International Journal of Safety and Security Engineering
Vol. 15, No. 8, August, 2025, pp. 1691-1701
Journal homepage: http://iieta.org/journals/ijsse

Risk Assessment of Industrial Domino Effects Using Stochastic Petri Nets

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https://doi.org/10.18280/ijsse.150814

Received: 9 July 2025
Revised: 9 August 2025
Accepted: 20 August 2025
Available online: 31 August 2025

Keywords:
cascading events, domino effect, dynamic risk assessment, Monte Carlo simulation, Petri nets modeling, process safety, probabilistic vulnerability models, quantitative risk assessment

ABSTRACT

The storage and handling of hazardous substances in industrial environments present a significant risk of catastrophic accidents, particularly due to domino effects, where an initial incident triggers a cascade of secondary events. Such scenarios can result in severe consequences for personnel, the environment, and infrastructure. This paper introduces a systematic methodology based on Petri net modeling to analyze and predict domino effects in industrial layouts. It is worth noting that Petri nets present a high-level modeling power able to capture potential dynamics such as sequential and competitive activities, synchronization, resource sharing, mutual exclusion (conflict situations), and complex stochastic processes. Unlike conventional risk assessment approaches that often fail to capture the dynamic and stochastic nature of cascading failures, the proposed framework enables the simulation of accident propagation by modeling process units and safety states as "places" and failure events as "transitions" in the Petri nets. The quantification is achieved using established probabilistic vulnerability functions, such as probit models for escalation vectors, and event frequencies derived from historical data or fault tree analysis, allowing the estimation of escalation path frequencies thanks to Monte Carlo simulation. This quantification offers enhanced insight into risk evolution and identifies critical escalation paths, thereby providing a robust decision support tool to safety managers for domino effect prevention and mitigation. The proposed approach was illustrated on a gasoline tank farm, where the considered primary event is a large bund fire. The obtained results are identical to those derived from some traditional approaches. The main limitation of Petri nets compared to traditional approaches is the difficulty of model validation, especially in the case of multiple escalation scenarios.

1. INTRODUCTION

Industrial facilities frequently store and process large quantities of flammable, toxic, and explosive substances, inherently exposing them to the risk of catastrophic accidents. A single initiating event, such as a fire, explosion, or toxic release, can trigger a domino effect, where the initial incident propagates to adjacent equipment, causing a cascade of secondary events with combined consequences far exceeding those of the primary event. Such low-frequency but high-consequence domino effects have historically been responsible for some of the most devastating accidents in the process industries [1].

The definition of domino effects remains nuanced within safety engineering, despite broad acknowledgment in industrial risk literature. Following Kadri and Chatelet [2], a domino accidental event is "an accident in which a primary event propagates to nearby equipment, triggering one or more secondary events, resulting in overall consequences more severe than those of the primary event". This propagation embodies complex, stochastic, and dynamic interactions among equipment and hazards.

The inherent complexity of domino effects arises from several factors: the probabilistic nature of escalation pathways, temporal evolution of accident scenarios, and synergistic interactions where multiple events concurrently amplify risk [3]. These complexities pose significant challenges for risk modeling and management. Many existing methodologies rely on static, threshold-based escalation models or simplified event chains valuable for screening but limited in capturing the true dynamism and uncertainty of domino effects.

A rich body of literature has developed numerous analytical and computational methods for domino effect modeling, each with distinct strengths and limitations. For example, early influential works [4-9] established empirically validated escalation thresholds and conditional probability models using Probits that remained benchmarks for estimating escalation likelihoods based on physical hazard intensities such as thermal radiation, blast overpressure, fragment projection, and toxic gas dispersion. Although these models are computationally efficient and grounded on physical phenomena, they generally neglect temporal dynamics since they assess static aspects and often do not adequately capture synergistic effects arising from simultaneous hazards or from the ways different hazards might combine or reinforce each other dynamically over time.

Qualitative approaches, such as MICADO [10] and Delvosalle's method [11], represented a simple methodology for preliminary analysis of domino effect hazards. However, they lack quantitative rigor for comprehensive risk evaluation. Khan and Abbasi [12] and Khan et al. [13] integrated deterministic and probabilistic approaches in software frameworks like DOMIFFECT, enabling systematic scenario treatment and decision support. More recently, Agent-Based Modeling (ABM) techniques have been employed to model installations as autonomous agents with behaviors and interactions evolving over time [14, 15]. Several researchers have used Computational Fluid Dynamics (CFD) tools that provide detailed, high-resolution physical modeling of fire, explosion, and toxic dispersion phenomena driving escalation [16]. Although they offer unparalleled accuracy for risk intensity and spatial distribution mapping, they are often difficult to dynamically integrate into probabilistic risk models. Approaches based on matrix and graph enumeration methods, as proposed by Zhou and Reniers [17] and Zhou and Reniers [18], systematically represented escalation influence among units and simulate accident propagation using iterative numerical techniques. These methods efficiently handle multi-vector and synergistic escalations and scale well computationally. However, the temporal evolution and nonlinear feedback inherent in domino effect scenarios are often oversimplified. Bayesian Networks (BNs) and Dynamic Bayesian Networks (DBNs) approach was introduced to offer graphical probabilistic models because they are capable of representing complex causal dependencies and updating event probabilities dynamically [19]. DBNs extend this capability by incorporating temporal dynamics and barrier performance assessment [20].

Despite the fact that each of these approaches contributes uniquely to the understanding of domino effects, a critical analysis reveals several gaps that hamper a comprehensive risk assessment, particularly for dynamic and complex scenarios. In fact, many predominant methods, including those relying on static escalation thresholds and simplified event trees [9, 13] fail to adequately capture the unfolding temporal nature and time-dependent vulnerabilities essential for realistic domino risk assessment. These models provide static snapshots rather than dynamic risk evolution. In addition, the integration of synergistic effects involving multiple physical phenomena (e.g., concurrent fire, explosion, and toxic releases) remains uncommon in most risk assessment methods, resulting in an incomplete understanding of combined consequences. Although fault tree-based approaches have improved the representation of such complexities, as shown in the study [21], significant challenges remain. High-fidelity models such as ABM and CFD offer detailed insights but are computationally expensive and data-intensive, limiting their application to large-scale or real-life scenarios and complicating their integration into dynamic probabilistic frameworks. Besides the abovementioned limitations, the non-consideration of input data uncertainty, due to incomplete or imprecise data on equipment characteristics, hazardous substances, and initiating events, may influence the robustness of the results.

Table 1. Comparative analysis of domino effect modeling approaches

Criterion	Level	Justification
Temporal Dynamics	Excellent	SPNs explicitly model concurrency and stochastic timings, enabling realistic, dynamic propagation representation [22]
	Good	ABM and CFD simulate accident progressions over time, capturing dynamics [15, 23] Bayesian Networks (BN/DBN): explicitly model temporal dependencies [24]
	Limited	Methods like Probit models and DOMIFFECT assess static or snapshot probabilities without detailed temporal evolution [25] ETA: static sequential event modeling; less suited for dynamic evolution [26]
Synergistic Effects	Excellent	SPNs inherently capture concurrent escalations and synergistic feedback pathways by specifying and analysing the behaviour of complex, distributed, and concurrent systems [26, 27]
	Good	ABM, CFD, and BN incorporate some interdependencies but may lack full systemic coupling [28, 29]
	Limited	DOMIFFECT: handles multiple escalation vectors but has less focus on dynamic evolution [26] ETA: mainly linear sequences, limited in handling multiple interacting events [26]
Computational Cost	Low / Moderate	Probit and DOMIFFECT models: have efficient computations suited for large-scale assessments [25] ETA: well-established analytical approach with low resources [26] SPNs balance model detail and resource demands via state-space reduction techniques [22, 30] Bayesian Networks (BN/DBN): computationally intensive for large networks [24]
	High	ABM and CFD require substantial computational power, limiting practical use [15, 23]
Data Requirements	Moderate	SPNs: reduce pure data dependence by integrating physical models with stochastic processes [22] DOMIFFECT: uses probit and threshold models [25] ETA: Needs probabilities for event branches [26]
	High	ABM, CFD, BN: need detailed operational, physical, and statistical inputs [14, 25, 31]
Scalability	Excellent	SPNs: use modular Petri nets efficiently, managing complexity and enabling large-scale modeling [22]
	Good	ETA: can be scaled for large, complex systems [25] Bayesian Networks (BN/DBN): can efficiently handle large-scale problems involving many variables and time slices through strategies like divide-and-conquer for structure learning or parameter sharing to reduce model complexity [31, 32] DOMIFFECT: Designed for typical chemical plant sizes [26]
	Limited	ABM and CFD: scale poorly due to computational complexity [15, 24]
Interpretability	Excellent	ETA: simple graphical and tabular presentation [25] SPNs' graphical, rigorously defined structure clarifies system behavior and dependencies [22]
	Good	Probit, BN: are structured and understandable by experts [29, 33] DOMIFFECT: practical tool with user-oriented interface [25]
	Poor	Complex ABM and CFD models are difficult to interpret [15], they generate complex simulation outputs requiring expert analysis [26]

For a more detailed comparison, Table 1 summarizes the main differences between existing modeling approaches based on a literature review.

To address the aforementioned limitations, this work proposes a novel and systematic methodology based on Stochastic Petri Nets (SPNs) for the dynamic modeling and prediction of domino effects in industrial plants. Indeed, SPNs provide a mathematically rigorous and graphical framework inherently well suited for modeling concurrent, asynchronous, and stochastic system behaviors, ideal for capturing the intrinsic timing characteristics of domino effects [34, 35]. The developed SPN-based framework is able to integrate deterministic and stochastic time delays and the different potential interdependencies, far beyond the capabilities of classical models. This methodology explicitly identifies critical accident escalation pathways and accurately quantifies their propagation likelihood based on probabilistic vulnerability functions (probit models), thereby facilitating stakeholders' understanding and communication, and providing actionable information for risk management. Unlike computationally intensive high-fidelity models, the SPNs solution is dynamic yet relatively simple, making it more practical for real-world industrial applications.

The remainder of this paper is organized as follows. Section 2 introduces the Petri nets' elementary structure and the respective modeling approach. Section 3 details the steps of the proposed methodology. Section 4 illustrates this methodology through a case study and provides the obtained results. A summary of the presented work, together with future research directions, is given in Section 5.

2. BRIEF INTRODUCTION TO PETRI NETS

Petri nets are now widely used in system safety. They offer a powerful tool that allows accounting for the various relationships that may exist. Sequential and competitive activities, synchronization, resource sharing, and mutual exclusion (conflict situations) can be easily represented. It is worth noting their ability to easily consider the temporal aspect in the model.

Petri nets were developed in 1962 by Carl Adam Petri [33], based on automata theory. A Petri net is a graphical notation with an underlying mathematical structure suitable for modeling discrete event systems. In the following, the presentation of Petri nets is deliberately limited to the necessary elements used in the context of this work. For more details, the reader can refer to references [36, 37].

2.1 Petri nets' structure

The structure of a Petri net can contain the following elements (Figure 1):

• **Places:** Represented by circles and placed upstream or downstream of transitions (a place may be both an input and output place for a given transition). They can represent the states of the system's components (working, failed, etc.).

• **Transitions:** Drawn as bars, they correspond to potential events that could modify the state of a Petri net if they occur (failures, repairs, etc.).

• **Arcs:** Connect places to transitions (upstream arcs) and transitions to places (downstream arcs). Arcs are labeled with their weights (a positive integer). This weight indicates the number of tokens consumed or created when crossing (firing) a transition. For example, the weight of an upstream arc can indicate the resources required to perform a given action, while that of a downstream arc can indicate the quantity resulting from that action. This weight is taken as 1 if it is not mentioned.

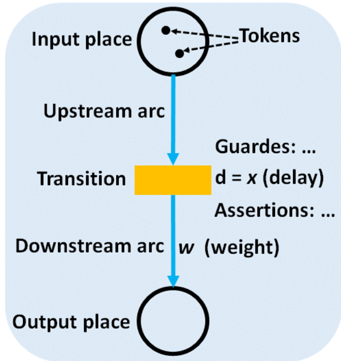

Figure 1. Petri nets elements

• **Tokens:** Represented by small solid dots. In basic Petri nets, tokens are the only things that characterize their dynamic structure. Each place can potentially contain zero or a positive number of tokens. The distribution of tokens at places is called marking, which defines the state of the system at a given time. Tokens go through transitions when events occur. For instance, a token can represent the presence or absence of a resource.

• **Predicates or guards:** Any formula that can be true or false, allowing the validation of transitions.

• **Assertions:** Any equation that updates certain variables when a transition is fired (triggered).

• **Transition enabling and firing:** A transition is valid (enabled) when all its input places contain at least the number of tokens required by each upstream arc (indicated by its weight) and all its associated predicates are 'true'. A transition is fired if it is enabled and the required delay has elapsed, i.e., the time between enabling and firing. This delay can be deterministic (constant delay) or stochastic (random delay, for example, negative exponential). In the latter case, the Petri net is called an SPN. If the delay is zero, enabling coincides with firing. These delays can represent, for example, the time required to execute a given task, failure times, etc.

• **When firing a transition:** Its input places lose as many tokens as specified by the weights of the respective upstream arcs, its output places gain as many tokens as specified by the weights of the respective downstream arcs, and the related assertions are updated.

2.2 Petri nets modeling approach

The different steps to model and evaluate a system with Petri nets are depicted in Figure 2 and described in the following.

• **Defining the context and objectives of the study:** This step allows for clearly identifying the boundaries of the studied system and the performance indicators to be measured: reliability, production level, stock level, unwanted events frequencies, etc. These indicators depend on corporate policy, normative and regulatory framework.

• **Collecting and analyzing system data (understanding the system):** The model is as valuable as the data used. This involves identifying the different activities and tasks, the support elements (parts, components) that carry them out, and their characteristics (states, conditions, events, and actions that cause changes, processing time, available resources, etc.). Furthermore, the various existing interrelations and dependencies should be specified. During this step, the different quantities involved in defining the system are assigned deterministic numerical values (constant delays, resource extents, capacity, etc.) or stochastic ones (failure and repair times, probability of a given event, rates, etc.). Note that the system description could be done using free text, tables, or figures as suitable.

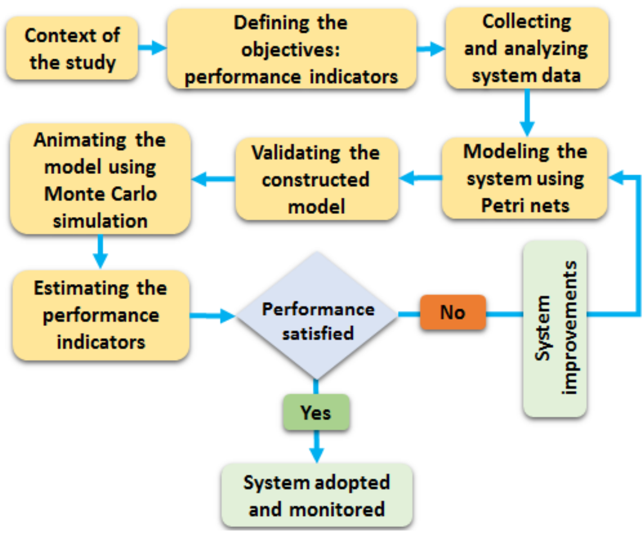

Figure 2. Petri nets modeling steps

• **Modeling the structure of the system using Petri nets:** The established model depends on the understanding of the system and the identified performance indicators. The states, conditions, or resources are represented as places (circles), and the events, actions, or processes that change the state of the system are described by transitions (rectangles). Relationships between states and events are characterized by directed arcs to show dependencies and flows. Arcs from places to transitions indicate the conditions required for events to occur, and arcs from transitions to places show the new conditions or states that result from the event's realization. Tokens should be added in the appropriate places to represent the initial state of the system. Petri nets should model all relevant states that may hold and all possible cause-and-effect relations that may take place. Successive refinements of the model could be necessary until the required level of detail for the analysis is reached. In addition, the analyst may adopt a modular approach (hierarchy) in order to simplify the model validation and maintenance.

• **Validating the constructed model:** Debug the constructed model and verify that it accurately represents the real system. This activity can be carried out using model property verification, step-by-step simulation (interactive simulation), etc.

• **Animating the constructed model:** This animation is performed by drawing random numbers (Monte Carlo simulation). In this paper, we consider the evaluation of Petri nets by Monte Carlo simulation, since analytical approaches based on transforming Petri nets into Markov chains are not applicable to most real systems. The unfolding of histories for a given observation period is carried out as follows:

1. Randomly generate a value for each of the model parameters (according to their distributions).

2. Place the parameter values representing durations (transitions firing times) in a schedule according to an ascending order.

3. Evolve the system marking based on these times and update the schedule (transitions firing times) iteratively, and return to the first step if necessary.

4. Continue the simulation (previous steps) until the first instant of the schedule exceeds the observation period for which the calculations are to be performed. A history is created.

5. Repeat steps 1 to 4 a large number of times (e.g., 10,000) to gather a statistically representative sample of what we are trying to evaluate.

• **Estimating the performance indicators of interest:** The evolution of the system simulated over a large number of histories makes it possible to statistically evaluate the information sought after, according to the objectives of the study, in terms of mean value, standard deviation, confidence intervals, etc.

• **Interpreting the results:** The results of the analysis shall be interpreted in a clear and concrete way. As such, informed decisions could be taken accordingly in order to improve the system performance: system reconfiguration, use of redundant equipment, adding a safety barrier, etc.

3. PROPOSED METHODOLOGY

In this study, we propose an advanced methodology based on SPNs, building upon the dynamic risk assessment framework presented in the study [22]. Our approach also incorporates recent advances in the quantification of synergistic effects, as emphasized by the Fire Synergistic Effect Model (FSEM) [38], which highlights the importance of temporal escalation and cumulative impacts on equipment time-to-failure (TTF) and escalation probability. The different steps of the proposed methodology are depicted in Figure 3. A brief presentation of these steps is given hereafter.

• **Scenario definition:** The process begins by identifying all credible accident scenarios within the facility, considering the characteristics of stored hazardous substances, facility layout, and known accident scenarios (historical accident data), following what was stated by Kadri and Chatelet [2].

• **Effect zone estimation:** For each primary event, the impact zone is estimated using predefined physical thresholds for escalation vectors such described by INERIS [10].

• **Escalation vector analysis:** The intensity of escalation vectors such as heat, blast, or toxic effects is then calculated. The escalation vector is the physical effect (thermal radiation, blast overpressure, fragments) produced by the primary event, which may cause the escalation of the accident to nearby equipment [38].

• **Vulnerability and probability calculation:** To quantify the likelihood that an escalation vector will cause failure, using probit models. The Purple Book (CPR 18E) provides the approach: "The probability of escalation is calculated using probit functions, which relate the intensity and duration of the escalation vector to the probability of failure of the target" [39]. Kamil et al. [22] further clarify: "The escalation probability is calculated using the probit model, which links the heat radiation (HF) received by the equipment to the probability of failure".

• **Petri nets model construction:** Use of Petri nets elements to capture the dynamic propagation of events. The Petri nets model is constructed by representing each process unit and its related states as places and potential events (ignition, escalation, failure, ...) as transitions. The tokens are used to materialize the dynamics inside de Petri nets and therefore indicate the current states [22].

• **Dynamic simulation:** The Petri net simulation is run to dynamically observe how domino effects propagate over time. This allows the estimation of domino effect scenarios. The simulation is performed according to the Monte Carlo approach [37, 40].

• **Results interpretation and risk quantification:** Finally, the output is analyzed to identify critical domino paths and quantify risk based on the obtained domino scenario frequencies. This would provide valuable information for prevention and mitigation strategies.

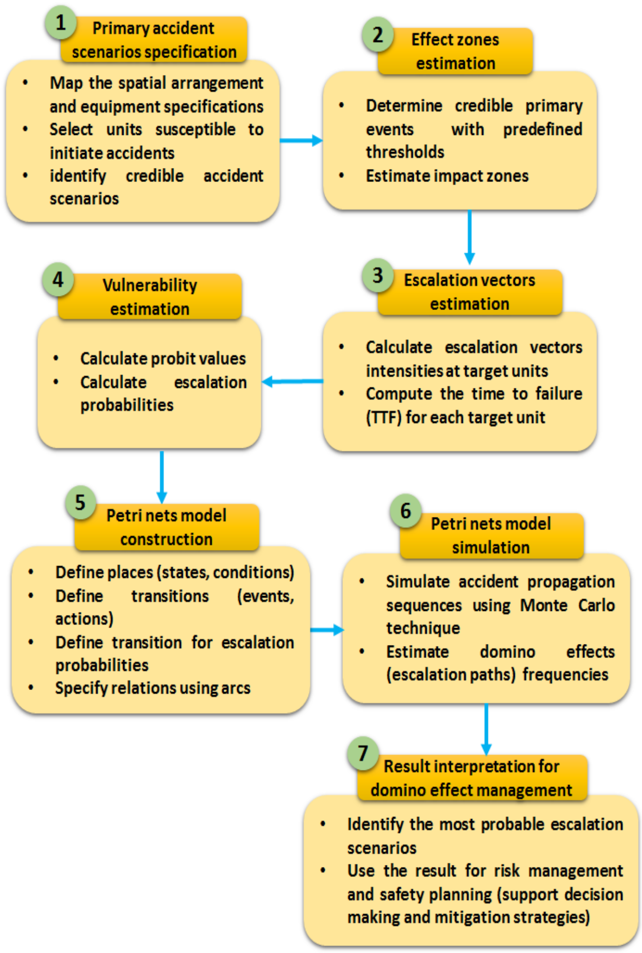

Figure 3. Steps of the proposed methodology

4. CASE STUDY: GASOLINE TANK FARM

4.1 System description

To demonstrate the proposed methodology, we apply it to a hypothetical case study of a gasoline tank farm. For the sake of simplicity, the studied scenario is demonstrated in a facility containing three identical atmospheric storage tanks (Tank 1, Tank 2, and Tank 3). Each tank has a diameter of 40 m and a height of 20 m, enclosed within an 80 m × 80 m retention bund. The tanks are arranged with 40 m spacing between Tank 1 and Tank 2, and between Tank 2 and Tank 3 (Figure 4). This configuration represents a common industrial layout where domino effects can propagate through HR or blast impacts.

This simplified layout provides a controlled environment to test and validate the proposed methodology, allowing clear observation of domino effect pathways and escalation probabilities.

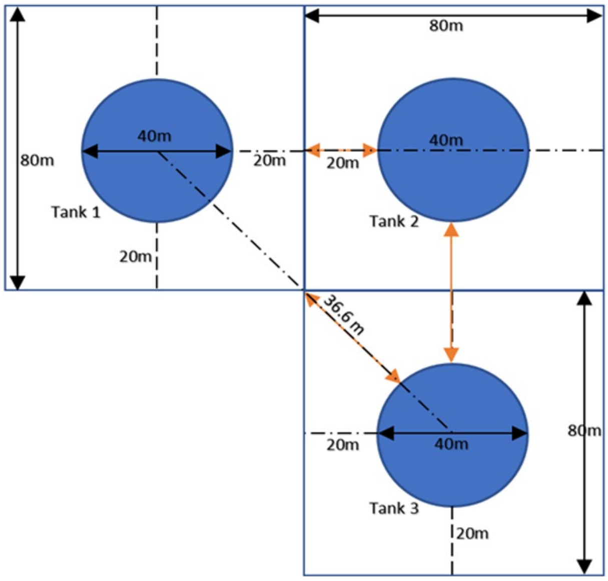

Figure 4. Schematic of the gasoline tank farm

We assume that a loss of containment (LOC) occurs in Tank 1, followed by an ignition (in our case, ignition probability of = 0.7), which causes a fire in Tank 1. The potential escalation scenarios relating to fire spreading to the neighboring tanks (Tanks 2 and 3) are presented in Figure 5. We will also examine which scenario is most likely to occur, while considering synergistic effects: the simultaneous burning of two tanks could increase the impact on the third tank. Through this process, we want to test whether our approach can help improve the safety system by enhancing our understanding and management of domino effect phenomena.

4.2 Estimation of escalation vectors

For each primary event, escalation vectors, specifically HR intensities, are calculated at neighboring tanks. The generic formula of the heat flux (thermal radiation) emitted by a pool fire and received by a target located at x meters from the center of the flame is given by Eq. (1) [39]:

$$\emptyset(x) = \emptyset_0 \cdot F(x) \cdot \tau(x) \tag{1}$$

where,

$\emptyset(x)$: heat flux at a certain distance x (received heat flux) (kW/m^2).

$\emptyset_0$: flame surface emissive power (kW/m^2).

$F(x)$: view factor. It is the fraction of the radiation falling directly on the receiving target.

$\tau(x)$: atmospheric transmissivity to thermal radiation.

There are several correlations for calculating these quantities. More details are given in the Purple Book [27]. The following considerations are taken into account during the calculation process: air relative humidity 70%, ambient temperature 15℃, wind speed 5 m/s, air density 1.161 Kg/m^3, gasoline mass burning rate per unit area 0.055 Kg/(m^2 s).

The resulting HR against distance is plotted in Figure 6.

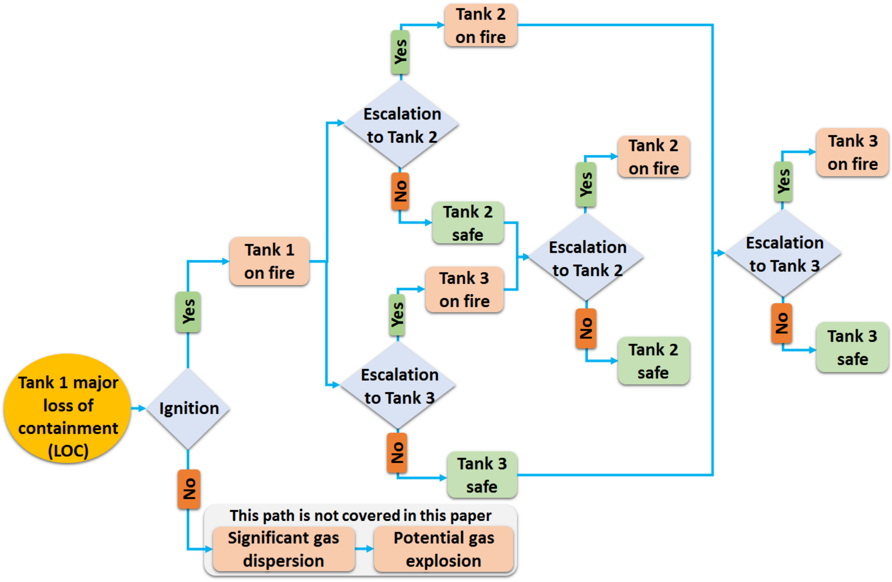

Figure 5. Potential escalation scenarios

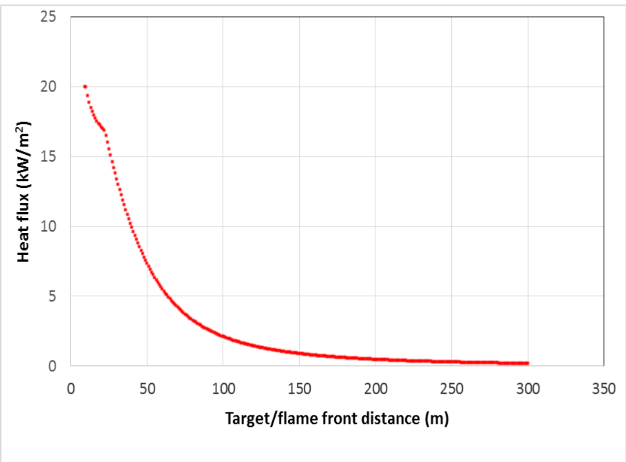

Figure 6. Heat flux versus distance

4.3 Time-to-failure calculation

Using the HR intensity, the TTF for each exposed tank is calculated with the following correlation [39]:

$$\ln \mathrm{TTF}_{Ta\to Tb} = -1.13 \cdot \ln(\mathrm{HR}_{Ta\to Tb}) - 2.67 \cdot \frac{V}{10^5} + 9.9 \quad (2)$$

where, HR is the heat radiation intensity (kW/m²) emitted from Tank *a* to Tank *b*, and *V* is the tank volume (m³). This formula captures the dynamic vulnerability of tanks exposed to thermal radiation, reflecting how longer exposure reduces structural integrity [39]. Note that $HR_{T1\to T2}$ = 17.11 KW/m² (for a distance of 20 m between the bund wall of Tank 1 and the wall of Tank 2) and $HR_{T1\to T3}$ = 10.87 KW/m² (for a distance of 36 m between the bund wall of Tank 1 and the wall of Tank 3).

4.4 Probit model for escalation probability

Once the value of *ln TTF* is calculated, it is possible to estimate the probability of escalation (PES) using the probit function. In this paper, only HR is considered as escalation vector. The corresponding probit function is given by Eq. (3) [39]:

$$\begin{cases} Y = 12.54 - 1.847 \cdot \ln \mathrm{TTF}_{Ta\to Tb} \\ PES = \dfrac{1.005}{\left(1+\exp\left(\frac{-Y}{0.6120}+\frac{5.004}{0.6120}\right)\right)} \end{cases} \quad (3)$$

Eq. (3) allows us to quantify the likelihood that the heated tank will fail and propagate the accident, integrating both intensity and duration of exposure [39]. The different *PES* related to the case study and the other relevant data are given in Table 1.

4.5 Construction of the Petri nets model

The Perti net of Figure 7 depicts the studied scenario, which addresses the potential fire propagation from Tank 1 to the neighboring Tanks 2 and 3. The GRIF software (Petri module) has been used for the establishment and simulation of the Petri net [41]. The different parameters used within the Petri net are gathered in Table 1. Note that equations of Table 2 were inserted in the Petri net module, and the quantities related to *ln TTF* and *PES* were automatically determined.

Table 2. Used parameters

Parameter	Definition	Value	Unit
V	Basic data	2500	m³
F_LOC	Basic data	5E-6	y⁻¹
P ignition	Basic data	0.7	-
HR_T12	Curve of Figure 4	17.11	KW/m²
HR_T13	Curve of Figure 4	10.87	KW/m²
HR_T23	HR_T12 + HR_T13	27.98	KW/m²
HR_T32	2 × HR_T12	34.22	KW/m²
ln TTF_T12	Eq. (2) with HR_T12	6.023	ln(s)
ln TTF_T13	Eq. (2) with HR_T13	6.536	ln(s)
ln TTF_T23	Eq. (2) with HR_T23	5.468	ln(s)
ln TTF_T32	Eq. (2) with HR_T32	5.240	ln(s)
YT12	Eq. (3) with ln TTF_T12	1.414	-
YT13	Eq. (3) with ln TTF_T13	0.467	-
YT23	Eq. (3) with ln TTF_T23	2.441	-
YT32	Eq. (3) with ln TTF_T32	2.861	-
PEST12	Eq. (3) with YT12	2.842E-3	-
PEST13	Eq. (3) with YT13	6.062E-4	-
PEST23	Eq. (3) with YT23	0.015	-
PEST32	Eq. (3) with YT32	0.030	-

Places 1, 7, and 10 represent the normal states of Tank 1, Tank 2, and Tank 3, respectively (each place has 1 token). Initially, the transition Tr1 is the sole enabled transition. This transition characterizes the event related to the Tank 1 LOC with a stochastic delay F_LOC = 5E-6 y^{-1}. During the simulation, this delay is generated randomly according to the exponential law: $d = -\ln z / \mathrm{F\_LOC}$, where z is a random number. After firing Tr1, the token is removed from place 1, and a token is added to place 2 corresponding to the LOC of Tank 1. The transition Tr2, relating to ignition possibility, becomes then enabled and triggered instantaneously (delay = drc 0, drc for Dirac law) according to a solicitation law (sol Pignition), where Pignition refers to the ignition probability = 0.7. During the simulation, a random number between 0 and 1 is generated. If this number is between 0 and 0.7, the token moves from place 2 to place 3, indicating that Tank 1 is on fire. In the contrary case, the token ends up in place 4, and therefore the LOC is controlled. If Tank 1 is on fire (place 3), there will be a possibility for Tank 2 and Tank 3 to be impacted. Thus, Transition Tr5 is immediately fired, and places 5 and 6 get one token each, making transitions Tr4 and Tr6 enabled, indicating a potential escalation for Tank 2 and Tank 3, respectively. These potential escalations are calculated according to Eq. (3). The triggering principle for transitions Tr4 and Tr6 is the same as for Tr2 (solicitation law according to the respective probability). If the fire propagates from Tank 1 to Tank 2 (according to the probability PEST12 = 2.842E-3), a token appears in each place 15 and 16. Note that place 15 is added to address the propagation of fire from Tank 2 to Tank 3 (same thing for place 11: to address the propagation of fire from Tank 3 to Tank 2). In case there is no direct propagation from Tank 1 to Tank 2 (marking of place 17 with one token), Tank 2 is still subject to fire propagation if Tank 3 is on fire. This reflects the synergic aspect of fire propagation. In fact, Tank 3 on fire (place 11) contributes with Tank 1 to the propagation of fire toward Tank 2: Tank 2 receives HR from the two tanks (HR_T32 = 34.22 kW/m^2). This results in a probability of escalation PEST32 = 0.03. Tank 2 may catch fire according to this probability by the firing of transitions Tr8 and Tr10, leading to the marking of place 16 with one token. The same explanations can be made regarding the spread of fire from Tanks 1 and 2 to Tank 3.

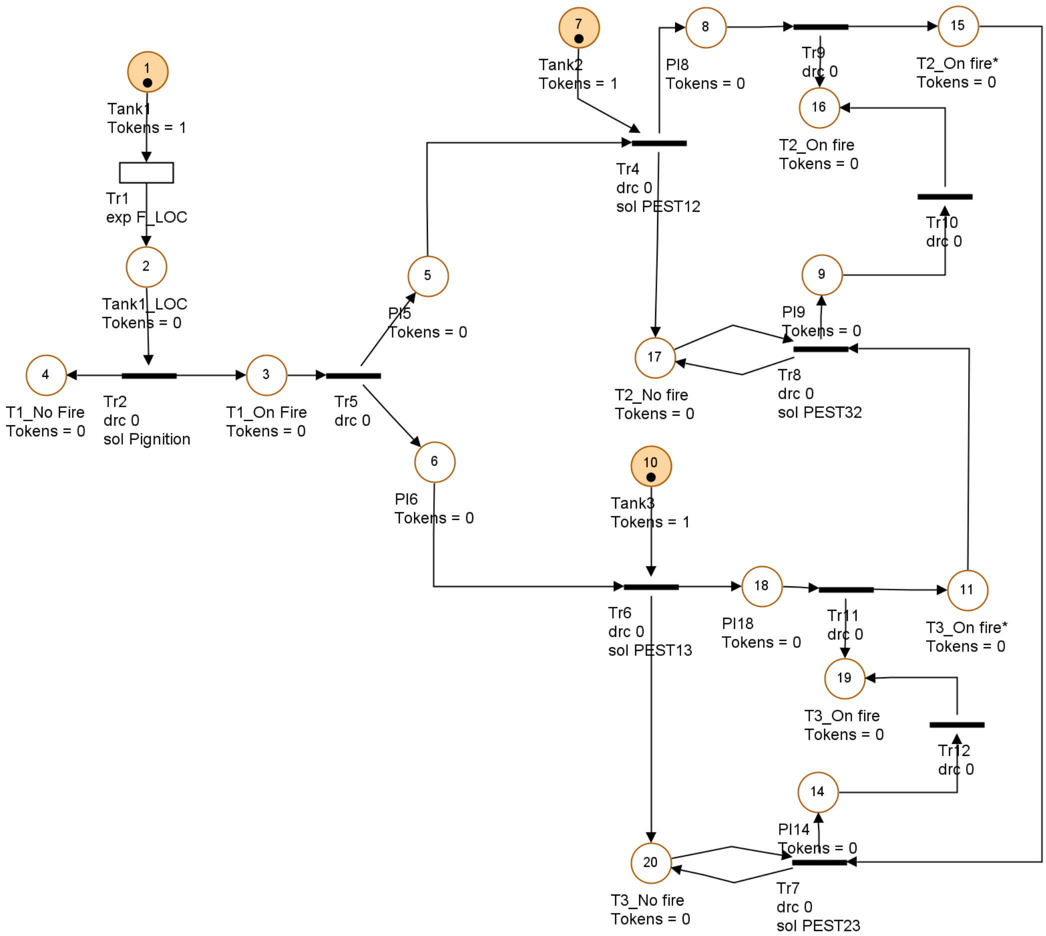

Figure 7. Petri net model for escalation paths

4.6 Petri nets simulation and numerical results

In the GRIF software, Petri nets are coupled with the Monte Carlo technique to simulate the model and statistically extract the quantities of interest. 1E+10 history has been performed over an observation period of 1E+3 years. The different transition frequencies related to escalation events (domino effects) are grouped in Table 2. In addition to these results and for comparison and validation purposes, Table 2 also presents the frequencies of the different scenarios obtained from other modeling approaches, namely: Bow-Tie (BT), Fault Tree (FT), and Bayesian Network (BN). The associated models are presented in Figures 8-10, respectively. The BT and FT models were created using GRIF software [41], while the BN model was developed using Netica software [42]. It should be noted that with the FT and BN approaches, it was necessary to build two separate models to capture the different escalation scenarios. This limits their ability to provide a holistic picture of the potential scenarios, and the modeling becomes unmanageable in case of several escalations. In contrast, BT and Petri nets offer a full and clear graphical representation of these escalations.

Moreover, the underlying mathematical expression of the BN does not allow for directly calculating the scenario frequencies, since the BN is a probability-based approach and the algorithm for frequency calculation is not yet available. Hence, in Table 2, the probabilities and frequencies are presented for each scenario, where the different frequencies were simply derived by multiplying the corresponding probabilities by the LOC frequency (5E-6 y^{-1}). This is not the case with the FT technique, for which frequency calculation codes have been available for a long time.

It should be noted that the BT formalism implemented in the GRIF software has a higher modeling power than traditional BT. This explains the relative simplicity of the model in Figure 8, thanks to the use of the AND gate.

The inspection of Table 3 reveals the following statements:

• BT, FT, and BN approaches unsurprisingly induce exactly the same numerical values, since the frequency derivation is based on the same analytical expressions backed by Boolean algebra.

• SPNs produce results almost identical to the previous ones thanks to statistical processing of the experienced behaviors associated with each history (10E+10 in total). This can be seen as a validation of the developed model and the proposed methodology in general. Note that the case study was defined in a way that it can be modeled using traditional approaches. SPNs could consider many features beyond their capabilities.

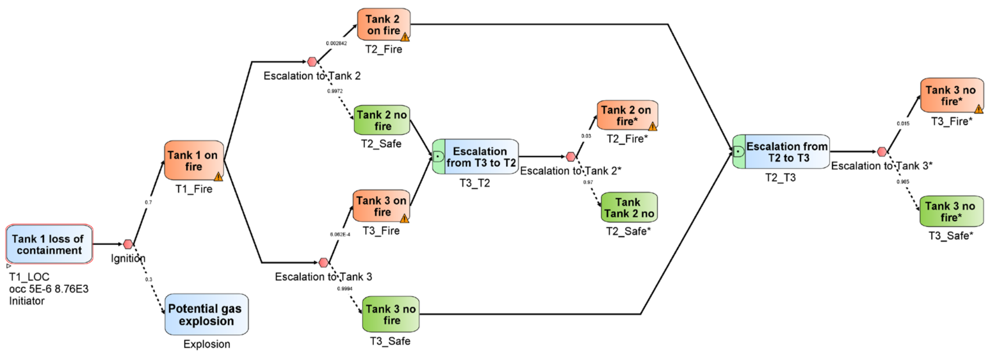

Figure 8. Bow-tie model for escalation paths

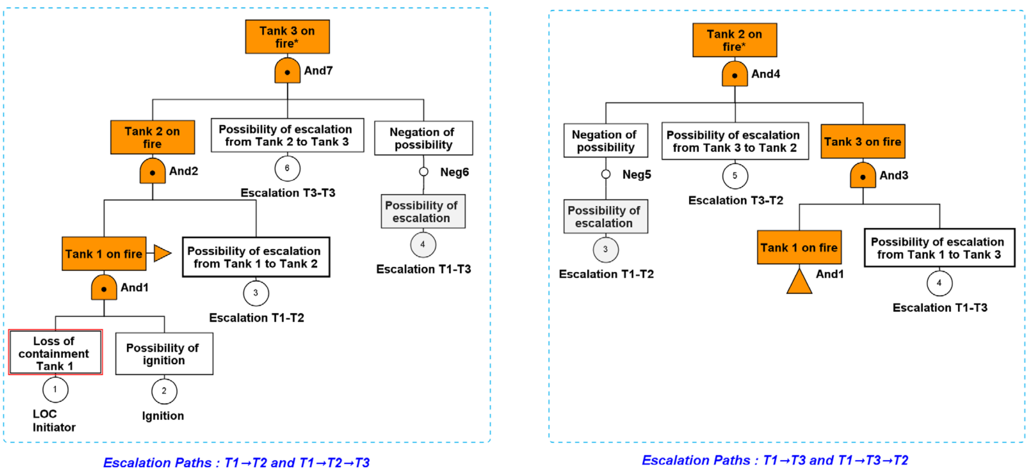

Figure 9. Fault tree model for escalation paths

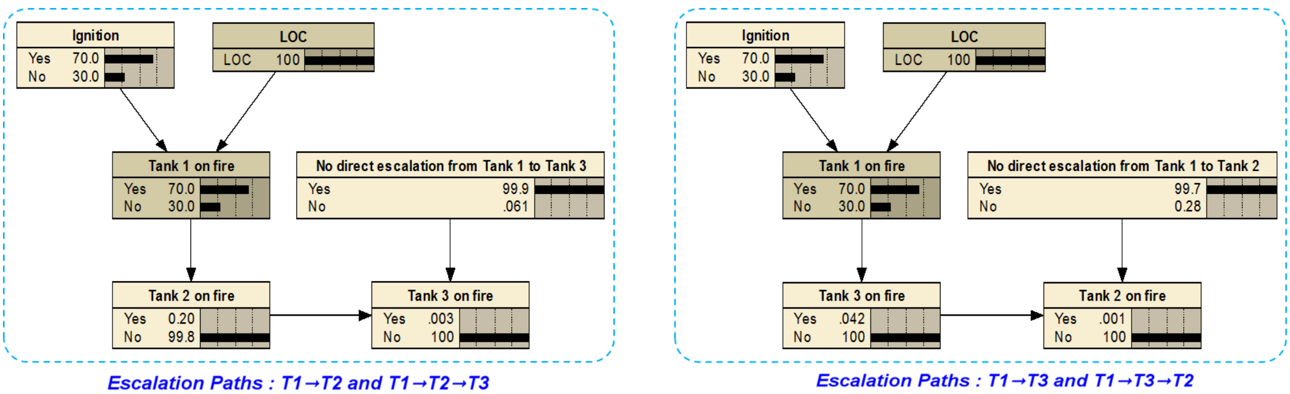

Figure 10. BN model for escalation paths

Table 3. Domino effects sequences frequencies (y-1)

Escalation Scenarios	Approaches					
	SPNs		BT	FT	BN	
					Probability	Frequency
Tank 1 on fire	Tr5	3.4999E-06	3.5000E-06	3.5000E-06	7.0000E-01	3.5000E-06
Tank 1 → Tank 2	Tr4	9.9507E-09	9.9470E-09	9.9470E-09	1.9894E-03	9.9470E-09
Tank 1 → Tank 3	Tr6	2.1249E-09	2.1217E-09	2.1217E-09	4.2434E-06	2.1217E-09
Tank 1 → Tank 2 → Tank 3	Tr12	1.5100E-10	1.4912E-10	1.4912E-10	2.9823E-05	1.4912E-10
Tank 1 → Tank 3 → Tank 2	Tr10	6.3300E-11	6.3470E-11	6.3470E-11	1.2694E-05	6.3470E-11

- The direct escalation from Tank 1 to Tank 2 is more likely (9.95E-09 y^{-1}) than that from Tank 1 to Tank 3 (2.125E-09 y^{-1}). This is explained by the greater distance between the bund of Tank 1 and the wall of Tank 3 (36.6 m) compared to that between the bund of Tank 1 and the wall of Tank 3 (20 m).
- The most probable full domino escalation path is: Tank 1→Tank 2→Tank 3, with a frequency of 1.51E-10 y^{-1}. The sequence Tank 1 → Tank 3 → Tank 2 happens with a lower frequency (6.3300E-11 y^{-1}). The previous statement explains these results.
- The different escalation sequences exhibit low frequencies compared to those usually used in risk acceptance criteria (for instance, 10^{-5} and 10^{-6} y^{-1}), indicating that the domino effect risk is acceptable and the current tank configuration may be adopted.
- Synergistic effects, such as combined HR from Tank 1 and Tank 2 on Tank 3 (see Table 2), significantly increase escalation probability (from PEST13 = 6.062E-4 to PEST23 = 0.015), demonstrating the importance of considering multiple simultaneous sources and therefore taking domino effects into account in risk assessment.

5. CONCLUSIONS

This paper emphasizes the effectiveness of Petri net modeling as a powerful tool for representing, predicting, and managing domino effects within industrial layouts. By providing a rigorous and dynamic framework, the proposed methodology enhances our ability to analyze complex accident propagation scenarios, thereby contributing significantly to the development of safer and more resilient industrial environments. Incorporating the Petri nets-based approach into safety management practices enables more accurate identification and quantification of escalation risks associated with hazardous substances. Consequently, it supports informed decision-making aimed at minimizing potential domino effect incidents, ultimately fostering greater protection for both communities and the environment. The proposed methodology uniquely integrates both physical (HR intensities) and probabilistic (probit) models together with the outstanding modeling capabilities of Petri nets animated by Monte Carlo Simulation. It was successfully illustrated on a gasoline tank farm, where the obtained results in terms of escalation frequencies were found to be identical to those derived from some traditional and established approaches, providing valuable information for process safety management.

To further strengthen this methodology, several improvements could be implemented to capture full domino effect complexity and ensure applicability and robustness. This may include: considering parametric uncertainty based on Monte Carlo sampling to increase the accuracy of the model output, Conducting sensitivity analysis to study how the variation in model output can be apportioned to changes in the input parameters, integrating more escalation vectors beside HR (blast, fragments, and toxic release), adopting hierarchical and modular Petri nets to ensure scalability and easier model validation and maintenance, integrating safety barriers and emergency response allowing evaluation of risk reduction strategies. It is worth noting that the GRIF software could account for the above-stated enhancements in an easy manner.

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NOMENCLATURE

TTF	Time to failure (s)
HR	Heat radiation (kW/m^2)
D	Diameter (m)
d	Distance (m)
H	Height (m)
LOC	Loss of containment
F_LOC	Loss of containment frequency (y^{-1})
P_Ignition	Probability of Ignition
PES	Probability of escalation
Y	Probit function
Tr	Transition
V	Volume (m^3)