that is located at 80 m from the distillation column became involved. Additionally there were cases where leaks can affect the control room within the installation where distillation column is located. The control room is allocated 20 m east from the column.

A macro was generated in Visual Basic where the different random variables of the process for a given number of tests were calculated. In each test, random variables are sampled according to their probability distribution functions; then source, dispersion and impact models are solved and the number of successful protection is accounted. It is worth mentioning that more than one incident could end up in accident. For example, a continuous leakage may produce a JF and a FF with affected distances larger than 80m, then the incident counts 2 accidents for this test. At the end of the total of tests, the SRI is estimated as the ration of the number of protected incidents divided by the total number of incidents (simulated tests).

It is suggested to incorporate alarms and control systems for pressure, temperature, flow and level to decrease the effects caused by instantaneous and continuous leakage of material by the rupture of pipes. Figure 3 shows typical alarms and control systems typically proposed for distillation column. A consequence analysis for failures in alarms and control systems has been used as follows:

1. Control system in the pump to feed the column. In the event of a failure where this control is inactivate, the flow may increase and decrease the temperature in the column. Then the heating fluid flow in the reboiler will increase causing a greater amount of steam in the column exceeding the cooling capacity of the condenser; finally, an excess pressure is generated in the column and a release will be produced.
2. Level control in the reflux drum: If this control fails and the tank is emptied, the steam quantity in the column increases and an overpressure is produced. In this case, venting is necessary to avoid a complete rupture of pipes and equipment.

3. Control system for pressure in the dome: A measurement detects the overpressure generated by failures in other systems and, if the alarm also fails, an overpressure above the MAWP may produce a full rupture.
4. Flow control of cooling fluid in the condenser: If the cooling unit is not sufficient then an overpressure may be produced and a venting valve should be activated to depressurize the column.
5. Control system for temperature at bottom of the column: There is a valve regulating steam feeding the reboiler. When the temperature controller detects an excessive increase, the steam flow decreases to prevent overpressure in the column. When the associated alarm fails, both flow of steam and temperature may continue increasing and a full rupture might be produced.
6. Dike for liquid containment: It is considered here that spray formed from continuous leakages due to pipes rupture or faults in seals for pumps and connections is not instantly vaporized but it condenses and forms a liquid pond that is contained in the dike. In this case, a vaporized fraction of 0.5 is considered.

Safety valves for venting material security systems, when above described systems 1, 2 and 4, described fail, allows opening a relief valve to prevent overpressure. This situation causes an instantaneous release with a time variable leakage that depends on the time lasting the venting. The flow is 5 kg/s and the time that the valve remains open is considered as a random variable with a discrete uniform distribution with values of 0.1, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, during 1 to 2 minutes. After this time, the pressure in the column should be slightly decreased and the safety valve closes again. If an ignition source exists during this event then UVCE and FF may be produced. On the other hand, when safety systems 3 and 5 fail 3 then a complete rupture of the unit may be produced, causing an instant leakage of all the material contained in the distilling column. BLEVE, UVCE and FF could be produced. Finally, if a source of ignition and a failure at the dike exist then the gaseous material that is not contained can cause a JF or a FF.

A program in Visual Basic has been developed to represent failures in the six safety systems above mentioned. The type of safety systems in the process is also considered as random variable with a discrete probability distribution. Table 4 shows the PFD for safety systems used in the distillation column. To start, the SRI was calculated for the process without protection systems. A total of 5000 tests were used in the estimation, as well as the types of adverse events that affect the neighborhood population and the control room. Then, six safety systems were considered to protect the process from events that could lead to partial and complete ruptures of pipes and process units. Finally, it considered that some of the six safety protections could fail and a redundant protection was incorporated. This second function of security could be a wall of containment, flame arrester, mitigation system, etc. PFD values used in this estimations are given in Table 4 whereas main results are given in Table 5. This table also indicates the results of the estimated SRI for all cases.

Table 4: Failure rates for components in the process

Safety System	PFD /year
Control system for feed pump	0.2517
Control system for reflux drum level	0.01
Control system for column top	0.1647
Control system in condenser	0.01
Control system for bottoms temperature	0.01
Dike	0.01
Flame arrester, blast wall, fire proofing, mitigation	0.001

Table 5: Safety resilience index for the system having different safety protections

Number of safety systems	**SRI**	**BLEVE**	**UVCE**	**FF (I)**	**JF**	**FF (C)**
0	0.64	0	2207	1367	10.1	686
1	0.97	0	12	7	0	311
2	1.00	0	0	0	0	0

By including safety functions, it is observed that the number of incidents becoming accidents decreases in comparison to the unprotected case. However, a function could occasionally fail. In the situation where two safety systems were implemented in the distillation column, the SRI became highly resilient though it is clear that these are stochastic events.

Conclusions

A resilience index is proposed in this work to be included in process safety. It provides a quantitative measure of the ability of protecting a given process. The proposed resilience index yields an estimation of the probability of failure/success of being protected with the combined protections already installed in the process. In addition, a strategy to estimate this index assuming a binomial distribution has been proposed and applied in a case-study to highlight the advantages of this method. It clearly results in an aggregated characteristic to consider while proposing protecting layers for processes. The case study considered several scenarios and final numerical values for the resilience index was determined considering different cases of safety protections. In this way, the index was quantified for several scenarios to find a single numerical value that indicates how adequate the implemented safety functions is.

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