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A real-time framework for performance optimization of safety culture in the oil and gas industry under deep uncertainty (Case study: a petrochemical plant)

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Abstract

This study proposes a real-time framework for performance optimization of proactive safety culture in the oil and gas industry. Safety culture indicators were extracted from the literature using a comprehensive literature review. The proposed framework is based on fuzzy data envelopment analysis (FDEA), artificial neural networks (ANN), and statistical methods. It is able to evaluate the real-time performance of any safety-critical plant in the oil and gas industry and determines the current status of each indicator. The required data were collected using a questionnaire which was distributed as a self-administered survey to 210 employees in Shiraz Petrochemical Company and 174 surveys were returned with a high response rate. The application of fuzzy logic along with stochastic efficiency frontier analysis has empowered the proposed hybrid framework to deal with deep uncertainty, and result in more reliable findings. The obtained results can help safety managers to improve the proactive safety culture of the organization. They also can use the presented framework for periodic safety evaluations and determine the effectiveness of the implemented correction plans. To the best of our knowledge, this is the first study that presents a real-time framework for performance optimization of safety culture under deep uncertainty in the oil and gas industry.

Keywords: Proactive safety culture, efficiency frontier analysis, performance optimization, safety-critical industry, fuzzy data envelopment analysis, artificial neural networks.

1- Introduction

Safety is one of the most important aspects of any safety-critical industrial unit. Besides the human injuries and loss, any accident in critical industrial units can result in a catastrophic scope. Oil, gas and petrochemical industry is the main pillar of the economy in Iran.

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Not only most of the oil, gas and petrochemical infrastructures in Iran are old and worn-out (Azadeh et al., 2017), but also the safety management practices are not adequate. Currently, more than seventeen million employees are working in oil, gas and petrochemical industry in Iran which highlights the need for health and safety practices. Although the Ministry of Labor and Social Affairs along with Ministry of Health and Medical Education are responsible for employees' safety and have proposed much legislation, the reports do not reflect any accident reduction in this industry. Due to the presence of flammable and explosive materials in the oil, gas and petrochemical plants, safety planning becomes much more significant. According to safety managers, proactive and preventive safety planning is the best solution to this problem.

Occupational injuries and illnesses can change the lives of too many people, including families, coworkers, and communities. Besides human loss and suffering which is immeasurable, financial burdens are other consequences of occupational accidents. The occupational safety is much more highlighted in critical industrial units such as petrochemical plants, refineries, and nuclear plants where the consequences are far more extensive. The traditional safety management was primarily investigating the system for repetitious accidents and near-misses. In other words, it was reactively concentrated on preventing accidents (Booth and Lee, 1995). As the industrial growth and revolution happened, the insufficiency of traditional safety management and the need for proactive safety management emerged. Therefore, safety management evolved in industrial units and became more important. In the past decades, various practitioners and researchers have investigated the accidents and indicated that human error is the main contributing factor to accidents. It is important to understand that this doesn't indicate the incompetency of the workers, and that's why changing people doesn't prevent accidents. As a matter of fact, human error is the last link of the chain that leads to an accident (Antonsen, 2017). As a result, terms such as Organizational Accident and Organizational Culture was introduced in the 1990s. The concept of safety culture emerged based on the stated ideas and safety climate which was introduced by Zohar (1980), as an effective proactive safety management approach. It is been stated that safety culture affects all parts of a system consistently. Therefore, it's much more effective than increased supervision (Parker et al., 2006). This concept was first introduced by the International Automatic Energy Agency (IAEA) during the analysis of the Chernobyl disaster. Safety culture can be described as the product of beliefs, values, attitudes, and norms which determine the effectiveness of health and safety management in an organization. Safety climate refers to a shared perception of safety management in an organization among employees, while safety culture is much deeper and defines the basic and fundamental assumptions about safety (Casey et al., 2017). It should be noted that although creating a safety culture is not easy, it is proven that it can be investigated based on employees' patterns of attitude (Glendon and Stanton, 2000). In other words, the lack of safety culture in an organization is mirrored by negative patterns of beliefs, values, attitudes, and motivations among human resources.

According to Mearns and Flin (1999), measuring safety culture in organizations requires a thorough investigation. In this regard, safety culture dimensions for the considered organization should be determined. Safety studies in the United States nuclear industry after the disaster of Chernobyl in 1995 resulted in the primary safety culture indicators, including effective communication, organizational learning, organizational focus, and external factors (Glendon and Stanton, 2000). Later, Reason in 1997 proposed the indicators of safety culture which includes safety information system, reporting culture, trust culture, flexibility, and willingness to reform (Reason, 2016). Westrum (1996) presented a safety culture evaluation framework based on three levels of safety culture sophistication, including Pathological, Bureaucratic and Generative. Fleming (2001) developed a safety culture framework based on five maturity levels, including emerging, managing, involving, cooperating, and continually. In order to measure safety culture in each level, he proposed ten safety culture indicators, including training, job satisfaction, trust, shared perceptions about safety, participation, safety resources, learning organization, communication, management commitment, and productivity versus safety. Hudson (2001) presented a safety culture framework based on the maturity model of Westrum (1993). He considered information sharing and trust as the most important factors in safety culture evolution through five stages, namely Pathological, Reactive, Calculative, Proactive, and Generative. Later, Parker et al. (2006) developed a framework for performance evaluation of safety culture based on the proposed frameworks by Westrum (1996) and Reason (2016). The authors stated that if an organization is on the Generative level of safety culture, it can plan for improvement of safety culture indicators using the framework of Reason (2016). Goncalves Filho et al. (2010) proposed a safety culture framework based on the maturity model of Hudson (2001) for proactive safety improvement in petrochemical plants. They considered information, organizational learning, involvement, communication, and commitment as safety culture indicators. The required data were collected using questionnaires and interview with safety managers and experts in three petrochemical plants around Brazil. Grote (2008) proposed a safety culture improvement framework for petrochemical plants based on four sets of indicators, including reflected radically of change, support for constructive redevelopment, and esteem for employees, and employee involvement. Hajmohammad and Vachon (2014) evaluated the interrelationships between safety culture and organizational, indicators including environmental practices, environmental performance, safety practices, safety performance, and financial performance. They have measured the safety culture based on management commitment and employee participation indicators. Hsu et al. (2008) developed a comprehensive framework for safety culture assessment in oil refinery plants. The proposed framework is composed of safety self-efficacy, supervision, safety awareness, and safety behavior along with their related prerequisites. Kao et al. (2008) proposed a safety culture assessment framework for petrochemical plants. They introduced eight safety culture dimensions, including safety commitment and support, safety attitude and behavior, safety communication and involvement, safety training and competence, safety supervision and audit, safety management system, organization accidents investigation and emergency planning. Martínez-Córcoles et al. (2011) investigated the interrelationship among safety culture, safety climate, leadership, and safety behaviors in nuclear plants using structural equation modeling. Håvold et al. (2017) proposed a safety culture framework for the shipping industry. They considered eleven safety culture dimensions, including satisfaction with safety activities, fatalism, communication, knowledge and competence, management attitude, job satisfaction, safety rules, and learning culture. Goncalves Filho and Waterson (2018) proposed a review of safety culture and maturity models. Jiang et al. (2019) conducted a survey to investigate the role of safety culture and climate in industrial units toward improving proactive safety. Zhang et al. (2019) proposed a safety assessment model for performance optimization of proactive safety in production management. It should be noted that there is also a vast literature on safety culture assessment in healthcare which is out of the scope of the present study. For more information on safety culture in healthcare, readers can refer to (Nieva and Sorra, 2003; Pronovost and Sexton, 2005; Flin, 2007; Hellings et al., 2007; Sammer et al., 2010; Halligan and Zecevic, 2011; Schwartz et al., 2019).

Although safety culture is one of the most effective proactive safety management approaches, various researchers have proposed methods and approaches for improving proactive safety in safety-critical industries in the past decade. Burns (2006) proposed a proactive deviation detection approach for improving safety in petrochemical plants. Chen and Yang (2004) developed a predictive safety index for improving proactive safety in petrochemical plants which was based on observed near-miss events and unsafe conditions. Curcuruto et al. (2015) proposed a proactive safety behavior-based approach for evaluating the safety performance in chemical plants. Although proactive safety can improve the safety significantly, reactive safety and investigation of deviations are necessary for building a resilient and safe workplace (Verma et al., 2018).

This study aims to present a real-time proactive safety framework for performance optimization of safety culture in safety-critical industries. The proposed framework is composed of a comprehensive set of safety culture indicators alongside a hybrid performance evaluation algorithm. The developed unique hybrid performance evaluation algorithm is composed of artificial neural networks (ANN), fuzzy data envelopment analysis (FDEA), and statistical methods. It is capable of dealing with severe uncertainty and determines the real-time performance of each safety culture indicator in the considered case study. The obtained results can help safety-critical industries managers in planning for proactive safety improvement. They can also evaluate the performance of safety indicators in multiple periods using the developed framework, in order to determine the effectiveness of implemented corrective plans. To the best of our knowledge, this is the first study that presents a real-time performance optimization framework for improving safety culture considering severe uncertainty in safety-critical industries.

The rest of this paper is organized as follows: The methodology of this study is presented in Section 2. Section 3 demonstrates the application of the proposed approach in a real case study. The obtained results and discussions are presented in Section 4. Lastly, Section 5 is dedicated to concluding remarks and directions for future research.

2- Methodology

Effective proactive safety management in the oil and gas industry is of great significance. One of the most important stages of developing such a safety management system is a real-time performance evaluation of proactive safety dimensions in the considered environment. Performance evaluation results in the determination of weaknesses and strengths of safety dimensions, and paves the way toward proactive safety improvement. In this regard, this study proposes a real-time performance optimization of safety culture indicators based on efficiency frontier analysis. Although the primary use of efficiency frontier analysis is investigating the productivity and efficiency of decision-making units (DMUs), and finally ranking them, it is a popular tool for investigating the relationship between multiple inputs and output variables in conceptual systems where the relationships among variables are complex and vague (Zhalechian et al., 2017). In other words, efficiency frontier analysis methods such as data envelopment analysis (DEA) usually evaluates the performance of a system by considering multiple inputs and output variables, however, in order to evaluate the role of input and output variables, it is possible to reverse this process. In this regard, a set of experts from the system who are aware of the system processes, express their knowledge about the role of the input and output variables which form the overall performance of the system. Therefore, the obtained efficiency score for each expert determines the overall performance of the system based on the related input and output variables from the correspondent point of view. The obtained set of efficiency scores from all participated experts depict the efficiency map of the system which demonstrates the real-time performance of the system (Azadeh et al., 2017). The schematic view of the stated approach is presented in figure 1.

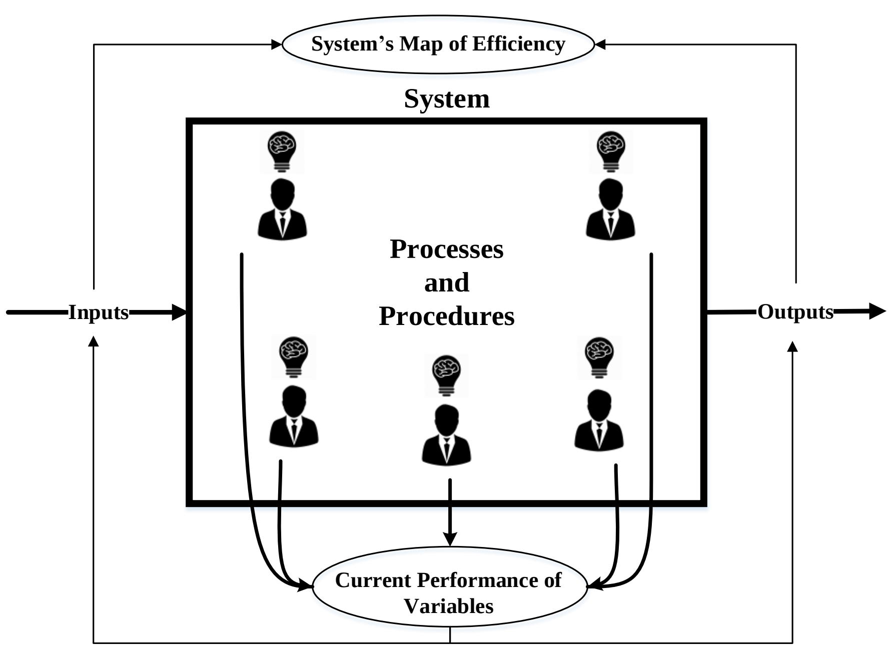

Fig 1. Real-time performance evaluation using efficiency frontier analysis

In order to calculate the efficiency scores in efficiency frontier analysis, various methods and models are developed which are primarily based on the traditional DEA models. DEA is a non-parametric method for evaluating the efficiency of DMUs based on multiple inputs and output variables. However, it is unable to deal with severe uncertainty and it only considers the linear relationships between variables (Heidari et al., 2017). Since the nature and relationships of safety culture indicators are complex, we need an efficiency frontier analysis tool which deals with severe uncertainty and complex relationships. In order to address the stated disadvantages of traditional DEA models, this study proposes a hybrid performance evaluation algorithm based on FDEA and ANN. FDEA is capable of handling severe uncertainty and considering the linear relationships among variables, while ANN considers non-linear relationships among variables alongside dealing with severe uncertainty. The main steps of the proposed framework are presented as follows.

Step 1. Identification of safety culture indicators

In order to evaluate and optimize safety culture, first, safety culture indicators should be identified. Each safety culture indicator covers a safety culture dimension in safety-critical industries. This study develops a comprehensive set of safety culture indicators based on the previous studies in the literature. Table 1 presents the considered safety culture indicators along with their supporting references.

Step 2. Data collection

In order to collect the required data, a standard questionnaire is designed based on the considered safety culture indicators (which is presented in Appendix A). Jam Petrochemical Company in Iran is considered as a real-life case study. Various managers and experts from different departments of the considered case study answered the questions of the questionnaire related to each safety culture dimension by assigning a number between 1 to 10 (1 is very low and 10 is very high). The developed questionnaire also collected the demographic features of the respondents. The reliability and validity of the collected data from the questionnaires are evaluated via Cronbach's alpha and statistical tests, respectively (Azadeh et al., 2017). The reliability and validity tests are performed in the SPSS® statistical package.

In order to deal with the uncertainty and variability of the collected deterministic data, this study implements a triangular fuzzification approach. Although various types of fuzzy membership functions are introduced in the literature, triangular fuzzy functions are offering the most efficient trade-off between simplicity and accuracy.

Table 1. The comprehensive set of proactive safety indicators extracted using literature survey

No.	Proactive safety indicator	Definition	Supporting references
1	Teamwork	The effective and collaborative effort of a group of people who work in the same environment toward common goals.	(Salaheldin and Zain, 2007; Hsu et al., 2008; Jones et al., 2013; Azadeh et al., 2017)
2	Management commitment	Management commitment indicates the management's willingness to invest, plan and devotion for improving safety in an organization.	(Fleming, 2001; Kao et al., 2008; Goncalves Filho et al., 2010; Hajmohammad and Vachon, 2014)
3	Information sharing and reporting culture	The willingness of employees to report all the safety issues, unusual events, and near-misses in an organization. Reporting safety issues facilitate awareness in the organization.	(Hudson, 2001; Hsu et al., 2008; Goncalves Filho et al., 2010; Azadeh et al., 2017)
4	Management support and reward system	Management should encourage employees who follow safety rules and report safety issues in the organization. The reward policy affects information sharing, safety behavior, and awareness, significantly.	(Hsu et al., 2008; Resnick, 2009; Lally, 2015; Probst, 2015; Saracino et al., 2015; Friend and Kohn, 2018)
5	Learning culture	Learning culture is the ability of the system to learn from past safety issues in order to respond to future unusual events effectively. It improves the knowledge, competence, and performance of the organization.	(Hsu et al., 2008; Goncalves Filho et al., 2010; Gotcheva et al., 2016; Antonsen, 2017; Azadeh et al., 2017; Håvold et al., 2017)
6	Communication and awareness	The willingness of the management to communicate its employees all safety-related issues. Hiding the system's vulnerabilities and failures prevent safety information sharing in the organization and learning culture.	(Kao et al., 2008; Goncalves Filho et al., 2010; Azadeh et al., 2017; Håvold et al., 2017)
7	Safety supervision and audits	Safety supervision indicates the supervisors' effort in investigating the workplace for safety issues and monitoring employees. Safety audit evaluates the performance of safety programs in the organization.	(Hsu et al., 2008; Kao et al., 2008; Kazaras et al., 2014; Lutchman et al., 2016; Karanikas, 2017)
8	Trust	Implementation of safety programs requires cooperation among employees. Employees should be able to depend on each other in preventing accidents. Trust is the key to effective cooperation.	(Goncalves Filho et al., 2010; Curcuruto et al., 2015; Mauriño, 2017)
9	Safety training and preparedness	Safety training is one of the most frequently used activities in improving safety preparedness. It increases the competence of employees in preventing accidents.	(Goncalves Filho et al., 2010; Namian et al., 2016; Mohammadfam et al., 2017; Tapp and Bravo, 2017; Rabbani et al., 2018)
10	Safety attitude and behavior	Creating a blame-free environment in improving safety culture is essential. Employees' openness about errors along with safety over productivity attitude is basic requirements of safety behavior in an organization.	(Burt et al., 2008; Monazzam and Soltanzadeh, 2009; Nasab et al., 2009; Tam and Fung, 2011)
11	Employee involvement	Employees should engage and participate in all safety-related activities and issues. Employees' involvement in safety analysis and management process provides them with responsibility and accountability which reduces accidents.	(Vredenburgh, 2002; Ariss, 2003; Hsu et al., 2008; Carmeli et al., 2010; Hajmohammad and Vachon, 2014)

Step 3. Fuzzy data envelopment analysis (FDEA)

The traditional DEA models were applicable for efficiency analysis of deterministic input and output variables, while in most cases data sets are not deterministic. Considering the vague and subjective nature of safety culture and related collected data, fuzzy programming can be an appropriate choice. This study employs a fuzzy logic based DEA model proposed by Azadeh and Alem (2010). Since all considered safety culture indicators are the larger-the-better type, they are all considered as output variables of the model. As for inputs of the model, a single dummy variable is been considered. The utilized FDEA model for R output variables $(r=1,2,...,R)$ J input variables $(j=1,2,...,J)$ and I DMUs is $(i=1,2,...,I)$ presented in model (1).

$$
\begin{aligned}
& Max\ \theta=\sum_{r=1}^{R}u_r\, y_{ri} \\
& \sum_{j=1}^{J}v_j\, x_{ji}=1 \\
& \sum_{r=1}^{R}u_r\, y_{ri}-\sum_{j=1}^{J}v_j\, x_{ji}\le 0 \\
& v_j,u_r\ge 0 \quad ;\forall\, j=1,2,...,J;r=1,2,...,R
\end{aligned} \tag{1}
$$

Where x_{jt} represents the standardized value of input variable j from DMU i and y_{ri} is the standardized value of output variable r from DMU i. Also, x_{ji} and y_{ri} are the fuzzy variables. Although various types of fuzzy membership functions are introduced in the literature, triangular fuzzy functions are the most efficient ones due to simplicity and accuracy. In order to transform the model (2) into the triangular fuzzified model, the α-cut method proposed by Chang and Lee (2012) is used. Lastly, the transformed α-cut based FDEA model is presented in model (2).

$$
\begin{aligned}
& x_{ji}=\left(x_{ji}^{l},x_{ji}^{m},x_{ji}^{u}\right),y_{ri}=\left(y_{ri}^{l},y_{ri}^{m},y_{ri}^{u}\right) \\
& Max\ \omega=\sum_{r=1}^{R}u_r\left(\alpha y_{ri}^{m}+(1-\alpha)y_{ri}^{l},\alpha y_{ri}^{m}+(1-\alpha)y_{ri}^{u}\right) \\
& \sum_{j=1}^{J}v_j\left(\alpha x_{ji}^{m}+(1-\alpha)x_{ji}^{l},\alpha x_{ji}^{m}+(1-\alpha)x_{ji}^{u}\right)=1 \\
& \sum_{r=1}^{R}u_r\left(\alpha y_{ri}^{m}+(1-\alpha)y_{ri}^{l},\alpha y_{ri}^{m}+(1-\alpha)y_{ri}^{u}\right)-\sum_{j=1}^{J}v_j\left(\alpha x_{ji}^{m}+(1-\alpha)x_{ji}^{l},\alpha x_{ji}^{m}+(1-\alpha)x_{ji}^{u}\right)\le 0 \\
& v_j,u_r\ge 0 \quad ;\forall\, j=1,2,...,J;r=1,2,...,R
\end{aligned} \tag{2}
$$

Where u_r represents the weight of output variables, while v_j is the weight of inputs. The optimum α-cut is selected based on the highest average efficiency scores from the set of 0.1, 0.25, 0.5, 0.75, and 0.9.

Step 4. ANN-based performance optimization algorithm
Many efficiency frontier analysis based approaches are introduced for performance evaluation and optimization of industrial and service-oriented systems in the past decades which were mostly based on DEA models. One of the main restrictive assumptions in DEA based approaches is considering the efficiency frontier deterministic which is sensitive to outliers (Yazdanparast et al., 2018). Azadeh et al. (2007) proposed an artificial neural network based algorithm. It was a non-parametric approach which considered the efficiency frontier stochastic. The authors indicated that such an approach is able to deal with heavy uncertainty and present more reliable results. This study utilized artificial neural networks multi-layer perceptron (ANN-MLP) model for calculating efficiency scores. The steps of the ANN-based performance optimization algorithm are as follows:

1. Data preparation
   The collected data for safety culture indicators should be divided into two sets, including a training data set and test data set. The conventional ratio in the literature is 70% for training data set, however, we examine other ratios including 60% and 80% in order to find the optimum ANN-MLP structure.
2. Parameter tuning
   The optimum ANN structure is determined based on the mean absolute percentage error (MAPE). In this regard, various ANN-MLP structures are evaluated using the different data set ratios (60%, 70%, and 80%). This procedure is called random search method. The search for optimum ANN structure continues until the MAPE reaches the acceptable error which is considered equal to 5%. In order to prevent overtraining in determining the optimum ANN structure and predicting the efficiency scores, repeated random sub-sampling validation method is used. In this method, the selected data for each data set is randomly changed and each structure is tested with 100 different data sets. The reported MAPE of each structure is actually the mean of 100 runs. This method is a known cross-validation method for problems with small available observations (Nasiri et al., 2017).
3. Efficiency calculation
   In order to calculate efficiency scores and obtain stochastic efficiency frontier the following calculation should be done:

$$E_{ir} = O_{real(ir)} - O_{ANN(ir)} \quad (r = 1, \dots, R \ and \ i = 1, \dots, I) \tag{3}$$

$$E'_{ir} = (E_{ir}/O_{ANN(ir)}) \quad (r = 1, \dots, R \ and \ i = 1, \dots, I) \tag{4}$$

$$E_k = \max(E'_r) \tag{5}$$

$$Sh_{ir} = E_k * \frac{O_{ANN(ir)}}{O_{ANN(ik)}} \quad (r = 1, \dots, R \ and \ i = 1, \dots, I) \tag{6}$$

$$F_{ir} = P_{ir}/(O_{ANN(ir)} + Sh_{ir}) \tag{7}$$

$$\bar{F}_i = \frac{\sum_{r=1}^{R} F_{ir}}{J} \tag{8}$$

Where $O_{real(ir)}$ is the real value of rth output variable from ith respondent, while $O_{ANFIS(ir)}$ represents the predicted value of rth output variable from ith respondent. Equation (3) calculates the error between the real and predicted values. Equation (4) calculates the relative error while E'_k represents the maximum relative error. Equation (5) calculates the shift frontier function for output variable r. The calculated efficiency scores for each output variable r are calculated in equation (7). Lastly, equation (8) presents the final efficiency scores of each DMU i. MATLAB V.2014 is used for running ANN-MLP different structures in this study. Appendix A presents the related MATLAB codes.

Step 5. Hybrid efficiency frontier
Obtaining a system's map of efficiency plays an important role in the accuracy of its performance optimization. Considering the subjective nature of safety culture indicators and its related uncertainty, in order to obtain an accurate map of efficiency, a reliable efficiency frontier approach is needed. This study proposed a unique efficiency frontier approach which utilizes the advantages of both DEA based models in the fuzzy environment with deterministic efficiency frontier and ANN-based models with stochastic efficiency frontier. In this regard, in order to calculate the hybrid map of the efficiency of safety culture in the considered case study, the mean efficiencies of the obtained results in Steps 4 and 5 are calculated.

Step 6. Sensitivity analysis
In order to perform the real-time performance evaluation of proactive safety indicators in the proposed framework using efficiency frontier analysis, first, the efficiency scores of the DMUs considering all input and output variables are calculated. The obtained efficiency scores depict the efficiency map of the considered system. Then, each variable is eliminated from the model once, and the efficiency scores are recalculated. The non-existence of the eliminated variable causes changes in the obtained efficiency scores and the efficiency map of the system. Comparing the obtained efficiency scores before and after the elimination of each variable from the model using statistical methods determines the real-time performance of the eliminated variable. The obtained results indicate the real-time status of each variable which can be Normal, Negative, or Positive. The safety managers can design improvement plans based on the obtained results in order to optimize the proactive safety through implementing safety culture.

3- Case study: a real-life petrochemical plant

Oil, gas, and petrochemical industries play an important role in the economy of Iran. National Iranian Oil Company (NIOC) is been in charge of all oil, gas and petrochemical policies in Iran, since 1951. Accessibility to the vast amount of oil and gas resources has made NIOC one of the largest oil companies in the world. Although Iran has a unique position in terms of oil and gas reserves in the world, its infrastructures are old. Besides, safety management practices are not adequate. These factors resulted in many safety issues and accidents which are threatening sixteen million workers in Iran. The Ministry of Health and Medical Education is responsible for the occupational health and safety (OHS) services and legislation, while the Ministry of Labour and Social Affair enacts and enforces the legal issues. According to this procedure, inspectorates from various ministries monitor health and safety regulations in industries (Vigeh et al., 2011). Although many efforts have been made, annual reports don't reflect accidents reduction especially in safety-critical industries in the past decade. Proactive safety practices are the missing key to create a safety culture and to reduce accidents in safety-critical industries in Iran. This study proposes a real-time framework for performance optimization of safety culture indicators in safety-critical industries.

3-1- Data collection

In order to demonstrate the application of the proposed framework, a real-life petrochemical plant in Iran is considered in this section. Shiraz Petrochemical Company was founded in 1959. It produces around 1,850,000 tons of various chemical and petrochemical products per year and is one of the major petrochemical plants in Iran. In order to collect the required data, the designed questionnaire based on the identified safety culture indicators is distributed among 210 employees of four different departments, including Health, Safety, and Environment (HSE), Technical Services, Maintenance, and Operation departments. After distributing the questionnaires, 174 completed questionnaires are collected. Figure 2 demonstrates the demographic features of the respondents. The reliability and validity of the collected data are evaluated in table 2.

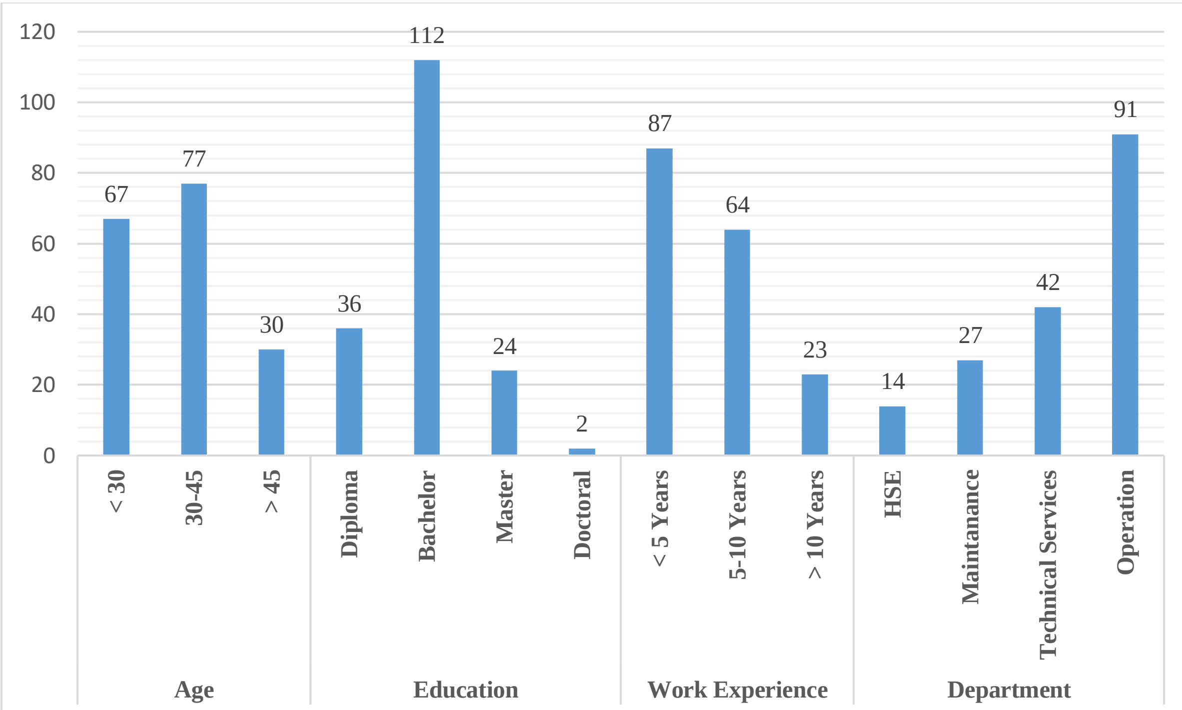

Fig 2. The demographic features of questionnaires respondents in the considered case study

Table 2. The obtained results for the reliability and validity of the collected data

Indicators	Cronbach's alpha	2 Sample t-test P-value
Teamwork	0.842	0.135
Management commitment	0.742	0.097
Information sharing and reporting culture	0.647	0.218
Management support and reward system	0.842	0.188
Learning culture	0.727	0.370
Communication and awareness	0.694	0.239
Safety supervision and audits	0.801	0.113
Trust	0.783	0.146
Safety training and preparedness	0.728	0.286
Safety attitude and behavior	0.786	0.312
Employee involvement	0.942	0.255

Note; In order to demonstrate the validity of the collected data two random samples are extracted from collected data for each indicator. 2 sample t-test is employed for comparing the mean of the collected samples. If the means of both random samples are equal, there is no significant difference between means. Therefore, the validity of the collected data for the considered indicator is acceptable (Confidence level is 95%).

Fuzzification of the collected data is performed based on equations (9-14).

$$x_{ji} = \left(x_{ji}^{l}, x_{ji}^{m}, x_{ji}^{u}\right), y_{ri} = \left(y_{ri}^{l}, y_{ri}^{m}, y_{ri}^{u}\right)$$

$$x_{ji}^{l} = Min\left(x_{ji}\right) \quad ;\forall i = 1,2,...,I \tag{9}$$

$$x_{ji}^{m} = x_{ji} \quad ;\forall i = 1,2,...,I \tag{10}$$

$$x_{ji}^{u} = Max\left(x_{ji}\right) \quad ;\forall i = 1,2,...,I \tag{11}$$

$$y_{ri}^{l} = Min\left(y_{ri}\right) \quad ;\forall i = 1,2,...,I \tag{12}$$

$$y_{ri}^{m} = y_{ri} \quad ;\forall i = 1,2,...,I \tag{13}$$

$$y_{ri}^{u} = Max\left(y_{ri}^{u}\right) \quad ;\forall i = 1,2,...,I \tag{14}$$

Where x_{ji}^{u} is the maximum value of input *j* for all DMUs $\left(i = 1,2,...,I\right)$, while x_{ji}^{l} is the minimum value of input j for all DMUs $\left(i = 1,2,...,I\right)$. Also, y_{ri}^{u} is the maximum value of output *r* for all DMUs $\left(i = 1,2,...,I\right)$, while y_{ri}^{l} is the minimum value of output *r* for all DMUs $\left(i = 1,2,...,I\right)$.

3-2- FDEA results

In order to use the presented FDEA model (model (1)), first, the optimum α-cut should be determined. The optimum α-cut for the FDEA model is determined based on the highest average efficiency of DMUs and normality of the obtained results (Heidari et al., 2017). Therefore, the efficiency scores are calculated with candidate α-cuts, including 0.1, 0.25, 0.5, 0.75, and 0.9. All FDEA calculations in this study are performed using AutoAssess package (Azadeh, 2007). According to the obtained results presented in table 3, the optimum α-cut is 0.1. The calculated efficiency scores using the optimum α-cut is presented in table 4.

Table 3. The obtained results for determination of FDEA optimum α-cut

Model	FDEA (α=0.1)	FDEA (α=0.25)	FDEA (α=0.5)	FDEA (α=0.75)	FDEA (α=0.9)
Distribution Companies' trust model	Mean efficiency: 0.929841 P-value of normality test: <0.005	Mean efficiency: 0.890472 P-value of normality test: <0.005	Mean efficiency: 0.875643 P-value of normality test: <0.005	Mean efficiency: 0.843109 P-value of normality test: <0.005	Mean efficiency: 0.804241 P-value of normality test: <0.005

Table 4. The obtained efficiency scores using the preferred FDEA model

DMU	Efficiency	DMU	Efficiency	DMU	Efficiency	DMU	Efficiency	DMU	Efficiency
1	1	36	1	71	0.8604073	106	0.7560755	141	1
2	0.8194991	37	0.8228513	72	0.8937509	107	0.9230037	142	0.7928352
3	1	38	1	73	1	108	1	143	1
4	1.003901	39	0.9263395	74	0.9411578	109	0.9569713	144	1
5	0.9316579	40	0.7560755	75	0.8925479	110	1	145	0.9816492
6	1	41	0.9230037	76	1	111	1.0015464	146	1
7	0.9893499	42	1	77	0.8194991	112	0.7703847	147	1
8	0.874723	43	0.9569713	78	1	113	0.9168361	148	1
9	1	44	1	79	1.003901	114	0.7630368	149	1
10	1	45	1.0015464	80	0.9316579	115	0.8435166	150	0.8446015
11	0.7853774	46	0.7703847	81	1	116	0.8955237	151	0.8899762
12	0.8698166	47	0.9168361	82	0.9893499	117	1	152	1
13	0.9375	48	0.7630368	83	0.874723	118	1	153	1
14	0.911222	49	0.8435166	84	1	119	0.8258185	154	0.8228513
15	0.8083674	50	0.8955237	85	1	120	0.7725255	155	1
16	0.7668035	51	1	86	0.7853774	121	0.9473928	156	0.9263395
17	1	52	1	87	0.8698166	122	1	157	0.7560755
18	0.8821426	53	0.8258185	88	0.9375	123	1	158	0.9230037
19	1.0989346	54	0.7725255	89	0.911222	124	0.9893499	159	1
20	1	55	0.9473928	90	0.8083674	125	0.874723	160	0.9569713
21	1	56	1	91	0.7668035	126	1	161	1
22	1	57	1	92	1	127	1	162	1.0015464
23	0.832318	58	1	93	0.8821426	128	0.7853774	163	0.7703847
24	1	59	1	94	1.0989346	129	0.8698166	164	0.9168361
25	0.7928352	60	0.8014002	95	1	130	0.9375	165	0.7630368
26	1	61	0.7708254	96	1	131	0.911222	166	0.8435166
27	1	62	1	97	1	132	0.8083674	167	0.8955237
28	0.9816492	63	0.7714712	98	1	133	0.7668035	168	1
29	1	64	1	99	0.8446015	134	1	169	1
30	1	65	1	100	0.8899762	135	0.8821426	170	0.8258185
31	1	66	1	101	1	136	1.0989346	171	0.7725255
32	1	67	0.9017119	102	1	137	1	172	0.9473928
33	0.8446015	68	1	103	0.8228513	138	1	173	1
34	0.8899762	69	0.8934538	104	1	139	1	174	1
35	1	70	1	105	0.9263395	140	0.832318	-	-

3-3- ANN results

In order to determine the optimum ANN-MLP structure, various structures are identified and investigated in Table 5. The obtained results indicate structure number 9 presents the least MAPE. The steps of ANN-based algorithm using the determined optimum ANN-MLP structure is used to calculate the efficiency scores. The calculated efficiency scores using the optimum ANN-MLP structure is presented in table 6.

3-4- Hybrid efficiency scores

The final hybrid efficiency scores are calculated based on both obtained sets of efficiency scores using FDEA and ANN. The hybrid efficiency scores are profited by the advantages of both FDEA and ANN models. According to the statistical tests in Figure 3, the obtained hybrid scores are less biased than FDEA scores. On the other hand, the obtained hybrid scores present higher efficiency scores than ANN scores. Therefore, the calculated hybrid scores depict a more reliable map of efficiency for the considered problem.

Table 5. The performance of different structures of ANN-MLP

No.	Training function	Number of hidden layers	Transfer function of the first hidden layer	Number of neurons in the 1th hidden layer	Transfer function of the second hidden layer	Number of neurons in the 2nd hidden layer	Transfer function of the output layer	MAPE			MAPE*
								Training data set ratio			
								60%	70%	80%	
1	LM	1	logsig	5	-	-	purelin	0.181	0.224	0.175	0.193
2	OSS	1	tansig	6	-	-	purelin	0.194	0.170	0.201	0.188
3	GDA	1	logsig	8	-	-	purelin	0.203	0.173	0.179	0.185
4	BFGS	1	logsig	10	-	-	purelin	0.145	0.174	0.148	0.156
5	LM	1	tansig	12	-	-	purelin	0.167	0.138	0.153	0.153
6	GD	1	logsig	14	-	-	purelin	0.102	0.107	0.115	0.108
7	BFGS	1	tansig	15	-	-	purelin	0.132	0.119	0.127	0.126
8	OSS	1	tansig	17	-	-	purelin	0.097	0.084	0.108	0.096
9	**LM**	**1**	**logsig**	**20**	**-**	**-**	**purelin**	**0.064**	**0.087**	**0.052**	**0.067**
10	GDX	1	tansig	22	-	-	purelin	0.088	0.105	0.092	0.095
11	GDA	1	logsig	25	-	-	purelin	0.147	0.129	0.128	0.135
12	BFGS	1	tansig	30	-	-	purelin	0.131	0.166	0.123	0.140
13	LM	1	tansig	35	-	-	purelin	0.197	0.204	0.185	0.195
14	OSS	1	tansig	40	-	-	purelin	0.174	0.192	0.234	0.200
15	GD	2	logsig	4	logsig	4	purelin	0.107	0.106	0.094	0.102
16	LM	2	logsig	6	tansig	6	purelin	0.089	0.081	0.096	0.089
17	GDA	2	tansig	8	logsig	8	purelin	0.078	0.069	0.092	0.080
18	BFGS	2	logsig	10	logsig	10	purelin	0.093	0.083	0.088	0.088
19	OSS	2	logsig	12	tansig	12	purelin	0.089	0.104	0.096	0.096
20	GDX	2	tansig	14	logsig	14	purelin	0.118	0.106	0.099	0.108
21	LM	2	logsig	16	tansig	16	purelin	0.132	0.118	0.122	0.124

Note; The last column, MAPE*, is equal to the mean of MAPE for considered training data set ratios.

LM: Levenberg-Marquardt back propagation; BFG: quasi-Newton back propagation; GD: Gradient descent back-propagation; GDA: Gradient descent with adaptive learning rule back propagation; OSS: One step secant back propagation; GDX: Gradient descent with momentum and adaptive learning rule back-propagation.

Table 6. The obtained efficiency scores using the optimum ANN-MLP structure

DMU	Efficiency	DMU	Efficiency	DMU	Efficiency	DMU	Efficiency	DMU	Efficiency
1	0.78204	36	0.81273	71	0.61749	106	0.60347	141	0.72383
2	0.68031	37	0.57993	72	0.65083	107	0.72035	142	0.54992
3	0.79237	38	0.68349	73	0.75708	108	0.77348	143	0.90273
4	0.83238	39	0.68342	74	0.69824	109	0.65348	144	0.89294
5	0.74238	40	0.60347	75	0.64963	110	0.75348	145	0.73873
6	0.79576	41	0.72035	76	0.78204	111	0.86835	146	0.82738
7	0.74894	42	0.77348	77	0.68031	112	0.52746	147	0.79835
8	0.68031	43	0.65348	78	0.79237	113	0.69348	148	0.74382
9	0.76397	44	0.75348	79	0.83238	114	0.58348	149	0.80237
10	0.78267	45	0.86835	80	0.74238	115	0.64238	150	0.60168
11	0.59845	46	0.52746	81	0.79576	116	0.67348	151	0.64706
12	0.54724	47	0.69348	82	0.74894	117	0.76348	152	0.74347
13	0.69458	48	0.58348	83	0.68031	118	0.79347	153	0.81273
14	0.6683	49	0.64238	84	0.76397	119	0.69343	154	0.57993
15	0.56545	50	0.67348	85	0.78267	120	0.63482	155	0.68349
16	0.52388	51	0.76348	86	0.59845	121	0.70447	156	0.68342
17	0.82723	52	0.79347	87	0.54724	122	0.6835	157	0.60347
18	0.63483	53	0.69343	88	0.69458	123	0.70238	158	0.72035
19	0.83746	54	0.63482	89	0.6683	124	0.74894	159	0.77348
20	0.82373	55	0.70447	90	0.56545	125	0.68031	160	0.65348
21	0.67834	56	0.6835	91	0.52388	126	0.76397	161	0.75348
22	0.78347	57	0.70238	92	0.82723	127	0.78267	162	0.86835
23	0.5894	58	0.79349	93	0.63483	128	0.59845	163	0.52746
24	0.72383	59	0.72383	94	0.83746	129	0.54724	164	0.69348
25	0.54992	60	0.55848	95	0.82373	130	0.69458	165	0.58348
26	0.90273	61	0.52791	96	0.67834	131	0.6683	166	0.64238
27	0.89294	62	0.75708	97	0.78347	132	0.56545	167	0.67348
28	0.73873	63	0.52855	98	0.80237	133	0.52388	168	0.76348
29	0.82738	64	0.76348	99	0.60168	134	0.82723	169	0.79347
30	0.79835	65	0.79835	100	0.64706	135	0.63483	170	0.69343
31	0.74382	66	0.75708	101	0.74347	136	0.83746	171	0.63482
32	0.80237	67	0.67835	102	0.81273	137	0.82373	172	0.70447
33	0.60168	68	0.78744	103	0.57993	138	0.67834	173	0.6835
34	0.64706	69	0.65053	104	0.68349	139	0.78347	174	0.70238
35	0.74347	70	0.75708	105	0.68342	140	0.5894	-	-

Table 7. The calculated hybrid efficiency scores

DMU	Efficiency	DMU	Efficiency	DMU	Efficiency	DMU	Efficiency	DMU	Efficiency
1	0.89102	36	0.906365	71	0.738949	106	0.679773	141	0.861915
2	0.749905	37	0.701391	72	0.77229	107	0.821677	142	0.671378
3	0.896185	38	0.841745	73	0.87854	108	0.88674	143	0.951365
4	0.91619	39	0.80488	74	0.819699	109	0.805226	144	0.94647
5	0.837019	40	0.679773	75	0.771089	110	0.87674	145	0.86019
6	0.89788	41	0.821677	76	0.89102	111	0.934175	146	0.91369
7	0.869145	42	0.88674	77	0.749905	112	0.648922	147	0.899175
8	0.777517	43	0.805226	78	0.896185	113	0.805158	148	0.87191
9	0.881985	44	0.87674	79	0.91619	114	0.673258	149	0.901185
10	0.891335	45	0.934175	80	0.837019	115	0.742948	150	0.723141
11	0.691914	46	0.648922	81	0.89788	116	0.784502	151	0.768518
12	0.708528	47	0.805158	82	0.869145	117	0.88174	152	0.871735
13	0.81604	48	0.673258	83	0.777517	118	0.896735	153	0.906365
14	0.789761	49	0.742948	84	0.881985	119	0.759624	154	0.701391
15	0.686909	50	0.784502	85	0.891335	120	0.703673	155	0.841745
16	0.645342	51	0.88174	86	0.691914	121	0.825931	156	0.80488
17	0.913615	52	0.896735	87	0.708528	122	0.84175	157	0.679773
18	0.758486	53	0.759624	88	0.81604	123	0.85119	158	0.821677
19	0.91873	54	0.703673	89	0.789761	124	0.869145	159	0.88674
20	0.911865	55	0.825931	90	0.686909	125	0.777517	160	0.805226
21	0.83917	56	0.84175	91	0.645342	126	0.881985	161	0.87674
22	0.891735	57	0.85119	92	0.913615	127	0.891335	162	0.934175
23	0.710859	58	0.896745	93	0.758486	128	0.691914	163	0.648922
24	0.861915	59	0.861915	94	0.91873	129	0.708528	164	0.805158
25	0.671378	60	0.67994	95	0.911865	130	0.81604	165	0.673258
26	0.951365	61	0.649368	96	0.83917	131	0.789761	166	0.742948
27	0.94647	62	0.87854	97	0.891735	132	0.686909	167	0.784502
28	0.845541	63	0.650011	98	0.901185	133	0.645342	168	0.88174
29	0.91369	64	0.88174	99	0.723141	134	0.913615	169	0.896735
30	0.899175	65	0.899175	100	0.768518	135	0.758486	170	0.759624
31	0.87191	66	0.87854	101	0.871735	136	0.91873	171	0.703673
32	0.901185	67	0.790031	102	0.906365	137	0.911865	172	0.825931
33	0.723141	68	0.89372	103	0.701391	138	0.83917	173	0.84175
34	0.768518	69	0.771992	104	0.841745	139	0.891735	174	0.85119
35	0.871735	70	0.87854	105	0.80488	140	0.710859	-	-

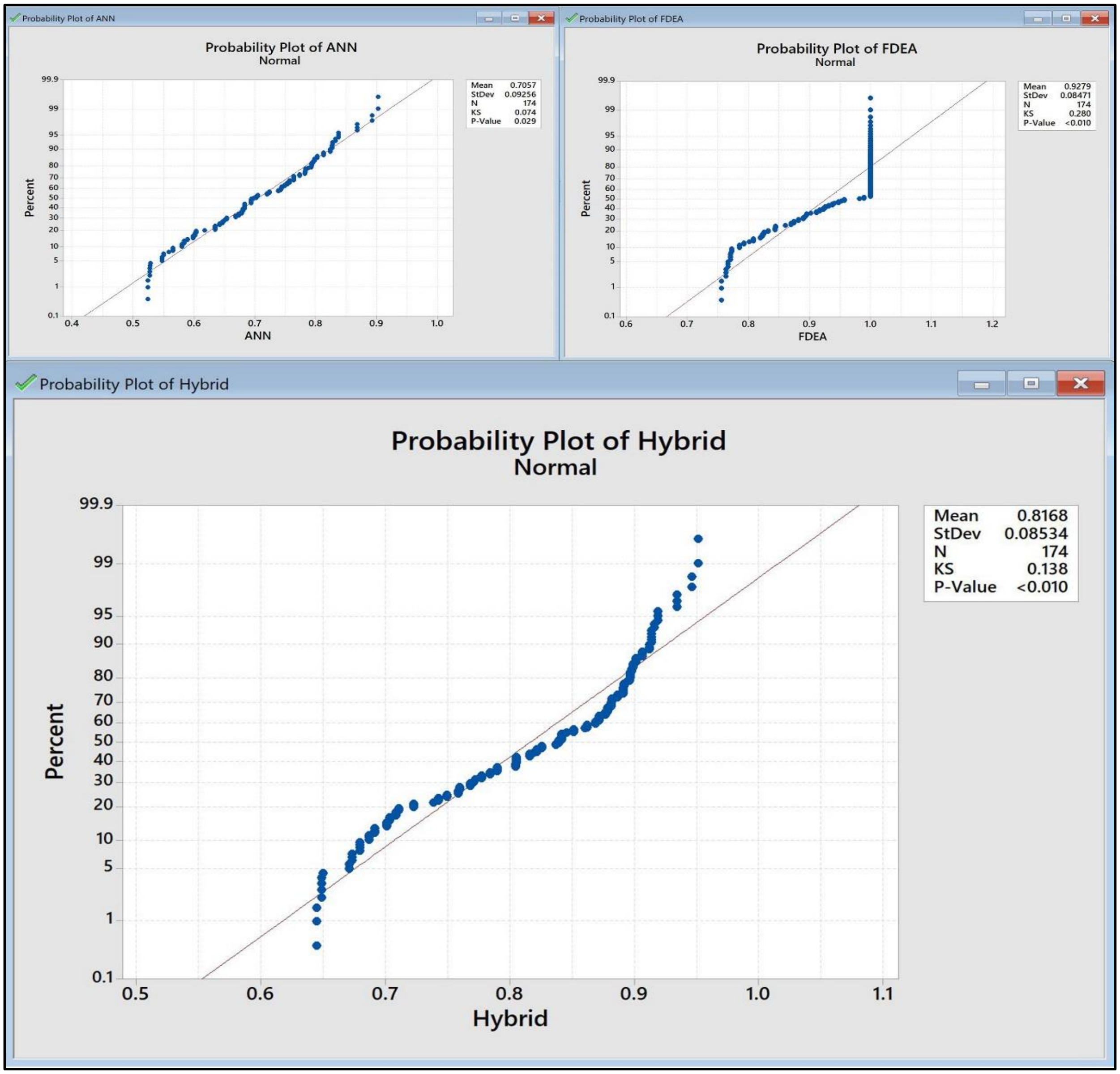

Fig 3. The superiority of the proposed hybrid framework

3-5- Sensitivity analysis

In this step, the real-time performance of each safety culture indicator in the considered case study is demonstrated. In this regard, sensitivity analysis is applied. The obtained results can help safety managers to improve proactive safety through the safety culture. The obtained results also indicate the weight of each safety culture indicator which can help decision makers in determining the priorities. The obtained sensitivity analysis results are presented in table 8.

Table 8. The obtained sensitivity analysis results

r	Safety Culture Indicators	Mean efficiency	Two-tailed paired t-test p-value	Mean efficiency comparison	Real-time performance	Weight
ψ	Full factor	0.81678	-	-	-	-
1	Teamwork	0.80075	0.000	$\mu_1 < \mu_\psi$	Positive	14.80%
2	Management commitment	0.81405	0.000	$\mu_2 < \mu_\psi$	Positive	2.52%
3	Information sharing and reporting culture	0.83813	0.000	$\mu_3 > \mu_\psi$	Negative	19.73%
4	Management support and reward system	0.83442	0.000	$\mu_4 > \mu_\psi$	Negative	16.30%
5	Learning culture	0.82249	0.000	$\mu_5 > \mu_\psi$	Negative	5.28%
6	Communication and awareness	0.82593	0.000	$\mu_6 > \mu_\psi$	Negative	8.46%
7	Safety supervision and audits	0.82312	0.000	$\mu_7 > \mu_\psi$	Negative	5.86%
8	Trust	0.80376	0.000	$\mu_8 < \mu_\psi$	Positive	12.02%
9	Safety training and preparedness	0.81941	0.000	$\mu_9 > \mu_\psi$	Negative	2.44%
10	Safety attitude and behavior	0.80549	0.000	$\mu_{10} < \mu_\psi$	Positive	10.42%
11	Employee involvement	0.81442	0.000	$\mu_{11} < \mu_\psi$	Positive	2.18%

Note; Weight of each safety culture indicator is calculated using the following equation:

$$\text{Weight}_r = \frac{|\mu_r - \mu_\psi|}{\mu_\psi} * 100 \tag{15}$$

4- Managerial discussions and insights

The proposed real-time performance evaluation framework investigated the current status of the safety culture indicators in Shiraz Petrochemical Company. In this section, managerial insights and management decisions are described based on the obtained results in the previous section. First, it should be noted that all of the presented discussions in this section are limited to the considered case study. The obtained results indicate that the real-time impact of “Teamwork”, “Management commitment”, “Trust”, “Safety attitude and behavior”, and “Employee involvement” is positive. However, the other considered safety culture indicators including “Information sharing and reporting culture”, “Management support and reward system”, “Learning culture”, “Communication and awareness”, “Safety supervision and audits”, and “Safety training and preparedness” have a negative impact. The calculated weights for negative and positive safety culture indicators can help managers in prioritizing the correction plants to improve proactive safety. In this regard, Figure 4 demonstrates the weight of safety culture indicators.

As depicted in figure 4, “Teamwork”, “Trust”, and “Safety attitude and behavior” are the most significant safety culture indicators with positive impact. In other words, employees’ interpersonal relationships with each other are quite great. They also mind about safety issues and follow safety procedures. On the other hand, “Information sharing and reporting culture” and “Management support and reward system” have the highest negative impacts in the considered case study. The obtained results suggest that managers should facilitate information sharing and design a reward system for reporting safety issues. It should be noted, the low level of reporting culture and information sharing results in a low level of learning culture in the long run. Therefore, it is extremely important to encourage employees to report safety issues. According to figure 5, the obtained results also indicate that the Operation Department has the lowest mean of efficiency which results in lowest proactive safety performance. On the other hand, HSE has the best real-time performance among departments. Therefore, planning correction plans in the Operation Department has the highest priority.

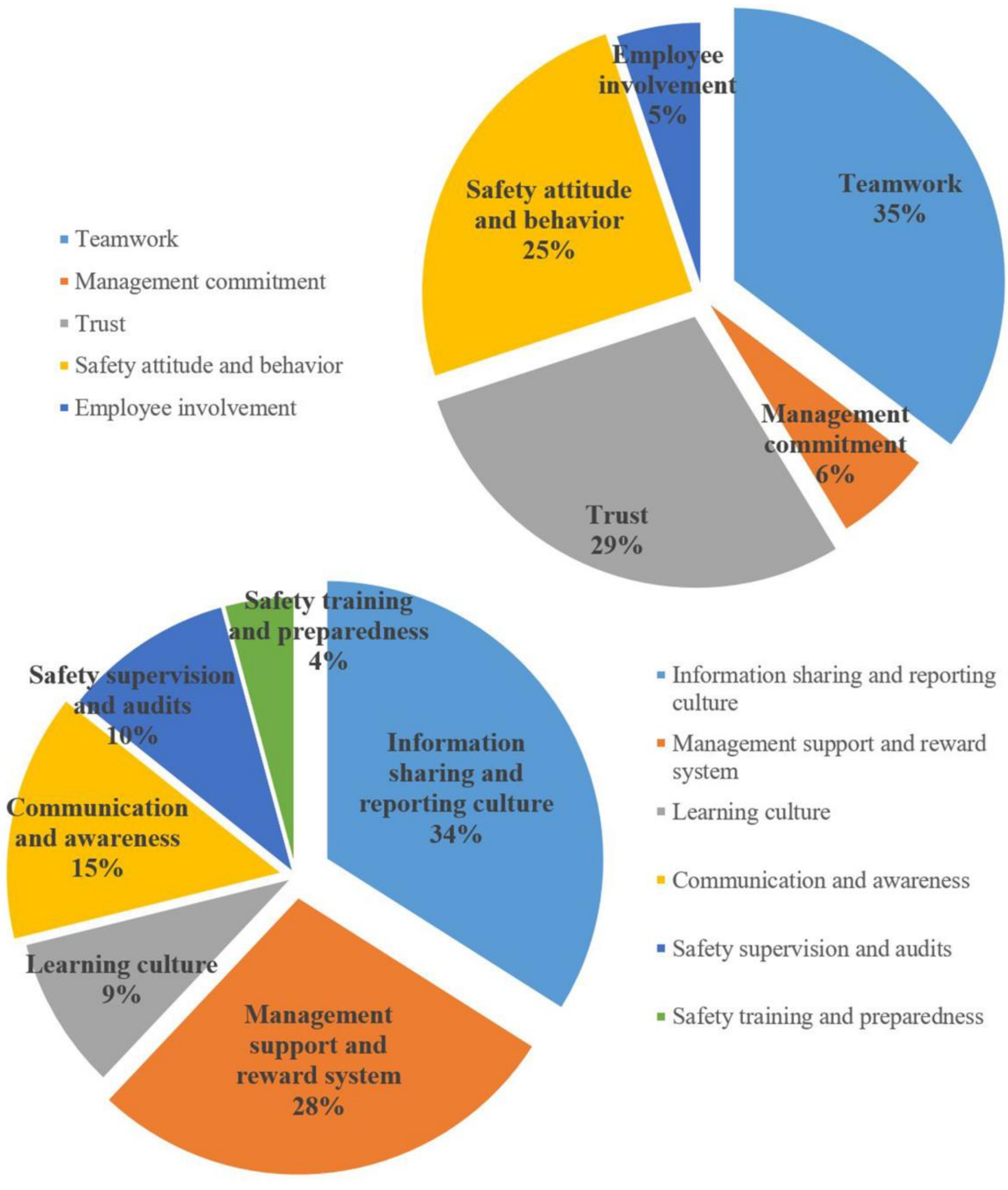

Fig 4. The weight of safety culture indicators for both negative and positive sets

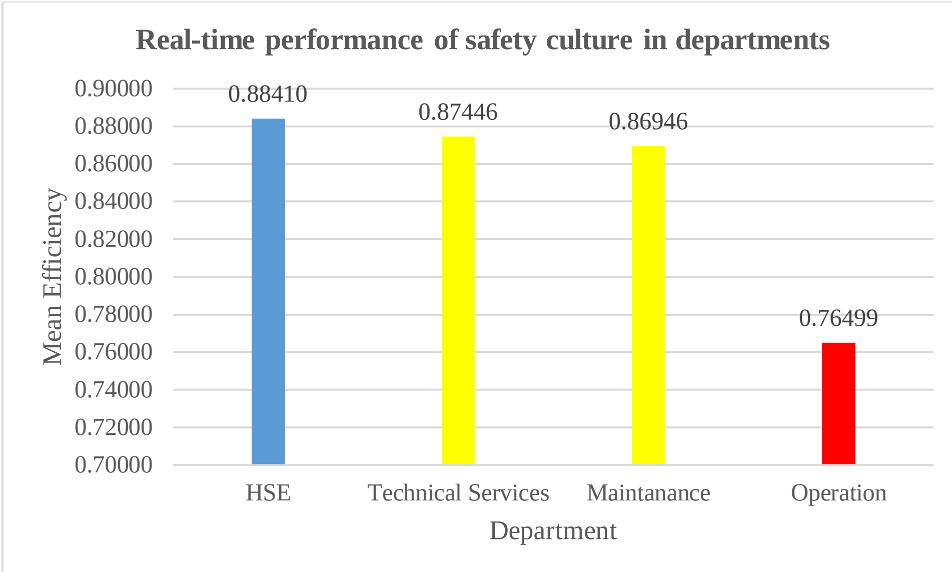

Fig 5. The real-time performance of safety culture in the considered departments

5- Conclusion

Safety is of paramount importance in oil and gas industry plants such as petrochemical plants where the consequences of failure may be catastrophic. In such systems, building a proactive safety culture is crucial. The current study proposed a real-time framework for performance evaluation of proactive safety culture in safety-critical industries. Proactive safety culture indicators were extracted from the literature using a comprehensive literature review. The proposed framework is able to evaluate the real-time performance of any safety-critical industry and determines the current status of each indicator. The obtained results can help safety managers to improve the proactive safety culture of the organization. They also can use the presented framework for periodic safety evaluations and determine the effectiveness of the implemented correction plans. The application of fuzzy logic along with stochastic efficiency frontier analysis has empowered the proposed hybrid framework to deal with deep uncertainty, and result in more reliable findings.

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Appendix A

Table A1. MATLAB codes for ANN-MLP

```
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by Neural Fitting app
% Created Feb 22 10:14:49 2017

x = xlsread('Inputs');
t = xlsread('Outputs');

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. NFTOOL falls back to this in low memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt

% Create a Fitting Network
hiddenLayerSize = [5 5];
TF = {'logsig','tansig','purelin'}
net = newff(x,t,hiddenLayerSize,TF);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse';  % Mean squared error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
  'plotregression', 'plotfit'};
net.trainparam.max_fail = 10
net.trainparam.min_grad = 1e-12
% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)
z = abs(e)
```

```
k = mean(z)
MAPE = mse(k)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t  .* tr.valMask{1};
testTargets = t  .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

figure;
plot(x,'k');
hold on;
plot(t,'r');
legend('x','t');
title('All Data');

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotfit(net,x,t)
%figure, plotregression(t,y)
%figure, ploterrhist(e)

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
if (false)
  % Generate MATLAB function for neural network for application deployment
  % in MATLAB scripts or with MATLAB Compiler and Builder tools, or simply
  % to examine the calculations your trained neural network performs.
  genFunction(net,'myNeuralNetworkFunction');
  y = myNeuralNetworkFunction(x);
end
if (false)
  % Generate a matrix-only MATLAB function for neural network code
  % generation with MATLAB Coder tools.
  genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
  y = myNeuralNetworkFunction(x);
end
if (false)
  % Generate a Simulink diagram for simulation or deployment with.
  % Simulink Coder tools.
  gensim(net);
end
```

Table A2. The sample items of the designed safety culture questionnaire

Teamwork	e.g. At my workplace, effective teamwork exists and employees work together for better results.
Management commitment	e.g. Top management keep track of safety issues and concerns reported by employees immediately.
Information sharing and reporting culture	e.g. I feel comfortable reporting the safety issues and concerns and believe that the reporting process is positive.
Management support and reward system	e.g. At my workplace, I can report errors and safety issues without worrying about the consequences.
Learning culture	e.g. At my workplace, safety and risk analysis avoid future problems.
Communication and awareness	e.g. Safety training and introduction to error cases are offered to employees at my workplace.
Safety supervision and audits	e.g. At my workplace, periodic inspections and safety audits have been effective in improving the employees' safety.
Trust	e.g. At my workplace, employees discuss safety issues with their colleagues and supervisors.
Safety training and preparedness	e.g. Safety training courses provided to the staff are useful and up to date at my workplace.
Safety attitude and behavior	e.g. At my workplace, treatment protocols and safety procedures are strictly followed.
Employee involvement	e.g. At my workplace, management involves employees in safety improvement plans.