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DOI
10.1016/j.jlp.2018.03.001

Publication date
2018

Document Version
Final published version

Published in
Journal of Loss Prevention in the Process Industries: the international journal of chemical and process plant safety

Citation (APA)
Khakzad Rostami, N., Amyotte, P., Cozzani, V., Reniers, G., & Pasman, H. (2018). How to address model uncertainty in the escalation of domino effects? *Journal of Loss Prevention in the Process Industries: the international journal of chemical and process plant safety*, *54*, 49-56. https://doi.org/10.1016/j.jlp.2018.03.001

Journal of Loss Prevention in the Process Industries 54 (2018) 49–56

Contents lists available at ScienceDirect

Journal of Loss Prevention in the Process Industries

journal homepage: www.elsevier.com/locate/jlp

How to address model uncertainty in the escalation of domino effects?

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ARTICLE INFO

Keywords:
Domino effect
Oil terminal
Dynamic Bayesian network
Model uncertainty
Graph theory

ABSTRACT

Modeling potential domino scenarios in process plants includes the prediction of the most probable sequence of events and the calculation of respective probabilities, so-called escalation probabilities, so that appropriate prevention and mitigation safety measures can be devised. Domino effect modeling, however, is very challenging mainly due to uncertainties involved in estimation of escalation probabilities (parameter uncertainty) and prediction of the sequence of events during a domino effect (model uncertainty). In the present study, a methodology based on dynamic Bayesian network is developed for identification of the most likely sequence of events in domino scenarios while accounting for model uncertainty. Verifying the accuracy of the methodology based on a comparison with previous studies, the methodology is applied to model single-primary-event and multiple-primary-event domino scenarios in process plants.

1. Introduction

A domino effect, also known as cascading event, is a sequence of events where an initial fire or explosion (primary event) causes damage to neighboring equipment or units and triggers other fires or explosions (secondary events), with overall consequences more severe than those of the primary event (Reniers and Cozzani, 2013). The propagation (escalation) of a primary event to secondary events occurs by means of physical phenomena such as heat radiation, blast wave, or fragment projection. These are termed escalation vectors in the context of domino effect analysis.

Domino effects are among high-impact low-probability events which have contributed to a number of catastrophic major accidents in the chemical and process industries (Khan and Abbasi, 1999; Darbra et al., 2010). Among others, are the notorious LPG explosions in a tank farm in Mexico in 1984 (Arturson, 1987), fires and explosions at the Hertfordshire Oil Storage Terminal in UK in 2005 (BBC, 2010), and the Caribbean Petroleum Refining tank explosions and fires in Puerto Rico in 2009 (CSB, 2015).

Domino effects are among high-consequence low probability events which due to their rarity (data scarcity) from one side and their complexity from the other side have not been well recognized in risk assessment and management of chemical and process plants. Only recently have regulations and standards such as Seveso Directive III (2012) urged chemical facilities to include the risk of domino scenarios in their safety assessment and emergency response planning. Rarity of domino scenarios along with large uncertainty embedded have made their modeling very challenging and feasible only based on over-simplifying assumptions.

In general, domino scenario modeling incorporates two main types of uncertainty:

- parameter uncertainty, which is the uncertainty involved in the prediction of potential accident scenarios (e.g., given a primary tank fire at tank T1, what would be the type of the secondary fire at the exposed tank T2, tank fire or pool fire?) and the estimation of escalation probabilities (e.g., what would be the probabilities of the secondary tank fire or pool fire?), and
- model uncertainty, which is the uncertainty associate to modeling the sequence of events during a domino scenario (cause-effect relationships). For instance, given a primary tank fire at tank T1, which tank(s) would sequentially become involved in the domino scenario as the secondary units, tertiary units, and so forth.

The two types of uncertainty are intertwined, that is, incorrect escalation probabilities can give rise to identification of unlikely sequences of events – or at least not the most likely one – while an improper identification of events' sequence can lead to incorrect escalation probabilities. Parameter uncertainty mainly arises from both the randomness of domino scenarios (aleatory uncertainty) and our lack

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https://doi.org/10.1016/j.jlp.2018.03.001
Received 1 August 2017; Received in revised form 13 February 2018; Accepted 1 March 2018
Available online 02 March 2018
0950-4230/

of knowledge (epistemic uncertainty) in predicting and identifying failure modes and failure probabilities of target units, type and severity of loss of containtment (minor, major, or catastrophic release), and the type of ensuing accident scenarios (pool fire, tank fire, BLEVE, etc.). Not to mention that uncertainties in environmental parameters (wind direction, wind speed, air temperature, humidity, etc.) and operational parameters (volume of chemical containtment, process pressure and temperature, etc.) add to or result in foregoing uncertainties.

With regard to parameter uncertainty, many studies have been conducted to estimate the escalation probability of primary events (Bagster and Pitblado, 1991; Gledhill and Lines, 1998; Khan and Abbasi, 2001; Vilchez et al., 2001; Cozzani and Salzano, 2004; Mingguang and Jiang, 2008; Landucci et al., 2009; Mukhim et al., 2017). Escalation of primary events take place mainly due to the damage probability of equipment such as storage tanks, distillation columns, etc. when exposed to a primary fire or explosion. Likewise, a number of techniques (Van den Bosch and Weterings, 1997; Assael and Kakosimos, 2010; Casal, 2017) and software tools (ALOHA, PHAST, etc,) have been developed to identify failure modes and potential accident scenarios.

Considering model uncertainty, however, fewer attempts have been made to model the propagation of domino effects (Delvosalle, 1998; Khan and Abbasi, 1998; Cozzani et al., 2005; Nguyen et al., 2009; Abdolhamidzadeh et al., 2010; Khakzad et al., 2013; Khakzad, 2015; Landucci et al., 2016). Due to the large uncertainties involved in predicting the sequence of events in domino scenarios, these studies have mainly been based upon random selection of secondary units (e.g., using binomial distribution as in Cozzani et al. (2005) or Monte Carlo simulation as in Abdolhamidzadeh et al. (2010)), ignoring concurrent events and synergistic effects (as in Landucci et al., 2016) simplifying assumptions (as in Khakzad, 2015).

Bayesian network (BN) is a robust technique for reasoning under uncertainty (Jensen and Nielsen, 2007) with an ample application in system safety due to its ability in handling data scarcity, expert opinion, parameter uncertainty, model uncertainty, conditional dependencies, and sequential failures. Having a sufficiently large and accurate database for the occurrence of events during a domino scenario, Bayesian parameter learning and model learning algorithms can be used to address both parameter and model uncertainty. Regarding the parameter uncertainty, given the model's structure M, the parameters $\hat{\theta}$ which lead to the maximum likelihood (or natural logarithm of the likelihood) of the dataset D can be determined as the best estimate of the parameters (Neapolitan, 2003):

$$\hat{\theta} = \max_{\theta} Ln\left(P(D|M;\theta)\right) \tag{1}$$

Likewise, regarding the model uncertainty, among model alternatives, the one which leads to the maximum likelihood (or natural logarithm of the likelihood) of the dataset can be identified as the best model structure. However, in order to prevent from data overfitting, a simpler model structure, i.e., a model with lower number of parameters k, is given priority over a more complex model structure. The both features of a desired model structure, that is, the maximum likelihood and the model simplicity, can be encoded in Bayesian Information Criterion (BIC), in the sense that, a model structure with the lowest BIC is the best model to choose (Neapolitan, 2003):

$$BIC = Ln(n)k - 2\,Ln(P(D|M;\hat{\theta})) \tag{2}$$

where n is the number of data points (observations) in the dataset D. A comprehensive discussion of parameter and model uncertainty can be found in Briggs (2000) and Cairns (2000).

However, the data scarcity arising from the rarity of domino effects along with the diversity of process plants and units involved in the previous accidents hampers the application of the foregoing learning algorithms to domino scenario modeling.

Khakzad et al. (2013) developed a methodology based on BN to model the escalation of domino scenarios, that is, the likeliest sequence of events which can be triggered by a primary event. Despite having merits such as accounting for conditional dependencies among the events and taking into account the role of synergistic effects,[1] identification of secondary events in their methodology introduces large model uncertainty into the domino scenario modeling. In their approach, among units exposed to the escalation vecotrs of a primary event (e.g., heat radiation emitted from a pool fire), identification of secondary units is forced to the model based on a comparison among the escalation probabilities of the target units. In other words, among two target units, the one with a higher escalation probability is selected as the secondary unit whereas the other one as the tertiary unit. Since escalation probabilities reflect the analyst degrees of belief rather than objective frequencies (which cannot easily be estimated due to the rarity of domino effects), the secondary units identified using this approach could be quite different from the ones in a real situation given the same primary event. Determining tertiary and quaternary units in the same way introduces even more model uncertainty in the escalation pattern of the domino effect, thus resulting in not necessarily the most likely sequence of events.

Khakzad (2015) introduced a dynamic Bayesian network (DBN) methodology to model the spatial and temporal escalation of domino effects in process plants. His methodology significantly alleviates the model uncertainty by letting the model decide the most likely sequence of events while taking into account all possible mutual interactions among the involved units rather than forcing the propagation pattern of the domino scenario to the model. The idea of considering all possible interactions among the units was later extended in the form of a graph theoretic approach to identify the vulnerable units contributing to possible domino scenarios in process plants (Khakzad and Reniers, 2015).

Our main purpose in this study is to establish a methodology based on DBN to tackle the model uncertainty in domino scenario escalationas. As such, parameter uncertainties involved in the calculation of escalation vectors (e.g., magnitude of a tank fire's heat radiation) and the estimation of escalation probabilities (e.g., escalation probability of an atmospheric tank exposed to certain heat radiation) is beyond the scope of this study. We will ilustrate that the developed methodology can be applied to model both accidental domino effects and intentional (e.g., triggered by terrorist attacks) domino effects, where in the latter the possibility of having more than one initiating event is higher (so-called multi-primary-event domino effects).

Compared to our previous works on domino scenario modeling (Khakzad et al., 2013, 2015), the main contribution of the present study can be considered from two viewpoints: (i) regarding our first attempt where we developed a methodology based on conventional BN (Khakzad et al., 2013), we will illustrate that application of conventional BN to domino scenario modeling (and possibly other types of cascading failures) is very likely to result in erroneous sequence of events and probabilities; (ii) with respect to our previous work where we developed a methodology based on DBN (Khakzad, 2015), we will demonstrate that given an inadequate number of time steps, even the application of DBN would not guarantee the most likely sequence of events since not all possible interactions among the units would be taken into account.

In Section 2, the fundamentals of BN and DBN are briefly presented. In Section 3, the drawbacks of the BN methodology developed in Khakzad et al. (2013) in capturing model uncertainty and thus underestimating (relative) escalation probabilities are discussed. The DBN developed in Khakzad (2015) is then modified to account for model uncertainty. In Section 4, the application of the methodology is

[1] Synergistic effect is referred to cooperation of events (e.g., a primary event and a secondary event) to escalate domino effect to other units (e.g., triggering tertiary events).

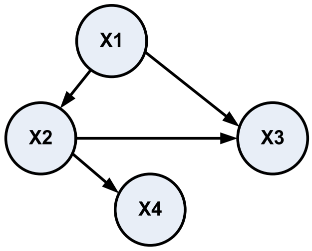


Fig. 1. Schematics of a conventional Bayesian network.

demonstrated via both single-primary-event domino scenarios (hereafter, SPE domino effects) and multi-primary-event domino scenarios (hereafter, MPE domino effects). Conclusions are presented in Section 5.

2. Bayesian networks

BN is a probabilistic method for reasoning under uncertainty (Jensen and Nielsen, 2007) in which random variables are represented by nodes and the conditional dependencies among them by directed arcs (Fig. 1). The type and strength of the dependencies can be encoded in form of conditional probability tables assigned to the nodes. Using the chain rule and the concept of d-separation, the joint probability of a set of random variables $U = \{X_1, X_2, ..., X_n\}$ can be factorized as the product of marginal and local conditional probabilities:

$$P(U) = \prod_{i=1}^{n} P(X_i|\pi(X_i)) \tag{3}$$

where $\pi(X_i)$ is the parent set of the node X_i. For instance, the joint probability distribution of the random variables X_1, X_2, X_3 and X_4 in Fig. 1 can exclusively be expanded as $P(X_1, X_2, X_3, X_4) = P(X_1)\,P(X_2|X_1)\,P(X_3|X_1, X_2)\,P(X_4|X_2)$.

DBN is an extension of ordinary BN that, compared to its predecessor, facilitates modeling of temporal evolution of random variables over time (Fig. 2(a)). Dividing the time line in a number of time intervals, DBN allows a node at the ith time slice to be conditionally dependent not only on its parents at the same time slice but also on its parents and itself at previous time slices:

$$P(U^{t+\Delta t}) = \prod_{i=1}^{n} P(X_i^{t+\Delta t}|X_i^{t}, \pi(X_i^{t}), \pi(X_i^{t+\Delta t})) \tag{4}$$

For example, according to the DBN in Fig. 2(a), the conditional probability of X_4 at the time slice $t + \Delta t$ can be presented as $P(X_4^{t+\Delta t}|X_2^{t+\Delta t}, X_3^{t}, X_4^{t})$. An abstract presentation of the DBN has been depicted in Fig. 2(b).

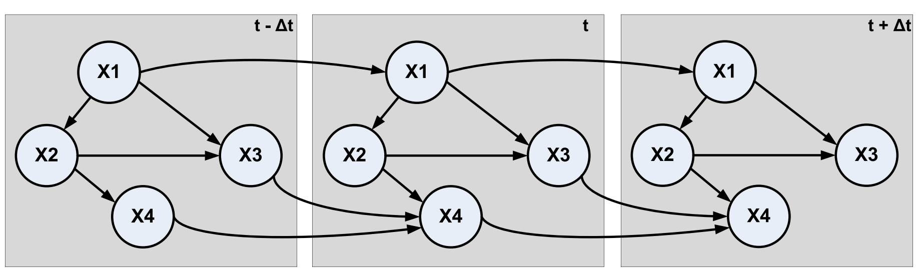
3. Application of Bayesian network to domino effect modeling

3.1. Conventional approach

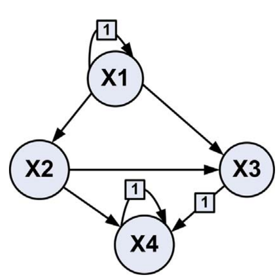
In this section, the BN methodology developed by Khakzad et al. (2013) is briefly revisited to build the modeling foundation for the rest of the study. In their approach, the hazardous units (i.e., vessels with credible amounts of flammable or explosive materials) are presented as nodes of the BN while the escalation vectors between the units are presented as directed arcs. Assuming there is a fire or an explosion at one of the units (i.e., the primary unit), the magnitude of the escalation vectors (i.e., heat or blast overpressure) received by adjacent units determines whether the adjacent units can be considered as secondary targets.

For atmospheric vessels a damage threshold of 15 kW/m^2 or 22 kPa for heat radiation or overpressure, respectively, has been proposed (Reniers and Cozzani, 2013); similarly, thresholds of 50 kW/m^2 or 16 kPa have been proposed for pressurized vessels (Reniers and Cozzani, 2013).

Knowing the intensity of escalation vectors, the conditional escalation probability of a target vessel can be estimated using probabilistic damage models expressed in the form of probit functions (Cozzani et al., 2005; Mingguang and Jiang, 2008; Mukhim et al., 2017). Among the target vessels, the one(s) with the highest escalation probability is identified as the secondary unit involved in the domino effect (second event in the sequence of events).



(a)



(b)

Fig. 2. (a) Schematics of a dynamic Bayesian network in three sequential time intervals. (b) The same Dynamic Bayesian network in an abstract presentation. The numbers attached to the arcs denote the number of time intervals to be taken into account.

Given that the secondary unit(s) is damaged, respective secondary events (fire, explosion, toxic release) and the magnitude of escalation vectors associated to fire or explosion can be identified, e.g., by event tree analysis considering the type of equipment, type of substance released, and the vicinity of ignition sources (Delvosalle et al., 2006). Following the same approach and considering possible synergistic effects, the tertiary units and ensuing events can be identified.

The methodology developed by Khakzad et al. (2013), however, suffers from two types of uncertainty: parameter uncertainty and model uncertainty:

Parameter uncertainty is embedded in the quantification of escalation vectors and estimation of conditional escalation probabilities (e.g., based on probit models), which are then used to determine the conditional probabilities (parameters) of the BN. This type of uncertainty is characteristic of most quantitative risk analysis studies, including previous attempts in modeling domino effects.

The second type of uncertainty, which is the scope of the present study, is model uncertainty – with respect to the methodology proposed in Khakzad et al. (2013) – which arises from identification of secondary units based on a comparison among the conditional escalation probabilities of target units exposed to a primary fire or explosion. As such, the sequence of events during a potential domino scenario would be forced to the developed BN.

To make the discussion more concrete, the application of the BN methodology (Khakzad et al., 2013) is demonstrated via a notional chemical plant consisting of four atmospheric storage tanks T1-T4 in Fig. 3(a). It is supposed that a tank fire (primary event) at T1 exposes T2 and T3 to heat radiation magnitudes above the threshold of 15 kW/m^2. The modeling is carried out under the assumption that the fire reaches a steady radiant heat intensity in the absence of fire protection systems and firefighting brigade.

Assuming that T2 and T3 are identical and receive the same heat radiation intensities, they both can be identified as secondary units (denote by the arcs from T1 to T2 and T3 in Fig. 3(a)), which in turn, can cooperate to cause damage to storage tank T4, thus escalating the domino effect to the next level (denoted by the arcs from T2 and T3 to T4 in Fig. 3(a)). The units of the same order (i.e., T2 and T3 in Fig. 3(a)) do not presumably impact one another.

Following the sequence of events shown in Fig. 3(a), that is, {T1} → {T2 or T3} → {T4}, the probability of the domino effect can be estimated as $P(T1, T2, T3, T4) = P(T1)\,P(T2 \cup T3|T1)\,P(T4|T2 \cup T3)$.

As can be noted from the right-hand side of the foregoing equation, the term (T2 U T3) does not imply that both T2 and T3 would necessarily be impacted by the fire at T1. If this is the case, that is, if the fire at T1 escalates to only one of T2 or T3, the sequence of events could be modeled using the BNs in Fig. 3(b) or 3(c). Considering Fig. 3(b), for instance, the sequence of events can be presented as {T1} → {T2} → {T4} → {T3}, where the arc from T1 to T3 denotes the synergy between T1 and T4 in order to escalate the domino effect to T3.

Considering a similar reasoning in Fig. 3(c), the collective possible sequence of events in Fig. 3(a) and (b), and 3(c) can be illustrated as a directed graph (not a BN, due to the cycles) in Fig. 3(d). As can be noted, the BN developed in Fig. 3(a) following the approach of Khakzad et al. (2013) is a subset of the directed graph shown in Fig. 3(d), that is, only one of the possibile domino scenarios given a primary fire at T1.

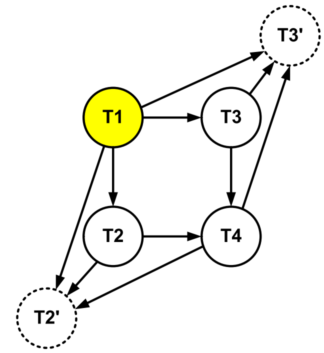


Fig. 4. Modeling all possible sequences of events as a Bayesian network given T1 as the primary unit. Auxiliary nodes have been denoted by dashed outline.

In other words, forcing the sequence of events in modeling a potential domino scenario merely based on respective escalation probabilities would undermine the possibility of other sequences of events, portraying a specific sequence of events out of all those possible, thus leading to an underestimation of escalation probabilities thereof. In the next section we discuss how such uncertainty in the modeling of the sequence of events can be handled.

3.2. Model uncertainty

3.2.1. Application of auxiliary nodes

In order to take into account all possible sequences of events as depicted in the cyclic directed graph in Fig. 3(d), the BN shown in Fig. 3(a) can be modified by adding auxiliary nodes T2′ and T3' as shown in Fig. 4 such that no cycle, which otherwise is not allowed in BN formalism, could take place.

The auxiliary node T2′ accounts for the possibility of T2 being impacted by T4 in case T3 happens to be the secondary unit, whereas the auxiliary node T3′ does the same for T3 in case T2 would happen to be the secondary unit. In either case, T4 would be the tertiary unit while one of T2' (surrogate of T2) or T3' (surrogate of T3) would be the secondary unit while the other the quaternary unit. It should be noted that when calculating the escalation probabilities of the units, the probabilities of T2′ and T3′ should be considered instead of T2 and T3. For the sake of clarity, the conditional escalaion probabilities of T2' is reported in Table 1 for all the possible state combinations of its parents, i.e., T1, T2, and T4 (see Fig. 4).

The conditional escalation probabilities $P_1 = P(T2' = Fire| T1 = Fire,\ T2 = Safe,\ T4 = Safe)$, $P_4 = P(T2' = Fire| T1 = Safe,\ T2 = Safe,\ T4 = Fire)$, and $P_{14} = P(T2' = Fire| T1 = Fire,\ T2 = Safe,\ T4 = Fire)$ in Table 1 can be calculated using a variety of techniques such as probit models (Cozzani and Salzano, 2004; Landucci et al., 2009; Mingguang and Jiang, 2008; Casal, 2017; Mukhim et al., 2017).

For the purpose of this study, i.e., addressing the model uncertainty, we use a linear relationship to proportionate the conditional escalation probability to the magnitude of the corresponding escalation vector while considering the threshold value. This relationship is only for demostrative purposes, to keep mathematical complexity at the minimum, and is not aimed at replacing probit models. For atmospheric

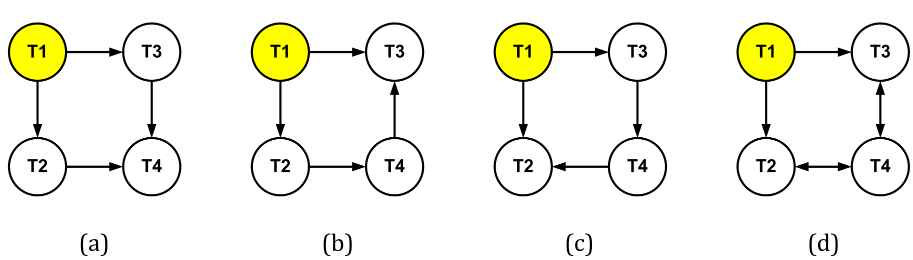


Fig. 3. (a) Sequence of events as a BN, where both T2 and T3 present equal escalation probabilities, and both are identified as secondary units. (b) Sequence of events as a BN, where both T2 and T3 present equal escalation probabilities, but only T2 is damaged and thus selected as the secondary unit. (c) Sequence of events as a BN, where both T2 and T3 present equal escalation probabilities, but only T3 is damaged and thus selected as the secondary unit. (d) All possible sequences of events as a directed graph, where either T2 or T3 can be selected as the secondary unit.

Table 1
Conditional escalation probabilities assigned to T2′.

T1	T2	T4	T2′	
			Fire	Safe
Fire	Fire	Fire	1	0
Fire	Fire	Safe	1	0
Fire	Safe	Fire	P_{14}	1- P_{14}
Fire	Safe	Safe	P_1	1 - P_1
Safe	Fire	Fire	1	0
Safe	Fire	Safe	1	0
Safe	Safe	Fire	P_4	1- P_4
Safe	Safe	Safe	0	1

vessels exposed to heat radiation of Q (kW/m^2), the conditional escalation probability may be calculated as:

$$P = 1 - \frac{15}{Q} \tag{5}$$

where 15 (kW/m^2) is the threshold value of heat for atmospheric vessels (Reniers and Cozzani, 2013). As such, for instance, $P_1 = P(T2' = Fire \mid T1 = Fire,\ T2 = Safe,\ T4{=}Safe) = 1 - \frac{15}{Q_{12}}$ and $P_{14} = P(T2' = Fire \mid T1 = Fire,\ T2 = Safe,\ T4{=}Fire) = 1 - \frac{15}{Q_{12} + Q_{42}}$, where Q_{12} and Q_{42} are the heat escalation vectors (kW/m^2) T2 received from fires at T1 and T4, respectively.

Nevertheless, the application of auxiliary nodes to capture model uncertainty in the sequence of events can become error prone and cumbersome specially when the size of the process plant under consideration and thus the respective BN grows. For instance, the BN developed to model the domino scenarios in a process plant comprising six storage tanks T1-T6, given a primary event at T1, has been depicted in Fig. 5. In the next section we demonstrate how DBN can be employed to model such model uncertainty without resorting to auxiliary nodes.

3.2.2. Application of dynamic Bayesian network

Khakzad (2015) developed a methodology based on DBN to model all possible interactions (escalation vectors) among the units during potential domino scenarios. This allows for modeling the evolution of a domino effect both spatially and temporally without forcing the identification of secondary units to the model, leaving the DBN to determine the propagation pattern based on all possible escalation vectors received by and/or emitted from the units. To address domino effect model uncertainty in the present study, we adopt a similar framework

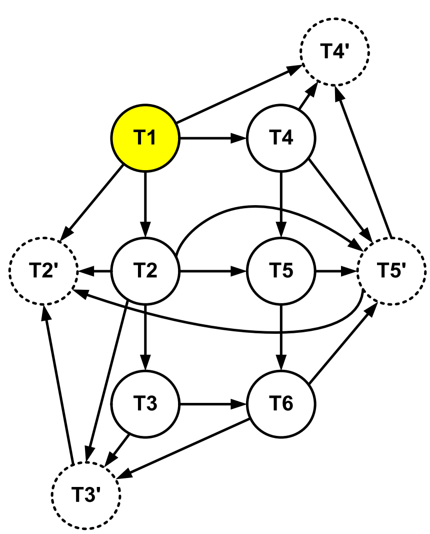


Fig. 5. Application of auxiliary nodes (dashed outlined) to address domino effect model uncertainty in a process plants with six storage tanks.

just for considering all possible sequences of events rather than modeling temporal evolution of domino scenarios.

In other words, in this study the DBN is employed to model the number of steps required for all the units to contribute to the domino effect via different sequences of events. As such, the transitional probabilities from one step to the next are time-invariant as in a conventional BN. The number of steps required to calculate the final escalation probabilities of the involved units can be derived from the representation of all possible sequences of events as a directed graph similar to the one depicted in Fig. 3(d).

In a directed graph, a path from the node X to Y is a sequence of nodes and edges starting from the former to the latter when each intermediate node can be traversed only once. Similarly, the geodesic distance between the nodes is the length of the shortest path from X to Y. The diameter of a graph is the length of the longest geodesic distance in the graph, i.e., the longest shortest path (Freeman, 1979). Considering the directed graph in Fig. 3(d), it can be seen that the diameter of the graph – the longest path from T1 to T4 – is equal to 2, indicating that it takes T1 two steps to reach (impact) T4, either via the path consisting of {T1} → {T2} → {T4} or the path consisting of {T1} → {T3} → {T4}.

The first path implies T3 is still safe and not engaged in the sequence of events; thus, one more step would be needed for T4 and T1 to cooperate to escalate the domino effect to T3 (synergistic effect), adding up to a total of three steps. Likewise, the second path implies T2 is still not engaged in the domino effect, and one more step would be needed for T4 and T1 to impact it, again adding up to a total of three steps. The DBN to model all possible sequences of events given a primary event at T1 has been depicted in three steps in Fig. 6.

According to Fig. 6, a primary fire at T1 in step 0 can escalate to either T2 or T3 in step 1 (the arcs from T1 in step 0 to T2 and T3 in step 1). The fire at T2 or T4, whichever is impacted by T1 and involved in the fire domino effect, can impact T4 in the next step (the arcs from T2 and T3 in step 1 to T4 in step 2). If the fire escalates to T4 in step 2, T4 can cooperate with T1 to impact T2 or T3, whichever is still safe, in step 3 (the arcs from T4 in step 2 to T2 and T3 in step 3).

3.3. An illustrative example

To make a comparison among the results of the conventional BN approach in Fig. 3(a), the modified BN with auxiliary nodes in Fig. 4, and the DBN in Fig. 6, we assume that T1-T4 are gasoline atmospheric storage tanks with a diameter of D = 33.5 m, height of H = 9.1 m, and capacity of V = 8000 m^3. Considering a tank fire as the most likely primary and secondary events, the magnitudes of heat radiation emitted and received by each tank are calculated in ALOHA (2016) consequence analysis software as reported in Table 2.

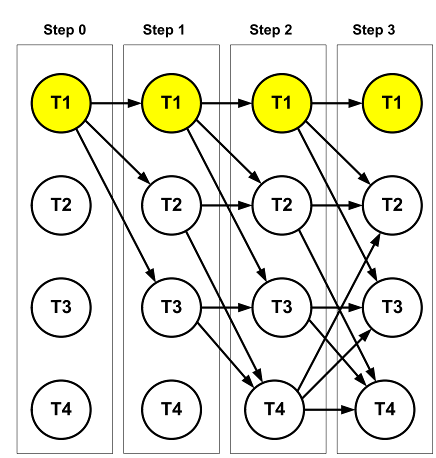


Fig. 6. Dynamic Bayesian network to address domino effect model uncertainty in a process plant comprising four units T1-T4. The domino effect initiates at T1.

Table 2
Heat radiation intensity (kW/m^2) Tj received from a tank fire at Ti. Values less than $15\ kW/m^2$ have not been taken into account.

Ti↓ Tj→	T_1	T_2	T_3	T_4
T_1	–	38	22	–
T_2	38	–	–	22
T_3	22	–	–	38
T_4	–	22	38	–

Table 3
Escalation probabilities given a tank fire at T1.

Unit	Conventional Bayesian network	Bayesian network with auxiliary nodes	Dynamic Bayesian network
T1	1.00	1.00	1.00
T2	0.61	0.86	0.85
T3	0.32	0.59	0.54
T4	0.36	0.36	0.36

Modeling the BNs shown in Figs. 3(a), 4 and 6 in GeNIe software (GeNIe 2.2), the calculated escalation probabilities of the storage tanks given a tank fire at T1 have been listed in Table 3. As can be seen, the results obtained from the modified BN using auxiliary nodes (Fig. 4) and the DBN (Fig. 6) are in good agreement, indicating that given a tank fire at T1 as the primary event, {T1} → {T2} → {T3} → {T4} would be the likeliest sequence of events in the domino effect.

It should be noted that for the DBN, the escalation probabilities calculated in the last step have been reported in Table 3. Considering the conventional BN methodology, however, not only the escalation probabilities of T2 and T3 differ from those obtained from the other methodologies, but also the sequence of events is different, i.e., {T1} → {T2} → {T4} → {T3}. The discrepancy between the results of the conventional approach and the developed methodologies, in terms of escalation probabilities and the order of events, underlines the important role of model uncertainty which, if not taken into account, can lead not only to underestimated escalation probabilities but also to an incorrect sequence of events in the domino effect modeling.

4. Application

The methodology developed in Section 3.2.2 can be employed to model an arbitrary number of domino scenarios triggered by single or multiple primary event(s). Domino effects initiated from a single primary event (SPE domino effect) are more likely to occur due to random failures since the probability of having more than one primary event at a time is very low. On the other hand, in the case of intentional man-made domino effects, especially those triggered by improvised explosive devices in terrorist attacks, the possibility of having more than one primary event (MPE domino effect) is higher (Reniers et al., 2008).

To demonstrate the application of the methodology, a tank farm consisting of six gasoline atmospheric storage tanks was considered in Fig. 7 with the same characteristics as reported in the illustrative example in Section 3.3. Considering tank fire as the envisaged primary and secondary events, the amount of heat radiation Tank Tj receives from Tank Ti has been calculated using ALOHA (2016) (Table 4). The DBN methodology can be extended to account for all types of SPE and MPE domino scenarios that may take place in the tank farm.

In the present section, we apply the methodology to model a SPE and a MPE domino scenarios, where the latter is more likely to take place as a consequence of an intentional attack with the aim of causing more extensive damage to the plant.

Fig. 7. Tank farm consisting of six atmospheric storage tanks containing gasoline. The tanks are identical, with a diameter of D = 33.5 m, height of H = 9.1 m, and capacity of V = 8000 m^3.

Table 4
Heat radiation intensity (kW/m^2) Tj receives from a tank fire at Ti. Values less than $15\ kW/m^2$ have not been taken into account.

Ti↓ Tj→	T_1	T_2	T_3	T_4	T_5	T_6
T_1	–	38	–	22	–	–
T_2	38	–	38	–	22	–
T_3	–	38	–	–	–	22
T_4	22	–	–	–	38	–
T_5	–	–	38	–	–	22
T_6	–	–	22	–	38	–

4.1. Scenario 1: single-primary-event domino scenario

Assuming a primary tank fire at T1, the representation of possible sequences of events can be shown as a directed graph in Fig. 8(a), where the primary unit is highlighted with the color yellow for the sake of clarity. As can be seen, the farthest node in the graph to T1 is T6; that is, T6 is the farthest node that can be impacted by the primary event at T1. As such, the longest shortest path (graph diameter) measured from T1 is equal to 3, which is the shortest distance (the number of edges or the number of nodes minus one) from T1 to T6 as: {T1} → {T2} → {T3} → {T6} or {T1} → {T4} → {T5} → {T6}.

As such, according to Section 3.2.2, the number of steps required for the DBN modeling would be equal to "graph diameter +1 = 4". Modeling the DBN shown in Fig. 9 in GeNIe software (GeNIe 2.2), the escalation probabilities were calculated for the 4th time step as listed in the first row of Table 5. Ranking the units based on their escalation probabilities in a descending order, the sequence {T1: 1.00} → {T2: 0.94} → {T4: 0.72} → {T3: 0.66} → {T5: 0.65} → {T6: 0.31} would be the likeliest order of events in the domino effect initiating at T1; the numbers in the brackets denote the unconditional escalation probabilities.

4.2. Scenario 2: double-primary-event domino scenario

In this scenario, it is assumed that there are two simultaneous tank fires at T1 and T6 (two primary events). This type of domino effect is more likely to occur in the case of intentional attacks (Reniers et al., 2008; BBC, 2015). The representation of possible sequences of events can be shown as the directed graph in Fig. 8(b), where the primary units are highlighted with the color yellow.

A can be seen, the farthest nodes that can be impacted by T1 are T2 and T4 (T3 and T5 are immediately impacted by T6 and thus will be ruled out) while the farthest nodes that can be impacted by T6 are T5 and T3 (T2 and T4 are immediately impacted by T1 and thus will be ruled out). In either case, the longest short distances measured from the primary units T1 or T6 are equal to 1, and thus the number of required steps to run the DBN would be equal to 2. The calculated unconditional

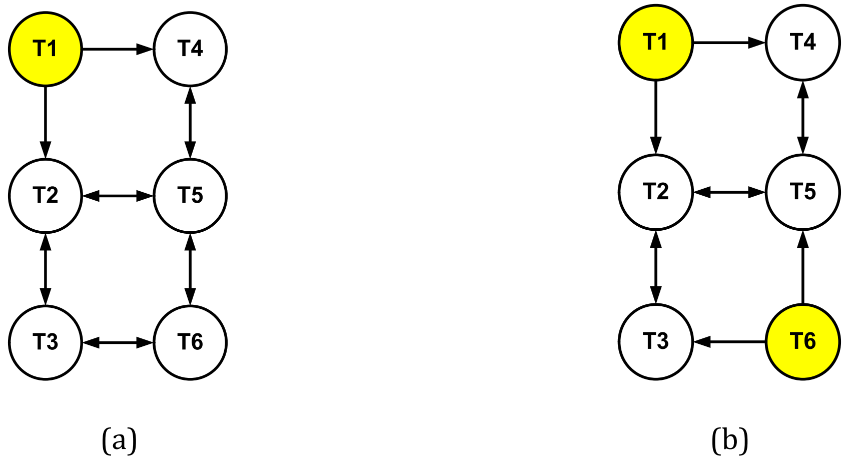


Fig. 8. (a) Directed graph to incorporate all possible sequences of events triggered by a primary event at T1 (SPE domino effect). (b) Directed graph to incorporate all possible sequences of events triggered by two simultaneous primary events at T1 and T6 (MPE domino effect).

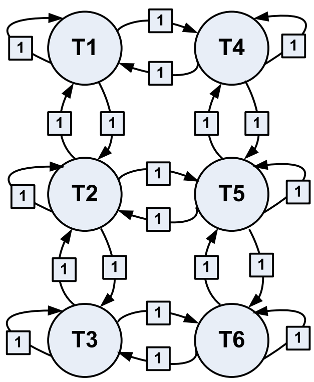


Fig. 9. Modeling of possible domino scenarios as a DBN.

Table 5
Unconditional escalation probabilities for the domino scenarios in Fig. 8.

Domino effect ↓ Unit→	T1	T2	T3	T4	T5	T6
Fig. 8(a): Probabilities in Step 4	1.00	0.94	0.66	0.72	0.65	0.31
Fig. 8(b): Probabilities in Step 2	1.00	0.61	0.32	0.32	0.61	1.00
Fig. 8(b): Probabilities in Step 4	1.00	0.98	0.91	0.91	0.98	1.00

escalation probabilities in the 2nd step are reported in the second row of Table 5. Rank ordering the units based on their escalation probabilities (Table 5), the most likely sequence of events would be {T1 and T6: 1.00} → {T2 and T5: 0.61} → {T3 and T4: 0.32}.

Making a comparison between the escalation probabilities calculated for the SPE and MPE domino effects in Table 5, at first glance the SPE domino scenario might seem to have resulted in higher escalation probabilities and thus more extensive damage. To identify the severity of the domino effects, however, the comparison between the two domino scenarios should be made based on a comparison between the escalation probabilities calculated at similar steps.

To this end, the escalation probabilities of the MPE domino effect at the 4th time step have also been calculated and listed in the last row of Table 5 so that they can be compared with the corresponding probabilities of the SPE domino effect listed in the first row of the table. It can be seen that given the same number of time steps (i.e., 4 steps), the escalation probabilities of the MPE domino effect would be higher than those of the SPE domino effect. It can also be noted that given enough steps, the escalation probabilities in both SPE and MPE domino scenarios would approach unity. This, in turn, emphasizes the need for an accurate calculation of the number of steps required for the analysis of the DBN.

5. Conclusions

In the present study, a methodology based on dynamic Bayesian network was developed to model the propagation of domino effects via the likeliest sequence of events that may take place. The methodology accounts for the uncertainties in identification of the sequence of events (model uncertainty), thus leading to a more accurate calculation of the escalation probabilities which are crucial for the risk assessment and management of domino effects.

Presenting possible domino scenarios as a directed graph, we illustrated that the graph diameter, if measured from the primary unit, can be used as a metric to identify the minimum number of time steps needed in the modeling of the corresponding dynamic Bayesian network so that all possible interactions among the units can be taken into account. This way, the most likely sequence of events during a domino scenario is identified by the model rather than being forced by the analyst (as is the case in conventional Bayesian network approach), which could otherwise result in incorrect or a less likely sequence of events. The methodology was demonstrated to be of great value in vulnerability assessment of process plants where the main emphasis would be on the ranking of the units based on their relative contribution to domino scenarios rather than their individual failure probabilities.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jlp.2018.03.001.

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