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A cost-robust approach to tackle man-made domino effects

Khakzad, Nima; Reniers, Genserik

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Low-capacity utilization of process plants: A cost-robust approach to tackle man-made domino effects

Nima Khakzad*, Genserik Reniers

Safety and Security Science Group, Delft University of Technology, The Netherlands

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ABSTRACT

Process plants can be potential targets to terrorist attacks with the aim of triggering domino effects. Compared to accidental domino effects where the possibility of having multiple primary events is very remote, man-made domino effects are likelier to be initiated from multiple units within the plant in order to increase the knock-on likelihood and thus causing maximum damage. In this regard, identification of critical units that - under attack - may lead to likelier and severer domino effects is crucial both to assess the vulnerability of process plants and subsequently to increase their robustness to such attacks. In the present work, we have applied graph theory and dynamic Bayesian network to identify critical units. Further, low-capacity utilization of process plants (e.g., by keeping some of the storage tanks empty) has been demonstrated as an effective strategy in the case of imminent terrorist attacks. As such, the robustness of the plant against intentional attacks can temporarily be increased while considering the cost incurred because of such a low-capacity utilization.

1. Introduction

Industrial plants and facilities have frequently been the targets of intentional attacks such as terrorist attacks, sabotage, and vandalism [1]. Fig. 1 depicts the number of attacks to industrial facilities among which are power towers and transformers in Thailand and The Philippines, power plants and gas compression facilities in Iraq, oil facilities in Libya, oil and gas pipelines in Yemen, Nigeria, Turkey, Pakistan, and Colombia, as well as oil wells in Iraq [1].

Intentional attacks, especially those launched by terrorists, are usually aimed at causing maximum damage in terms of, among others, loss of lives and assets. As such, it seems reasonable to expect an "intelligent attacker" to aim for triggering domino effects in process facilities. In the chemical and process industries, the term "domino effect" is referred to a chain of fires and/or explosions triggered by a primary fire or explosion at a process vessel [2]. The escalation of primary fire(s) or explosion(s) (primary events) to secondary fires or explosions (secondary events) occurs by means of heat radiation, fire impingement, fire engulfment, blast wave, or projectile fragments, which are known as escalation vectors. Although rare, domino effects have contributed to a number of catastrophic accidents such as for instance explosions at a liquefied petroleum gas facility in Mexico in 1984 [3], fires and explosions at an oil storage terminal in the UK in 2005 [4], and tank farm explosions and fires in Puerto Rico in 2009 [5].

In the case of intentional attacks with improvised explosive devices (IEDs) such as pipe bombs and car bombs, the blast wave of detonation can severely damage process vessels and result in major release of flammable chemicals, which in contact with the heat of detonation, are very likely to ignite and lead to domino effects. Compared to accidental domino effects where the possibility of having multiple primary events is very remote, in intentional domino effects, it is likelier that multiple vessels are simultaneously attacked in order to increase (from the attacker's viewpoint) the possibility and severity of potential domino effects. The relatively recent attack to a French chemical plant in July 2015 [6] is an example of such multi-target attacks in which two chemical storage tanks, nearly 500 m away from each other, were attacked with IEDs, leading to tank fires.[1]

Due to the catastrophic consequences of domino effects, many researches have been devoted to their modeling and risk assessment in chemical and process facilities [7–14]. A multitude of previous work has been devoted to accidental domino effects whereas only a few works has been dedicated to intentional domino effects [15–18]. Comparing intentional and accidental domino effects, aside from the higher likelihood of multiple primary events in intentional domino effects, the likelihood of targeting the most critical vessels in the former is much higher than the latter. This is because, if the attacker is considered a rational decision maker [19], he would plan to maximize the expected utility of his attack

[1] Remainings of some IEDs were also found near a third storage tank though it did not cause any damage.

* Corresponding author.
E-mail address: n.khakzadrostami@tudelft.nl (N. Khakzad).

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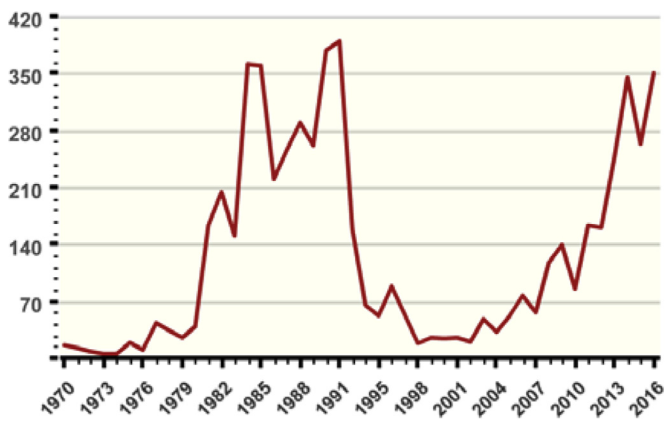


Fig. 1. Number of attacks to utilities (1970–2016) [1].

[20] via attacking the vessels with the highest possibility of triggering domino effects and thus inflicting maximum damage to the plant.

The axioms required for a presumably "rational decision maker" might be violated by a real decision maker [20]. Nevertheless, the assumption of a "rational attacker" who wishes to maximize the expected outcome of his attack would seem to result in conservative preventing and mitigating strategies by defenders since the most severe damage would be anticipated.

Khakzad and Reniers [21] demonstrated that modeling potential domino effects in a process plant as a directed graph, graph centrality metrics such as closeness and betweenness can be used to identify process vessels with the largest contribution to domino effects. Using a similar approach, Khakzad et al. [22] combined graph metrics with multi-criteria decision analysis so as to find an optimal fire protection of process plants against domino scenarios.

In the present study, we aim to develop a methodology based on graph theory and Bayesian network to assess and reduce the vulnerability of process plants in face of targeted domino effects. The developed methodology is shown to be effective in temporarily increasing the robustness[2] of existing process plants against intentional attacks (which are aimed at triggering severe domino effects) particularly without making macro-layout changes to the plant. In Section 2, the fundamentals of graph theory, Bayesian network, and multi-criteria decision making are briefly recapitulated. In Section 3, a demonstrative example is used to develop the methodology based on graph theory, followed by its validation using dynamic Bayesian network. Application of the methodology to a case study and the results are in Section 4. The conclusions are drawn in Section 5.

2. Background

2.1. Graph theory

Domino effects in a process plant can be modeled as a directed graph $G = \{V, E\}$ where the process vessels are considered as the vertices of the graph, $V = \{v_1, v_2, \dots, v_n\}$, and the escalation vectors among the vessels as the edges of the graph, $E = \{e_{12}, e_{13}, \dots, e_{ij}\}$ [21]. For instance, if vessel v_1 is on fire, the heat radiation that v_2 receives from v_1 is indicated as e_{12}. In a weighted graph, a set of numerical values can be assigned to either the vertices or the edges of the graph. A weighted graph can be presented as $G = \{V, W_v, E, W_e\}$ in which W_v and W_e are weight vectors allocated to the vertices and the edges, respectively.

In a directed graph, a path from v_i to v_j is a sequence of edges starting from the former to the latter when each intermediate vertex can be traversed only once. Similarly, the geodesic distance between the vertices, denoted by $d_{ij} = d(v_i, v_j)$, is the length of the shortest path from v_i to v_j.

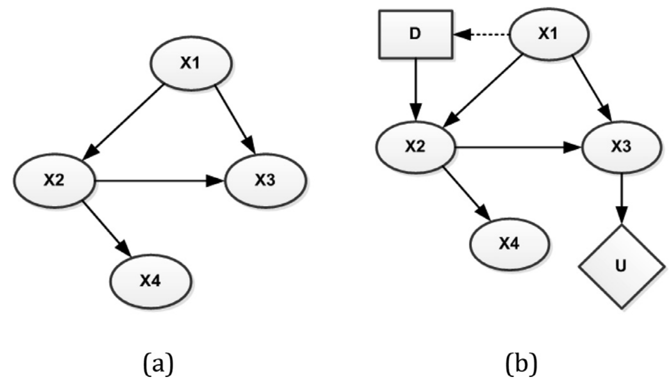


Fig. 2. (a) Bayesian network. (b) Influence diagram.

Based on the concept of geodesic distance, a number of graph metrics can be used to describe the characteristics of either the nodes of a graph or the graph itself. Among such metrics, closeness centrality scores are very popular. The out-closeness of v_i, $C_{out}(v_i)$, can be defined as the number of steps needed to reach every other node of the graph from v_i; the in-closeness $C_{in}(v_i)$, on the other hand, is the number of steps needed to reach v_i from every other node of the graph [23]:

$$C_{out}(v_i) = \frac{1}{\sum_j d_{ij}} \tag{1}$$

$$C_{in}(v_i) = \frac{1}{\sum_j d_{ji}} \tag{2}$$

Based on the centrality scores of a graph's nodes given in Eqs. (1) and (2), the closeness scores of the graph can be measured. As such, the out-closeness of the graph can be calculated as:

$$C_{out}(G) = \frac{\sum_{i=1}^{n} C_{out}(v_i)}{n} \tag{3}$$

2.2. Bayesian network and influence diagram

Bayesian network (BN) is a graphical tool for reasoning under uncertainty [24,25]. In a BN, the joint probability distribution of a set of random variables is represented in terms of conditional probabilities. In a BN (Fig. 2(a)), random variables are represented by nodes (in the form of an ellipse) while the direct dependencies among the nodes are represented by directed arcs. Satisfying the Markov condition – which states that a node (e.g., X_4) is independent of its non-descendants (i.e., X_1 and X_3) given its parents (i.e., X_2) – a BN factorizes the joint probability distribution of its nodes as the product of the conditional probability distributions of the variables given their parents:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i | Pa(X_i)) \tag{4}$$

where $Pa(X_i)$ is the parent set of the variable X_i. Considering the BN in Fig. 2(a), $P(X_1, X_2, X_3, X_4) = P(X_1)\, P(X_2|X_1)\, P(X_3|X_1,X_2)\, P(X_4|X_2)$.

A BN can be extended to an influence diagram (Fig. 2(b)) using two additional types of nodes, decision node D and utility node U [25] in order for decision making. Decision and utility nodes are conventionally displayed as rectangles and diamonds, respectively. A decision node incorporates a number of decision policies. A decision node should be assigned as the parent of nodes the probability distributions of which depend on decision policies (e.g., the arc from the decision node D to X_2). Likewise, the decision node should be the child of nodes the states of which have to be known to the decision maker before making decision (e.g., the dashed arc from X_1 to the decision node D). The utility node U incorporates utility values (positive or negative) to represent the

[2] In the present study, we use "robustness" as an antonym of "vulnerability".

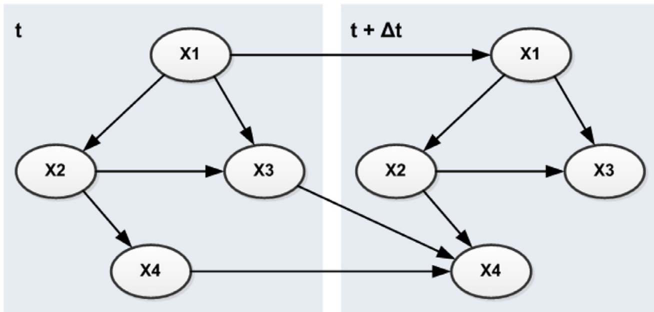


Fig. 3. Schematics of a dynamic Bayesian network in two sequential time intervals.

preferences of the decision maker as to the outcomes of each decision policy.

Considering three decision policies for node $D = \{d_1, d_2, d_3\}$ and a binary node $X_3 = \{x_3^+, x_3^-\}$ in Fig. 2(b), node U should include six utility values, one for each pair of decision policies and the states of X_3. As such, the expected utility of each decision policy can be calculated; for example, the expected utility of the 2nd decision policy d_2 can be calculated as:

$$EU(d_2) = \sum_{X_3} P(X_3|d_2)\, U(d_2, X_3) = P(x_3^+|d_2)\, U(d_2, x_3^+) + P(x_3^-|d_2)\, U(d_2, x_3^-) \quad (5)$$

Assuming a rational decision maker [19], the decision policy with the maximum expected utility can be selected as the optimal decision, d^* [25]:

$$d^* = \underset{d_i}{arg\ max}\ EU(d_i) \text{ for } i = 1, 2, 3 \quad (6)$$

A dynamic Bayesian network (DBN) is a replication of ordinary BN over time, that compared to its predecessor, facilitates explicit modeling of temporal changes of random variables. Dividing the timeline into 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. Fig. 3 shows a DBN where the probabilities at a time slice are conditioned on the same and previous time slices:

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P\left(X_i^{t+\Delta t}|X_i^t, \pi(X_i^t), \pi\left(X_i^{t+\Delta t}\right)\right) \quad (7)$$

According to the DBN in Fig. 3, the conditional probability of X_4, for example, at the time slice $t + \Delta t$ is $P(X_4^{t+\Delta t}|X_2^{t+\Delta t}, X_3^t, X_4^t)$.

2.3. Pareto optimization

In real-life decision making problems, decision criteria that influence the decision making process are usually in conflict. Multi-criteria decision analysis (MCDA) techniques have been developed with the aim of helping decision makers deal with such complex situations. Due to the conflicting nature of decision criteria, it is usually unlikely to make a decision which satisfies all the decision criteria. In MCDA, a Pareto-optimal solution is a decision alternative for which there are no other alternatives where the value of a criterion can be improved without worsening or maintaining the value of other criteria. A set of Pareto-optimal solutions refers to a number of such decision alternatives which are normally prioritized based on the preferences of a decision maker.

The method of "reference point" is one of the techniques in bi-criteria decision analysis, which intuitively represents the preferences of a decision maker based on aspiration and reservation vectors [26]. An aspiration vector is composed of the best values of the criteria whereas a reservation vector contains the worst values of the criteria. The aspiration and reservation vectors identify "Utopia" and "Nadir" points, respectively.

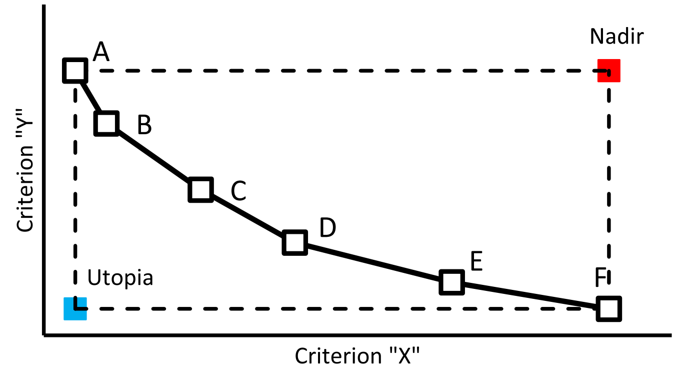


Fig. 4. Reference-point decision analysis.

Optionally, a decision maker can define his preferred solution between aspiration and reservation levels, and based on the distances of Pareto-optimal solutions from Utopia and Nadir points. Fig. 4 schematizes a reference point decision making technique, comprising a set of Pareto-optimal solutions, i.e., points A–F, and Utopia and Nadir points. Accordingly, the solution which is the closest/farthest (e.g., using Euclidean distance) to/from the Utopia/Nadir point can be determined as the best solution:

$$\rho_i = \sqrt[2]{\left(x_i - x_U\right)^2 + \left(y_i - y_U\right)^2} \quad (8)$$

where ρ_i is the Euclidean distance of the i-th Pareto-optimal point from Utopia point; x_i and x_U are the values of the criterion X of the ith point and Utopia point, respectively; y_i and y_U are the values of the criterion Y of the ith point and Utopia point, respectively. It should be noted that the application of the reference point technique implies the equal importance of the decision criteria to the decision maker.

3. Vulnerability of process plants to targeted attacks

In this section, using a simple example, we will demonstrate via both a graph theoretic approach and DBN approach that targeted attacks to the units with the highest out-closeness score would result in the most severe domino scenarios in a process plant than attacks to any other units do. In Section 4, the graph theoretic approach and pareto optimization will be applied to a more complex case study to show the low-capacity utilization of process plants as a way of increasing their robustness to intentional attacks.

3.1. An example

For the sake of clarity, we use a demonstrative example to help develop the methodology. Fig. 5(a) displays an oil terminal consisting of six gasoline storage tanks with a diameter of $D = 30.5$ m, height of $H = 9.1$ m, and capacity of $V = 8000$ m^3. Considering tank fires as the likeliest scenario anticipated from an attack with IEDs [6], the amounts of heat radiation Tank *Tj* receives from Tank *Ti* are calculated using ALOHA software [27] as reported in Table 1, assuming a wind speed of 2 m/s from NW, 25% relative humidity, and air temperature of 18 C.

Since all the storage tanks are atmospheric, the heat radiation threshold cable of causing damage and thus triggering a domino effect is considered as 15 kW/m^2 [11]. As such, heat radiation intensity values less than this threshold are not presented in Table 1.

3.2. Vulnerability assessment

3.2.1. Application of graph metrics

Modeling possible domino effects in a process plant as a directed graph (Fig. 5(b)), Khakzad and Reniers [21] showed that process vessels with higher out-closeness centrality scores can lead to relatively severer

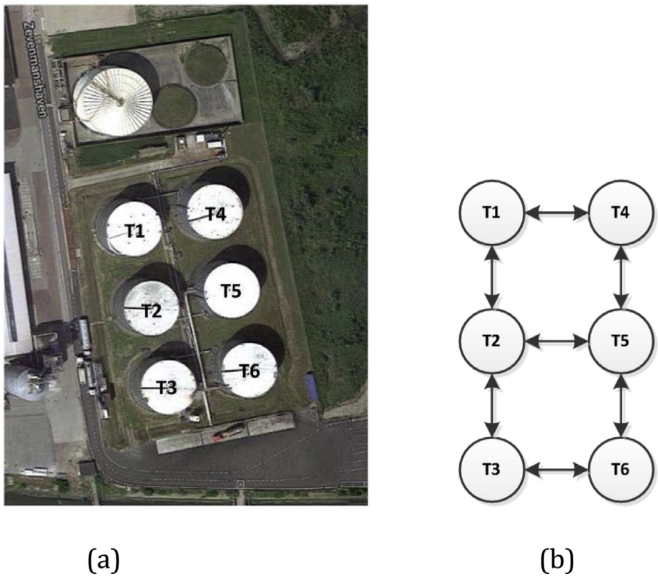


Fig. 5. (a) An oil terminal consisting of six gasoline storage tanks. (b) Representation of possible domino scenarios as a directed graph.

Table 1
Heat radiation intensity (kW/m^2) *Tj* receives from a tank fire at *Ti*. Values less than 15 kW/m^2 are not presented.

Ti↓	*Tj*→	*T1*	*T2*	*T3*	*T4*	*T5*	*T6*
T1		–	38	–	22	–	–
T2		38	–	38	–	22	–
T3		–	38	–	–	–	22
T4		22	–	–	–	38	–
T5		–	22	–	38	–	38
T6		–	–	22	–	38	–

Table 2
Out-closeness centrality of the storage tanks shown in Fig. 5.

Storage tank	*T1*	*T2*	*T3*	*T4*	*T5*	*T6*
C_{out}(Tank)	0.556	0.714	0.556	0.556	0.714	0.556

domino effects if ignited or exploded as primary vessels. Following their work in the present study, we aim to investigate if intentional attack to a limited number of process vessels with the highest out-closeness scores (node out-closeness) would result in the severest domino scenario than attack to any similar number of other process vessels.

To this end, the directed graph in Fig. 5(b), which has been drawn based on mutual interactions between the storage tanks in Table 1, is modeled in igraph package [28]. The storage tanks' out-closeness scores are presented in Table 2, indicating *T2* and *T5* as the tanks with the highest out-closeness. As such, a single attack to *T2* or *T5* should trigger a severer domino effect than a single attack to any other storage tank. Likewise, simultaneous attacks to both *T2* and *T5* are expected to result in a severer domino effect than a multi-attack to any other combination of two tanks.

For this purpose, we consider a number of single attack (Fig. 6(a)–(c)) and double-attack scenarios (Fig. 6(d)–(f)), where, for the sake of clarity, the targeted vessels are highlighted. Modeling the graphs in Fig. 6 in igraph [28], the out-closeness scores of the graphs, as an indication of graph vulnerability to domino effects [22], are presented in Table 3 (1st row).

As can be seen, among single-attack scenarios, the graph presented in Fig. 6(b) has the highest graph out-closeness, indicating that a single attack to *T2* (or *T5*) would lead to the severest single-primary-event domino effect. Likewise, among double-attack scenarios, the graph presented in Fig. 6(e) has the highest graph out-closeness score, indicating that a double-attack to both *T2* and *T5* would result in the severest double-primary-event domino effect. In the next section, we will compare the results obtained from the application of graph metrics with those of a BN approach.

3.2.2. Application of dynamic Bayesian network

We use a methodology based on DBN to model all possible sequences of events during domino effects in the oil terminal [14]. Fig. 7 displays the DBN to model possible single- and multiple-primary-event domino effects in the plant shown in Fig. 5. The DBN has also been extended to an influence diagram by adding the node Utility to the nodes at the last time slice to account for the damage inflicted upon the storage tanks.

To model the single-primary-event domino effect triggered by an attack to *T1*, for example, the state of node *T1* at the first time slice, denoted by t = 0, is instantiated to "*T1* = Tank fire" while the states of the other nodes at $t = 0$ are instantiated to "Safe".[3] Based on the assigned marginal and conditional probabilities, the developed DBN computes unconditional probabilities of the storage tanks at each time slice. For the sake of exemplification, the conditional probabilities assigned to node *T4* at 2nd time slice, i.e., $t = 1$, are reported in Table 4.

In Table 4, the probabilities P_1, P_5, and P_{15} are also known as escalation probabilities, and can be calculated using a variety of techniques such as probit models [10,11] based on the intensity of the escalation vector (e.g., heat radiation) and type and size of target vessels. For the purpose of this study, which is the identification of critical vessels based on their relative contribution to domino effects, we use a linear relationship to proportionate the escalation probability to the magnitude of heat radiation. Since a threshold of 15 kW/m^2 has been proposed for atmospheric vessels exposed to heat radiation [10], the linear relationship in Eq. (9) could be used. It should be noted that Eq. (9) is only for demonstrative purposes and is not aimed at superceding the well-known probit models:

$$P = 1 - \frac{15}{Q} \tag{9}$$

where Q (kW/m^2) is the heat radiation received by an atmospheric vessel.[4] As such, for instance, $P_{15} = P(T4^{t=1} = \text{Tank fire} \mid T4^{t=0} = \text{Safe}, T1^{t=0} = \text{Tank fire}, T5^{t=0} = \text{Tank fire}) = 1 - \frac{15}{Q_{14}+Q_{54}} = 1 - \frac{15}{22+38} = 0.75$, where Q_{14} and Q_{54} are the heat escalation vectors (kW/m^2) *T4* receives from *T1* and *T5*, respectively, as listed in Table 1.

In the present study, for illustrative purposes, we assign a utility of −10.0 to a tank damaged either due to attack with IEDs or due to escalation of subsequent domino effects. Similarly, the utility of a safe tank is 0.0. For example, if an attack to *T1* triggers a domino effect involving *T2* and T4, the respective utility value incorporated in the node Utility in Fig. 5 is *U* (*T1* = Tank fire, *T2* = Tank fire, *T3* = Safe, *T4* = Tank fire, *T5* = Safe, *T6* = Safe) = −30.0.

Simulating the DBN in GeNIe [29], the expected disutility of single- and double-attack scenarios (due to possible single-primary-event and double-primary-event domino effects that can be triggered by which) are calculated as listed in Table 3 (2nd row). As can be seen, among the single-attack scenarios, the attack to T2 would result in the largest disutility (−49.45) whereas among the double-attack scenarios, the attack to both *T2* and *T5* would result in the largest disutility (−58.68). Clearly enough, the results of the DBN analysis are in complete agreement with those of the graph-theoretic approach in the previous section. As a result, in a process plant, graph out-closeness score can be used as an indication of the plant's vulnerability to domino effects triggered from intentional (or accidental) damage to process vessels.

[3] In the present study, the storage tanks are considered to have two states, namely "Tank fire" and "Safe".

[4] A threshold of 45 kW/m^2 has been proposed for pressurized vessels exposed to heat [10].

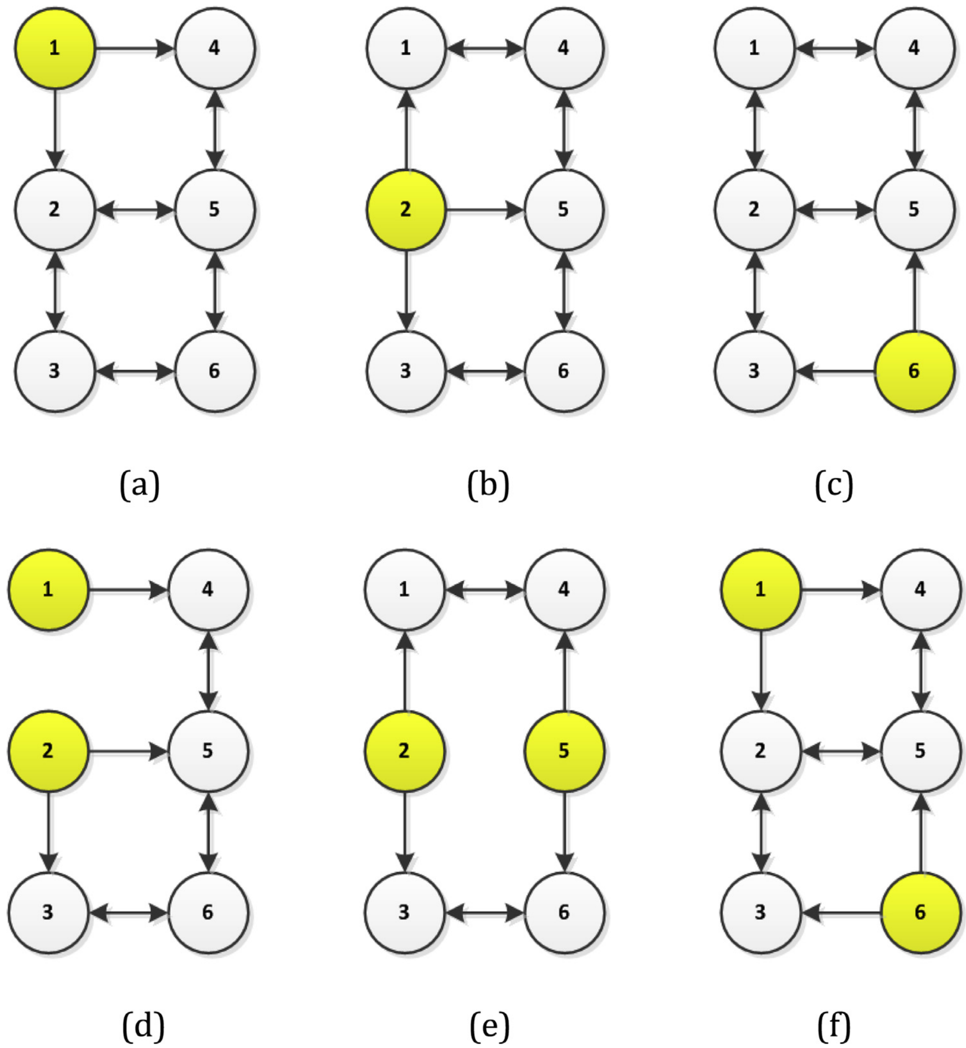


Fig. 6. (a) Domino effect triggered by attack to *T*1. (b) Domino effect triggered by attack to *T*2. (c) Domino effect triggered by attack to *T*6. (d) Domino effect triggered by attack to *T*1 and *T*2. (e) Domino effect triggered by attack to *T*2 and *T*5. (f) Domino effect triggered by attack to *T*1 and *T*6.

Table 3
Graph out-closeness and utility values for single-attack and double-attack scenarios depicted in Fig. 6. Utility values have been calculated using DBN in Fig. 7.

Graph	Single-attack			Double-attack		
	Fig. 6(a)	Fig. 6(b)	Fig. 6(c)	Fig. 6(d)	Fig. 6(e)	Fig. 6(f)
C_{out}(Plant)	0.180	**0.423**	0.180	0.142	**0.208**	0.117
Utility	−42.86	**−49.45**	−42.86	−52.81	**−58.68**	−56.77

Table 4
Conditional probability table of node *T*4 at t = 1 in Fig. 7.

$T4^{t=0}$	$T1^{t=0}$	$T5^{t=0}$	$T4^{t=1}$	
			Tank fire	Safe
Tank fire	Tank fire	Tank fire	1	0
Tank fire	Tank fire	Safe	1	0
Tank fire	Safe	Tank fire	1	0
Tank fire	Safe	Safe	1	0
Safe	Tank fire	Tank fire	P_{15}	1 - P_{15}
Safe	Tank fire	Safe	P_1	1 - P_1
Safe	Safe	Tank fire	P_5	1 - P_5
Safe	Safe	Safe	0	1

4. Application of the methodology

In the previous section, it was demonstrated that targeted attacks to critical units, that is, the units with the higher out-closeness scores, would lead to more severe domino scenarios in a process plant. As such, virtual elimination of critical units, e.g., by emptying the critical storage tanks via emergency drainage or fluid transfer or shutting down the critical process vessels, would be expected to increase the robustness of the process plant against such intentional domino scenarios.

However, since the elimination of critical units would result in a low-capacity utilization or partial shutdown of the plant, incurring costs due to business interruption and plant startup, it has to be performed via a cost-benefit analysis so that an optimal strategy can be adopted. Since the benefit gained from such a low-capacity utilization would be an increase in the robustness of the process plant, we refer to it as a cost-robust analysis. The methodology for cost-robust low-capacity uti-

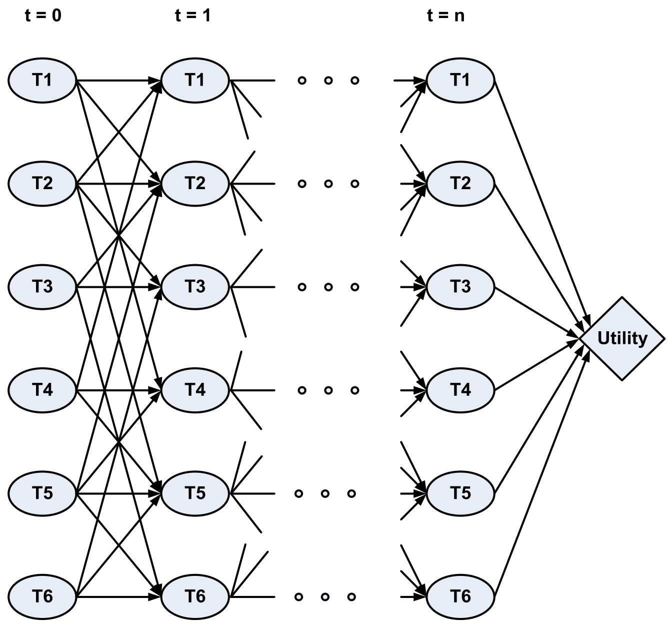


Fig. 7. Dynamic Bayesian network to model possible sequences of events during domino scenarios.

Table 5
Out-closeness scores of the storage tanks shown in Fig. 8.

Storage tank	*T1*	*T2*	*T3*	*T4*	*T5*	*T6*	*T7*	*T8*
$C_{out}(T_i)$	0.70	0.64	0.70	1.0	0.78	0.64	0.86	0.70

lization of process plants as a means of tackling intentional domino scenarios can be summarized as follow:

(i) model domino scenarios in a process plant as a directed graph;
(ii) identify critical units and calculate the vulnerability of the process plant based on out-closeness scores;
(iii) sequentially eliminate the critical units (in a descending fashion) and calculate the plant's residual out-closeness (the average of the out-closeness scores of the remaining units) as an indication of the plant's robustness;
(iv) calculate the cost incurred due to the virtual elimination of critical units;
(v) use an optimization technique to decide the optimal (cost-robust) number of critical units to remove.

The application of the methodology has been exemplified using a case study in the following sections.

4.1. Case study

To demonstrate the application of the methodology, consider the tank farm in Fig. 8(a) comprising eight atmospheric storage tanks of oil with a diameter of $D = 33.5$ m, height of $H = 15.2$ m, and capacity of 13,000 m^3. Considering tank fires as the primary and secondary events, possible fire escalation patterns during domino effects are presented as the directed graph in Fig. 8(b).

The intensity of heat radiation between the tanks has been calculated by ALOHA [27] as listed in Table A.1 in the appendix, assuming the same weather conditions as of the illustrative plant in Fig. 5. Following the same approach as in Section 3.2.1, possible domino scenarios (propagation of fire) were modeled using a directed graph (Fig. 8(b)), and the out-closeness scores of the tanks (node out-closeness centrality) were calculated using igraph package [28] as presented in Table 5. Storage tanks 4, 7, and 5 are accordingly the ones with the highest out-closeness scores in a descending order.

4.2. Cost-robust utilization

To prevent or delay the escalation of domino effects, especially in the case of fire propagation, usually a variety of fire protection measures is considered in process plants. Safety measures, including fire protection systems, can generally be classified into inherently safer techniques, engineering (passive and active) protection systems, and emergency response measures [30].

Inherently safer techniques such as an adequate separation distance between hazardous vessels or adopting less hazardous chemicals and operations [31,32] are among macro-layout changes which are usually applicable in the design stage of process plants. Where macro-layout changes (inherent protection) are not possible, micro-layout modifications such as adding passive and active protection systems (add-on protection) can be considered, including sprinkler systems, water deluge systems, emergency shutdown systems, and fireproofing [33]. Emergency response measures such as firefighting can be integrated with engineering protection systems to further delay and control fire escalation.

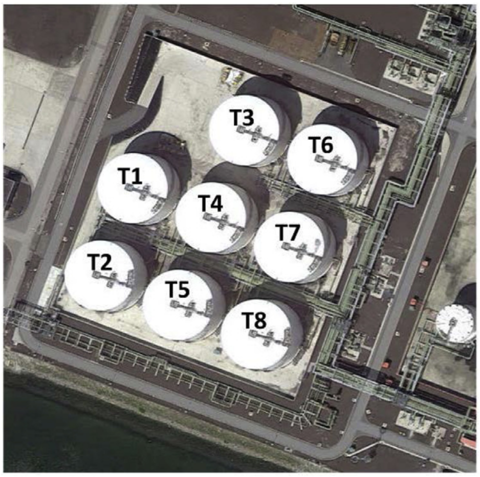
In the present study, low-capacity utilization of process plants as a temporary way of increasing their robustness against impending intentional domino effects is examined. Provisionally reducing the inventory of hazardous chemicals in face of imminent terrorist attacks can significantly reduce the severity and extent of damage. Since low-capacity utilization of a process plant can inflict losses in the form of, among others, loss of revenue or adverse impacts on downstream industries and supply chain, it should be performed based on a cost-benefit analysis. Since the benefit gained from such low-capacity utilization would be an increase in the robustness of the plant, we refer to it as a cost-robust analysis instead.

Based on the out-closeness scores of the storage tanks in Table 5 as an indication of their criticality with respect to intentional attacks, a number of plans can be considered for low-capacity utilization of the plant. The plans, their costs and resulting plant out-closeness scores as an implication of plant robustness have been listed in Table 6. To calculate the graph out-closeness scores resulting from the implementation of each plan, the escalation vectors emitting from respective storage tank(s) have been removed from the graph in Fig. 8(b) and the modified graph's out-closeness has been recalculated. For example, since T4 would be empty for Plan 1, there would not be any directed arcs (escalation vectors) from T4 to the other storage tanks (nodes) in the graph even if T4 is damaged under attack. As can be seen from Table 6, the plant's out-closeness decreases with an increase in the number of empty tanks.

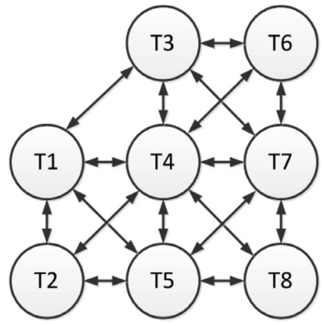
In order to calculate the cost of each plan, we, for illustrative purposes, assume that the cost the plant incurs due to operating under lower capacity can be estimated using an exponential relationship as presented in Eq. (10).

$$C = 1000\ \exp(n - 1) \tag{10}$$

where C is the cost (Euro), and n is the number of empty tanks. The exponential utility function given in Eq. (10) is a concave utility function to indicate the risk aversion [34] of the plant's owner (decision maker) toward the low-capacity utilization of the plant. In other words, the cost incurred grows exponentially with lowering the capacity of the plant. This is because, a number of storage tanks should presumably be in operation in order to keep the plant running even though at a reduced efficiency. Thus, any excessive number of empty storage tanks would be largely averted by the plant owner. However, it should be noted that Eq. (10) is not suitable for process plants with storage tanks of different chemicals, as in the current form, it only accounts for the number of identical tanks with the same volume and the same type of chemical. Having the cost and graph out-closeness of the plans, a "reference-point" optimization technique (Fig. 9) can be used to identify the optimal cost-robust plan for low-capacity utilization of the plant in face of imminent terrorist attacks.



(a)



(b)

Fig. 8. (a) An oil terminal consisting of eight atmospheric storage tanks of oil. (b) Possible fire escalation scenarios as a directed graph.

Table 6
Low-capacity utilization plans.

Plan ID	Description	Graph's out-closeness C_{out}(G)	Cost (€)	Distance from Utopia (ρ_i)
0	No tank is empty	0.322	0	0.231
1	*T4* is empty	0.291	1000	0.223
2	*T4* & *T7* are empty	0.282	2718	0.332
3	*T4*, *T7* & *T5* are empty	0.169	7389	0.743
4	*T4*, *T5*, *T7* & *T1* are empty	0.091	20,085	2.01

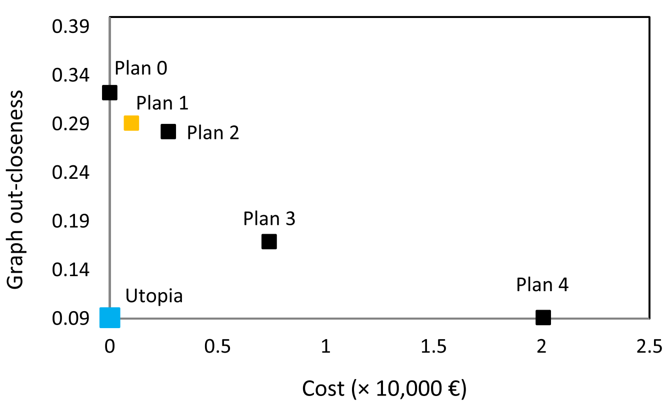


Fig. 9. Application of reference-point decision making to identify optimal strategy for low-capacity utilization.

As displayed in Fig. 9, the point with the lowest cost and highest robustness (the lowest graph out-closeness) is presented as Utopia, which is the closest node that can be identified as the optimal plan. Using Eq. (8), Plan 1 (to empty tank *T*4) turns out to have the shortest distance to Utopia (last column in Table 6), and thus being identified as the optimal cost-robust strategy.

4.3. Discussion

In the present study, we proposed a low-capacity utilization of process plants as an effective way of increasing the plant's robustness against targeted attacks. The term "targeted attack" can basically be taken as an implication of a "rational attacker" with the complete knowledge of the process plant's layout, types of chemicals, and operations, who tries to maximize the expected utility of his attack by targeting the most critical units of the process plant, hoping for triggering the most severe domino effect scenarios. As pointed out in the introduction section, in most real-life situations a decision maker would not always comply with the axioms of "rational decision making".

Particularly, in security risk assessment of hazardous facilities, the identification of target units by attackers can be influenced by a number of factors, including but not limited to the type of attackers (external, internal, hybrid), ease of access and egress for attackers, the intention of attackers, type of weapon and means of delivery, availability and efficacy of physical security barriers, units' attractiveness, etc. For instance, an attacker with the intention of causing mass casualties would be more attracted to a small cylinder of toxic gas such as chlorine rather than to a large storage tank of gasoline despite the fact that the latter could trigger a domino scenario [18].

On top of that, as argued by Bhashyam and Montibeller [35], the expected utility sought by attackers from an attack could be quite "irrational" from defenders' perspective, as, for example, an Islamic suicide bomber would take into account the afterlife in paradise in his expected utility too. As such, setting optimal low-capacity utilization strategies for process plants under the presumption of attackers targeting critical units with the aim of triggering severe domino scenarios should be limited to "rational" attackers with the intention of causing maximum property damage.

Aside from the assumption of a "rational attacker", the application of pareto optimization technique for deciding an optimal low-capacity utilization plan under cost and robustness concerns, which in turn, implies equal importance of both decision criteria in decision making. However, the weights of decision criteria can be tailored in accordance with the level of threat determined by intelligent services. For instance, in case of elevated or imminent threat levels [36], the robustness may take priority over the cost, resulting in a heavier weight for the robustness. Given different weights of cost and robustness, other multi-criteria decision making techniques capable of accounting for relative importance of decision criteria, such as AHP, TOPSIS, and ELECTRE, can be employed [37].

Apart from the above-mentioned modeling features and assumptions, the developed methodology outdoes previous relevant works in several aspects. Among others, Khakzad et al. [22] applied graph metrics and pareto optimization to find an optimal fire protection of process plants against accidental domino scenarios. In their work, for one thing, only single-primary-event domino scenarios were considered, presuming that fire protection of any number of critical units would be an optimal strategy compared with the fire protection of the same number of other units. In the present study, however, not only the possibility of multiple-primary-event domino scenario has been accounted for but also via a Bayesian network methodology it has been demonstrated that protection of critical units, as many as the limited resources allow, would be an optimal strategy – taken for granted in [21,22].

5. Conclusions

In the present study we employed graph theory to assess the vulnerability of process plants to domino effects triggered by intentional attacks. We also compared the results obtained from the graph theoretic approach with those obtained from a dynamic Bayesian network approach to find a good agreement between the two methodologies.

Applying both graph theoretic and dynamic Bayesian approaches, it was demonstrated that a simultaneous attack to process vessels with the highest out-closeness centrality scores would result in more extensive domino effects compared to attacks to any other configuration, thus causing maximum damage within the plant. In this regard, a plant's out-closeness score, that is the average of the out-closeness scores of the process vessels in the plant, was illustrated to represent the plant's vulnerability to such intentional domino effects.

We proposed low-capacity utilization of process plants as a temporary way of reducing their vulnerability (or alternatively, increasing their robustness) to intentional domino effects in the case of impending terrorist attacks (for example, in the case of elevated or imminent alerts [36]). To determine the optimal low-capacity utilization plan, we employed the reference-point optimization technique to make a trade-off between the cost the plant incurs and the robustness the plant gains, both due to low-capacity utilization.

Although the focus of the present study has been on intentional domino effects, the developed methodology – both graph theoretic and dynamic Bayesian network approaches – can also be applied to increase the robustness of process plants to accidental domino effects. This is because, the process vessels with the highest out-closeness would contribute the most to both intentional and accidental domino effects if happen to be the primary events (in the former by intention and in the latter by chance). The developed methodologies can be used in the design phase of process plants so as to design inherently safer and securer plant layouts.

Appendix

Table A.1
Heat radiation intensity (kW/m^2) *Tj* receives from a tank fire at *Ti*. Values less than 15 kW/m^2 are not presented.

Ti↓	*Tj*→	1	2	3	4	5	6	7	8
1		–	46	23	58	24	–	–	–
2		42	–	–	23	55	–	–	–
3		24	–	–	45	–	59	24	–
4		61	25	44	–	46	23	55	24
5		23	58	–	42	–	–	22	56
6		–	–	59	25	–	–	46	–
7		–	–	24	60	25	44	–	46
8		–	–	–	23	57	–	42	–

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ress.2018.03.030.

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