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A Multi-Objective Model to Optimal Selection of Safety Measures in Oil and Gas Facilities

Aliakbar Eslami Baladeh[1], Morteza Cheraghi[2*], Nima Khakzad[3]

[1] Department of Industrial Engineering and Management System, Amirkabir University of Technology, Tehran, Iran. a.eslami@aut.ac.ir

[2*] Department of Health, Safety & Environment (HSE), School of Environment, College of Engineering, University of Tehran, Tehran, Iran. cheraqi@ut.ac.ir

[3] Faculty of Technology, Policy, and Management, Delft University of Technology, The Netherlands. n.khakzadrostami@tudelft.nl

Abstract:

Optimal selection of safety measures (SMs) is a challenging task for safety managers due to its importance, complexity, and incapability of traditional approaches in considering all the aspects of SMs optimal selection. Sophisticated mathematical models can be used to overcome the limitations of traditional approaches. However, setting the objective functions while considering their priorities as well as possible synergistic effects of the SMs on the hazards are still among the main concerns in the development and application of mathematical models.

The present study is aimed at developing a methodology to optimize the SMs selection while addressing the aforementioned challenges and considering both the budget and the risks. To do so, first the Pareto set of the solutions is obtained by NSGA-II technique - a multi-objective genetic algorithm technique - where a lexicographic model is used to select the optimal solution from the Pareto set based on the priority of the objective functions. A pessimistic strategy is used to account for the synergistic effects and the overlaps between the selected SMs.

Two mathematical models are developed to represent different policies in optimal SMs selection in a gas wellhead and surface facility. The results show a notable difference between the two policies, indicating the importance of setting proper objective functions in multi-objective optimization problems. The results also show that the methodology is able to effectively satisfy different safety management policies and constraints with no need for much extra information except the cost and impact of SMs on the hazards' risk.

Key words: Safety measures; Lexicographic model; Genetic algorithm; Multi-objective optimization.

Notation

i	hazard number $i=1,2,\ldots,m$
j	safety measure number $j=1,2,\ldots,n$
x_j	state of j^{th} safety measure (decision variable)
S_i	severity of occurrence of i^{th} hazard without any SM
P_i	probability of occurrence of i^{th} hazard without any SM
S'_{ij}	updated severity of occurrence of i^{th} hazard after application of j^{th} SM
P'_{ij}	updated probability of occurrence of i^{th} hazard after application of j^{th} SM
R_i	risk number of i^{th} hazard without SM
R'_i	updated risk number of i^{th} hazard after SMs selection
c_j	cost of implementation of j^{th} SM
C	total available budget for SMs selection

1. INTRODUCTION

Risk management is performed to find potential hazards of a system and select an optimal set of Safety Measures (SMs) to reduce the likelihood and effects of the hazards (Rasmussen 1997). SMs identification and optimal selection play a key role in implementing risk management strategies (Abrahamsen et al. 2018).

To find the optimal set of SMs, the SMs are usually assessed based on different aspects such as their cost and their contribution to the system risk reduction. These aspects in turn are influenced by two main factors: the available resources (e.g., the budget) and the safety management policy (i.e., the propose of SM allocation) (Bahr 2014). Different techniques and methodologies have been developed for ranking and selecting the SMs considering either or both factors.

The hierarchy of controls is a classical technique to prioritize SMs (Barnett and Brickman 1986, Weinberg et al. 2009). In this technique, SMs are classified in different categories, and then selected based on the priority of each category according to the hierarchy of controls (Gomes and Gomes 2014). For instance, according to OSHA 3071 (OSHA 2002), safety measures are classified in three categories: (i) engineering measures such as enclosure, interlocks, machine guards, and exhaust ventilation, (ii) administrative measures such as training, work permits, and signs , and (iii) Personal Protective Equipment (PPE). The priority of each safety measure is defined by its category: for example, safety measures in the engineering category are usually preferred over safety measures in the administrative category. Similarly, according to ISO 17776 (ISO:17776 2016), safety measures are classified in the five categories prevention, detection, control, mitigation, and emergency response, in a descending priority. Other standards and guidelines such as ANSI/AIHA Z10 (ANSI/AIHA 2012), MIL-STD-882E (MIL-STD-882E 2005), OHSAS 18001 (OHSAS:18001 2007) and BS 8800 (BS 2004) have their own hierarchy of controls for SMs selection.

Cost-benefit analysis is another technique for optimal SMs selection (Helle et al. 2015, Xu and Lambert 2015, Wang et al. 2018) where a SM will be selected only if its implementation cost is less than its risk reduction. Cost-effectiveness analysis has also been used as an alternative to cost-benefit analysis for comparing and selecting the SMs (Lindhe et al. 2011, Reniers and Van Erp 2016; Khakzad et al., 2018).

Most of the developed methodologies, however, fall short in accounting for the synergy of SMs: Several SMs may be applicable to control, mitigate or omit the consequence of a single hazard; likewise, a SM could affect multiple hazards (Barnett and Brickman 1986). Thus, for an optimal selection of SMs, it is crucial to identify all the relevant SMs and to investigate their potential synergistic effects, overlaps and dependencies (Arends et al. 2005; Caputo et al. 2011, Casson Moreno et al. 2018). Due to possible synergies and dependencies, the total risk reduction resulting from a set of SMs would not necessarily be equal to the sum of individual risk reductions (Caputo et al. 2011).

Mathematical optimization techniques have significantly improved the time and the accuracy of optimal SMs selection considering different factors at the same time. However, the developed techniques have usually failed to account for the interaction and overlap of SMs or have not considered the priority of objective functions in accordance with the safety management policies.

To address the shortcomings of the previous models, in the present study, we will develop a multi-objective mathematical model based on Genetic Algorithm (GA) for optimal selection of SMs. model To this end, Hazard and Operability Analysis (HAZOP) is used to identify the hazards, their risk, and relevant SMs in gas wellhead facilities. To consider possible overlaps among SMs, a new pessimistic strategy is used while for considering the priority of objective functions a lexicographic function is used. To demonstrate the capability of the model in practice, it is applied to optimal SMs selection at a gas wellhead as a critical system in the oil and gas industry.

The importance of safety in gas wellhead and surface facilities has been recognized in the previous works (Lavasani et al. 2011; Cheraghi et al., 2019). In spite of major developments in design and operation of gas wellheads, faults and catastrophic accidents still occur in them.

The rest of this paper is organized as follow. Section 2 presents some previous studies devoted to the development and applications of mathematical models for optimal SMs selection, GA and HAZOP. In Section 3, the multi-objective model is developed with considering synergetic effects. Section 4 describes the gas wellhead and surface facilities as a case study. In Section 5, the methodology is applied to the case study and the results are presented and discussed. Section 6 concludes the research.

2. LITERATURE REVIEW

2.1. Mathematical approach in safety measure selection

By increasing the number of hazards in a system, the number of SMs increases too. Each SM could be in either operational or failure state; thus the total number of possible states for a system with N SMs is 2^N (Caputo et al. 2011). Therefore, in a system with large number of SMs, the evaluation of all the possible sets of applicable SMs could become extremely time-consuming and even intractable. To overcome this issue and to consider system constraints and SMs interaction, mathematical models and optimization techniques have widely been used for selecting an optimal set of SMs.

Caputo et al. (Caputo et al. 2011) used GA to find minimum system cost considering SMs' cost and the cost of damage. Caputo et al. (Caputo et al. 2013) introduced effectiveness, cost, efficiency, range, applicability, and functionality as the criteria of SMs optimal selection. They constructed a multi goal model to consider these criteria and used knapsack technique to find the exact solution of the model.

Researchers have considered a variety of factors in the selection of SMs , including the impact of SM on product quality (Segawa et al. 2016) and system failure probability (Toppila and Salo 2017), previous implementation of SMs in similar cases (Casson Moreno et al. 2018), as well as SMs' level of confidence (Andersen et al. 2004), response time (Andersen et al. 2004), reliability (Directorate 2002), availability (Badreddine et al. 2014), robustness (Hollnagel 1995), and maintainability (Rollenhagen 1997). Caputo et al. (Caputo et al. 2013) developed a method based on Analytic Hierarchy Process (AHP) with 15 factors to prioritize SMs for industrial machinery.

Risk matrix is a popular technique to analyze and rank hazards based on their probability and severity (Ni et al. 2010). Reniers and Sorensen (Reniers and Sörensen 2013) showed that hazard ranking could change in the risk matrix by SMs implementation. They proposed a mathematical model to find a portfolio of SMs that maximizes the total benefit of the system with a certain budget. They solved the model using knapsack problem, assuming that SMs are mutually independent; in other words, in their work, the effect of a SM on a hazard was calculated independently from the other SMs, so the final risk of a hazard after implementing the selected SMs was equal to the sum of individual effects of all the SMs (Reniers and Sörensen 2013).

Todinov and Weli (Todinov and Weli 2013) applied dynamic programming to maximize the total risk reduction of a system in the railway industry, assuming mutually independent SMs. Yuan et al. (Yuan et al. 2015) proposed an optimization method for the optimal selection of SMs with an application in dust explosions by simultaneously optimizing the total cost and the total risk reduction of the system using a knapsack approach. Todinov (Todinov 2014) presented a dynamic programming approach to find the optimal risk-reduction options and considered cost and risk-reduction of system as an objective function.

Janssens et al. (Janssens et al. 2015) built a mathematical model for optimally selection of SMs in order to maximize the time-to-failure of a chemical installation considering domino effects. Considering mutually independent SMs, Cheraghi et al. (Cheraghi et al. 2018) combined hierarchy of controls and mathematical models for optimal selection of SMs in the power industry, with the total risk reduction as the objective function.

2.2. The genetic algorithm technique

Mathematical programming techniques have been developed to find the exact solution of optimization problems. However, the problems which could be solved by mathematical programming are limited to those that follow some specific conditions. For instance, linear programming can find optimal solution of problems with a linear objective function and linear equality and inequality constraints with continuous variables (Dantzig 2016). When variables are discrete, integer or binary, programming techniques like Branch and Bound and Knapsack Problem could be used (Nemhauser and Wolsey 1988). In problems with nonlinear objective functions or a non-convex solution space, obtaining optimal solution by exact methods are difficult, and the effort needed to tackle them grows exponentially with the problem size (NP-hard problem) (Rothlauf 2011).

In some problems, the decision maker looks for a solution that could satisfy different objective functions. To formulate this type of problems, multi-objective optimization techniques can be used. Multi-objective optimization problems usually result in a Pareto set of solutions in which none of the objective functions could be improved without deteriorating the other objective functions (Collette and Siarry 2013). There are some approaches to select the final solution from a Pareto set. The weighted-sum method is one of such approaches that translates a multi-objective problem to a single objective problem by assigning weights to the objective functions according to their importance and then combining them into a single objective function (Deb and Deb 2014).

Lexicographic approach is another method to solve multi-objective problems when an objective dominates the others (Marler and Arora 2004). In this technique, according to the priority of the objectives, first the optimal solutions based on the first objective (the most important one) are determined, and then if there are some solutions with the same value, the ones that result in a better value for the second objective are kept, and so on until all the objectives are satisfied in a descending order of priority (Marler and Arora 2004).

Metaheuristic algorithms have been proposed as another alternative to solve a wide range of problems while dealing with the issue of NP-hard (Glover and Kochenberger 2006). The solutions found by these algorithms are, however, near to optimal. GA is a well-known metaheuristic algorithm (Holland John 1975) capable of finding the optimal solutions of complex problems. GA has been widely used in the last two decades and in a variety of application domains (Goldberg 2006).

GA searches different areas of a solution space (non-convex, discontinuous, and multi-modal) to find a Pareto set of solutions which satisfies multiple objectives. Due to local and global search and population-based methodology, GA has been the most applicable metaheuristic technique in multi-objective optimization problems (Konak et al. 2006).

All the solutions in GA approaches are coded as chromosomes, consisting of some genes, and are evaluated by a fitness function to show the value of the solutions. In the first generation, GA randomly creates initial solutions while in the next generations new populations are created by 2 techniques: crossover and mutation. In crossover, two chromosomes are selected from the best pervious solutions as the parents which using crossover function generate a new offspring. In mutation, genes of selected chromosomes are randomly changed according to the mutation function to create a new solution and avoid getting trapped in local optimum solutions. Finally, after a certain number of generations, the best chromosome is offered as the solution of the problem (Goldberg 2006).

Many extensions have been developed to improve the speed and performance of GA; Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) (Deb et al. 2002) is one of the most popular of them (Li and Zhang 2009). GA has also been used in context of system safety (Busacca et al. 2001).

2.3. Hazard identification and risk evaluation techniques

Risk evaluation, prioritizing hazards, helps safety managers to improve safety of system more effectively. Many techniques have been developed to identify and analyze hazards of systems such as Failure Mode and Effect Analysis (FMEA), hazard identification studies (HAZID), Job Safety Analysis (JSA), and Hazard and Operability Analysis (HAZOP).

HAZOP was introduced by the Institute of Chemical Industry during 1960s and it relies on using guidewords and process parameters to find deviations of the planned process and determine its causes and consequences (Dunjó et al. 2010). HAZOP is able to analyze complex systems by dividing them into simpler subsystems and using keywords to ensure that all possible hazards and operation problems are identified (Dunjó et al. 2010). In HAZOP, after the identification of hazards, the risk index of the hazards is calculated by a risk matrix or simply by multiplying the severity of consequence (S) and the occurrence probability (P) of each hazard.

HAZOP is a popular method in hazards analysis and risk assessment and is widely used in various application areas (Baybutt 2015, Janošovský et al. 2016). It is also widely used in the process industries for identifying potential hazards and operability problems (Ahn and Chang 2016, O Herrera et al. 2018; Cheraghi et al., 2019). During HAZOP, the main causes of hazards and relevant SMs along with their cost and effectiveness can also be identified.

3. METHODOLOGY:A MULTI-OBJECTIVE MODEL TO OPTIMAL SAFETY MEASURES SELECTION

The proposed methodology aims to find an optimal combination of SMs so as to optimize the system performance while considering the SMs' synergistic effect and different safety managerial policies (i.e., different priority of objective functions). The overall framework of the methodology is illustrated in Fig. 1.

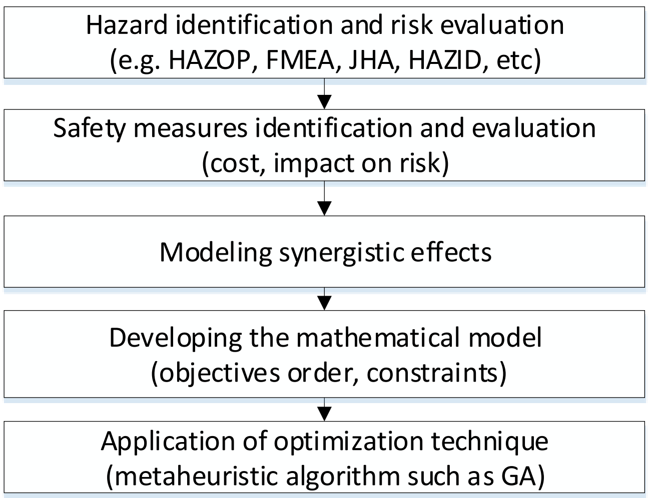

Fig.1. Proposed framework for optimal SMs selection.

3.1. Hazard identification and risk evaluation

In the first step, all potential hazards of the system must be identified, for instance, using HAZOP, FMEA, JHA, HAZID. Based on the available information, the system's size and complexity, and the experience and expertise of the analyst, any of the foregoing techniques can be used as long as the hazards, their risk, and relevant SMs can be identified. In this methodology, it is assumed that the risk of each hazard is calculated by multiplying its occurrence probability and the severity of its consequence (Equation (1)) which can be evaluated using a 1 to 10 numeric scale as in Tables 1 and 2 (Kotek and Tabas 2012):

$$R_i = P_i \times S_i \tag{1}$$

where R_i denotes the risk of i^{th} hazard, and P_i and S_i indicate, respectively, the probability of occurrence and the severity of i^{th} hazard before any SM implementation.

Table 1: Scale for ranking the severity of hazards' consequences (Liu et al. 2013)

Rating	Effect	Severity of effect
10	Hazardous	Failure is hazardous, and occurs without warning. It suspends operation of the system and/or involves noncompliance with government regulations
9	Serious	Failure involves hazardous outcomes and/or noncompliance with government regulations or standards
8	Extreme	Product is inoperable with loss of primary function. The system is inoperable
7	Major	Product performance is severely affected but functions. The system may not operate
6	Significant	Product performance is degraded. Comfort or convince functions may not operate
5	Moderate	Moderate effect on product performance. The product requires repair
4	Low	Small effect on product performance. The product does not require repair
3	Minor	Minor effect on product or system performance
2	Very minor	Very minor effect on product or system performance
1	None	No effect

Table 2: Scale for ranking the occurrence probability of hazards (Liu et al. 2013)

Rating	Probability of occurrence	Failure probability
10	Extremely high: failure is almost inevitable	>1 in 2
9	Very high	1 in 3
8	Repeated failures	1 in 8
7	High	1 in 20
6	Moderately high	1 in 80
5	Moderate	1 in 400

Rating	Probability of occurrence	Failure probability
4	Relatively low	1 in 2000
3	Low	1 in 15,000
2	Remote	1 in 150,000
1	Nearly impossible	<1 in 1,500,000

3.2. Safety measures identification and evaluation

In this step, all possible SMs must be identified. Then, each of them should be evaluated considering its cost and impact on the hazard's risk. The cost of each SM consists of all related costs like supply, implementation, maintenance and training cost. The risk of each hazard could be reduced by lowering its occurrence probability or the severity of its consequences. To analyze effect of a SM on a hazard, the change of risk criteria (occurrence probability and severity) for each hazard before and after implementing the SM should be estimated.

3.3. Modeling synergistic effect

When more than one SM can be applied to a hazard, and the SMs are not mutually independent, the interaction between the SMs should be measured and taken into account. Caputo et al. (Caputo et al. 2011) proposed a normalized function for this purpose; however, their technique needs more information than the effect of SMs on hazards' risk, including the minimum and maximum potential effect of SMs on the hazards, and the degree of intensity (0-100%) at which a SM is applied to a hazard.

In the present study, we use a pessimistic strategy to account for the interaction of SMs. In this strategy, when applying more than one SM to a hazard, only the minimum updated risk of the hazard resulting from the individual implementation of SMs is considered instead of the updated risk which may result from the implementation of all the SMs. This would conservatively (in the worst case scenario) assure that the combined updated risk would be equal or less than the minimum individually updated risk. Compared to the technique of normalized function, this approach does not require any more information about SMs.

SM optimization model aims to find an optimal combination of all the potential SMs. So, the decision variable x_j can be defined as:

$$x_j = \begin{cases} 1 & \text{if the j} - \text{th safety measure is implemented} \\ 0 & \text{else} \end{cases} \qquad (2)$$

The pessimistic strategy can be mathematically modelled using Eq. (3), where R'_i denotes the updated risk of the i^{th} hazard (i.e., the risk after implementing the SMs)

$$\mathrm{R}'_i = \min\left\{p_i, p'_{i1}, p'_{i2}, ..., p'_{ij}\right\} \times \ \min\left\{s_i, s'_{i1}, s'_{i2}, ..., s'_{ij}\right\} \quad , \ \forall j \in x_j = 1 \qquad (3)$$

Although Equation (3) is developed for two risk criteria, it can easily be extended to include more risk criteria in other risk evaluation techniques.

3.4. Building mathematical model

The goal of SMs selection optimization depends on the safety management policy of the decision maker (e.g., the oil & gas company). However, (i) minimizing the maximum risks of the hazards and (ii) maximizing the total risk reduction are very common safety management policies (Caputo et al. 2013, Kang et al. 2016). We consider these two policies to demonstrate the application of the methodology.

3.4.1. Model (I): Minimizing the maximum risk

In this model, the decision maker intends to find the optimal combination of SMs to reduce the risk of each individual hazard as low as possible. However, usually the available budget (C) is not sufficient to reduce the risk of all the hazards to the desirable level. As a result, managers may decide to minimize the risks of the hazards with the highest risks with the minimum budget expenditure (i.e., minimizing the total cost of SMs). The model can be mathematically presented as in Eq. 4.

$$\begin{aligned}
&\text{lexicographic} \quad f(x) = \left(f_1(x), f_2(x)\right) \\
&\qquad\qquad\qquad f_1(x) = minimax \ \mathrm{R}'_i \qquad , i \in 1,2,...,m \\
&\qquad\qquad\qquad f_2(x) = \min \sum_{j=1}^{n} c_j x_j \\
&s.t: \\
&\qquad \sum_{j=1}^{n} c_j x_j \le C \qquad\qquad , j \in 1,2,...,n \\
&\qquad x_j \in \left\{0,1\right\} \qquad\qquad , j \in 1,2,...,n
\end{aligned} \qquad (4)$$

In Eq. (4), the lexicographic function is used first to obtain an optimal solution from the Pareto solution set, and then to emphasize that the first objective function $f_1(x)$, i.e., minimizing the maximum risks, should be given priority over the second objective function $f_2(x)$, i.e., minimizing the cost of SMs. In this approach, between all the solutions that optimize $f_1(x)$ the one resulting in the best value of $f_2(x)$ could be selected as the optimal selection of SMs.

3.4.2. Model (II): Maximizing the total risk reduction

In this model, the decision maker intends to allocate all the available budget to the implementation of SMs so as to achieve the maximum total risk reduction still with a focus on the hazards with the highest risks. As such, "maximizing the total risk reduction" would replace "minimizing the total cost" as the secondary objective function (note that minimizing the risk of the hazards with the highest risks is still the primary objective function). In other words, after the model manages to minimize the highest risks, the remaining budget would be spent on maximizing the total risk reduction. The model can mathematically be presented in Eq. 5.

$$
\begin{aligned}
&\text{lexicographic} \quad f(x)=\left(f_1(x),f_2(x)\right)\\
&\qquad\qquad f_1(x)=minimax\ \mathrm{R}'_i \qquad\qquad ,i\in 1,2,\dots,m\\
&\qquad\qquad f_2(x)=\max\sum_{i=1}^{m}\left(\mathrm{R}'_i-\mathrm{R}_i\right)\\
&s.t:\\
&\qquad \sum_{j=1}^{n}c_j x_j\le C \qquad\qquad\qquad ,j\in 1,2,\dots,n\\
&\qquad x_j\in\left\{0,1\right\} \qquad\qquad\qquad ,j\in 1,2,\dots,n \qquad (5)
\end{aligned}
$$

3.5. Developing optimization technique

The general approach in dealing with multi-objective optimization problems is to find a complete Pareto set of optimal solutions, i.e., a set of solutions by which none of the objective functions can be improved without degrading the other objective functions. If there are x SMs, each of Models I and II consists of 2^X possible solutions at most. As a result, for a large system with many potential SMs (a large x) finding the optimal solution through combinatorial models would be highly time-consuming. Moreover, considering the synergetic effects of SMs makes the exact methods like Knapsack problem ineffective (Todinov 2014).

Metaheuristic algorithms such as GA (Holland 1992, Goldberg 2006, Konak et al. 2006) could effectively be used to find a Pareto set of optimal solutions when the number of possible solutions is too large. GA has effectively been used in system safety optimization problems (Busacca et al. 2001) and SMs optimal selection (Caputo et al. 2011). In the present study, a GA approach developed by Deb et al. (Deb et al. 2002), known as NSGA-II, is suggested to solve the lexicographic functions presented in Models I and II to find the Pareto set of optimal solutions.

4. CASE STUDY: GAS WELLHEAD AND SURFACE FACILITIES

To illustrate the capability of the proposed model in hazardous industrial facilities, a gas wellhead and surface facility is considered as the case study. After the drilling and completion of a gas well, the formation fluids are conveyed through the well to the surface. At the surface, the produced fluids are transferred from the wellhead through flowlines to gathering center facilities and from there to refinery.

Hydraulic control panel is the key equipment in the gas wellhead and surface facilities that is a failsafe shutdown system to protect personnel and the environment from wellhead fire. If any failure requiring an immediate shutdown occurs (e.g., leakage in downstream piping and a subsequent overpressure), operating and shutting safety valves could reduce the likelihood of major accidents.

At a depth of about 60 to 80 meters in the well, a downhole safety valve called Sub-Surface Safety Valve (SSSV) is installed in the upper wellbore and can be actuated as a failsafe in an emergency situation by a command which receives from the hydraulic control panel. Another safety valve, which operates like SSSV, is Surface Safety Valve (SSV). The SSV is a hydraulically actuated failsafe valve in the Christmas Tree at the surface. The Christmas Tree is an assembly of spools, fittings, and valves. The primary function of Christmas Tree is to control the flow of the produced fluids during production. Christmas Tree provides additional functions such as pressure relief and chemical injection. Two master valves are fitted to the Christmas tree to allow the well to flow or shut the well in.

Due to the criticality of master valves, usually two master valves are considered as redundancy, a Lower Master Valve (LMV) and an Upper Master Valve (UMV). During normal production, these two valves are kept fully open. In addition, two wings - a production wing and a kill wing - are fitted to the Christmas Tree. The production wing is used to control and isolate the flow from the wellbore whereas the kill wing is used for injecting the fluids. The valve at the top is called swab valve and is used for vertical access. Chokes are devices with an orifice installed in the line to control the fluid flow rate or downstream pressure during production, and are usually mounted close to the Christmas tree in the flowline. These chokes can be in fixed or adjustable modes of operation (Lavasani et al. 2011, Devold 2013, Cheraghi et al. 2019). Fig. 2 illustrates the Christmas Tree and some related facilities.

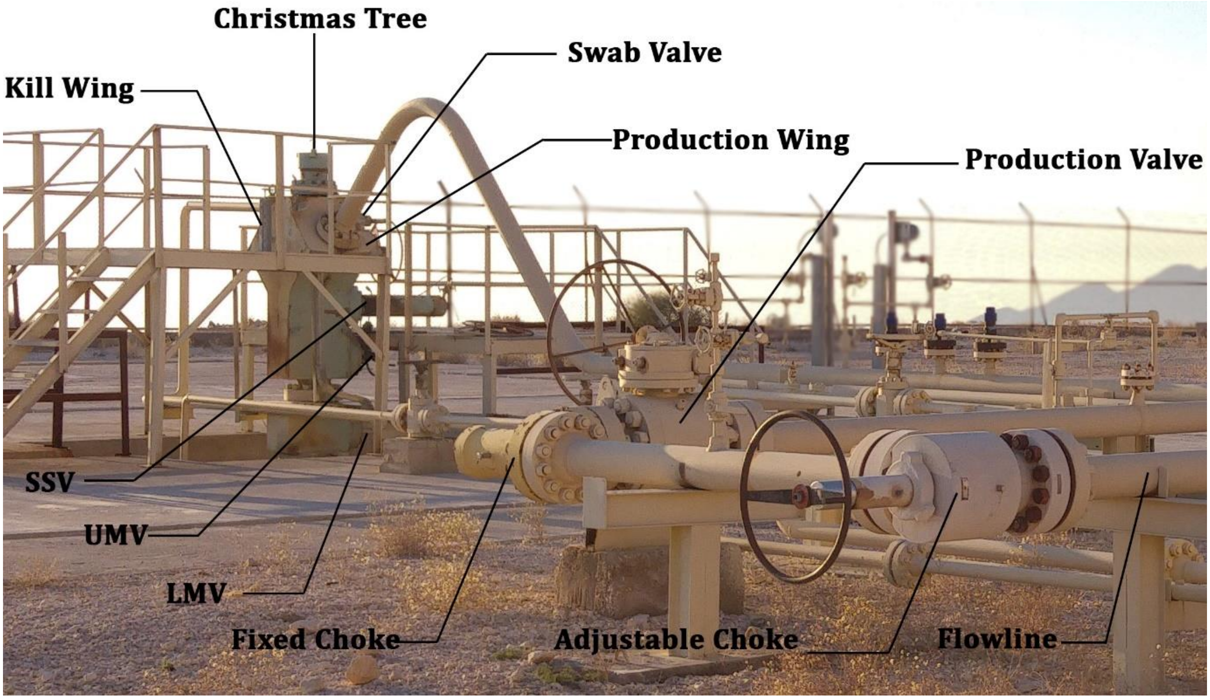

Fig.2. The Christmas Tree and some related facilities.

To reduce the corrosion in the downstream equipment, and to prevent metering problems, liquids should be removed from the produced natural gas. Therefore, a separator is located in the flowline to mechanically separate sour liquids from produced fluids. Corrosion inhibitor chemicals are used to reduce the rate of corrosion. A storage tank with two pumps are used for injecting the corrosion inhibitor chemicals into the flowline. Other important equipment in the gas wellhead and surface facilities includes a header and trunk line for connecting the flowlines of several wells into a single gathering line, a flare and a burn pit for unpredicted or predicted firing of fluids and a pig receiver to retrieve the pig from gathering center to wellhead. (Devold 2013, Cheraghi et al. 2019)

Although many attempts have been made to develop automated expert systems for HAZOP, most HAZOPs in the process industry are still performed manually via a team of experts (Dunjó et al. 2010). In the present study, to identify and evaluate the potential hazards and related SMs in the gas wellhead and surface facilities, a multi-disciplinary team of seven experienced members was consulted, including a commissioning manager, a project engineer, a process engineer, an instrument and control engineer, an operating and maintenance personnel, a cost engineer, and a hazard leader.

The overall objective of the HAZOP was the identification and evaluation of SMs for potential hazards related to malfunctioning or maloperation of the wellhead and the flowline, the header and the trunk line, the corrosion inhibitor injection system, the pig receiver, the flare and the burn pit facilities. This resulted in fifty hazards as listed in Table3.

Table 3. Identified hazards of gas wellhead and surface facilities by HAZOP analysis.

Hazard No. (i)	Deviation	P_i	S_i	R_i	Causes	Consequences
1	No/less flow of gas	6	3	18	Closure of SSSV, failure of hydraulic control panel (e.g., leakage in tubing, power failure, pump failure, and transmitter failure)	Loss of production
2	No/less flow of gas	7	3	21	Closure of SSV, failure of hydraulic control panel (e.g., leakage in tubing, power failure, pump failure, and transmitter failure)	Loss of production
3	No/less flow of gas	1	3	3	Closure of manual valve (e.g., production valve, LMV, and UMV) on Christmas Tree	Loss of production
4	No/less flow of gas	1	3	3	Closure of adjustable choke valve	Loss of production
5	No/less flow of gas	2	3	6	Plugging of Grit Trap or fixed/adjustable choke valve by debris/grit	Loss of production
6	No/less flow of gas	6	3	18	Failure of FCV 244 or failure of any elements of the control system to close more	Loss of production
7	No/less flow of gas	5	3	15	Closure of MOV 224	Loss of production
8	No/less flow of gas	4	8	32	Closure of MOV 254	Increase pressure upstream of the valve and possibility of damage to line due to over pressure
9	Well blowout	2	10	20	Failure of Christmas Tree due to any reason.	Toxic gas release to atmosphere.
10	High level in the separator	6	3	18	Failure of LCV 138 under the separator or any elements of the control system to close more	Sour liquid carry over to downstream and thus increasing the rate of corrosion, increasing liquid hold-up in flow lines, gradual increasing of the back pressure
11	High level in the separator	2	3	6	Closure of any manual drain valve downstream of LCV 138	Sour liquid carry over to downstream and thus increasing rate of corrosion, increasing liquid hold-up in flow lines, gradual increasing of the back pressure
12	Low level in separator	6	4	24	Failure of LCV 138 under the separator or any elements of the control system to open more	Toxic gas blow-by to burn pit leading to loss of gas
13	High Pressure	2	9	18	Fire case	Possibility of damage to the separator due to over pressure
14	More flow of gas	2	2	4	Failure of FCV 244 or any elements of the control system to open more and or more opening of adjustable choke valve	Possibility of damage to the flow lines and downstream equipment due to over pressure
15	Leakage/rupture	5	6	30	Corrosion, erosion, aging, gasket failure, ring failure, insulating joint failure, thermal tension, etc.	Toxic gas release, risk of personnel injury, loss of material, the environmental pollution and loss of production
16	Leakage/rupture	2	8	16	Corrosion, erosion, aging, gasket failure, ring failure, insulating joint failure, TPD, thermal tension, etc.	Risk of reverse flow
17	Fire case	3	9	27	Ignition of released gas	Damage to facilities
18	No/less flow of the corrosion inhibitor	2	4	8	Closure of manual valve on pump discharge by error	Damage to pump and thus the environmental pollution
19	High level	2	3	6	More filing of tank by error or failure of LG	Overfilling of inhibitor, and thus the environmental pollution
20	Low level	4	4	16	Consumption and not refilling by failure	Possibility of damage to pump and also flow cut off in the flow lines
21	High pressure	6	1	6	Failure of PCV 350 on burn pit ignition system to open more	Improper ratio of fuel/air, leading to not burning of the pilot
22	High pressure	6	1	6	Failure of PCV 330 on flare ignition system to open more	Improper ratio of fuel/air, leading to not burning of the pilot
23	High pressure	6	2	12	Failure of PCV 334 on flare/ burn pit pilot gas to open more	Loss of gas
24	High level	5	5	25	Not draining liquids in proper time by error or by failure of level indication system (level control system in flare K.O Drum has been changed from automatic to manual).	Accumulation of liquid, overflow to flare header and damage to flare stack, flaming rain, and the risk of the environmental pollution and personnel injury
25	Low level	5	4	20	Operator failure to close drain valve in proper time	Possibility of purge gas/sour gas blow-by to burn pit and thus uncontrolled burning and toxic dispersion
26	Loss of performance	4	5	20	Failure of PCV 334 on flare/burn pit pilot gas to close more	Loss of pilot gas and possibility of venting of unburned relief gas and dispersion of flammable and toxic gas

Hazard No. (i)	Deviation	P_i	S_i	R_i	Causes	Consequences
27	Loss of performance	4	5	20	Flame out condition due to any reason	Loss of pilot gas and possibility of venting of unburned relief gas and dispersion of flammable and toxic gas to area
28	Loss of performance	4	2	8	Failure of PCV 330 on flare ignition system to close more	Delay in ignition
29	Loss of performance	4	2	8	Failure of PCV 350 on burn pit ignition system to close	Delay in ignition
30	Loss of performance	4	2	8	Failure of flame front ignitor system	Delay in ignition
31	Corrosion	5	5	25	Corrosive environment in K.O drum	Damage to K.O Drum and risk of fire, the environment pollution, toxic gas release and risk of personnel injury
32	High pressure	2	3	6	Thermal expansion during box-up or fire case	Damage to pig barrels and facilities due to over pressure
33	Pig receiver problems	3	1	3	Failure of PCV 283 to open more. (In current condition, the PCV 283 is used as a manually operated valve).	Regarding to PCV 283 is fully open during pigging operation so no major issue of concern is identified
34	Pig receiver problems	3	1	3	Failure of PCV 283 to close more	Stopping pigging operation
35	Pig receiver problems	3	3	9	Failure of PCV 283 to close more	During emergency shutdown, flow lines will not depressurize properly (while MOV 256 and MOV 255A open simultaneously)
36	Pig receiver problems	5	8	40	Opening of Pig Receiver door when it is pressurized	Possibility of personnel injury due to toxic gas release
37	Pig receiver problems	3	8	24	Opening of Pig Receiver door when it is pressurized	Fire
38	Corrosion	4	8	32	Corrosive environment in Barrel	Damage to Barrel and the risk of fire, the environment pollution, toxic gas release and risk of personnel injury
39	Isolation	3	5	15	Any lines that are out of service	Risk of fire, the environment pollution, toxic gas release and risk of personnel injury
40	No/less flow of gas	4	2	8	Decreased/cut-off of flow from upstream	Loss of production
41	No/less flow of gas	4	2	8	Closure of MOV 208 and or Closure of MOV 221/222 by error	Loss of production
42	No/less flow of gas	3	8	24	Closure of MOV 208 and or Closure of MOV 221/222 by error	Increase pressure upstream of the valve and possibility of damage to relevant well flowline due to over pressure and the risk of relevant well trip.
43	No/less flow of gas	4	3	12	Closure of MOV 317/417 by error	Loss of production
44	No/less flow of gas	3	9	27	Closure of MOV 317/417 by error	Increased pressure upstream of the valve and possibility of damage to the flow lines due to over pressure and risk of well trips
45	No/less flow of gas	4	3	12	Not receiving in downstream	Loss of production
46	No/less flow of gas	3	9	27	Not receiving in downstream	Increased pressure and possibility of damage to relevant facility
47	High pressure	2	10	20	Thermal expansion during box-up or fire case	Possibility of damage to line and equipment due to over pressure
48	High pressure	6	3	18	Hold-up in pipeline	Back pressure for upstream facility and wellhead
49	Leakage/rupture	5	10	50	Corrosion, erosion, aging, gasket failure, ring failure, insulating joint failure, TPD, thermal tension, etc.	Toxic gas release, risk of personnel injury, loss of material, the environmental pollution and loss of production
50	Fire case	3	10	30	Ignition of released gas	Damage to facilities

The potential SMs for each hazard and their approximate implementation cost were identified by the HAZOP team, resulting in 56 SMs as reported in Table 4.

Table 4: Safety measures of the gas wellhead and surface facilities

SM No. (j)	Safety measure description	Cost (c_j, USD)
1	Consider a bypass line for preventing of hydraulic oil leakage of push-buttons	1600
2	Installation of PT with low alarm in control room on X-tree close to local PI-203.	2000
3	Consider proper Pressure alarm (by using PSL or new PT) for Hydraulic system in control room for predicting or alerting about conditional of 2SV/3SV.	2200
4	Consider alarm low in control room for FT-244.	600
5	Consider Limit Indicator for 2SV	1500
6	UV-224 should be tight shut-off	20000
7	FS-253 should be repaired and brought back to service to actuate alarm and actuate interlock to shutdown well	200
8	For easy maintenance of PSV-252 with minimum time, consider locked open isolation valve on upstream of PSV,	800
9	Installation of LT with LAH/LAL on separator,	2000
10	The important alerts (light) should be changed to audio alarm,	800
11	Considering fusible plug on wellhead to close 3SV and 2SV	600
12	Considering three push bottoms for emergency shutdown of wells	300
13	Considering proper flame and heat detector system	2400
14	Fire alert	400
15	Design pig launcher/receiver facilities and pipeline for intelligent pigging operation,	40000
16	Coating of pipelines to be checked and damaged items should be repaired with proper coating,	4000
17	Repair cathodic protection for pipelines	500
18	Considering H_2S gas detector	2200
19	Supply gas masks	500
20	Consider NRV on flow line	2000
21	To concert yard of well with reinforced concrete	2000
22	Considering CH_4 gas detector	2000
23	PSV on pump discharge should be brought back to service	300
24	Consider overflow line for corrosion inhibitor tank	1600
25	FS-205 should be repaired and brought back to service only for alarm and not permissive to start the well	200
26	Considering Local PI after PCV-350	200
27	Considering Local PI after PCV-330	200
28	Considering Local PI after PCV-334	200
29	Installation of LSHH on K,O Drum for actuates alarm and activates well shutdown system	2000
30	Develop proper procedure for regular checking of level in and equipment in flare K.O Drum area	600
31	Develop SOP for turning on pilot before drainage	600
32	Considering thermocouples on flare tip	500
33	Considering thermocouples on burn pit tip	500
34	High energy spark generators to be considered	10000
35	Considering three pilot lines	4000
36	Considering three igniter and three flame shooting lines	5000
37	Proper internal coating should be considered for K.O Drum	1000
38	Considering H_2S gas detector for K,O Drum area	2200
39	Considering proper flame and heat detector system for K.O Drum area	2400
40	Fire alert for K.O Drum area	400
41	Considering CH_4 gas detector for K.O Drum area	2000
42	For easy maintenance and inspection of PSV-259, changed the PSV to the flanged type PSV	700
43	Barrel doors to be selected properly for easy opening and minimum leakage	600
44	Installation of local PI on barrel	200
45	Slope and drain location for barrel connections and it's lines to be improved	1400
46	Leaked liquid in barrel should be drained regularly	400
47	Any lines that are out of service should be blinded to prevent leakage	200
48	Consider isolation valves on PSV-220 discharge for easy maintenance	1000
49	Consider isolation valves on PSV-301 discharge for easy maintenance	1000
50	Consider isolation valves on PSV-401 discharge for easy maintenance	1000
51	Considering three push bottoms in gathering center area for emergency shutdown	300
52	Considering proper flame and heat detector system in gathering center area	4200

SM No. (j)	Safety measure description	Cost (c_j, USD)
53	Fire alert in gathering center area	600
54	Considering H_2S gas detector in gathering center area	3400
55	To concert yard of gathering center with reinforced concrete	4500
56	Considering CH_4 gas detector	2700

Table 5 presents the updated probability P'_{ij} and severity S'_{ij} of the i-th hazard (Table 3) after the implementation of the j-th SM (Table 4).

Table 5: Updated (reduced) probability and severity of hazards after application of SMs

Hazard i	SM j	P'_{ij}	S'_{ij}	Hazard i	SM j	P'_{ij}	S'_{ij}	Hazard i	SM j	P'_{ij}	S'_{ij}
1	1	5	3	18	23	2	1	42	4	3	7
	2	6	1	19	24	1	3		7	3	5
	3	6	2	20	25	3	3		8	3	7
	4	6	2	21	26	4	1	44	4	3	8
2	1	6	3	22	27	4	1		7	3	7
	2	7	1	23	28	4	2		8	3	8
	3	7	2	24	29	2	5		48	3	8
	4	7	2		30	4	5		49	3	8
	5	6	2	25	19	5	3		50	3	8
3	2	1	1		31	4	4	46	4	3	8
	4	1	2	26	19	4	4		7	3	7
4	4	1	2		28	4	3		8	3	8
5	4	2	2		32	4	4		48	3	8
6	4	6	2		33	4	4		49	3	8
7	4	5	2	27	19	4	4		50	3	8
	6	3	3		32	4	4	47	48	2	9
8	4	3	7		33	4	4		49	2	9
	6	2	8		34	2	5		50	2	9
	7	3	4		35	2	5		51	2	8
	8	3	7	28	32	4	1		52	1	9
10	9	3	3		34	2	2		53	1	9
				29	33	4	1	48	8	6	2
	10	5	3	30	32	4	1		48	6	2
11	9	1	3		33	4	1		49	6	2
	10	1	3		34	2	2		50	6	2
12	9	3	4		36	2	2	49	15	3	10
	10	5	4	31	19	5	4		16	4	10
13	7	2	7		37	3	5		17	3	10
	8	2	8		38	5	4		19	5	9
	11	2	6		39	5	4		51	5	8
	12	2	7		40	5	4		54	5	9

Hazard i	SM j	P'_{ij}	S'_{ij}	Hazard i	SM j	P'_{ij}	S'_{ij}	Hazard i	SM j	P'_{ij}	S'_{ij}
	13	1	8		41	5	4		51	3	8
	14	1	8	32	42	2	2		52	3	9
	4	2	1		19	5	7	50	53	3	9
14	7	2	1	36	43	2	8		55	2	10
	8	2	1		44	2	8		56	2	10
	12	5	4	37	43	1	8				
	15	3	6		44	1	8				
15	16	4	6		13	4	7				
	17	3	6		14	4	7				
	18	5	5		18	4	7				
	19	5	5	38	19	4	7				
	12	2	6		22	4	7				
	15	1	8		45	2	6				
16	16	1	8		46	2	7				
	17	1	8		13	3	4				
	20	2	4		14	3	4				
	11	3	6	39	18	3	4				
	12	2	7		19	3	4				
17	13	3	8		22	3	4				
	14	3	8		47	1	5				
	21	2	9								
	22	2	9								

5. Results and discussion

The available budget for risk reduction in the case study is assumed as 30,000 USD. Mathematical models for the gas wellhead and surface facilities are developed according to Equations (4) and (5)with the parameters m=50, n=56, and C=3000. The optimal solutions for the models obtained by GA are displayed in Table 6.

Table 6: Optimal solutions of Models (I) and (II)

Safety measure (j)	Model I: x_j	Model II: x_j	Safety measure (j)	Model I: x_j	Model II: x_j	Safety measure (j)	Model I: x_j	Model II: x_j
1	0	1	20	0	1	39	0	0
2	0	1	21	0	0	40	1	0
3	0	0	22	0	0	41	0	0

Safety measure (j)	Model I: x_j	Model II: x_j	Safety measure (j)	Model I: x_j	Model II: x_j	Safety measure (j)	Model I: x_j	Model II: x_j
4	0	1	23	0	1	42	0	1
5	0	0	24	0	1	43	0	1
6	0	0	25	0	1	44	1	0
7	1	1	26	0	1	45	0	1
8	0	0	27	0	1	46	1	1
9	0	1	28	0	1	47	0	1
10	0	0	29	0	1	48	0	0
11	0	1	30	1	0	49	0	0
12	1	1	31	0	1	50	0	1
13	0	0	32	0	1	51	1	1
14	0	1	33	0	1	52	0	0
15	0	0	34	0	0	53	0	1
16	0	0	35	0	1	54	0	0
17	1	1	36	0	0	55	0	0
18	0	0	37	0	1	56	0	1
19	0	1	38	0	0			

The results of Models (I) and (II) along with a case when all the 56 SMs are selected without any budget constraint (Model III) are shown in Table 7.

Table 7: Comparison of results of Models I, II, and III

Model	Model (I)	Model (II)	Model III
Total cost (USD)	2,900	29,900	144,700
Total risk reductions	192	393	406
Max R_i'	$R'_{12}=R'_{49}=R'_{50}=24$	$R'_{49}=24$	$R'_{49}=24$
Number of selected SMs	8	32	56

Hazard number 49, toxic gas release from the header and the trunk line, was found as the hazard with the highest risk in each model. If all the relevant SMs (SMs number 15, 16, 17, 19, 51, 54) are allocated to this hazard, its risk could be reduced to R'_{49}= 24 (Table 8). This hazard is the bottleneck of the system, indicating that the risk of the individual hazards cannot be lowered than 24. It can also be noted that the minimization of the total cost as the second goal in Model (I) prevents from allocating the total budget to optimal SMs selection. That is, although there are many solutions for lowering the highest risk to 24, the second goal in Model I leads to the most frugal solution.

Table 8: SMs for hazard number 49 (i=49)

SM number (j) and cost	$P'_{49\|j}$	$S'_{49\|j}$
15 (40000[NKR-T1] USD)	3	10
16 (4000 USD)	4	10
17 (300 USD)	**3**	**10**
19 (500 USD)	5	9
51 (500 USD)	**5**	**8**
54 (3400 USD)	5	9
Min R'_{49}	**3×8=24 (800 USD)**	

Comparing the results of Models II and III in Table 7, it is demonstrated that in Model II, the selected 32 SMs have resulted in a total risk reduction of 394 units, which is only 12 units less than the total risk reduction of 406 units when all the 56 SMs are selected in Model III. In other words, there are 24 SMs (56 in Model III - 32 in Model II = 24) with a total cost of 114,000 USD (144,700 - 29,900 = 114,000) which can be used to reduce the total risk by only 13 units.

Fig. 3 compares the risk of hazards before and after the implementation of the SMs, demonstrating the higher efficiency of Model II in reducing the risks. However, the risk of hazards 49, 36, 8, and 38, which are the riskiest hazards in a descending order (50, 40, 32, 32 units of risk, respectively) has about equally been reduced using both Models I and II due to the identical first objective functions (minimizing the maximum risks) in the both models.

Fig. 4 shows the changes in the amount of risk before (the dashed line) and after implementing the SMs, indicating a nearly identical performance for Model II (total cost of SMs: \$29,900) and Model III (total cost of SMs: \$144,700). It is also evident that hazards with a higher risk have experienced a higher risk reduction.

Compared to the previous works, the methodology we have developed in the present study offers more flexible objective functions (minimax risk) and employs a lexicographic function to help the decision maker prioritize them. In addition, the proposed pessimistic strategy for modeling synergetic effects among the SMs needs no more information than the impact of each SM on the hazards.

Despite its advantages, the developed methodology is very data-intensive as it relies on quantitative values of risk criteria (in this study, hazard's probability and severity) as well as the cost and the impact of SMs on the hazards. That being said, the application of semi-quantitative risk assessment techniques such as HAZOP which can lead to subjective and often inaccurate values of risk (and updated risk) can largely affect the outcomes of the optimization, resulting in a locally optimal or non-optimal set of SMs.

Another modeling feature worth more investigation is the definition of risk (Equation (3)) and its impact on the optimal selection of SMs. In the present study, we focused on the risk of individual hazards and defined the objective functions in such a way that those individual risks could be minimized. Nevertheless, the total risk of a system failure would be different than the risk of its hazards and failure modes due to the dependencies and common-cause failures. For instance, for a system with m hazards (some of which being dependent) and n SMs (some of which having synergistic effects), the system's risk can be defined as:

$$R'_{System} = P(h_1, h_2, \ldots, h_m | x_1, x_2, \ldots, x_n)\, C(h_1, h_2, \ldots, h_m, x_1, x_2, \ldots, x_n) \qquad (6)$$

where h_i and x_j are, respectively, the i-th hazard and j-th SM; P(h|x) is the conditional joint probability of the hazards given the SMs, and C is the total cost of the hazards and the cost of SMs. The benefit of defining the system risk as Equation (6) would be twofold because in addition to considering the dependencies among the hazards, the synergistic effect of SMs can be taken into account with no need for employing the pessimistic strategy or other techniques.

The foregoing drawbacks, i.e., the application of semi-quantitative risk assessment techniques such as HAZOP, focusing on the risk of hazards instead of the system risk, and neglecting the dependencies among the hazards and SMs, can largely be alleviated by employing more sophisticated accident scenario modeling and risk assessment techniques such as Bayesian networks. However, it should be noted that the incorporation of probabilities and costs in a single objective function as in Equation (6) would significantly limit the capability of the decision maker in prioritizing the risk over the budget or vice versa in the optimization.

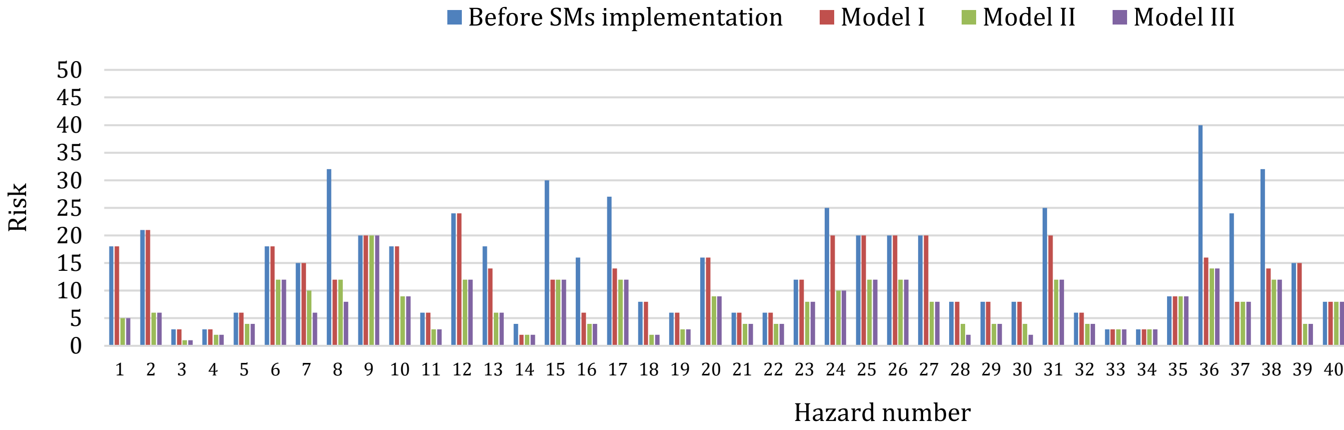

Fig.3. Comparison of the efficiency of Models I, II, and III in reducing the risk of hazards.

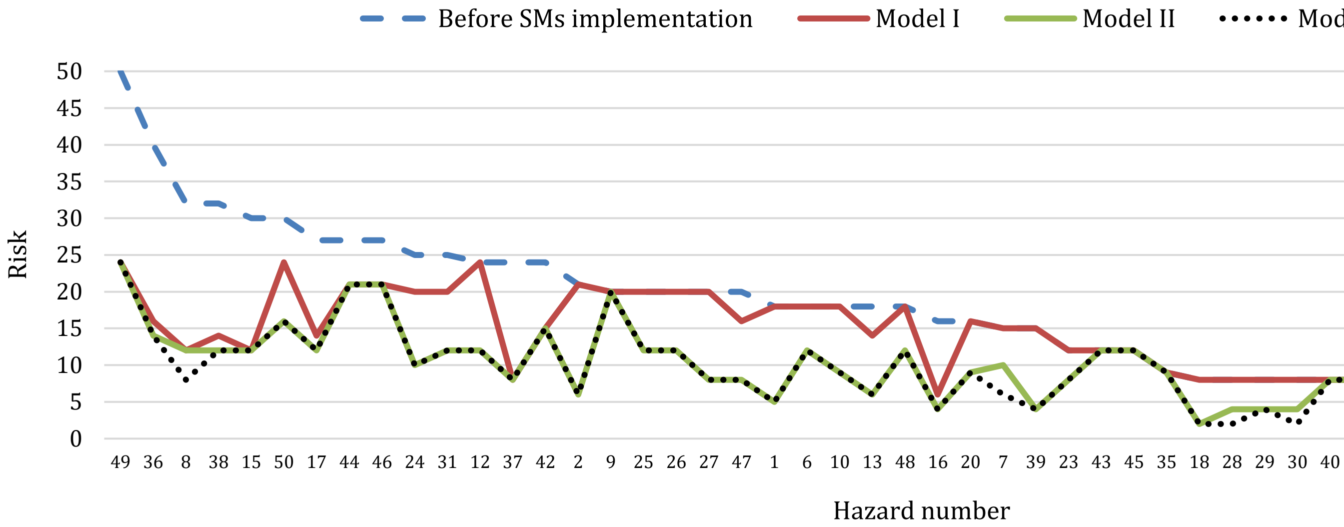

Fig.4. Difference between the primary risk (dashed line) and the residual risks of the hazards in a descending order.

6. CONCLUSIONS

In the present study, an innovative multi-objective optimization approach was developed for optimal selection of safety measures in engineering systems. In this approach, lexicographic function was used to prioritize the objective functions, and genetic algorithm was used to find the Pareto set of optimal solutions. To demonstrate the application of the methodology, we considered two objective functions: (i) minimizing the risk of hazards with the highest risk, and (ii) either minimizing the total cost or maximizing the total risk reduction.

The methodology was applied to optimal selection of safety measures for a gas wellhead and surface facility, demonstrating the importance of defining and prioritizing the objective functions in optimization problems. Although the methodology was developed with two objective functions and one constraint (the available budget), it can readily be extended, without loss of generality, to more complex multi-objective optimization problems owing to the flexibility of the lexicographic function and the genetic algorithm. However, it should be noted that adding new objective functions increases the complexity of the problem, and can thus decrease the performance of the methodology in terms of the processing time and the quality of the optimal solution.

In the developed methodology, the risk plays a key role, as one of the objective functions, in the optimal selection of safety measures. As such, due care should be given to the way the risk is defined (is it the risk of the system that matters or is it the risk of individual hazards?) in the light of dependencies arising from the common-causes of the hazards and the synergistic effects of the safety measures.

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