Probabilistic Modeling of Failure Domino Effects in Chemical Plants

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***Abstract*—Chemical process plants are subject to risk caused by the handling and storage of hazardous substances. Major accidents may occur, particularly in those unfortunate circumstances when a triggering event produces a cascading accident that propagates to other units, a failure propagation scenario known as *domino effect*. An important aspect of designing such industrial plants is to properly arrange hazardous equipment such that, in the event of failures, cascading effects are minimized. In this work, we present a modeling approach to perform a probabilistic analysis of the likelihood of domino effects caused by propagating vapor cloud explosions. The approach combines the modeling of accident propagation based on physical properties of gas clouds, such as released mass and explosion distance, with the probabilistic modeling of cascading effects based on Stochastic Petri Nets. The proposed methodology is subsequently applied to a case study where different layouts of atmospheric gasoline tanks are analyzed, in order to evaluate the likelihood of domino effect occurrence.**

***Index Terms*—Vapor cloud explosion, Stochastic Petri net, Domino effect, Risk analysis.**

I. Introduction

Because of the hazardous properties of the substances involved in most chemical processes, process plants are often subject to many types of risks. The likelihood of occurrence of unsafe scenarios or accidents may be also dependent on several factors, such as wrong plant designs or incorrect management of equipment. The consequences of these events tend to be disastrous, particularly when major accidents occur [1]. These kind of events are usually related to an initial hazardous event or scenario that subsequently escalates to greater and more dangerous magnitudes. Escalation may trigger a chain of unwanted events whose effects progressively increase both in space and time, until producing a single, major accident. When this happens, we talk about a failure *domino effect* [1].

Failure domino-effects in chemical plants can occur because of a handful of reasons. The very first occurring event in the chain of unwanted scenarios is known as the *triggering* or *initiating* event. This is usually a fire (either pool fire, jet fire, flash fire, fire ball, etc.) or an explosion (Vapor Cloud Explosion - VCE, Boiling Liquid Expanding Vapor Explosions - BLEVE). Subsequent events can be of any kind, and are not necessarily exclusive, meaning that a triggering jet fire can end up causing both a BLEVE and a fire ball [2].

In this specific work, we study the domino effect of Vapor Cloud Explosions (VCEs), where both the main triggering event and the subsequent events are VCEs [3]. VCEs occur when a large amount of flammable material is released into partially congested atmospheres and such material does not ignite immediately [4]. Rather, it accumulates and generates a *cloud* of flammable vapor, i.e., gas or mist, with enough chemical energy to generate flame speeds that accelerate to sufficiently high velocities to produce significant increase of vapor pressure (*overpressure*).

VCEs are particularly dangerous because they can easily provoke explosions that lead to domino effects, due to the accumulation of hazardous (flammable) material in a growing cloud [5]. The explosion generated from such events can rise to destructive levels, making them one of the worst possible cases in chemical industry. As a consequence, analyzing domino effects of VCEs is of special importance for guaranteeing the safety in this industrial domain [6]. Several works have studied the behavior of VCEs, their possible causes and their consequences [7] [8] [9]. A major challenge in studying VCEs lies on the fact that domino effects add up uncertainty, and their actual impact is difficult to be quantified. Some studies have performed risk assessments on VCEs, although very few have tried modeling and assessing the impact of domino effects caused by VCEs [10].

The objective of this work is to help understanding safety hazards in chemical plants, by proposing a systematic approach to quantify the probability of occurrence of failure domino effects after an initiating VCE event. To this end, we propose a modeling approach that combines mathematical models of the physical characteristics of VCEs, with a Petri net model to assess the impact of the actual propagation effects. The approach consists of three phases: i) we first characterize the likelihood of occurrence of VCEs affecting chemical process units, then ii) we mathematically model the consequences of a VCE in terms of the impact that the energy release may have on neighboring units, and finally, iii) these two elements of risk are embedded into stochastic Petri net models that are used to represent the spatial arrangements of the process units of the chemical plant, and to simulate the propagation of events (explosions), finally estimating the probability of failure domino effects affecting different parts of the plant.

The rest of this paper is organized as follows. Section II introduces the modeling methodology we use to obtain the failure domino-effect probability estimation, and Section III details the chemical characteristics of VCEs that are relevant for the sake of our modeling, along with important concepts for understanding the propagation of undesired events. Section IV presents the stochastic Petri net model that will be used to estimate the propagation of failure domino effects. In Section V, a case study based on atmospheric gasoline tanks is presented and modeled using our approach to provide an example of application. Finally, in Section VI, concluding remarks and future enhancement possibilities of this work are presented and discussed.

II. Methodology

VCEs are dangerous events that besides entailing capital losses and operation disruptions also represent extreme safety hazards for personnel operating in chemical plants. An explosion occurring at an element of the process may propagate to other equipment units and produce other kinds of unwanted events. In this work, we restrict ourselves to consider only initiating events of VCE type, and we also assume that secondary or propagated ones are also of that type, ignoring other unwanted events different to VCEs.

In the following we provide an overview of the proposed methodology (Section II-A), together with the main assumptions on which it is based (Section II-B), as well as the measures of interest that we aim to calculate (Section II-C).

A. Overview

We model VCEs as probabilistic occurring events, according to the methodology graphically described in Fig. 1. The methodology we propose consists of three steps: i) modeling of initiating events, ii) modeling of one-step propagation, iii) modeling of domino effects using Petri nets. Step i) basically consists in characterizing the failure process, that is, determining the distribution of initiating events. Step ii) consist in determining individual propagation probabilities between equipment i and j, based on their distance and mathematical models of VCE physical characteristics. Finally, in Step iii) all this information is aggregated in a modular SAN model representing the domino effect process. Such model is evaluated by discrete-event simulation to obtain the final metrics.

Models for the distribution of the time to the occurrence of different types of failures have been proposed in the literature. For instance, a commonly accepted approach [11] for chemical process equipment is to use the Weibull distribution to represent the random nature of failure times. In this work, we use the negative exponential distribution to model the time to failure of equipment units. The negative exponential random variable is a special case of the Weibull distribution family, which assumes that the failure hazard is constant, i.e. no aging effects occur that increase failure likelihood over time. Suppose the chemical plant comprises a set $E_1, E_2, \ldots, E_n$ of n equipment units. We model the time to failure of equipment unit E_i as being a independent non-negative random variable TTF_i, with known probability distribution of parameter $\lambda_i > 0$ (failure rate), whose cumulative probability distribution has the following analytic form:

$$Prob[\mathrm{TTF}_i \leq t] = 1 - e^{-\lambda_i \cdot t}, \quad t \geq 0,\ i = 1, 2, \ldots, n. \quad (1)$$

The expected value of the time to failure TTF_i is given by λ_i^{-1}.

The triggering VCE event may occur at any of the equipment units. The time of its occurrence is a random variable $\mathrm{TE} = min_i\{\mathrm{TTF}_i\}$, which for the well-known properties of the independent exponential distributions is again an exponential distribution of rate $\lambda_1 + \lambda_2 + \cdots + \lambda_n$. We will only consider one triggering event, and all other VCEs that may possibly happen would be caused by direct or indirect propagation of the initial one.

For a chain of failure events to occur, the energy released in the initiating VCE must be sufficiently high to affect the neighboring units. Obviously, the odds of event propagation depend not only on the amount of released chemical energy, but also on the closeness of other equipment and on the susceptibility of the involved substances to ignition. Moreover, the domino effect is not deterministic, but rather probabilistic (propagation may not happen). Several studies in the literature have proposed statistical models to predict the likelihood of a piece of equipment being affected by the explosion of neighboring units. We shall be using those type of models to parametrize a stochastic Petri net model that accounts for the possible routes of VCE propagation. In particular, we shall be extracting from the studies in the literature the probability p_{ij} of a VCE type of failure propagating from unit i to unit j, as a function of the distance between units and of the released energy.

We will use a Stochastic Petri Net modeling for representing the occurrence of the initiating and of the propagating events. Petri nets are useful mathematical tools for modeling, analyzing and simulating different kinds of systems, which were initially proposed in 1962 by Petri in his Ph.D. dissertation thesis to model concurrent systems [12]. They have two basic types of modeling elements: places, depicted as hollow circles and representing states of the system, and transitions, depicted as empty rectangles, which represent system changes or occurrence of events. Places can have tokens, which model entities, depicted as black dots, and the number of tokens in a place at a certain moment is called the *marking* of the place.

Tokens move across the places of a Petri-net according to connections between places and transitions and transitions and places, which specify enabling conditions for the events associated to transitions as well as the changes in the marking of the places upon their occurrence. The rules that specify the dynamic evolution of the marking are called *firing rules*

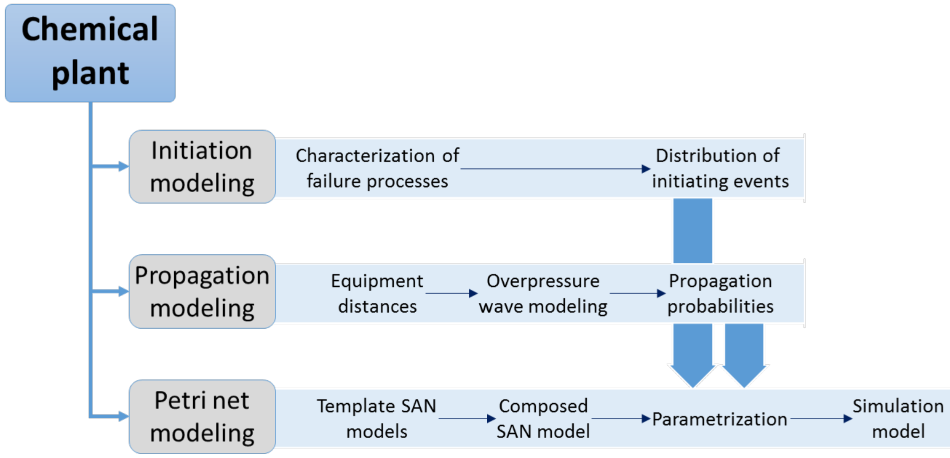


Fig. 1: Workflow of the proposed approach.

[13], and are easily understood by observing the example of a Petri net shown in Fig. 2. The example shows a possible modeling of the state of a unit which can be functioning (a state represented by place `Up`) or failed (modeled by place `Failed`). The event leading to failure requires a token in place `Cause` to be present in order to occur. Upon failure, a token will be deposited in place `Failure`, enabling the two transition `Repair`, which will obviously restore the state of the unit, as well as transition `Propagation`, which as suggested by its name might be used to model a further cause of failure for another process unit.

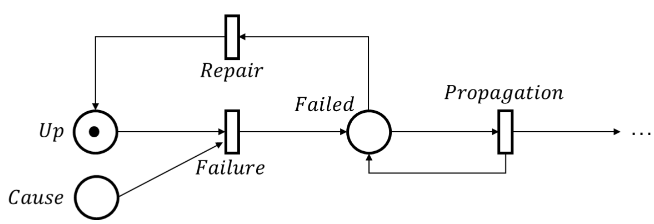


Fig. 2: Petri net example.

Although the originally proposed Petri nets did not include probabilistic elements, it is quite natural to consider the time associated to transitions as being drawn from probabilistic distributions. This classes of Petri nets is often called Stochastic Petri Nets. The firing of tokens can be also dependent on complex functions of the markings, and it is possible to conduct Monte Carlo simulations to evaluate interesting measures about the likelihood of the occurrence of events. We shall be using in this work the class of Stochastic Petri Nets called Stochastic Activity Networks (SAN), used by the Möbius modeling tool [14], which features useful extensions that allow for compact models and faster simulation [15].

B. Assumptions

The main assumptions on which we base our methodology are listed in the following.

1) The time to failure of a process unit, causing leakage of flammable material, is characterized by an exponential distribution.
2) The only unwanted event resulting from leakage of flammable material is a VCE. In fact, in this work we are specifically interested in assessing the probability of occurrence of a domino effect following a VCE event.
3) A failure occurring in a tank immediately causes a VCE. As explained in Section III this is not the case in reality, as some additional conditions must hold. However, by assuming a deterministic occurrence of VCEs upon unit failure we are considering the worst-case scenario.
4) A process unit may be affected by a VCE only once for the duration of the analyzed scenario.
5) Propagation of a VCE event to a nearby equipment, if it occurs, is instantaneous (i.e., the propagation delay is negligible).

These assumptions are reasonable considering that our objective is analyzing exactly the chain of VCE events. Relaxing these assumptions, particularly item 2) above, is part of our future work.

C. Measures of Interest

The objective of this work is provide stakeholders (e.g., chemical plant owners) with a tool to compare different design choices in planning the layout of chemical infrastructures. For this reason, we focus on concise metrics that can provide a good indication of the safety (i.e., absence of catastrophic failures [16]) of the analyzed configuration.

With this in mind, we define the following measures:

- $F^X(t)$, defined as the probability that unit X will be affected by a VCE not later than t;
- $N_{fail}(t)$, defined as the average number of process units that will be affected by a VCE before or on time t.

The first measure can be used as an indication of how good is, with respect to VCE risk, the placement of an individual piece of equipment. The second measure is instead an indication of the overall safety level of the whole layout scenario with respect to other alternatives.

To be able to calculate such metrics we first have to characterize the occurrence of VCE events and their propagation (Section III), and then construct the model representing the domino effect (Section IV).

III. Characterization of VCE Events

Equipment in a process plant may fail, causing unwanted consequences. For a failure to happen, a root cause (also called initiating event) must firstly occur; then some other intermediate events may happen until the final failure effect, or failure mode, happens. After a failure has happened, it may produce more severe consequences (also called final events), which may depend on other external events.

The main focus of this work are Vapor Cloud Explosions, which are final events. In the middle, the considered failure mode is the loss of containment, i.e., a leak. VCE events are essentially the explosion of a "vapor cloud", an agglomeration of an important amount of flammable mass. These clouds can be formed due to the accumulation of vapor itself, or from liquid spills which are consequently evaporated. Once the cloud is formed there is a risk it may explode. However, in order for the cloud to be able to produce an explosion, the following three main conditions must hold.

1) The substance in the cloud must be within its flammability limits. These are temperature limits within which it is possible for a flammable substance to ignite, depending on the kind of substance.
2) Ignition must be delayed. In case the cloud starts burning before it is completely formed, other fire scenarios would occur instead of a VCE. Such other events are out of the scope of this paper.
3) Turbulence must be present in the cloud. The release mode of the substance (a jet, for instance) can trigger this turbulence. Interaction with close-by objects may also work as partial confinement, and generate turbulence within the cloud.

Once the explosion happens, a part of the chemical energy produced by the combustion reaction will turn into mechanical energy, resulting in a blast wave. Blast waves produce a pressure increase that builds up in a first moment due to the combustion, but that subsequently diminishes thanks to the expansion of gases [17]. This increase of pressure is called *overpressure*, and it characterizes the blast wave of any explosion. The amount of overpressure depends on the type of explosion. In this work we focus on detonation processes (i.e., large and instantaneous explosions) [18].

Immediately after the explosion starts, an over-pressure peak is produced, which moves through space diminishing as distance increases. The *blast estimation* methods model the dependence of the overpressure from the distance from the detonation point and the amount of mass released, to allow quantifying the overpressure experienced at a certain distance from the explosion point.

There is not an agreed way of performing blast estimation, and three main methods are most commonly used:

- *TNT-equivalency*, which first calculates the equivalent mass of TNT that would generate such explosion, and the uses this value for further over-pressure calculations.
- *Multi-energy*, which bases its calculations on the fact that the explosion behavior is in large part determined by confined parts of a vapor cloud.
- *Baker-Strehlow-Tang*, which differs slightly compared to the multi-energy method in that the strength of the blast wave is proportional to the maximum flame speed that the cloud has reached. In this model, the speed is an input parameter.

While it is true that all models have their advantages and disadvantages, in this work we will use the multi-energy method as the basis for overpressure calculation, given its simplicity in terms of required input parameters, and its wide acceptance concerning the faithful representation of the dynamics of an explosion [19].

The *multi-energy method* algorithm for calculating the overpressure, for a given distance of interest, is summarized in the following steps [1].

1) **Cloud characterization**. This step aims at finding the amount of released mass in the cloud, which often requires dispersion calculations. Since these calculations are not the main focus of this work, an overall mass is approximated for cloud calculations. This mass must at least correspond to the stoichiometric quantity required for combustion to occur.
2) **Calculation of released energy**. The amount of released energy will correspond to the product of the volume of the mixture and the amount of energy released per cubic meter. The volume used in this step must take into consideration the mass calculated in the previous step. However, only the *confined part* of the cloud, i.e., the part of the cloud that is in a confined space or obstructed should be considered, as unconfined parts would burn out without significantly increasing the pressure.
3) **Distance scaling**. Scaling laws exist for modeling the physical properties of explosions, which relate the properties of blast waves from different explosions. Such laws allow extrapolating the blast wave properties of explosions from data obtained under different conditions (e.g., different amount of explosive, distance). Based on E, the released energy calculated in the previous step, a *scaled distance* $\bar{R}$ is first calculated, as a function of the distance R and the atmospheric pressure P_a, as follows:

$$\bar{R} = R(P_a/E). \quad (2)$$

4) **Overpressure calculation**. From the scaled distance $\bar{R}$, a corresponding scaled overpressure can be found based on a Sachs-scaled side-on overpressure graph, as the one shown in Fig. 3. Such charts correlate dimensionless (scaled) values of over-pressure and distance, based on the assumed source strength or severity of the explosion,

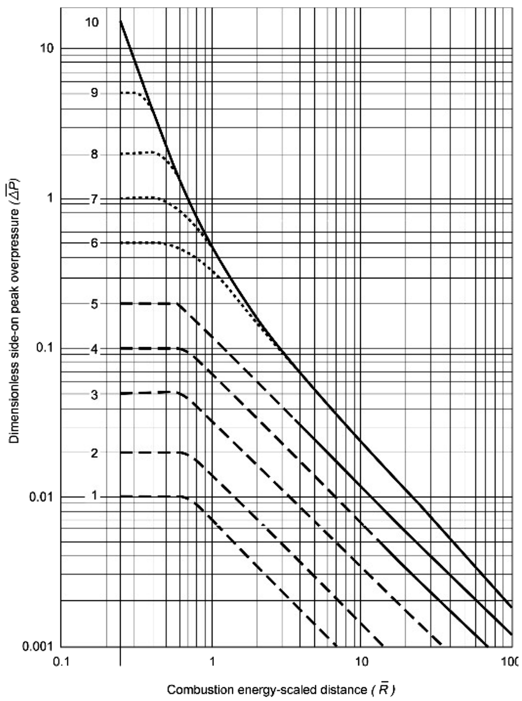


Fig. 3: Sachs-scaled side-on overpressure chart [1].

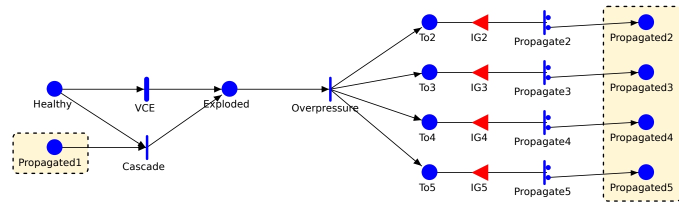
which ranges from 1 (lowest) to 10 (highest). This value must be specified for the cloud according to the partial confinement in the area. A value of 7 is used in this work (corresponding to congested areas). Once the scaled overpressure has been determined, the final overpressure value is found by a further rescaling by P_a, the atmospheric value.

After the first event has happened (i.e., a vapor cloud has exploded), it can propagate to other equipment, resulting in a domino-effect. That is, if other hazardous equipment is present nearby, the overpressure generated by the explosion may damage it, causing the release of additional flammable material, which in turn may generate other VCE events.

This propagation is not deterministic, but rather probabilistic, as it depends on several factors. Several literature approaches have developed empirical models to relate escalation probabilities to overpressure received from a blast wave, e.g. [20]. For instance, the authors of [21] proposed a *probit* model to estimate the escalation probability from overpressure values of vapor cloud explosions in atmospheric tanks, by first determining a factor Y as follows:

$$Y = -18.96 + 2.44 ln(\Delta P), \tag{3}$$

with ΔP being the over-pressure, and then using $\phi(\cdot)$, the cumulative density function of the standard normal distribution, to calculate P_e, the escalation probability, as $P_e = \phi(Y - 5)$. The obtained probability value P_e is thus the probability that a VCE event would escalate to another equipment located at a certain distance R, causing a subsequent VCE event. Based on the specific scenario to be analyzed, such probability values



λ	Rate of occurrence of the initial VCE event
n	Total number of tanks
$\{p_2, \ldots, p_n\}$	Probability of propagation to nearby tanks

Fig. 4: Template SAN model for an atmospheric tank.

need to be estimated for each value of the distance between pair of equipment that might propagate a VCE event. We shall be using these estimated probabilities to parametrize a SAN model that allows predicting by simulation the domino effects likelihood result of an initiating VCE.

IV. SAN Model of VCE Chains

A. Template Models

One of the objectives of the approach we are proposing is to facilitate the evaluation of the VCE risk associated to different scenarios in a chemical plants. To achieve this objective we adopt a "template-based"' approach for the construction of the SAN model, in which a library of basic parametric models are first defined. Then, such models are instantiated multiple times and connected together to obtain the global models corresponding to the intended scenarios.

The reusability and maintanability of models is therefore improved: submodels can be modified in isolation from the rest of the model, can be substituted with more refined implementations, and can be rearranged based on modifications in system configuration. Most importantly, using such approach facilitates the automated composition of SAN models for different scenarios based on their high-level specification [22].

B. The Tank Model

In this work, we exemplify the template-based modeling by using only a single template, the `Tank` model. This is justified by the specific case study we will be dealing with in Section V. Its graphical representation using the SAN notation is shown in Fig. 4, together with its parameters. Places highlighted with a dashed yellow rectangle are *interface places* of the template, that is, those that will be used for composition with other instances. Parameters of the template are the rate of occurrence of the initial VCE event in the tank (λ), the number of nearby pieces of equipment which may be affected by propagation (n), and the probability that propagation of the VCE actually occurs for each of them ($p_1, \ldots, p_n$).

Note that the image in Fig. 4 actually shows the structure of the model for a tank with four neighboring units (i.e., $n = 5$), as the ones that will be used in the case study presented in Section V. The number of nearby units is however configurable with parameter n, and the model can be automatically altered to reflect a different value. The structure of the model is described in the following.

The `Healthy` place represent a tank that is in good conditions (i.e., no leaking of flammable material) and it initially contains one token. A tank in good conditions may be affected by a VCE for two reasons: either i) it is the one directly causing the initiating event, or ii) it is affected by propagation from a VCE occurring in one of the nearby pieces of equipment.

The first case is represented by the `VCE` activity, which is exponentially distributed with rate λ and is enabled when there is a token in the `Healthy` place. When it fires, it means that a leakage of flammable material has occurred, and the subsequent VCE event occurred (as per assumptions in Section II-B). The token is then removed form the `Healthy` place, and one is added to the `Exploded` place.

The second case, in which the tank is affected by incoming propagation, is represented by place `Propagation1` and the immediate activity `Cascade`. `Propagation1` is an interface place, that is, it is shared with other instances of the `Tank` template, representing the other tanks in the scenario. In case one of the other tanks successfully propagates a VCE event to the tank represented by the model (assume tank #1), a token gets added to place `Propagation1`. Such token triggers activity `Cascade`, which removes the token from `Propagation1` and adds one to `Exploded`.

Independently from the reason why a VCE event has been triggered, the presence of a token in `Exploded` triggers the `Overpressure` instantaneous activity, representing the propagation of the overpressure wave and the possible triggering of a cascading VCE event. Propagation to each individual tank occurs with a different probability, based on the distance at which the other tank is located (see Section II). This aspect is modeled by the instantaneous activities $\texttt{Propagate}_X$, each one representing propagation to a different tank. Each of these activities may have two different outcomes (cases), probabilistically chosen: propagation occurs (p_X) or not ($1 - p_X$). The actual probability values $\{p_2, \ldots, p_n\}$ are parameters of the template model, and are calculated in the previous step.

In case propagation occurs, a token is added to the corresponding $\texttt{Propagated}_X$ places (e.g., `Propagated2` for tank #2). Such places are also interface places, and are analogous to `Propagated1` for the other instances of the `Tank` template model. This is how the modeling of the domino effect is achieved, and any VCE event in a tank can cascade multiple times, potentially causing a VCE event in all the tanks in the scenario.

C. Overall Model and Measures Specification

The overall model of a scenario is thus obtained by creating multiple instances of the `Tank` template model, and connecting together all the $\texttt{Propagated}_X$ interface places having the same name.

This is illustrated, visually, in Fig. 5. All the instance of the template are connected using the Rep/Join state-sharing formalism [23] (Fig. 5b). In this way, cascading effects of VCE events are automatically taken into account by the SAN model (Fig. 5a).

Once the model of the complete scenario has been constructed, the measures defined in Section II-C need to be specified in terms of the SAN model. This is typically done defining reward variables [24].

In our case, the target measures can be computed as follows.

- $F^X(t)$ is the expected value, at time t, of the following reward variable:
$$\mathcal{R}^X = \begin{cases} 1 & \text{if } \#(\texttt{Tank}_X.\texttt{Healthy}) = 0 \\ 0 & \text{otherwise}, \end{cases}$$
where $\#(\texttt{Tank}_X.\texttt{Healthy})$ is the marking of the `Healthy` place in the Xth instance of the `Tank` template.
- $N_{fail}(t)$ is the expected value, at time t, of the following reward variable:
$$\mathcal{R}_{fail} = n - \sum_{k=1}^{n} \#(\texttt{Tank}_K.\texttt{Healthy}),$$
where $\#(\texttt{Tank}_K.\texttt{Healthy})$ is the marking of the `Healthy` place in the Kth instance of the `Tank` template, and n is the total number of tanks in the scenario.

V. Case Study

As it is common practice in the literature, atmospheric storage tanks containing gasoline are considered for the evaluation of the proposed methodology.

Five different layout scenarios are chosen for the five tanks, which are shown in Figures 6 to 10. Thanks to the proposed modeling methodology, the SAN model for the domino effect remains unaltered, and only the propagation probabilities change for the five scenarios. The figures show the distances that need to be determined in order to calculate the P_e probabilities with the procedure described in Section III. Parameters a and b, which define the size of the considered area, are set to 80 meters and 120 meters, respectively.

In the following we perform two distinct evaluations:

- a *what-if* analysis, considering the deterministic failure of Tank #1;
- a transient analysis, considering random failures of tanks.

All the results have been obtained by discrete-event simulation using the simulator provided with the Möbius framework [14]. When not specified otherwise, each data point has been computed with a confidence interval of 1% relative width and a confidence level of 95%, on at least 10^4 simulation batches.

A. What-If Analysis

In this evaluation we perform a what-if analysis, understanding the impact of a failure of Tank #1 in terms of the likelihood of occurrence of a VCE domino effect. The results of the evaluation of F^X and N_{fail} for the five scenarios are shown in Fig. 11. Since we assumed that propagation among tanks is instantaneous, we evaluate such metrics at time $t = 0$, which is also the time when the initiating event occurs. Results for Tank #1 have not been included in the figures, because it

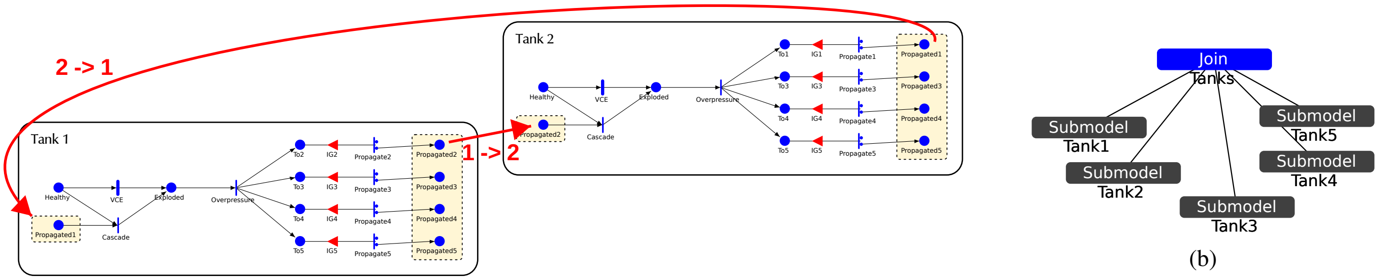


Fig. 5: Multiple instances of the `Tank` template model are connected together using the Join state-sharing formalism (b). In this way cascading effects are automatically taken into account by the SAN model (a).

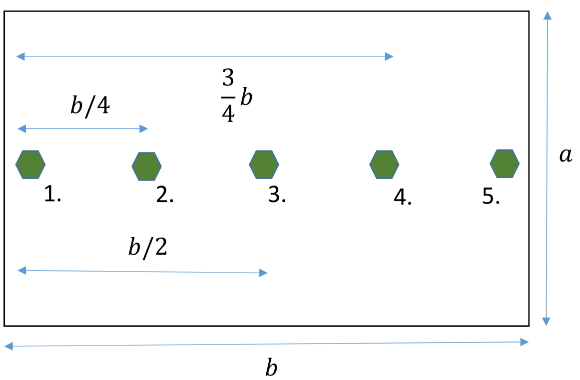


Fig. 6: Layout of Scenario **A**.

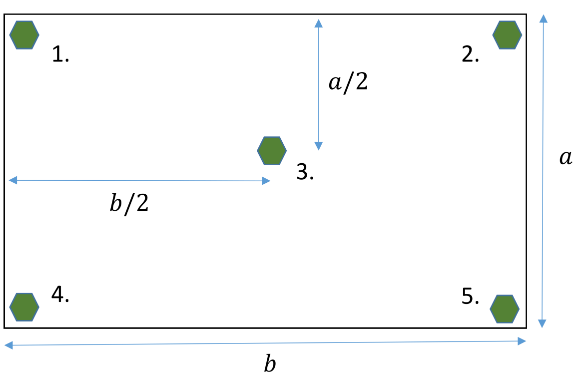


Fig. 7: Layout of Scenario **B**.

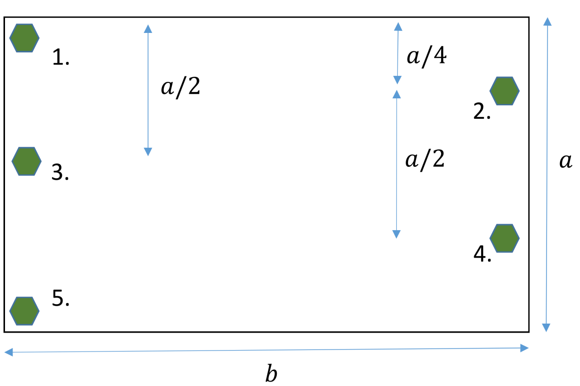


Fig. 8: Layout of Scenario **C**.

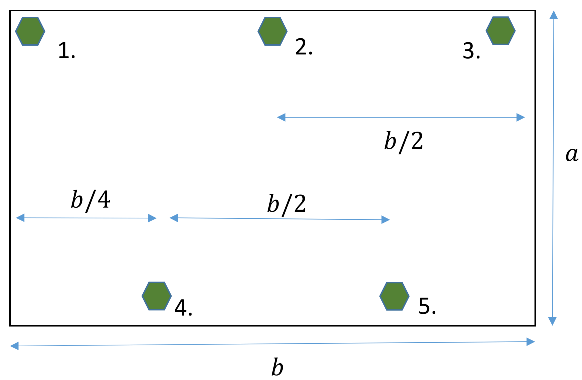


Fig. 9: Layout of Scenario **D**.

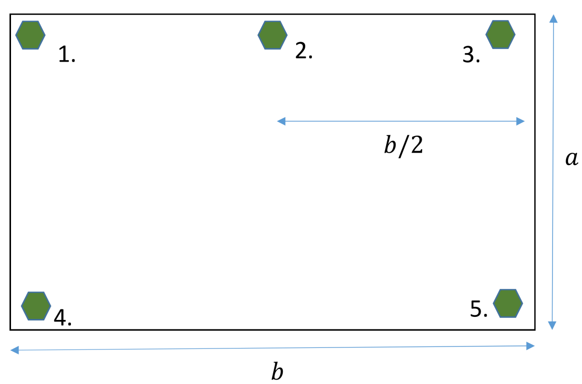
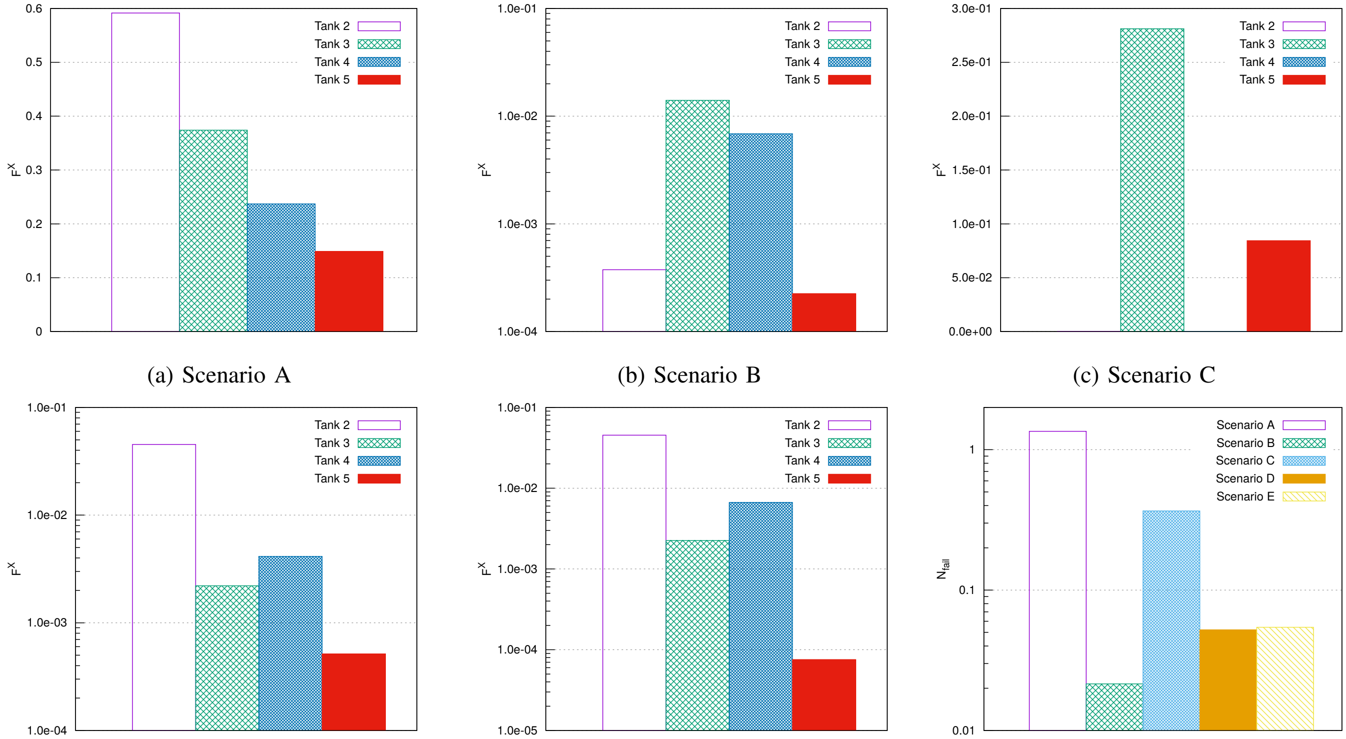


Fig. 10: Layout of Scenario **E**.

is assumed that the initiating event occurs in such tank for all scenarios, and as such F^1 is constant with value 1.0.

Overall, it can be seen that the model has produced consistent results. In fact, the layout with a linear placement of tanks (Scenario A) has the highest individual probabilities of explosion among all the scenarios. This is indeed the configuration in which tanks are closer, with a minimum distance between them of $b/4$ (i.e., 30 meters). When the average spacing between equipment is increased, it is clear that it is less probable for the VCE to affect adjacent equipment. Overall, scenarios A and C present the highest probability of domino effects, while Scenarios B, D and E are less risky in comparison to the other layouts.

However, a greater distance from the first tank (which,



(a) Scenario A (b) Scenario B (c) Scenario C

(d) Scenario D (e) Scenario E (f) N_{fail} – All Scenarios

Fig. 11: Results of the what-if analysis assessing the impact of a VCE occurring on Tank #1. The evaluation is performed at the instant of time immediately following the occurrence of the initiating event. Figures (a)–(e) depicts the probability of occurrence of a VCE event on different tanks in different scenarios. Figure (f) depicts the average number of tanks affected by VCE for each scenario.

we recall, in this evaluation always serves the purpose of generating the initiating event) does not necessarily mean a lower probability of explosion, as closeness with other equipment can trigger domino effects. Such effect can be clearly seen in Scenario A, where the closeness of all equipment among each other rises the probability of domino effects to one order of magnitude above all of the other scenarios. In fact, in Scenario A even for equipment that is farther from the detonation point (Tank #5), the probability of being affected by the VCE domino effect is one order of magnitude higher than the maximum experienced by any tank in Scenarios B, D, and E.

By analyzing the plots for F^X (Fig. 11(a)–(e)) it is not straightforward to understand which of the five scenarios is the safest one under the stated assumptions. For example, in Scenario B the probability of propagation for Tank #2 is lower than in Scenario D, but for Tank #3 it is the opposite. Similarly, the probability of propagation for Tank #5 is the lowest in Scenario E, but for Tank #2 it is the lowest in Scenario B.

The overall safety of the different layouts with respect to a VCE occurring on the first tank can be better understood by analyzing the N_{fail} metric (Fig. 11f). From that figure, it can be clearly understood that, under these assumptions, Scenario B is the one resulting in the lowest number of tanks being impacted on average by the domino effect, while D and E are almost equivalent with respect to this metric. There is however a difference for Tank #5, which has a lower value of F^X in the last scenario because it is farther from the initiating event, and far enough from the other tanks as well.

This kind of evaluation can help identify certain patterns that, although clear in those two specific scenarios, can be more difficult to devise in complex layouts. Also, this evaluation has highlighted the complementary nature of the two proposed measures in performing what-if analysis.

B. Transient Analysis

In this section we perform a transient analysis of the model, that is, we evaluate how the probability of VCE domino effect occurrence changes with time. In this evaluation we assume that the initiating event can occur in any of the five tanks, and will occur according to a Time-To-Failure (TTF) following an exponential distribution. Values for the failure rate of atmospheric gas tanks have been set based on the data in [25], considering the equipment "3.6.1.1 VESSELS-ATMOSPHERIC-METALLIC". Based on such data the average failure rate for such equipment is 0.985 failures per 10^6 hours, that is, $\lambda = 9.85 \cdot 10^{-7}$ hours^{-1}.

We used such value to perform the evaluation reported in Fig. 12, in which the average number of tanks that have

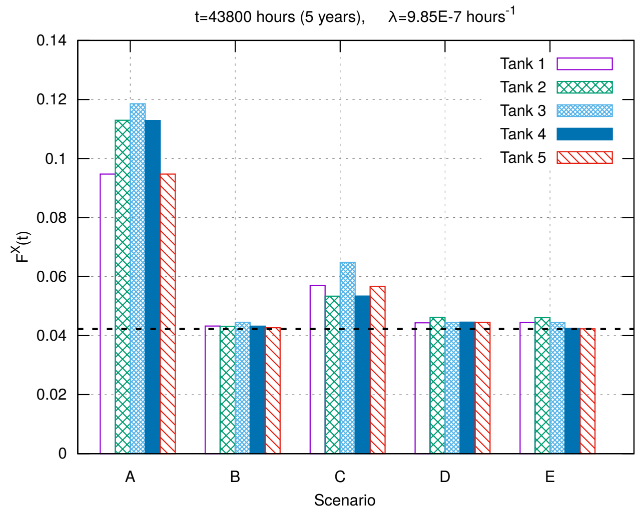


Fig. 12: Probability of a VCE affecting different tanks on the different scenarios, assuming a random initial event. Values of $F^X(t)$ with $t = 43800$ hours $= 5$ years.

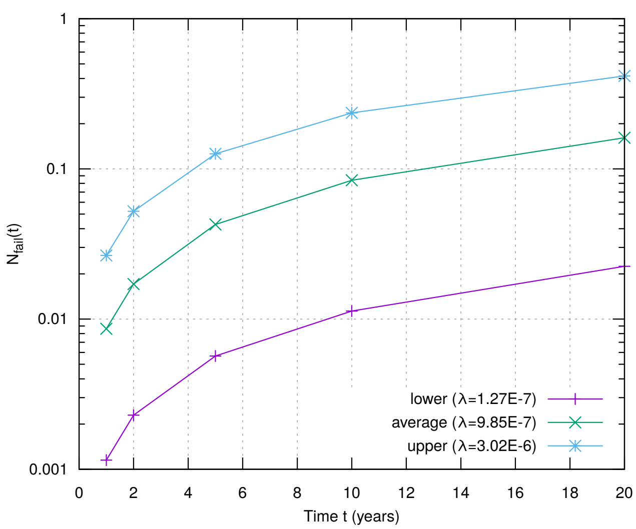


Fig. 13: Average number of tanks affected by a VCE event, at different time points and with different rates of occurrence of the initial event.

suffered a VCE (either because of a tank failure or a domino effect) is analyzed for an instant of time of 43800 hours, roughly corresponding to 5 years.

The results confirm the ones obtained in the previous evaluation, that is, Scenarios A and C are the ones that are most affected by the domino effects of VCEs. The results in Fig. 12 also confirm that the model is able to accurately distinguish tanks based on their location. In fact, looking at results for Scenario A, the highest probability of explosion is for Tank #3, then for Tank #2 and Tank #4, and finally for Tank #1 and Tank #5. This is consistent with the layout of Fig. 11a, in which Tank #3 has the minimum average distance from the other tanks.

The most interesting result are however the values obtained for Scenarios B, D, and E. While they confirm that these three layouts are almost equivalent, the figure also shows another interesting result. For each tank in these scenarios, the probability of being affected by a VCE is almost the same. Furthermore, this value is very close to the the value of the cumulative distribution function of the exponential distribution regulating the failure process of individual tanks. In fact:

$$Prob[\text{TTF} \leq t] = 1 - e^{-\lambda t} = 1 - e^{-(9.85 \cdot 10^{-7})(43800)} \approx 0.042,$$

which is highlighted in the figure by a dashed black line. As visible in the figure, this value is very close to the value of $F^X(t)$ obtained for all the tanks in Scenarios B, D, and E. This means that, in such layouts, *the domino effect does not add significant contribution to the probability of a tank being affected by a VCE*. The same is not true for Scenarios A and C, which instead are significantly affected. This demonstrate the usefulness of the approach, and how it could be used in practice.

Finally, Fig. 13 shows a more classical example of application of the framework, which is used to understand how the average number of tanks affected by VCE changes with time and with the occurrence rate of the initiating event. This kind of analysis is useful to plant owners to understand if higher quality equipment is needed and/or to plan periodic maintenance or replacement of equipment. The failure rates used in the figure are taken from the same source [25], which contains "lower", "average" and "upper" value for the failure rate of atmospheric vessels.

VI. Conclusions and Future Work

The approach we proposed has obtained consistent results, succeeding in the goal of modeling and predicting the consequences of vapor cloud explosions taking into account domino-effects. In the process, a general model for tank explosion was developed, together with the support for distance variation. Also, probit models were used to estimate escalation probabilities between equipment, summed to an estimated but effective method of blast calculation. Further research must be conducted in terms of domino effect exposure, specifically on more robust models containing other kinds of unwanted events, leading to a more accurate calculation of domino effect probabilities. Dispersion calculations are also important for partial confinement and turbulence calculations within the vapor cloud, in order to maintain coherence with assumptions of the multi-energy method.

Another direction for future work consists in improving the modularity of the Petri nets model and automating model construction, directly taking as input a layout of the chemical plant. In this perspective, we plan to investigate the application of Model-Driven Engineering (MDE) techniques [26], with the objective to automatically derive our probabilistic model from a high-level description of the physical layout of the infrastructure under analysis.

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References

[1] J. Casal, *Evaluation of the Effects and Consequences of Major Accidents in Industrial Plants*, ser. Industrial Safety Series, vol. 8. Elsevier Science, 2008.

[2] J. Wesevich, P. Hassig, L. Nikodym, V. Nasri, and J. Mould, "Accounting for channeling and shielding effects for vapor cloud explosions," *Journal of Loss Prevention in the Process Industries*, vol. 50, pp. 205–220, 2017.

[3] D. M. Johnson, G. B. Tomlin, and D. G. Walker, "Detonations and vapor cloud explosions: Why it matters," *Journal of Loss Prevention in the Process Industries*, vol. 36, pp. 358–364, 2015.

[4] M. Javidi, B. Abdolhamidzadeh, G. Reniers, and D. Rashtchian, "A multivariable model for estimation of vapor cloud explosion occurrence possibility based on a Fuzzy logic approach for flammable materials," *Journal of Loss Prevention in the Process Industries*, vol. 33, pp. 140–150, 2015.

[5] E. D. Mukhim, T. Abbasi, S. M. Tauseef, and S. A. Abbasi, "Domino effect in chemical process industries triggered by overpressure—Formulation of equipment-specific probits," *Process Safety and Environmental Protection*, vol. 106, pp. 263–273, 2017.

[6] N. Khakzad, G. Reniers, R. Abbassi, and F. Khan, "Vulnerability analysis of process plants subject to domino effects," *Reliability Engineering and System Safety*, vol. 154, pp. 127–136, 2016.

[7] J. Geng, K. Thomas, and Q. Baker, "A study of the blast wave shape from elongated VCEs," *Journal of Loss Prevention in the Process Industries*, vol. 44, pp. 614–625, 2016.

[8] S. Zhang and Q. Zhang, "Influence of geometrical shapes on unconfined vapor cloud explosion," *Journal of Loss Prevention in the Process Industries*, vol. 52, no. September 2017, pp. 29–39, 2018.

[9] C. Ramírez-Marengo, C. Diaz-Ovalle, R. Vázquez-Román, and M. S. Mannan, "A stochastic approach for risk analysis in vapor cloud explosion," *Journal of Loss Prevention in the Process Industries*, vol. 35, pp. 249–256, 2015.

[10] G. Atkinson, E. Cowpe, J. Halliday, and D. Painter, "A review of very large vapour cloud explosions: Cloud formation and explosion severity," *Journal of Loss Prevention in the Process Industries*, vol. 48, pp. 367–375, 2017.

[11] Center for Chemical Process Safety, *Guidelines for Improving Plant Reliability through Data Collection and Analysis*. American Institute of Chemical Engineers, September 2010.

[12] C. A. Petri, "Kommunikation mit automaten," Ph.D. dissertation, Universität Hamburg, 1962.

[13] J. Zhou and G. Reniers, "Modeling and analysis of vapour cloud explosions knock-on events by using a Petri-net approach," *Safety Science*, vol. 108, pp. 188–195, 2018.

[14] G. Clark, T. Courtney, D. Daly, D. Deavours, S. Derisavi, J. M. Doyle, W. H. Sanders, and P. Webster, "The Möbius Modeling Tool," in *Proceedings 9th International Workshop on Petri Nets and Performance Models (PNPM'01)*, September 11-14 2001, pp. 241–250.

[15] J. Zhou and G. Reniers, "Petri-net based evaluation of emergency response actions for preventing domino effects triggered by fire," *Journal of Loss Prevention in the Process Industries*, vol. 51, pp. 94–101, 2018.

[16] J. Rushby, "Critical system properties: survey and taxonomy," *Reliability Engineering & System Safety*, vol. 43, no. 2, pp. 189–219, 1994, special Issue on Software Safety.

[17] S. Park, B. Jeong, B. S. Lee, S. Oterkus, and P. Zhou, "Potential risk of vapour cloud explosion in FLNG liquefaction modules," *Ocean Engineering*, vol. 149, pp. 1–15, 2017.

[18] R. K. Eckhoff and R. K. Eckhoff, *Chapter Two – Gas and Vapor Cloud Explosions*, 2016.

[19] R. Raman and P. Grillo, "Minimizing uncertainty in vapour cloud explosion modelling," *Process Safety and Environmental Protection*, vol. 83, no. 4B, pp. 298–306, 2005.

[20] J. Zhou and G. Reniers, "Petri-net based cascading effect analysis of vapor cloud explosions," *Journal of Loss Prevention in the Process Industries*, vol. 48, pp. 118–125, 2017.

[21] V. Cozzani and E. Salzano, "The quantitative assessment of domino effects caused by overpressure: Part I. Probit models," *Journal of Hazardous Materials*, vol. 107, no. 3, pp. 67–80, 2004.

[22] L. Montecchi, P. Lollini, and A. Bondavalli, "A DSL-Supported Workflow for the Automated Assembly of Large Stochastic Models," in *Proceedings of the 10th European Dependable Computing Conference (EDCC'14)*, Newcastle upon Tyne, UK, May 13-16, 2014, pp. 82–93.

[23] W. H. Sanders and J. F. Meyer, "Reduced base model construction methods for stochastic activity networks," *IEEE Journal on Selected Areas in Communications*, vol. 9, no. 1, pp. 25–36, January 1991.

[24] A. Zimmermann, *Stochastic Discrete Event Systems—Modeling, Evaluation, Applications*. Springer, 2008.

[25] Center for Chemical Process Safety, *Guidelines for Process Equipment Reliability Data with Data Tables*. American Institute of Chemical Engineers, 1989.

[26] D. C. Schmidt, "Guest editor's introduction: Model-driven engineering," *Computer*, vol. 39, no. 2, pp. 25–31, February 2006.