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Optimizing safety barrier allocation to prevent domino effects in large-scale chemical clusters using graph theory and optimization algorithms

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ABSTRACT

Domino effects are high-impact low-probability events that can have catastrophic consequences. To prevent and to reduce risks related to such events, safety barriers (SBs) are crucial. However, the initiation, propagation, and stopping processes of domino effects are characterized with complexity and uncertainties and hence they are unpredictable. This makes it challenging to allocate SBs based on predicted probabilities. In this study, a multi-objective optimization model which integrates graph theory with Non-dominated Sorting Genetic Algorithm II (NSGA-II) was proposed to allocate add-on SBs effectively. Graph metrics were used to quantify the escalation risks related to storage tanks and to optimize the allocation of add-on SBs, thereby minimizing the consequences of a domino effect under a budget constraint. The results of the case study demonstrate great efficiency in finding globally optimal strategies with a largest reduction of 94.3% in the out-closeness score due to the implementation of add-on SBs, allowing decision-makers to choose the most preferable investment strategy in face of domino effect risk. Our study therefore provides a novel approach to achieve an optimal allocation of add-on SBs globally and can be useful in preventing domino effects in large-scale chemical clusters equipped with a large number of storage tanks.

1. Introduction

As the demand for energy grows larger, chemical industrial clusters are showing a trend of expansion and centralization, along which the level of co-existed hazard rises. Being high-impact low-probability (HILP) events that can have catastrophic consequences (Khakzad, 2015), domino effects were defined by Reniers and Cozzani (2013) as a phenomenon that a primary unwanted scenario propagates to nearby installations, triggering a chain of accidents, resulting in overall consequences more severe than those of the primary event. Chen et al. (2012) analyzed 318 domino effects and discovered that 41.8% of which initiated in the chemical storage area. Fire accounts for 52.4% of the escalation events in process and storage plants, making it the most common primary domino scenario (Darbra et al., 2010). Therefore, fire-induced domino effects in chemical storage areas are chosen as the accident scenario to be analyzed in the current study. For the prevention of domino effects, safety barriers (SBs) play a crucial role in mitigating and preventing such catastrophic events, the probability of fire escalation can be reduced by several orders of magnitude with SBs in place (Khakzad et al., 2017a). How to cost-effectively allocate various types of add-on SBs within a budget range to achieve a trade-off between economy (cost) and safety (expected benefit) has become a real-life problem.

To tackle the risk assessment and evolution modeling of domino effects, methodologies based on event tree analysis (ETA) (Alileche et al., 2017), Bayesian networks (BNs) (Khakzad et al., 2013; Khakzad, 2015), Petri-net models (Zhou and Reniers, 2017; Zhou et al., 2023), Monte Carlo simulations (Abdolhamidzadeh et al., 2010), graph metrics (Khakzad and Reniers, 2015) have been well developed in the last two decades. Compared to the earlier studies of domino effect modeling of which the models were mostly static and over-simplified, more emphases have been laid on the dynamic evolution (Khakzad, 2015; Chen

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Nomenclature

T	Set of storage tanks.
U	Set of different types of SBs.
K	Set of the allocation strategy of SBs.
B	Safety investment budget, in €.
P_u	The PFD value of safety barrier u
Q_{th}	Threshold value of heat radiation, in kW/m^2.
φ_u	Intensity reduction factor of safety barrier u.
$H_{k,u}$	Binary value, equals to one if safety barrier u is included in the allocation strategy k, zero otherwise
R	Expected benefit under different allocation strategies of SBs.
$H_{k,u}$	Binary value, equals to one if safety barrier u is included in the allocation strategy k, zero otherwise.
$C_{i,k}$	The cost of the allocation strategy k for tank i, in €
$c_{i,u}$	The cost of safety barrier u for tank i, in €
$Cout_i$	Mitigated out-closeness score of tank i
E_i	Economic loss of tank i due to domino effect, in €
$q_{i,j}$	Heat radiation emitted from tank i to tank j, in kW/m^2
$d_{i,j}$	Weighted heat radiation emitted from tank i to tank j
$S_{i,k}$	Binary value, equals to one if allocation strategy k is appliable to tank i, zero otherwise
θ_k	Reduction ratio of the heat radiation under allocation strategy k.
$X_{i,k}$	Binary decision variable, equals to one if plan k for tank i is selected, zero otherwise

et al., 2022), synergistic effect (Ding et al., 2020b; Hou et al., 2022) and risk management (Khakzad et al., 2014, 2017b; Chen et al., 2020a) of domino effects in recent years. It should be noted that current studies with relate to the risk assessment of domino effects are mainly based on predicted probabilities, which suffer a drawback that estimation may be unreliable as they are based on insufficient knowledge and inappropriate assumptions (Johansson et al., 2013). In fact, the initiation, propagation, and stopping processes of domino effects are characterized with complexity and uncertainties and hence they are unpredictable.

Vulnerability analysis, on the other hand, can better explain the composition and critical elements of risk from the hazard sources (Huang et al., 2022). Khakzad and Reniers (2015) defined vulnerability as the capability of a unit or process plant to foster either the onset or the escalation of potential cascading effects. The focus of the vulnerability analysis is to explore the system weaknesses by identifying the critical units in a systematic way (Johansson et al., 2013), meaning that the relative importance is given more emphasis than the precise values of failure probability during the analysis of domino effects. Specifically, the methodology based on graph theory has been proven to be effective in the vulnerability analysis by identifying the critical units through certain graph metrics (Khakzad et al., 2017b, 2016; Khakzad and Reniers, 2015), especially for domino effect analysis of large-scale chemical clusters, therefore it is adopted in this study to conduct further analysis.

As for the management of domino effects, among the five research domains that Chen et al. (2020b) pointed out, the optimization of barriers in the area of safety barrier management is the main study object of this work. It was until around a decade ago that the performance of SBs was explicitly analyzed for domino effect assessment. Landucci et al. (2016), (2015) quantitatively analyzed the performance of SBs in reducing the domino risk through methodologies based on Layer of Protection Analysis (LOPA) and ETA, the developed procedure as well as the obtained results have been widely used by relative studies. In addition, methodologies based on dynamic Bayesian networks (DBNs) (Khakzad et al., 2017a), bow-tie diagrams (Ding et al., 2020a) and simulation approaches (Yuan et al., 2023) were also proposed for the performance assessment of SBs. With the performance (i.e., availability and effectiveness) of SBs being quantified, more recent studies have been working on the optimization of SBs as summarized in Table 1.

Each of the listed studies can be considered consisting of two major parts, i.e., risk assessment and optimization of SBs. It can be seen that BNs have been applied by many of these studies as a tool to effectively model the domino-related risks. Meanwhile, the shortcoming of which is obvious, it lies in the fact that the computation complexity grows exponentially with the network growing larger, also the changes of propagation path due to various combinations of add-on safety barrier allocation make it even harder to model the decision-making process. In terms of the optimization of SBs, among the researches listed in Table 1, the budget constraints of safety investment were usually randomly selected in the related studies, without considering the most profitable budget range where a trade-off can be achieved between safety investment and domino risk. Thus, there is a need to develop an effective model to investigate the budget range where safety investment is the most reasonable, and the way to optimally allocate add-on SBs under this budget for the prevention of domino effects in large-scale chemical clusters.

Generally, risk assessment and the optimization are two essential elements of the decision-making process of safety investment, usually accompanied by various conflict of interests where different decision objectives should be balanced meticulously to achieve a desirable outcome. In the realm of multi-objective optimization, genetic algorithms (GA) have been very popular in solving such problems, yet they have never been used to solve allocation problems related to domino effect vulnerability assessment based on graph theory, known for its effectiveness in identifying the most dangerous units in chemical areas. Therefore, it is necessary to develop a model which take advantage of both graph theory and the GA to achieve the optimization objectives.

In the present study, a multi-objective optimization model was developed for the optimal allocation of add-on SBs in chemical clusters. This work aims to illustrate the efficiency of the proposed methodology in selecting the optimal solution as well as reducing the risk of fire-induced domino effects especially in large-scale chemical clusters. Graph theory was innovatively integrated with NSGA-II to achieve a global optimum, rather than choosing the “optimal” solution from pre-defined strategies (Khakzad et al., 2016). Moreover, the selection processes of the appropriate safety investment budget and the optimal allocation strategy under this very budget were demonstrated through an industrial case study. The remainder of this paper is organized as follows. Section 2 presents the theoretical basis of this study. The methodology developed for the optimal allocation of SBs is presented in Section 3. Then, the proposed approach is demonstrated through an illustrative case in Section 4. Section 5 provides the results and discussion of the current study. Finally, conclusions are presented in Section 6.

2. Theoretical basis

The framework of the methodology is shown in Fig. 1. The proposed approach is composed of four steps. Starting with the domino vulnerability analysis, where graph theory is applied to model storage tanks and the intensity of heat radiation as vertices and edges, respectively, to obtain the centrality scores for the vulnerability analysis of the tank area before the implementation of add-on SBs. Step 2 aims to quantify the performance of SBs under different allocation strategies, an intensity reduction model is proposed based on previous studies. The structuring of the safety investment optimization model is presented in Step 3, two cases are developed and solved with NSGA-II, one is for the evaluation and selection of a preferable safety investment, the other is for the allocation problem under the selected budget constraint. Finally, the obtained results are further analyzed in Step 4.

Table 1
Previous researches related to the optimal allocation of SBs.

Publications	Methodologies		Scenarios	Optimization objectives
	Risk assessment	Allocation of safety investment		
(Khakzad et al. (2017b)	graph theory	multicriteria decision analysis techniques such as reference point	fire-induced domino effects	total cost of passive fire protection and the graph level out-closeness score
Mancuso et al. (2017)	Bayesian Belief Networks	implicit enumeration algorithm coded in C++ language	system failure in nuclear systems	minimize the expected disutility
Khakzad et al. (2018)	Bayesian networks	limited memory influence diagram (LIMID)	fire-induced domino effects	expected utilities of fireproofing plans
Janssens et al. (2015)	predefined hazard scenarios	metaheuristic approach coded in C++ language	domino event	maximize the time-to-failure (ttf) of a chemical installation
Eslami Baladeh et al. (2019)	HAZOP	NSGA-II and a lexicographic model	a gas wellhead in the oil and gas industry	minimizing the maximum risks; maximizing the total risk reduction
Mancuso et al. (2019)	dynamic Bayesian networks	implicit enumeration algorithm coded in C++ language and linked to GeNIe Modeler	time-dependent accident scenarios	minimizing the expected disutility
Chen et al. (2020a)	dynamic graph	"PROTOPT" optimization algorithm based on "maximin" strategy	intentional domino effects	maximizing the minimum NPVB
Du et al. (2020)	conventional approach	heuristic algorithm using MATLAB	fire-induced domino effects	total number of fatalities and the losses caused by domino effects
Guo et al. (2022)	event tree analysis and probit models	R_minmax uncertain decision criterion and cost-effective risk reduction optimization model	worst-case domino scenario	risk and economic cost
Yuan et al. (2023)	Simulink-based dynamic barrier modeling	cost-effectiveness analysis combined with genetic algorithms	barrier maintenance optimization for safety and security scenarios	maximizing the effectiveness of barrier; minimizing the cost
Khakzad (2023)	approach based on thermal dose	Dijkstra's algorithm and mathematical programming	evacuation considering major tank fires	minimize the risk of casualties
Di Maio et al. (2023)	dynamic phenomenological model	four different multi-objective optimization algorithms	NaTech accidents	the mitigative power of the system and the cost of the improvements

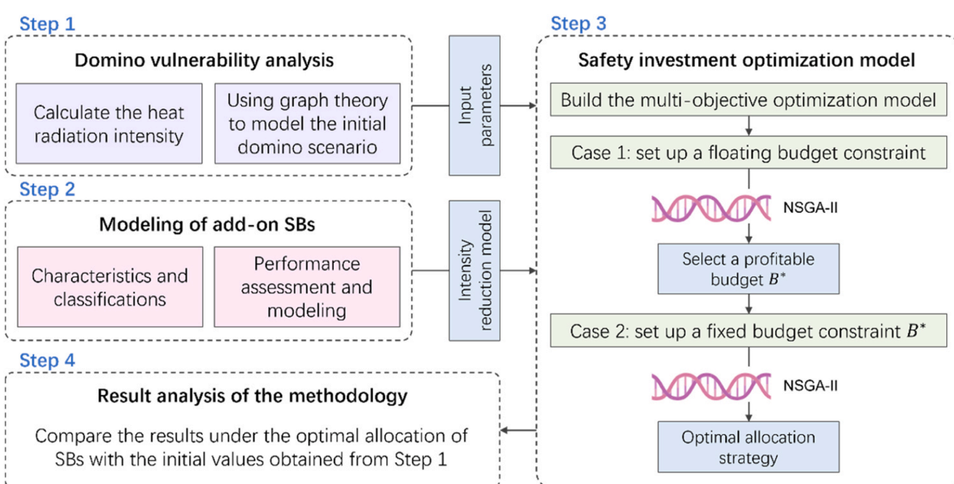

Fig. 1. Framework of the proposed approach.

2.1. Graph theory

In mathematics, a graph is an ordered pair $G = (V, E)$ comprising a set of vertices $V = \{v_1, v_2, \ldots, v_n\}$ and a set of edges $E = \{e_1, e_2, \ldots, e_m\}$. Weighted directed graphs are directed graphs (digraphs) with weights assigned to their arrows. In a directed graph, a walk from the vertex v_i to v_j is a sequence of vertices and edges starting from v_i and ending in v_j when each intermediate vertex can be traversed several times. A path, however, is a walk from v_i to v_j where each intermediate vertex is traversed only once. As for the weights of elements in a graph, a set of numerical values can be assigned to either the vertices or edges of the graph which can be denoted as w_V and w_E, respectively (Khakzad and Reniers, 2015). The geodesic distance between v_i and v_j, denoted by $d_{ij} = d(v_i, v_j)$, is equal to the sum weights of the edges in the shortest path from v_i to v_j. If there is no path between v_i and v_j, then $d_{ij} = \infty$. We refer to only edge weights in the current study, thus a graph G can be defined as $G = (V, E, W)$, a triplet formed by a finite set of n vertices, a set of directed edges and a set of positive weights.

In graph theory, centrality concepts were first developed in social network analysis to measure the importance of nodes (vertices) in a network, many metrics and indices related to centrality have been proposed to specifying the components as well as their interrelationships over the years. Among which "degree", "closeness", and "betweenness" measures (Freeman, 1978) have been very popular. According to Freeman, in order to account for their contributions in identifying most critical vertices or to rank different structures at a graph level, they are further divided into two categories: vertex-level metrics (point centrality) and graph-level metrics (graph centrality).

- Vertex-level metrics

The degree of a vertex v_i, $C_D(v_i)$, is the number of edges that are incident to the vertex in unweighted graphs, whereas in weighted graphs it is equal to the total weights of related edges. The degree of a vertex can be further unfolded into in-degree and out-degree depending on the head ends or tail ends of the arrow adjacent to the vertex.

$$C_D(v) = \deg(v) \tag{1}$$

The closeness $C_C(v_i)$ of a vertex v_i calculated as the reciprocal of the sum of the length of the shortest paths between the vertex and all other vertices in the graph. Similarly, the out-closeness $C_{C-out}(v_i)$ is defined to be the inverse of the total distance from v_i to every other vertex, while the in-closeness $C_{C-in}(v_i)$ otherwise.

$$C_{C-out}(v_i) = \frac{1}{\sum_j d_{ij}} \tag{2}$$

$$C_{C-in}(v_i) = \frac{1}{\sum_i d_{ji}} \tag{3}$$

Betweenness centrality $C_B(v_i)$ of v_i is based upon the frequency with which a vertex falls between pairs of other vertices on the shortest or geodesic paths connecting them, it is defined as the ratio of the distances between all pairs of other nodes (i.e., between v_j and v_k, $j \neq i \neq k$) that traverse v_i, denoted as $d_{jk}(v_i)$, to the total distance within the graph regardless of whether or not they traverse v_i:

$$C_B(v_i) = \sum_{j,k} \frac{d_{jk}(v_i)}{d_{jk}} \tag{4}$$

While in case of comparing the above centrality of points from different graphs, there is a need for a measure that is independent of network size. Therefore, for a graph with n vertices, these centrality measures need to be standardized as follows:

$$C_D^{'} = \frac{C_D}{n-1} \tag{5}$$

$$C_C^{'} = C_C \times (n-1) \tag{6}$$

$$C_B^{'} = \frac{2 \times C_B}{(n-1) \times (n-2)} \tag{7}$$

- Graph-level metrics

From the perspective of a whole network, graph-level metrics are introduced to measure the compactness of a graph as an extension of the point centrality. Based on the three above-mentioned distinct properties, the corresponding graph-level metrics can be generated. According to Khakzad and Reniers (2015), let $C_X(v_i)$ be one of the vertex-level metrics defined above, $C_X(v^*)$ be the largest value of $C_X(v_i)$ for any vertex in the network, the graph-level centrality measure C_X can be calculated as:

$$C_X = \sum_{i=1}^{n} [C_X(v^*) - C_X(v_i)] \tag{8}$$

2.2. Optimization based on NSGA-II

For multi-objective optimization problems with generally conflicting objectives, evolutionary algorithms such as GA are proved to be well-suited for this class of problems by using specialized fitness functions and introducing methods to promote solution diversity (Konak et al., 2006). It is a well-known metaheuristic algorithm capable of solving multi-variable, nonlinear, and combinatorial optimization problems through a process of selection, crossover and mutation. A simplified scheme of GA is shown in Fig. 2.

Being one of the most popular variations of GA, NSGA-II is an improved version of NSGA, which is also a well-known evolutionary algorithm to find Pareto-optimal solutions in multi-objective problems. Comparing to other constraint-handling strategies, the application of NSGA-II has shown great advantages in solving more complex and real-world multi-objective optimization problems (Deb et al., 2002).

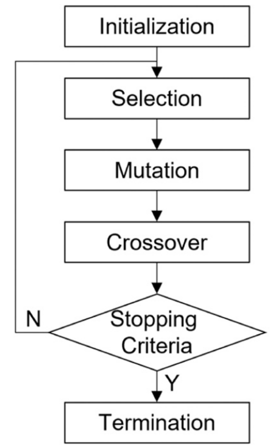

Fig. 2. Scheme of genetic algorithm.

However, in spite of the high efficiency of NSGA-II, it should be clarified that a strict optimality cannot be necessarily guaranteed considering the uncertainties and objectives with conflictions, our goal in this work is to adopt NSGA-II as a tool to find the "best possible" solution(s) to the developed multi-objective mathematical model, and the final choice can be made by the decision-makers.

3. Methodology

3.1. Vulnerability analysis of domino effect

In order to analyze the vulnerability of a storage plant in case of a potential domino effect with pool fire as its primary accident scenario and heat radiation intensity as its escalation vector, the application of the graph theory is demonstrated through a simplified hypothetical example modified from the work of Khakzad et al. (2017b) to which a pressurized vessel is added to account for different types of SBs. Fig. 3 shows the layout of the hypothetical chemical storage plant comprising of four atmospheric vessels (T1-T4) and a pressurized vessel (P1).

For illustrative purposes, the accident scenario and escalation vector have been considered to be only pool fire and heat radiation (kW/m^2), respectively. The heat radiation intensities emitted from T_i to T_j (denoted as q_{ij}) can be calculated using Areal Locations and Hazardous Atmospheres (ALOHA) (U.S. Environmental Protection Agency, 2016), which is a freely accessible software adopting commonly-used mathematical models to present the consequences of an accident scenario (Khakzad, 2015).

The chemical cluster in Fig. 3 can be modeled as a weighted directed graph where $T = \{1, 2, \ldots, 5\}$ refers to the storage tanks as vertices. In

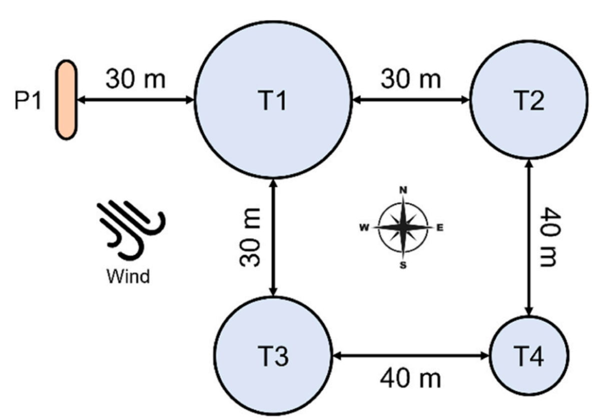

Fig. 3. Schematic of a hypothetical chemical storage plant.

particular, the pressurized vessel P1 is denoted as T5 to unify the narrative of the storage tanks in this case. Due to the deterministic nature of the present study, we include the failure probabilities in the form of the expected weights of the directed edges to represent the potential domino effects, denoted as d_{ij}, which is assigned as the ratio of the threshold value and the calculated heat radiation associated with the edge as shown in Eq. (9), where q_{ij} denotes the heat radiation intensities emitted from T_i to T_j, the threshold values Q_{th} for atmospheric and pressurized vessels are 15 kW/m^2 and 40 kW/m^2 (Cozzani et al., 2006), respectively. Thus, a larger value of d_{ij} means a longer distance between T_i and T_j, resulting in a weaker impact.

$$d_{ij} = \frac{Q_{th}}{q_{ij}} \tag{9}$$

Plot the tank area as a weighted digraph, the related centrality metrics, i.e., out-closeness scores, betweenness scores and out-degree of each tank, can be calculated using the "centrality" function in MATLAB. To measure the vulnerability of the entire chemical cluster, the standardized graph-level out-degree can also be calculated according to Eq. (8).

It should be noted that different from unweighted graphs, whose degree centralities are measured by the number of edges, the degree value of a vertex is positively correlated with its importance, while in weighted graphs the degree value of a vertex is calculated based on the weights assigned to the edges, therefore, a smaller value means a more compact structure around the vertex, thus making it more crucial comparing to other vertices. Follow the above-mentioned procedures, the initial centrality metrics of the tanks in the illustrative chemical cluster can be acquired. In terms of vertex-level metrics, T1 and P1 are considered to be the most dangerous units in the tank area. T1 is also identified as the most crucial unit in facilitating the propagation of domino effect since the betweenness score for which is the highest. The results achieved in the vulnerability assessment of a potential domino effect can be adopted as the basis of the optimization model, they can be further compared with the final results under the optimal allocation strategies to demonstrate the efficiency of the proposed approach.

3.2. Modeling of add-on safety barriers

According to AIChE (Grossel, 2002), SBs were classified into three categories, i.e., passive barriers, active barriers, and procedural and emergency measures. However, we only consider the first two since the current study is focused on add-on SBs. The availability, effectiveness and heat radiation intensity reduction factor of different SBs were scrutinized and quantified based on previous studies for the allocation problem, and the results were used to model the performance of SBs in terms of different accident scenarios. The definitions of the three properties (Landucci et al., 2015) are listed as follows:

- Availability (P), defined as the probability of failure on demand (PFD) of the safety barriers;
- Effectiveness (η), defined as the probability that the safety barrier, once successfully activated, will be able to prevent the escalation;
- Intensity reduction factor (RF, denoted as φ), represents the reduction in the heat load due to the presence of add-on SBs, i.e., $Q_m = \varphi \times Q$, where Q_m is the mitigated heat radiation and Q is the original heat radiation without SBs.

A generic active protection device is a system or a barrier which requires either power or external activation to trigger the protection action where a sequence of detection-diagnosis-action is needed (Lees, 1996). This type of protection systems aims to deliver a firefighting agent either to extinguish the flame or to cool the equipment walls (Ovidi et al., 2021). Three types of active add-on SBs are included and analyzed in this study:

(i) Automatic fire sprinkler systems (SPS) are designed to activate if a fire develops in their area of protection and limit or suppress the further development of the fire (Frank et al., 2013). Water is the only fire-fighting agent considered under the term of SPS, this type of protection is typically installed on atmospheric tanks to provide effective control of primary fire and prevention of fire spread in nearby units.
(ii) Foam-water sprinkler systems (FWS) use additional water-based foam as the fire-fighting agent to suppress the primary fire. They are considered to be more effective than conventional SPS and are usually at a higher price.
(iii) Water deluge systems (WDS) provide a spray curtain on exposed surfaces to absorb heat radiation, this type of safety barrier is typically installed on pressurized vessels to shield the target vessel from a primary fire.

A generic passive protection device is a system or a barrier which does not require either energy or external activation to provide the protection action (Grossel, 2002), it can mitigate the physical effects imposed by external fire exposure on the target. Among which fireproof coating (FPC) is selected as the only passive add-on SB in this paper.

This type of SB prolongs the time to failure (*ttf*) of the target vessel through high performance fireproofing materials applied on the external surface of the equipment. It should be noted that instead of quantitatively analyzing the time dependence of FPC in detail by means of *ttf*, this paper is dedicated to solving the allocation problem of safety investment. Thus, for illustrative purposes, in this study we assign a reduction factor $\varphi = 0.1$ to demonstrate the protective effect of FPC. To account for the availability and effectiveness of FPC, a conservative PFD value $P = 1 \times 10^{-3}$ (Grossel, 2002) and an effectiveness value $\eta = 0.999$ (Landucci et al., 2016) are used for the consideration of degradation phenomena of FPC.

The aim of the current study is to search for the safety investment strategy with the optimum combination of SBs, different from previous works which is mainly based on pre-defined plans, we intend to use exhaustive search to achieve a global optimum. However, the accident scenarios may grow exponentially with the growing number of SBs as well as the combination of them (e.g., the plan may involve a single SB or the combination of both active and passive barriers). Table 2 shows the input parameters of protection plans considered in this work, most of the values are derived from previous studies. To account for the interaction of SBs when two of them combined together, a pessimistic strategy derived from Eslami Baladeh et al. (2019) is adopted, in which the minimum PFD and RF values of the selected SBs are considered conservatively instead of those resulted from the implementation of all SBs.

Therefore, in order to measure the vulnerability of the tank area in case of a fire-induced domino effect and the effect of a protection plan, the change of heat radiation intensity for each tank before and after the implementation of the plan should be estimated. Let $K = \{1, 2, \ldots, r\}$ be a set of allocation strategies of SBs. Considering the indicators of different SBs, θ_k, the reduction ratio of the heat radiation intensity under safety barrier allocation plan k ($\forall k \in K$) can be calculated as follows:

$$\theta_k = \sum_{v \in \{1,2\ldots V\}} \prod_{u \in O} \begin{cases} P_u, Y_{u,v} = 1 \\ (1 - P_u)\varphi_u \eta_u, Y_{u,v} = 0 \end{cases} \tag{10}$$

$$V = 2^A \tag{11}$$

$$A = \sum\nolimits_{u \in U} H_{k,u} \tag{12}$$

Where P_u is the PFD of SB u; φ_u and η_u are reduction factor and effectiveness of SB u, respectively; V is the number of combinations of the scenarios whether the allocated SBs fail or not; a set $O = \{u | H_{k,u} = 1, u \in U\}$ consists of the SBs which are selected for the allocation strategy; A is the number of the allocated SBs; $Y_{u,v}$ denotes for whether SB u fails or not

Table 2
Input parameters of protection plans (Landucci et al., 2015) implemented in the proposed model for the case study in Section 4.

k	Protection plan	PFD (P_i)	Effectiveness (η_i)	Intensity reduction factor (φ_i)	Cost (c_i)	Other descriptions
1	No SBs implemented	1	N.A.	N.A.	N.A.	
2	SPS (bladder tank)	3.76×10^{-3}	0.954	0.35 (Janssens et al., 2015)	250 K€ (Janssens et al., 2015)	Only considered for atmospheric storage tanks
3	FWS (in-line educator)	5.43×10^{-3}	0.954	0.25 (Janssens et al., 2015)	350 K€ (Janssens et al., 2015)	Only considered for atmospheric storage tanks
4	WDS	4.33×10^{-2}	1	0.5	200 K€	Only considered for pressurized vessels
5	FPC	1×10^{-3}	0.999	0.1[a]	410 €/m^2 (Paltrinieri et al., 2012)	
6	SPS+FPC	Composite probability	0.999[a]	Depend on the working condition of each safety barrier	$c_2 + c_5$	Only considered for atmospheric storage tanks
7	FWS+FPC		0.999[a]		$c_3 + c_5$	Only considered for atmospheric storage tanks
8	WDS+FPC		0.999[a]		$c_4 + c_5$	Only considered for pressurized vessels

[a] Assumed values for illustrative purposes.

under the accident scenario v, equals to 1 if it fails, zero otherwise, $v \in \{1, \quad 2\ldots V\}$, $u \in O$.

In the present study, a simple composite probability, i.e., gate type "a" in the work of Landucci et al. (2015), is applied in the performance assessment of both active and passive protection systems, in which availability is expressed as PFD, multiplied by a single probability value expressing the probability of barrier success in the prevention of the escalation. Note that due to the deterministic nature of the proposed methodology, failure probability is not considered in the calculation of centrality metrics, instead, those metrics are calculated based on expected heat radiation (i.e., expected weight) (Khakzad et al., 2017b), which is the product of the unmitigated heat radiation intensity and θ_k to stand for the mitigated heat radiation intensity after implementing safety barrier k. Finally, the centrality metrics of the tanks can be updated based on the mitigated heat radiation intensities to account for the effectiveness of different sets of SB allocation strategies in the following optimization model.

3.3. Building the mathematical model

When it comes to the allocation of safety investment, the main issue should be focused on how to balance the cost and return in a most effective way due to the marginal diminishing effect of safety investment. Moreover, the amount of the limited budget is also a key factor in reducing the domino risk due to the implementation of different SBs.

To facilitate a more nuanced understanding of the challenges outlined previously, the mathematical problem that requires modeling and subsequent optimization is delineated as follows. Within expansive chemical storage areas, the effective allocation of safety resources to mitigate the risks and consequences associated with domino effects emerges as a significant real-world challenge. These domino effects are identified as the primary optimization objectives of this research. They may be defined as either singular or multiple targets, represented by diverse hazard indices, which are selected based on the preferences of the decision-makers. The principal constraint of this optimization problem, analogous to a knapsack problem, is the budget allocated for the acquisition of additional safety barriers (SBs). Leveraging the findings from vulnerability analysis and incorporating data pertaining to supplementary SBs as input variables, this study endeavors to identify an optimal solution within a predefined budgetary framework. Specifically, it aims to allocate safety resources in the most cost-effective manner to avert domino effects. The elaboration of this mathematical model is comprehensively presented in the subsequent sections of this document.

This paper relates domino effect risk to economic cost through a "risk reduction" value R (referred to expected benefit in this work, a representation of the relative risk reduction), denoted as the sum product of the reduction in the out-closeness score $\Delta Cout$ and the property loss E of each tank (Eq. (13)), where $\Delta Cout$ is the difference between the initial out-closeness score of tank i ($Cout_i^0$) and the reduced score after implementing SBs ($Cout_i$). Note that in the present study, only the consequence caused by property damage is considered, which refers to the cost of replacement of the storage tank and the chemicals stored in the tank.

$$R = \sum_{i \in T} E_i \left(Cout_i^0 - Cout_i \right) \tag{13}$$

Despite maximizing the expected benefit from a macroscopic angle, decision-makers may give more attention to the most dangerous unit, that is, the storage tank with the highest out-closeness score in this study. Therefore, minmax criterion (Aissi et al., 2009) is introduced in order to search for the optimal allocation of SBs which minimizes the out-closeness score of the most dangerous unit. A budget B is designated as a constraint in the developed model.

To mathematically state the problem, let $T = \{1, 2, \ldots, m\}$ be a set of storage tanks, set $U = \{1, 2, \ldots, n\}$ denotes different types of SBs, based on the vulnerability analysis of the storage plant as well as the input parameters achieved from above, the mathematical model with two objective functions can be developed as follows:

$$\text{lexicographic} f(x) = (f_1(x), f_2(x))$$

$$f_1(x) = \max R$$

$$f_2(x) = \min\max Cout_i \, , i \in T\# \tag{14}$$

$$s.t.\ X_{i,k} = \{0, 1\}, \forall i \in T, \forall k \in K \tag{15}$$

$$\sum\nolimits_{k \in K} X_{i,k} = 1, \forall i \in T \tag{16}$$

$$X_{i,k} \le S_{i,k}, \forall i \in T, \forall k \in K \tag{17}$$

$$\sum\nolimits_{i \in T} \sum\nolimits_{k \in K} C_{i,k} X_{i,k} \le B \tag{18}$$

$$C_{i,k} = \sum\nolimits_{u \in U} c_{i,u} H_{k,u}, \forall k \in K \tag{19}$$

$$q_{i,j} = q_{i,j}^0 \sum\nolimits_{k \in K} \theta_k X_{i,k}, \forall i \in T, \forall j \in T \tag{20}$$

The objective function $f(x)$ in Eq. (14) is divided into two objectives $f_1(x)$ and $f_2(x)$, in a lexicographic order, these objectives can be ranked by the decision maker in order of preference or importance. The first objective function $f_1(x)$ aims to search for the combination of SBs which maximizes the total risk reduction, while the second one $f_2(x)$ minimizes the out-closeness score of the most crucial unit, these scores can be calculated through the method in Section 2.1.

More specifically, the constraints are described as follows. Constraint (15) represents the decision variable whether strategy k is selected for tank i or not. Constraint (16) guarantees that only one strategy can be selected for tank i to reduce the heat radiation intensity in the decision process. Because of the properties of certain SBs, for example, WDS is not applicable for atmospheric tanks, constraint (17) is used to make sure the selected strategies are suitable for each unit. The total cost of each strategy is calculated and limited to a predefined budget B in Constraint (18). Constraint (19) is used to compute the cost of each allocation strategy ($C_{i,k}$) for tank i under strategy k, different from $c_{i,u}$, the values of $C_{i,k}$ vary between tanks with different surface areas due to the cost of FPC. Constraint (20) is used to calculate the heat radiation intensity considering the effect of SBs, in which θ_k can be computed through Eqs. (10) – (12).

3.4. Optimization technique based on NSGA-II

It can be calculated that for a chemical cluster consisting of m storage tanks and a number of r allocation strategies of SBs ($m \in T, r \in K$), a maximum number of m^r can be generated to consider all the combinations of allocation strategies, making it extremely difficult to conduct an exhaustive search, therefore the application of evolutionary algorithms becomes necessary. To achieve a global optimum, the developed mathematical model was further coded with program language in MATLAB, a tailored optimization algorithm, NSGA-II, was applied in order to solve the multi-objective optimization problem. Fig. 4 shows the flowchart of the NSGA-II developed in this study.

The solving process of the developed NSGA-II model is basically made up of three parts as shown in Fig. 4, that is, the input phase, the real number encoding and decoding phase, and the evolution phase. Firstly, it starts with the setup of objective function and constrains, $Cost(i, inds)$ denotes the amount of money already used for tank i under the scheme number $inds$. Input the calculated parameters along with the initial values $i = 1$ and $U = 0$, representing the tank ID and the initial cost, respectively. In the second phase, the data of the storage tank is encoded in binary where the code length is n and the range of value for each gene is set to [0,1]. Search for the applicable sets of plans S for tank i, the number of these sets is denoted as K, read the randomly created gene for tank i, $Gene(i)$, and the scheme number of the selected plans can be calculated. Update U and repeat the procedure until all tanks are considered, the initial population can be generated, and the problem is thus abstracted into a binary string that can be operated with cross mutation. Finally, to better elaborate the evolution phase, the simplified flow chart in Fig. 4 is further described as follows: 1) sort the initial population P_t (size N) based on the nondomination, offspring population Q_t (size N) can be generated after selection, crossover and mutation, a population R_t (size $2N$) is created by combining P_t and Q_t; 2) perform a non-dominated sorting on R_t, meanwhile calculate the crowding distance of the element in each non-dominated front, select the most suitable elements to form a new parent population P_{t+1} (size N) based on the nondomination and crowding distance; 3) generate the new offspring population Q_{t+1} (size N) through selection, crossover and mutation, combine P_{t+1} and Q_{t+1} to obtain a new population R_{t+1} (size $2N$). Repeat the procedure until the stopping criteria is satisfied, i.e., the maximum number of generations in this study. However, note that it is not the scope of this study to elaborate the GA theory, it is adopted as an effective tool to solve the aforementioned problem. More detailed illustrations of NSGA-II and GA can be found in previous studies (Deb et al., 2002; Konak et al., 2006; Caputo et al., 2011; Di Maio et al., 2023).

4. Case study

In order to demonstrate the novel optimization model developed in this paper, a large-scale chemical cluster is considered. The layout is shown in Fig. 5, this facility consists of 20 storage tanks with different configurations and substances, among which T1-T14 are atmospheric vertical cylindrical tanks and P1-P6 are pressurized spherical tanks. The main features of the storage tanks are presented in Table 3.

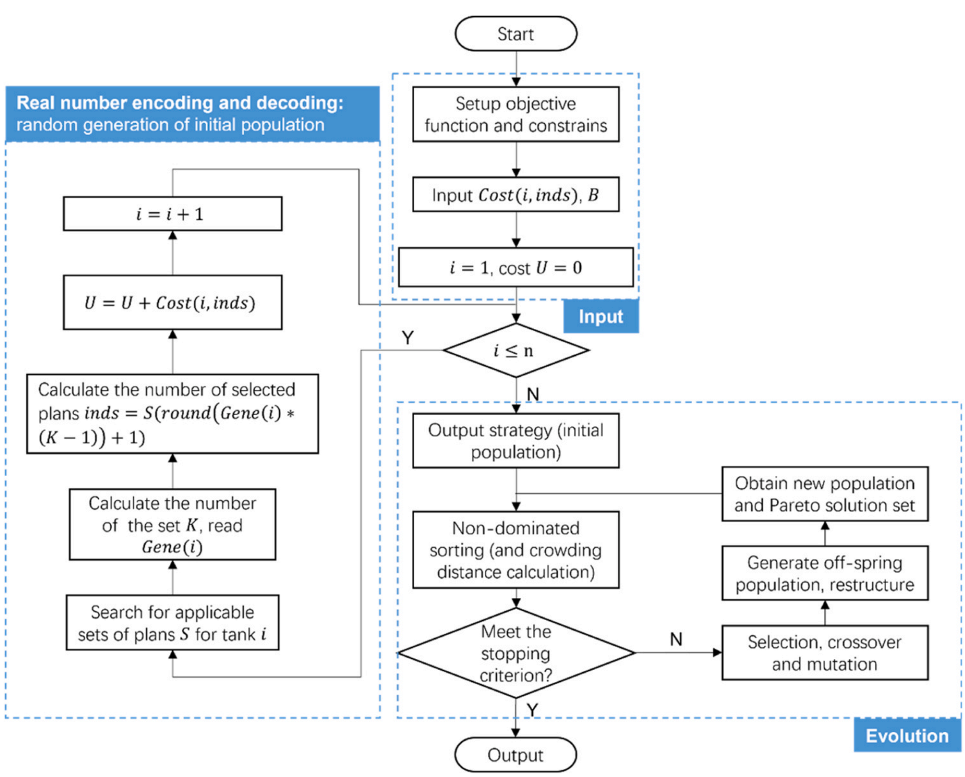

Fig. 4. Flowchart of the NSGA-II developed for the allocation of SBs.

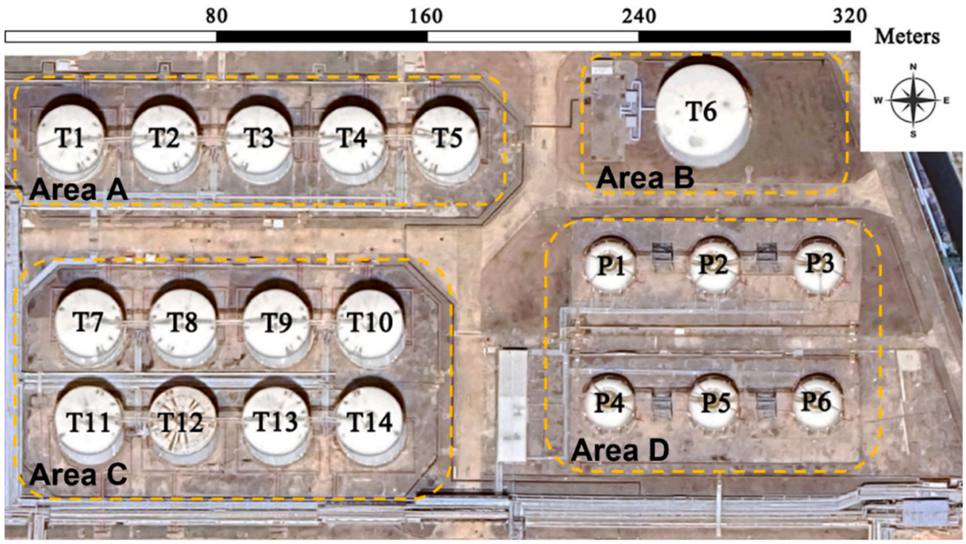

Fig. 5. Layout of a chemical storage area.

Table 3
Main features of the storage tanks in Fig. 5.

	Tank ID	Substance	Design Pressure (MPa)	Diameter (m)	Height / Length (m)	Surface area (m^2)	Capacity (m^3)	Inventory (ton)	Value (M€)
Area A	T1, T2, T5	Sec-Butyl acetate	0.1	15	17	977	3000	2000	1.8
	T3-T4	Sec-Butyl acetate	0.1	15	17	977	3000	2500	2.2
Area B	T6	Toluene	0.1	22	15	1416	5700	4800	3.8
Area C	T7-T9	Sec-Butyl acetate	0.1	16	17	1055	3418	2500	2.3
	T10-T12	Sec-Butyl acetate	0.1	16	17	1055	3418	2000	1.9
	T13-T14	Sec-Butyl acetate	0.1	16	17	1055	3418	3200	2.8
Area D	P1, P5-P6	Propane	2	12	12	452	1000	450	0.8
	P2-P4	Propane	2	12	12	452	1000	300	0.6

Assuming a prevailing atmospheric condition with a weather temperature of 25 ℃, a relative humidity of 25%, a partly cloudy sky and the stability class D, the wind speed is set to be 5 m/s measured at 5 m above the ground and gusting from the South East, the leak point is a circular opening with a diameter of 20 cm at 2 m above the bottom of the tank.

The calculation of initial heat radiation intensity for each tank is performed through ALOHA, and the results are reported in Appendix A, Table A.1. The storage area was modeled as a weighted directed graph in Fig. 6, the values of the calculated heat radiation intensity are represented by the width and color of the edges, while the size and color of the vertices stand for the out-closeness scores of each tank. The initial centrality scores without SBs can be calculated and listed in Table 4, the most dangerous tanks in terms of the three indexes are identified in bold numbers, it can be indicated that P1 is the most dangerous unit with the highest out-closeness and the lowest out-degree values, and T5 appears to contribute the most to the propagation of domino effect for its largest betweenness score. In terms of the mitigating effect of add-on SBs, eight allocation strategies involving four types of SBs are considered as listed

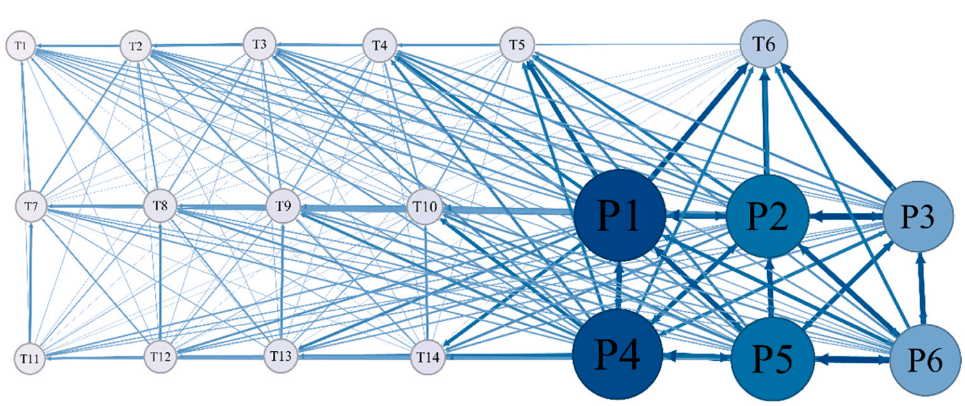

Fig. 6. Storage area of Fig. 5 as a weighted directed graph.

Table 4
Initial vertex-level centrality scores without SBs.

Tank ID	Out-closeness	Betweenness	Out-degree	Tank ID	Out-closeness	Betweenness	Out-degree
T1	0.198	0	33.121	T11	0.227	0	27.017
T2	0.233	0.094	23.869	T12	0.265	0.038	18.921
T3	0.269	0.152	16.868	T13	0.295	0.023	12.250
T4	0.269	0.175	11.807	T14	0.315	0.026	8.293
T5	0.312	**0.491**	8.740	P1	**1.584**	0.152	**0.631**
T6	0.603	0.456	6.172	P2	1.393	0.164	0.718
T7	0.236	0.041	26.288	P3	1.119	0	0.894
T8	0.282	0.211	18.363	P4	1.551	0	0.645
T9	0.306	0.146	12.127	P5	1.408	0	0.710
T10	0.339	0.363	7.740	P6	1.129	0	0.886

in Table 2, Section 3.2.

The numerical parameters of the NSGA-II can affect the quality of the solutions, therefore they should be carefully selected. For example, a rather small population size is not able to guarantee a sufficient solution space for the algorithms, too high of the population size can bring about divergence and a decrease in its robustness. Literature guidelines suggest a population size in the range of 20–100, a crossover rate between 0.6 and 0.95, and a mutation rate of 0.005–0.01 (Caputo et al., 2011). However, the selection of optimal parameters did not result in any uniform policy from earlier efforts, as it relies on the input data and genetic coding to some extent (Reddy et al., 2004). Therefore, these parameters should be set referring to empirical guidelines and then tuned according to the actual conditions.

With the purpose of promoting computational efficiency while maintain the robustness, trials with different parameters have been conducted to find the ones more suited for this study. In particular, the NSGA-II was run with a population size of 100, a maximum number of generations of 150, a crossover rate of 0.6 and a mutation rate of 0.01, within the ranges suggested in the literature. After defining the input parameters of the proposed model, two cases were further analyzed in order to achieve the trade-off. The first case aims to select the most cost-effective budget B^* to allocate the SBs by setting a floating range of budget, while the second case attempts to find the optimal strategy based on this very budget.

Case 1. Floating budget.

It can be computed from Table 2 that the minimum and maximum possible values of the actual cost are 0 and 13,255,730 €, respectively. Therefore, a budget range of 0–14 M€ was designated and the model was run every 0.1 M€ (140 times totally) with the run time of 1402.384 seconds (with experiment platform of Microsoft Windows 10, Intel 3.60 GHz, MATLAB R2021b). In summary, each set of the output parameters contains: (1) budget; (2) actual cost; (3) expected benefit; (4) minmax out-closeness score with its (5) corresponding tank ID; (6) allocation strategy. These results are presented and discussed in Section 5.

Case 2. Fixed budget.

Set a fixed budget B^* based on the value achieved from Case 1, run the optimization model for 500 times to choose the optimal set of SB allocation strategy with better outcomes for the prevention of domino effect. The average runtime for Case 2 is 9.52 seconds, and the obtained results are also discussed in Section 5.

5. Results and discussion

Due to the nature of multi-objective optimization problems, multiple equally good solutions to the same problem can be produced by NSGA-II. After running the optimization model in MATLAB, a total of 420 sets of solutions were generated for Case 1 with a budget range from 0 to 14 M€, the main indexes are shown in (Fig. 7).

The values of expected benefit (f_1) shows a rapid growth from 0 to 2.7 M€ in Fig. 7. The reason is that, at the beginning of the process, more resources are given to either the tank with the higher value or the one with a higher out-closeness score due to an insufficient budget, i.e., T6 with a value of 3.8 M€ (Table 3) and P1 with an initial out-closeness score of 1.584 (Table 4), the mitigation effect due to the implementation of SBs is relatively evident. The $\min\max Cout_i$ (f_2) in this period, on the other hand, basically remains at the same value (1.55), which is the value of the pressurized vessel P4, more attention has been drawn to the atmospheric tanks with a higher value of property since the first priority of the proposed model is to reduce the consequence of a potential domino effect. A significant fluctuation can be witnessed between the budget range of 2.7 and 3.8 M€ for both objective functions. After examining and analyzing the relevant data, we drew a possible conclusion that the two objective functions might conflict greatly within this budget range, so that wide differences exist between the neighboring outputs. A steady yet slower increase follows afterwards, indicating that the expected benefit has become less cost-effective as the investment grows, which is in accordance with the marginal diminishing effect. And eventually a maximum value of 15,226,671 is achieved with an actual cost of 13,255,730 €. Therefore, the fixed budget value B^* is set to be 3.8 M€ for further analysis in Case 2.

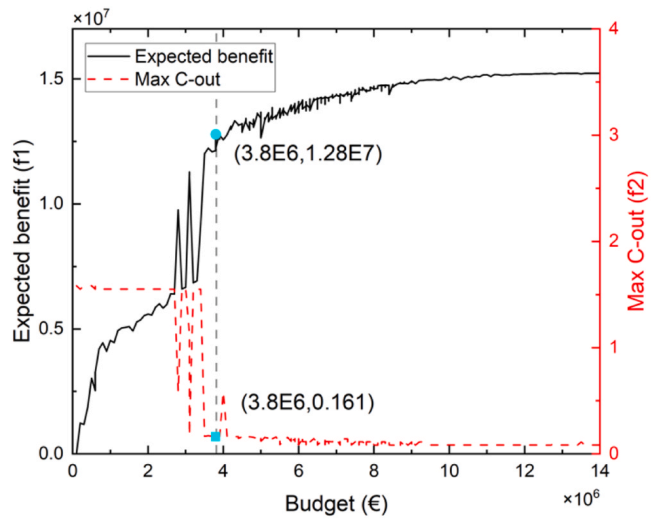

Fig. 7. Variation trends of two objective functions in Case 1.

In general, 919 sets of solutions were generated in Case 2 after running the model for 500 times, the frequency of SB strategy k for each tank in all solutions can be found in Table 5, Fig. 8 shows their corresponding relative frequency in a more intuitive way. It is obvious that due to the insufficient budget, the choice of SB strategies is comparatively limited. In particular, strategy 5 is more preferable for pressurized vessels P2-P6, while for P1, strategy 8 predominates in all the options because of its relatively higher risk. As for the atmospheric tanks, those with lower out-closeness scores (i.e., T1-T3, T7-T8, T11-T12) are largely

Table 5
Frequency of SB allocation strategies for each tank considering all solutions in Case 2, *k* refers to the SB strategies listed in Table 2.

k	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	P1	P2	P3	P4	P5	P6
1	876	806	527	84	16	5	801	650	158	2	892	829	303	55	4	65	79	69	69	84
2	12	47	261	651	312	35	42	137	550	606	4	48	534	565	0	0	0	0	0	0
3	8	12	12	58	192	243	16	37	83	152	4	22	26	125	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	22	14	10	20
5	23	54	119	126	399	485	60	95	125	159	19	20	53	169	407	746	818	545	734	803
6	0	0	0	0	0	138	0	0	3	0	0	0	3	5	0	0	0	0	0	0
7	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	508	93	0	291	106	12

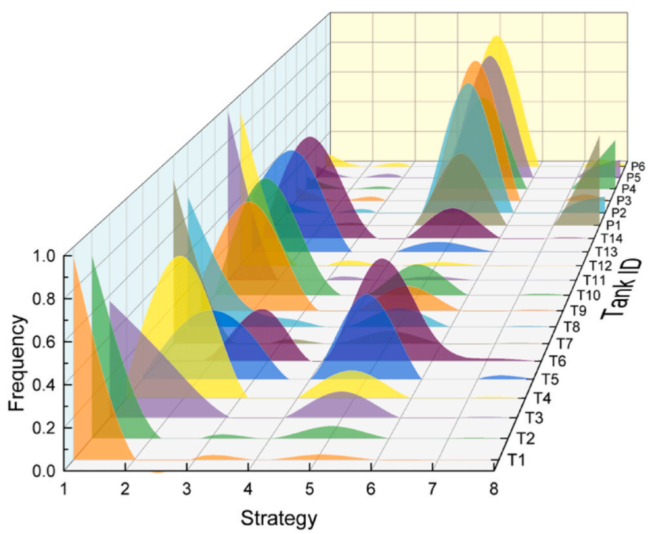

Fig. 8. Relative frequency of each strategy in all solutions.

allocated under strategy 1, meaning that no SBs are implemented. While the rest of the tanks with intermediate out-closeness values tend to have more choices, among which strategy 2, 5 and 3 show a higher percentage.

Fig. 9 is the Spearman correlation coefficient (Myers and Sirois, 2006) analysis diagram of the 919 sets of strategies generated from the model. The correlation strength of the allocation plan for each tank is quantitatively presented by a value between −1 and 1, denoted by different colors. It can be witnessed that there are certain positive correlations between the selection of SB strategies within a single set of solution, especially for the tanks which are geographically close to each other. For example, the Spearman correlation coefficient between P2 and P5 is 0.63 with a p-value less than 0.01, it can be assumed that there is a significant positive correlation between P2 and P5, in another word, the decisions of the SB allocation plan for P2 and P5 are closely connected. Moreover, those tanks within the same area (Fig. 5) are tend to have tighter correlations than those crossing different areas, which is in accordance with real-life situation.

Further, the occurrence number of each set of strategies is counted for the selection of the optimal allocation strategy under the budget B^*. In order to select the optimal solution from the equally good solutions produced by NSGA-II, three sets of strategies with the most frequent occurrence times are chosen for further analysis, they are marked as “a”, “b” and “c” and the details of the three solutions are shown in Table 6.

More specifically, to better describe the allocation strategy, we take solution *a* with a set of SBs [1 1 2 2 5 5 1 1 2 2 1 1 2 2 8 5 5 5 5 5] as an example. A combination of FWS and FPC is chosen for the most dangerous unit P1 considering its high performance in reducing heat radiation intensity; T5-T6 and P2-P6 are equipped with FPC for their relatively higher out-closeness scores; SPS is selected for T3-T4, T9-T10 and T13-T14; and finally, the rest of the storage tanks are not equipped

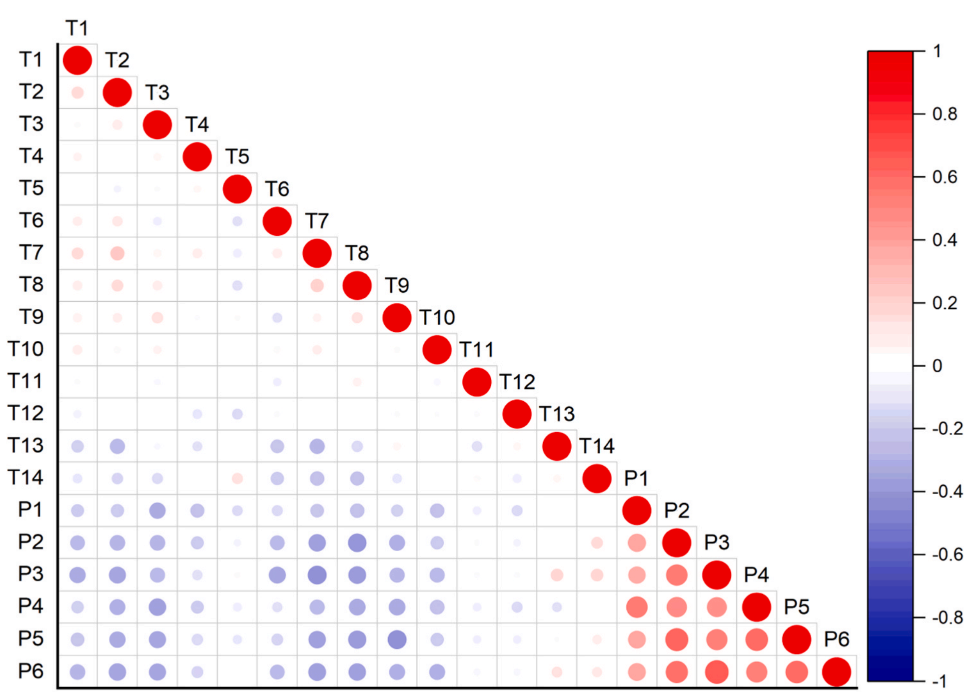

Fig. 9. Correlation analysis diagram of SB allocation strategies for Case 2.

Table 6
Details of the three sets of solutions chosen for comparison.

Solution ID →	*a*	*b*	*c*
Allocation strategy[b]	[1 1 **2** 2 **5** 5 1 **1** 2 2 1 1 2 2 **8** 5 5 **5** 5 5]	[1 1 **1** 2 **5** 5 1 **1** 2 2 1 1 2 2 **8** 5 5 **8** 5 5]	[1 1 **2** 2 **3** 5 1 **2** 2 2 1 1 2 2 **5** 5 5 **5** 5 5]
Times of occurrence	18	13	8
Actual cost	3793,050	3743,050	3792,480
Expected benefit	12,856,565	12,685,889	12,786,540
Minmax-ed *Cout* and corresponding tank ID	0.163 (P4)	0.152 (P5)	0.164 (P6)
Graph-level out-degree	1182.95	1210.36	693.73

[b] Different allocation plans of the three solutions are identified with bold numbers.

with any SBs.

Among the three sets of outcomes in Table 6, solution *c* is considered to be the worst due to its unsatisfying performance related to out-degree and out-closeness score, which are 693.73 and 0.164, respectively. As stated in Section 3.1, the smaller a graph-level degree value is, the more compactness the structure presents, thus making it more crucial (dangerous), and the discrepancy in the last row of Table 6 is evident. Solution *a* shows the most frequent occurrence (18/919 times) with a largest expected benefit value of 12,856,565. While solution *b* outperformed *a* in terms of out-closeness score and the actual cost, the out-degree values of the two solutions are around the same. Thus, between the equally good solutions *a* and *b*, the optimal allocation strategy can be selected based on the preference of decision-makers.

For the better demonstration of the optimal SB allocation strategies in reducing the domino risks, comparisons of centrality metrics have been made between the initial ones (see Table 4) and the three sets of allocation strategies listed above. In Fig. 10, three vertex-level centrality

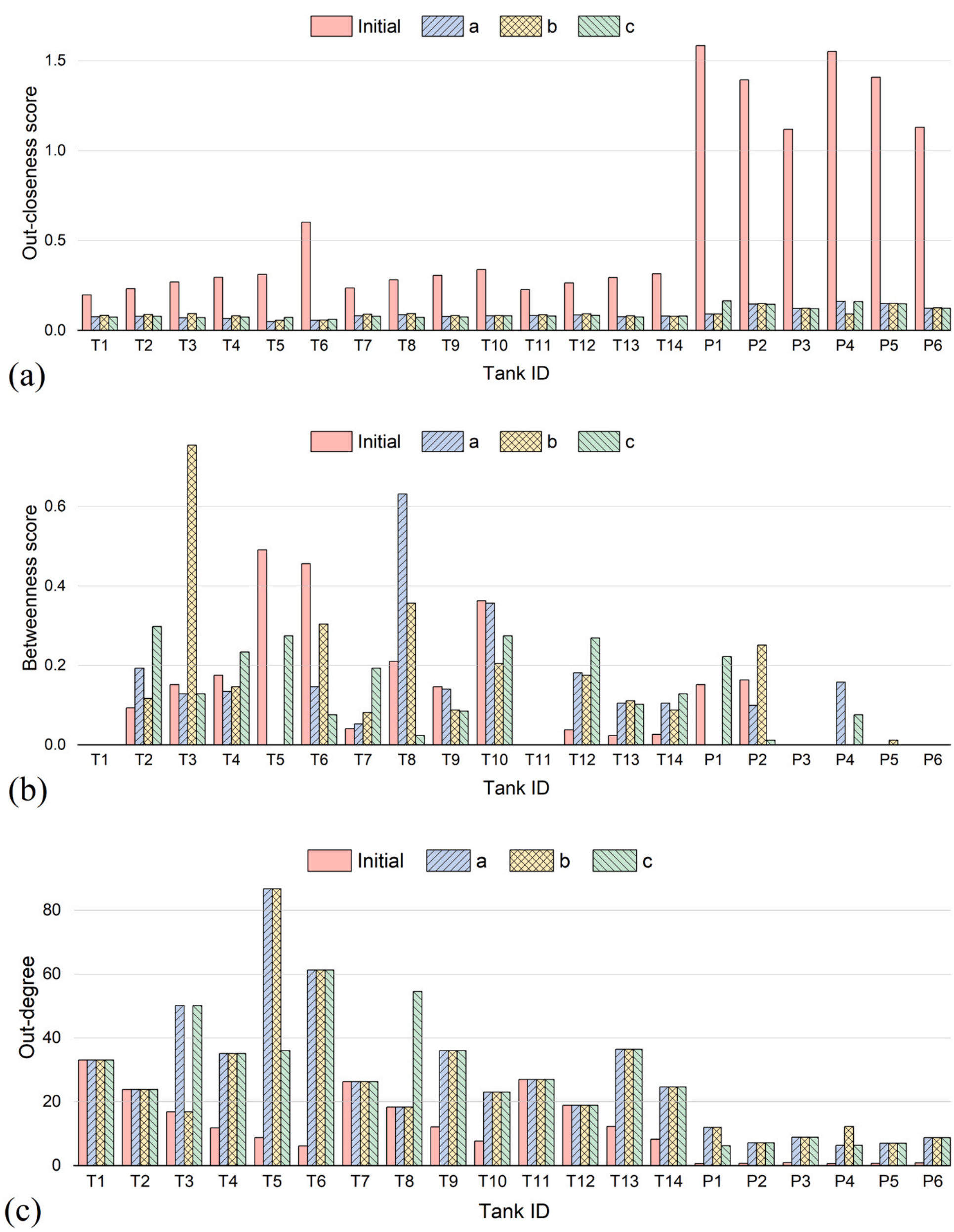

Fig. 10. Comparison between the initial and three sets of allocation strategies in terms of (a) out-closeness score, (b) betweenness score and (c) out-degree under the budget of 3.8 M€.

metrics, i.e., (a) out-closeness score, (b) betweenness score and (c) out-degree are compared. It can be seen that the protection strategy not only alters the metrics of the tanks notably, also the rank order shows a completely different pattern after the implementation of SBs.

Comparing the results of out-closeness scores in Fig. 10 (a), the reduction effect of six pressurized tanks is much more notable, with a largest reduction of 94.3% (out-closeness score of P1 drops from 1.584 to 0.091). Great discrepancies can be noticed from the initial out-closeness scores where P1 was considered to be the most dangerous unit, while with the optimal allocation of SBs, the differences of which have become insignificant, indicating an over-all risk reduction. Generally, solution *a* shows a higher efficiency in reducing the out-closeness score, six pressurized tanks yield the largest values both before and after the implementation of SBs, indicating their risks in initiating the potential domino effect in the chemical cluster.

The betweenness scores in Fig. 10 (b) show a greater diversity, which is due to the nature of betweenness centrality being a ratio of the distances between all pairs of other nodes that traverse the vertex to the total distance within the graph, which is a relative value. Thus, comparisons should be made within each set of solutions. In the initial phase, the largest betweenness scores are presented by T5, T6 and T10, in a descending order, indicating their relative importance in accident propagation. However, the rank orders vary between the three solutions under different allocation strategies, the values of T10 show an overall higher level considering all sets of results, it should be given more attention accordingly. Nevertheless, the betweenness scores of pressurized tanks are lower than that of atmospheric ones, making them less important in propagating domino effects.

By contrast, a uniformity in all of the four cases can be observed for the out-degree values in Fig. 10 (c). The values increase with the implementation of SBs, P1-P6 are identified to be the most dangerous tanks due to their lower out-degrees, which is in accordance with the results from Fig. 10 (a).

In this section, the results of the two cases described in Section 4 were presented and discussed in depth. A reasonable budget $B^* = 3.8$M€ is selected through the results obtained from Case 1 with a budget range from 0 to 14 M€, and two equally optimal sets of SB allocation strategies were produced by the multi-objective optimization model given the budget constraint B^*. The results demonstrate a considerable reduction of the potential domino effect risk, the most dangerous units as well as the ones facilitate the propagation of the accident are also identified through the proposed model.

6. Conclusions

In this paper, an innovative multi-objective optimization approach has been presented. The aim of this study is to search for the optimal allocation strategy of add-on SBs in case of potential fire-induced domino effects. In this approach, graph theory was innovatively integrated with NSGA-II to find the globally optimal solutions. Two objective functions were defined in the mathematical model for different purposes of domino risk reduction, the model was further demonstrated through an industrial case study, in which the selection process of an appropriate safety investment budget and the optimal allocation strategy under this very budget was introduced in detail. The main conclusions are drawn as follows:

(1) The developed model shows great efficiency in finding the globally optimal solutions from all sets of allocation strategies. The most cost-effective safety budget and globally optimal solutions can be quickly obtained through the developed model, offering decision-makers choices to select the best strategy based on their preferences for risk. In addition, the most dangerous units and those dedicate the most to the accident propagation can also be identified.

(2) This approach is effective in dealing with the uncertainties of domino effects by adopting relative risk in the vulnerability analysis rather than predicted probabilities, avoiding the influence of the presence of numerous installations or complex variations of escalation paths.

(3) The model developed in the present work can be managed easily and is more suitable for chemical clusters with numerous installations. In addition to heat radiation intensity, other escalation vectors such as overpressure can also be taken into account, it can further be applied to even larger chemical clusters storing multiple hazardous substances.

(4) To advance this work, future research will concentrate on the strategic allocation of safety resources. This will involve examining the interplay among different escalation vectors throughout the dynamic progression of domino effects. For clarity, certain input data in the case study have been simplified. However, a more thorough investigation is warranted to accurately assess the performance of various safety barriers (SBs), drawing upon both experimental results and historical data.

Declaration of Competing Interest

The authors declare that they have no conflicts of interest to this work.

Acknowledgement

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Appendix A. - Heat radiation intensity obtained for the case study

Table A.1
Heat radiation intensity obtained for the case study, in kW/m^2.

Source ↓	Target																			
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	P1	P2	P3	P4	P5	P6
T1	0.0	14.5	6.6	2.8	1.5	0.6	9.5	8.5	4.4	2.1	3.4	3.3	2.3	1.4	0.7	0.5	0.3	0.6	0.4	0.3
T2	26.7	0.0	14.5	6.6	2.8	0.8	10.0	9.5	8.5	4.4	3.5	3.4	3.3	2.3	1.1	0.7	0.5	0.9	0.6	0.4
T3	11.9	26.7	0.0	14.5	6.6	1.2	7.7	10.0	9.5	8.5	3.2	3.5	3.4	3.1	1.8	1.0	0.6	1.3	0.8	0.6
T4	5.9	11.9	26.7	0.0	14.5	2.1	4.1	7.7	10.0	9.5	2.3	3.2	3.5	3.4	3.5	1.7	1.0	2.0	1.2	0.8
T5	2.6	5.9	11.9	26.7	0.0	4.4	2.2	4.1	7.7	10.0	1.6	2.3	3.2	3.5	8.4	3.1	1.5	3.1	1.9	1.1
T6	1.2	1.8	2.9	5.4	12.3	0.0	1.2	1.8	2.8	5.0	1.1	1.5	2.2	3.3	35.3	35.3	23.1	6.8	6.7	6.0
T7	21.0	20.4	10.2	4.5	2.4	0.7	0.0	14.7	10.1	3.7	14.7	7.5	6.0	2.9	0.8	0.6	0.4	0.4	0.6	0.8
T8	19.7	19.8	16.3	7.2	4.7	0.9	26.5	0.0	14.7	10.1	11.2	14.7	7.5	6.0	1.3	0.8	0.5	1.3	0.8	0.5
T9	10.6	19.7	19.8	16.3	7.2	1.4	11.6	26.5	0.0	14.7	7.0	11.2	14.7	7.5	2.3	1.2	0.8	2.3	1.2	0.8
T10	5.0	10.6	19.7	19.8	16.3	2.7	4.3	11.6	26.5	0.0	3.4	7.0	11.2	14.7	5.1	2.2	1.2	4.9	2.2	1.2

(continued on next page)

Table A.1 (*continued*)

Source ↓	Target																			
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	P1	P2	P3	P4	P5	P6
T11	6.2	6.0	4.3	2.6	1.6	0.7	26.5	11.2	5.9	2.7	0.0	14.7	6.6	2.8	0.8	0.5	0.4	0.8	0.6	0.4
T12	6.2	6.2	6.0	4.3	2.6	0.8	17.6	26.5	11.2	5.9	26.5	0.0	14.7	10.1	1.3	0.8	0.5	1.3	0.8	0.5
T13	4.6	6.2	6.2	6.0	4.3	1.2	9.5	17.6	26.5	11.2	11.6	26.5	0.0	14.7	2.2	1.3	0.8	2.5	1.3	0.8
T14	2.8	4.6	6.2	6.2	6.0	1.9	5.2	9.5	17.6	26.5	4.3	11.6	26.5	0.0	4.5	2.1	1.2	5.1	2.2	1.2
P1	18.5	23.8	30.6	39.4	52.0	63.0	18.7	24.2	31.6	41.2	18.7	24.3	31.6	41.3	0.0	58.2	37.1	50.3	45.0	33.6
P2	14.0	17.8	22.8	29.4	37.9	65.4	14.1	18.1	23.6	30.7	13.6	17.3	22.2	28.4	72.0	0.0	58.1	49.4	50.2	44.9
P3	10.8	13.5	17.2	22.0	28.4	61.0	10.9	13.8	17.7	23.0	10.6	13.3	16.9	21.6	44.6	72.0	0.0	39.6	49.4	50.2
P4	16.9	21.3	26.5	32.3	37.2	36.9	18.6	24.3	31.7	41.5	18.6	24.2	31.5	41.2	60.3	52.3	36.5	0.0	58.1	37.0
P5	13.4	16.7	21.1	26.5	32.6	38.9	14.2	18.3	23.8	31.0	14.2	18.2	23.7	30.8	57.6	60.5	52.5	72.1	0.0	58.2
P6	10.4	12.9	16.2	20.4	25.6	38.9	11.0	13.9	17.9	23.2	11.0	13.9	17.8	23.1	43.5	57.6	60.5	44.7	72.1	0.0

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