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Performance assessment of human resource by integration of HSE and ergonomics and EFQM management system: A fuzzy-based approach

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Performance assessment of human resource by integration of HSE and ergonomics and EFQM management system

A fuzzy-based approach

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Abstract

Purpose – The purpose of this paper is to present an integrated framework for performance evaluation and analysis of human resource (HR) with respect to the factors of health, safety, environment and ergonomics (HSEE) management system, and also the criteria of European federation for quality management (EFQM) as one of the well-known business excellence models.

Design/methodology/approach – In this study, an intelligent algorithm based on adaptive neuro-fuzzy inference system (ANFIS) along with fuzzy data envelopment analysis (FDEA) are developed and employed to assess the performance of the company. Furthermore, the impact of the factors on the company's performance as well as their strengths and weaknesses are identified by conducting a sensitivity analysis on the results. Similarly, a design of experiment is performed to prioritize the factors in the order of importance.

Findings – The results show that EFQM model has a far greater impact upon the company's performance than HSEE management system. According to the obtained results, it can be argued that integration of HSEE and EFQM leads to the performance improvement in the company.

Practical implications – In current study, the required data for executing the proposed framework are collected via valid questionnaires which are filled in by the staff of an aviation industry located in Tehran, Iran.

Originality/value – Managing HR performance results in improving usability, maintainability and reliability and finally in a significant reduction in the commercial aviation accident rate. Also, study of factors affecting HR performance authorities participate in developing systems in order to help operators better manage human error. This paper for the first time presents an intelligent framework based on ANFIS, FDEA and statistical tests for HR performance assessment and analysis with the ability of handling uncertainty and vagueness existing in real world environment.

Keywords Aviation industry, EFQM, ANFIS, Adaptive neuro-fuzzy inference system, European federation for quality management, Fuzzy data-envelopment analysis, Health, safety, environment and ergonomics, Performance-assessment and analysis, HSEE, FDEA

Paper type Research paper

Introduction

Due to the environmental changes, most systems may approach entropy and tend to get out of control; thus, continuous performance evaluation is necessary for system management. Two of the main problems in performance evaluation of organizations and companies are the lack of appropriate strategies and patterns. Despite rapid gains in technology, human resources (HRs) are ultimately responsible to ensure the safety and success of different industries with man-machine systems such as aviation and

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petrochemical industries (Hendry, 2012). HRs must continue to be flexible, knowledgeable, efficient and dedicated while exercising appropriate judgment. Meanwhile, the industries continue to make major investments in equipment, training and systems which have long-term implications. Because technology continues to evolve faster than the ability to predict how HRs will interact with it, the industry can no longer depend as much on experience and intuition to guide decisions related to human performance. Instead, a comprehensive scientific-based tool is essential for evaluating human performance implications in training, procedures and design just as developing a new wing requirements sound aerodynamic engineering in aviation industry (Trifonov-Bogdanov *et al.*, 2013).

Since national and global environments experience unexpected accidents, a health, safety, environment and ergonomics management system (HSEEMS) is the viable alternative to predict, control and cope with these accidents that may have an important role in system performance. Through HSEEMS, organizations can identify incidents before occurrence and take necessary preventive actions in this regard. Given the raised issues, this study for the first time presents an integrated management system (i.e. health, safety, environment and ergonomics-European federation for quality management (HSEE-EFQM)) for performance evaluation and analysis. Aviation industries are among the growing and larger industries, playing a major role in aiding economic growth, world trade, international investment and tourism, and are therefore central to the globalization taking place in many other industries. Consequently, design and correct implementation of an intelligent framework for performance evaluation and analysis of such these important industries can undoubtedly lead to improvements and economic growth. The purpose of health and safety management system is to eliminate or minimize the risk for employees and other interested parties that may be at safety risks as a result of the organization activities (De Oliveira Matias and Coelho, 2002).

Business excellence refers to the highest degree of performance (Antony and Bhattacharyya, 2010). Achieving excellence is hugely dependent on application of particular management tools, techniques and practices as well as the commitment and involvement of all the people within the organization. The EFQM excellence model was formed in 1988 by 14 leading European companies. EFQM is a framework to evaluate organizations' achievements and progress toward excellence, enhance awareness about the importance of quality and high performance, and inspire firms to improve competitiveness through continuous improvement and deployment of processes (Andersen *et al.*, 2000; Moeller *et al.*, 2000). The model is split into two areas (enablers and results) with balanced weights (50-50). The enablers indicate how the organization functions. The resulting criteria cover both intangible and tangible performance (e.g. organizational reputation, strong relationship with customers and employees' capability) (Uygur and Sümerli, 2013). The five enabler criteria are leadership, strategy, people, partnerships and resources and processes, products and services, and the four "result" criteria are customer results, people results, society results and key results. These criteria are listed in Table I.

Literature review

Evaluation of different integrated management systems and international standards (e.g. ISO 9001 and OHSAS 18001) is conducted in many organizations and various industries for improving performance. By integration of different management systems such as those for occupational health management, environmental management and risk (or safety) management with business excellence models, the performance can be improved in a remarkable way (Seghezzi, 2001). Below, some of the recent studies conducted in this context are reviewed.

Table I.
Definition of EFQM's criteria

Area	Criteria	Definition
Enablers	Leadership	Leaders of excellent organizations are flexible. They envisage the future and makes it happen, acting as role models for its values and ethics and inspiring trust at all times
	Policy and strategy	An excellent organization attempt to achieve its mission, vision and values by establishing a stakeholder-focused strategy, and all the policies, plans and activities are performed and deployed in regard to the strategy
	People	An excellent organization makes best use of its workforce and values, motivates and rewards them to use their skills and knowledge for the benefit of the organization
	Partnerships and resources	Excellent organizations plan and manage external partnerships, suppliers and internal resources. Excellent organizations plan and manage partnerships and resources including information technologies to reach effective operation of processes
	Processes	Excellent organizations design, manage and improve processes, products and services with the aim of generating acceptable value for all stakeholders including customers
Results	Customer results	Excellent organizations achieve outstanding results that meet or go beyond the need and expectations of their customers and gain high levels of customer satisfaction
	People results	Excellent organizations achieve outstanding results that meet or go beyond the need and expectations of their people and attain high levels of people satisfaction
	Society results	Excellent organizations achieve the best results for associated stakeholders within society
	Key performance results	Excellent organizations achieve the key performance results committed to in their policy and strategy

Desa *et al.* (2013) studied the connection between OHSAS 18001 performance efforts and performance measures in an automotive industry in Malaysia. They considered occupational safety and health, planning, implementation and operation, monitoring and correction, management review, and continuous improvement as the performance efforts. Rajaprasad and Chalapathi (2015) analyzed critical success factors influencing the implementation of OHSAS 18001 standard using interpretive structural modeling in an Indian construction organization. They considered the factors as follows: safety culture, safety performance, sustainable construction, continual improvement, management commitment, conducive working environment, morale of employees, safety policy and safety training.

There has been increasing interest among researchers in the theory and application of different excellence models including EFQM in the last decade (Mohammad Mosadeghrad, 2013; Favaretti *et al.*, 2015). Antony and Bhattacharyya (2010) redefined excellence as the ability of a performance variable to impact on other performance variables in an organization, and then developed a conceptual framework for measuring organizational performance by a summated scale average method and organizational excellence by total correlation method in small-to medium-sized enterprises. Harrington and Voehl (2013) analyzed innovation management, emphasized its significance as a key operational discipline and introduced it as a critical tool to achieve organizational excellence.

By implementing an appropriate quality management (QM) system, a cultural shift in the organization along with an improvement in the way workforces work together and feel about involvement and participation, as well as in organizational structure are achieved. These concerns are the main functions of the HR. In other words, the implementation of a QM system is not possible without HR's leadership. Performance management is taken into account to be an important step toward developing and improving HR performance (Izvercian *et al.*, 2014). A performance appraisal framework, well established, works to support HR activities in order to maximize effectiveness. Therefore, HRM and QM have significant influences on the HR performance (Hart and Schlesinger, 1991).

The review of literature shows that companies that have more than one formal management system will benefit significantly by integration all their systems into one integrated management system, where environmental, occupational health, safety and any sector specific management systems are fully harmonized, and work seamlessly in association with the HR, business planning, procurement, finance, operations, administration and other systems. In one hand, workforces (as internal customers) require work environments that are environmentally benign healthy and safe. On the other hand, external customers require services/products that are safe and present no negative environmental concerns (Rahimi, 1995).

Motivated by the significance of HSEEMS and EFQM models in companies' achieving success and competitiveness, this paper aims to present an intelligent framework designed for assessing and analyzing performance by taking into account these two concepts together. The framework is designed based on fuzzy theory that is a multi-valued logic and it is similar to human interpretation and thinking. Fuzzy theory is an applicable tool in order to deal with vague and indecisive ideas as well as to cope with the complexities existing in real world. The algorithm uses the advantages of both adaptive neuro-fuzzy inference system (ANFIS) (such as the ability of combining the explicit knowledge representation with the learning power of artificial neural networks) and fuzzy data envelopment analysis (FDEA). Data envelopment analysis is a mathematical programing approach which aims to maximize the performance of decision-making units (DMUs) with the capability of handling multiple inputs and outputs. Subsequently, the performance of the organization from viewpoints of HSEEMS and EFQM model is analyzed statistically to indicate the effect of each factor of HSEE and each criterion of EFQM on the system's performance.

Methodology: the proposed framework

This section presents the methodology employed to achieve the goals of this study as well a brief introduction to the required tools. The proposed framework (as presented in Figure 1) is made up of three main phases containing data collection, performance assessment and sensitivity analysis of results. First, it is required to gather data with respect to HSEE and EFQM. To do so, two standard questionnaires; one for HSEE and one for EFQM, are designed and then distributed among the staff of an aviation company located in Tehran, Iran. After the definition of the indicators, the questionnaires are designed using the previous valid questionnaires in literature (Azadeh and Zarrin, 2016) as well as opinions of industrial consultants. After confirmation of the internal validity of the questionnaires, they were distributed among 100 personal, and 80 questionnaires were soundly returned. Therefore, the response rate is 80 percent that is appropriate and acceptable.

As shown in Table II, using linguistic terms with the corresponding assigned triangular fuzzy numbers (as the most typical fuzzy set membership function), each personnel can answer the questions. The fuzzy logic is used by referring this fact that human description and perception of physical and biological systems are far from the accurately defined by mathematical terminology. In other words, we cannot always describe the human way of inference and their judgment with crisp variables. Once the data are collected, the data sets are defuzzified using a common and useful technique, i.e. center of gravity. Then, the reliability and validity of the questionnaires are examined by Cronbach's α and factor analysis, respectively.

In the second phase (performance assessment), an intelligent algorithm based on ANFIS as well as FDEA model are used to calculate the HR performance of the company. Two methods are employed for performance assessment in order to take advantages of both methods simultaneously. On the one hand, ANFIS is a network-based method and a complementary tool for the common techniques of the performance studies. This algorithm is

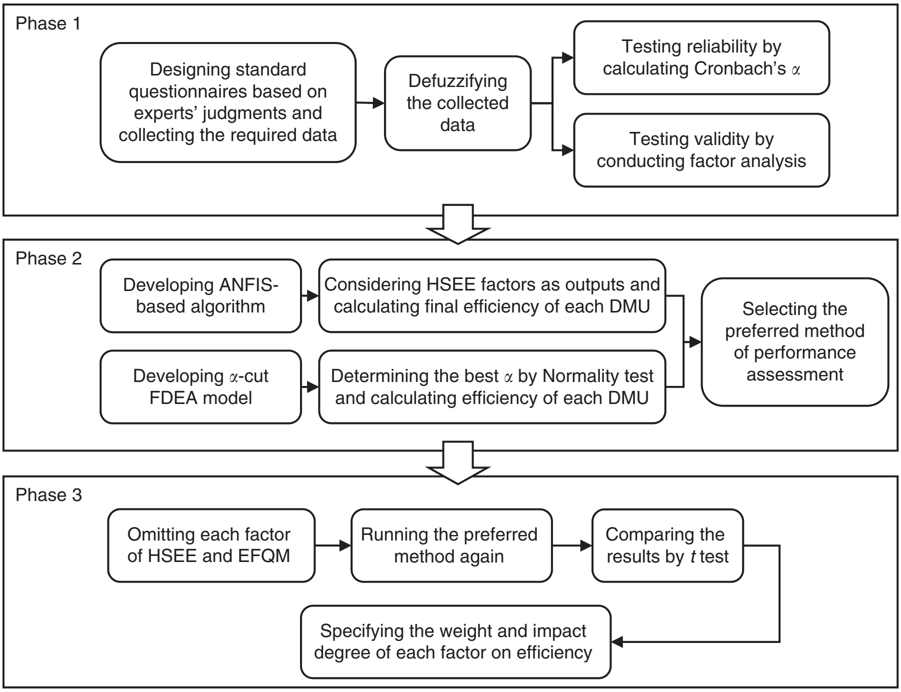

Figure 1.
The proposed framework

Table II.
Linguistic terms and the corresponding triangular fuzzy numbers

Linguistic term	Triangular fuzzy number
Strongly agree	(0.75, 1, 1)
Agree	(0.5, 0.75, 1)
Uncertain	(0.25, 0.5, 0.75)
Disagree	(0, 0.25, 0.5)
Strongly disagree	(0, 0, 0.25)

able to find a fuzzy stochastic frontier based on a set of input-output data set and does not require explicit assumptions about the functional structure of the stochastic frontier. On the other hand, FDEA is a fuzzy mathematical programing approach which optimizes the performance score. FDEA develops a function whose form is determined by the most efficient DMUs.

The last phase of the study yields worthwhile results for the company's managers. The aim of this phase is to find out how each factor of HSEE and EFQM affects company's performance. For this purpose, each factor is left out of the data set, and then the performance scores of the DMUs are recomputed, and the results are compared, through statistical techniques, to those obtained in the presence of all factors. One important point that should be noted is that the analysis is conducted on the preferred method between ANFIS-based method and FDEA for performance assessment. The preferred method has the highest robustness to noise inserted into the data.

ANFIS

ANFIS is a combination of neural networks and fuzzy systems to create a strong data modeling tool. The structure of a fuzzy inference system (FIS) is similar to a model that receives adequate amounts of data as inputs and maps them on the input to determine membership functions according to the characteristics of the data. The reason for using this method in this research is that the effective factors are determined based on the judgments of experts; therefore, there is some uncertainty in the data.

ANFIS-based algorithm

After selecting the input and output variables, the best structure of ANFIS is determined as follows:

(1) Dividing the data set into two sub-sets containing test and training.

(2) Designing FIS: in this stage, to achieve a FIS with the best quality of teaching and assessment, we will design a FIS with different parameters such as functions to create a basic fuzzy system (IniFis), initial value of step size, value of error goal, etc.

(3) Executing the designed FIS for training data and determining the relative error using the formula $\text{MAE} = 1/n \sum_{t=1}^{n} \left|A_t - F_t/A_t\right|$, where n is the number of DMUs (personnel) and A_t and F_t denote the actual value and the predicted value of tth DMU, respectively. If the value of the error is acceptable, it is desired to go to the next step.

(4) Performing the designed FIS for testing the data and choosing the best network by setting its parameters so that it can have the least amount of error.

To compute the performance of the ith unit, the error (E_i) between the actual output ($P_{\text{Actual}(i)}$) and the output obtained from the best structure of ANFIS ($P_{\text{ANFIS}\times(i)}$) should be calculated using Equation (1) (Delgado, 2005; Liao *et al.*, 2007):

$$E_i = \left|P_{\text{Actual}(i)} - P_{\text{ANFIS}\times(i)}\right|, \ \ i = 1, 2, \ldots, n \tag{1}$$

Then, the shift frontier function of ANFIS$\times$ $\left(E_i'\right)$ is calculated by Equation (2) to obtain the effect of maximum positive error:

$$E_i' = \frac{E_i}{P_{\text{ANFIS}\times(i)}}, \ \ i = 1, 2, \ \ldots, n \tag{2}$$

This attribute does not only consider the largest error, but it is calculated for each unit. To achieve this goal, finding the largest $\left(E_i'\right)$ determines the unit with the best performance. Assume that unit j has the largest $\left(E_i'\right)$ value. Therefore, according to Equation (2) the following equation holds true:

$$E_j' = \max_i \left(E_i'\right) \tag{3}$$

Subsequently, the transfer size (T_i) is different for DMU$_i$ (i*th* personnel) and it is calculated by using the following equation:

$$T_i = E_j' \times \left[\frac{P_{\text{ANFIS}\times(i)}}{P_{\text{ANFIS}\times(k)}}\right], \ \ i = 1, 2, \ldots, n \tag{4}$$

Finally, the performance scores (F_i) can be calculated by the following equation:

$$F_i = \frac{P_{\text{Actual}(i)}}{\left(P_{\text{ANFIS}\times(k)} + T_i\right)} \tag{5}$$

Data envelopment analysis

DEA is a nonparametric method to evaluate the performance and calculate the efficiency/performance of a finite number of DMUs with multiple inputs and outputs. DEA is actually based on a series of optimizations using linear programming that covers all the data. FDEA can be considered as a common way to solve the related problems caused by the uncertainty in qualitative data sets. The reason to use this method is that many indicators of decision-making units act as judges and have uncertain nature. The applied fuzzy Banker, Charnes and Cooper (BCC) model for ranking decision-making units can be presented as Equations (6) and (7) (Banker *et al.*, 1984). In these models, α is a parameter belonging to the interval [0, 1]. The model may be known as a parametric linear programming model that can be used to obtain an optimal solution for any values of α. The first model calculates lower bound of performance scores (Equation (6)) and the second one calculates upper bound (Equation (7)) of the scores:

$$\text{Min } \theta$$

s.t. :

$$\begin{aligned}
&\theta\left(\alpha x_{ip}^{m}+(1-\alpha)x_{ip}^{u}\right) \geqslant \sum_{j=1}^{n}\tau_i\left(\alpha x_{ij}^{m}+(1-\alpha)x_{rj}^{u}\right), \quad i=1,\,2,\,\ldots,\,I;\\
&\alpha y_{rp}^{m}+(1-\alpha)x_{rp}^{u} \leqslant \sum_{j=1}^{67}\tau_j\left(\alpha y_{rj}^{m}+(1-\alpha)x_{rj}^{u}\right), \quad r=1,\,2,\,\ldots,\,O;\\
&\sum_{j=1}^{n}\tau_j = 1;\\
&\tau_j \geqslant 0,\ \ j=1,\,\ldots,\,n.
\end{aligned} \tag{6}$$

$$\text{Min } \theta$$

s.t. :

$$\begin{aligned}
&\theta\left(\alpha x_{ip}^{m}+(1-\alpha)x_{ip}^{l}\right) \geqslant \sum_{j=1}^{n}\tau_i\left(\alpha x_{ij}^{m}+(1-\alpha)x_{rj}^{l}\right), \quad i=1,\,2,\,\ldots,\,I;\\
&\alpha y_{rp}^{m}+(1-\alpha)x_{rp}^{l} \leqslant \sum_{j=1}^{67}\tau_j\left(\alpha y_{rj}^{m}+(1-\alpha)x_{rj}^{l}\right), \quad r=1,\,2,\,\ldots,\,O;\\
&\sum_{j=1}^{n}\tau_j = 1;\\
&\tau_j \geqslant 0,\ \ j=1,\,\ldots,\,n.
\end{aligned} \tag{7}$$

Considering that the aim of this research is the performance analysis of DMUs on the basis of the output parameters, the output-oriented BCC model is used and performance of each DMU is also obtained based on Models 1 and 2 for different α values (Banker *et al.*, 1984). Since α shows the uncertainty level of data, whatever α level approaches zero, there is higher uncertainty in the problem. In contrast, the closer α to one, the higher certainty of data; and, thereby, the fuzzy system gets closer to a certain system. Referring to the central limit theorem, when the data are collected from various sources and are associated with accumulated error, the best value of α can be selected using normality test.

Experiment: the case study

The airline considered as the case study of this paper was established and started its operations in 1980 and located in Tehran, Iran. The company has about 350 employees. The questionnaires have been sent to 100 people of two main departments, namely, maintenance, engineering and supply department (MESD) and quality assurance/quality control (QA/QC) department. MESD has the dynamic responsibility for the maintenance tasks of the company and its numerous customers' different types of aircraft. QA/QC department guarantees that all engineering and maintenance activities be in line with national and international flight standards. They also are responsible to inspect and checkup aircrafts and pertinent systems during engineering and maintenance process.

Results and discussions

This section reports the results obtained by implementing the proposed framework on a real case study to show the applicability of it. The reliability coefficients of all the questions in both questionnaires are calculated using Cronbach's α. The values of this statistic for each factor are reported in Table III. According to the results, the values of Cronbach's α for both questionnaires are more than 0.6 and they are acceptable (Helms *et al.*, 2006). Therefore, the reliability of the questionnaires is approved.

To test the construct validity (unidimensionality) of items, an exploratory factor analysis using principal component extraction with a varimax rotation is separately conducted (Kaynak, 2003) for HSEE and EFQM questionnaires. The examination of eigenvalues and screen test results revealed nine factors of EFQM and four factors of HSEE. Kaiser-Meyer-Olkin statistic as well as p-value of Bartlett's test are calculated to show that the correlation matrix between at least some of the variables are positively correlated and the number of data for establishing factor analysis is sufficient (do Valle *et al.*, 2004). The results of this analysis are presented in Table IV.

Results of ANFIS-based algorithm

In order to calculate the performance score using the ANFIS-based algorithm, we need to select the input and output variables. Factors of HSEE and EFQM are positive, meaning they should be maximized in an optimization model, they should be considered as output variables. On the other hand, the developed ANFIS-based algorithm needs both input and output data, and fail to operate appropriately with dummy data. Consequently, it is necessary to take into account the factors of one of these concepts as the input variables and those of the other concept as the output variables. Consulting with the experts, we decided to take HSEE factors as the outputs and those of EFQM as the inputs due to slightly more significance of HSEE.

The performance scores of DMUs are determined from HSEE and EFQM points of view. For this purpose, first, it is essential to identify appropriate scenarios. Because we select four factors of HSEE as the output variables, there will be four scenarios. Each scenario is made of one factor of HSEE as the output and the other factors as input variables. Next, 65-90 percent of the data are used as the training data set and the remaining account for the test data set. Different structures of ANFIS are run and the relevant MAE values are calculated. Each structure is run 100 times to handle possible noise. Therefore, the MAE value associated with each architecture for each scenario is equal to the average of MAEs related to different numbers of training and test data for 100 times.

Using the best structures of ANFIS for each output variable (scenario), the performance score of each DMU (personnel) is calculated by the proposed intelligent algorithm. In other words, we have four performance scores for each DMU, so the average value of these scores are considered as the final performance score. These scores with the related ranks are shown in Figure 2.

Concept	KMO	Bartlett's test *p*-value	Item	Question	Loading	Cronbach's α
European Foundation for Quality Management excellence model (cumulative total variance = 87.979%)	0.767	0.000	Leadership	Q1	0.901	0.888
				Q2	0.745	
				Q3	0.903	
			Policy and strategy	Q4	0.846	0.822
				Q5	0.740	
				Q6	0.776	
			People	Q7	0.829	0.735
				Q8	0.912	
				Q9	0.913	
			Partnerships and resources	Q10	0.752	0.791
				Q11	0.914	
				Q12	0.911	
			Processes	Q13	0.817	0.764
				Q14	0.880	
				Q15	0.748	
			Customer results	Q16	0.804	0.692
				Q17	0.903	
				Q18	0.878	
			People results	Q19	0.912	0.604
				Q20	0.851	
				Q21	0.727	
			Society results	Q22	0.890	0.893
				Q23	0.907	
				Q24	0.856	
			Key performance results	Q25	0.872	0.625
				Q26	0.869	
				Q27	0.798	
Health, safety, environment and ergonomics management system (cumulative total variance = 74.763%)	0.817	0.000	Health	Q1	0.808	0.790
				Q2	0.796	
				Q3	0.873	
			Safety	Q4	0.879	0.669
				Q5	0.757	
				Q6	0.818	
			Environment	Q7	0.809	0.770
				Q8	0.849	
				Q9	0.862	
			Ergonomics	Q10	0.871	0.634
				Q11	0.775	
				Q12	0.856	

Table III.
Results of factor analysis of EFQM and HSEE

Results of FDEA

At this stage, FDEA with different α-cuts are used to calculate the performance score of the DMUs. Subsequently, the best level of α is determined by performing normality test on the efficiencies obtained from 14 different values of α (Azadeh *et al.*, 2015). The Shapiro-Wilk test is used for testing of normality. Since the values of the factors considered in this study are determined based on the experts' judgments, the uncertainty and complexity of the data are inevitable. Therefore, FDEA model is used to evaluate performance. Since the objective of this study is to maximize the output variables with constant inputs, output-oriented upper bound and lower bound FDEA models are selected for performance evaluation, and different α-cuts in the range of [0, 1] are intended. The results of normality test for upper bound and lower bound FDEA models at each level of α-cuts are shown in Table IV. Note that, the best model is highlighted in the table.

α-cuts	df	Upper bound model Statistic	p-value	Mean	SD	Lower bound model Statistic	p-value	Mean	SD
0.01	80	0.977	0.041	1.260	0.177	0.959	0.039	1.146	0.147
0.05	80	0.995	0.044	1.239	0.174	0.983	0.046	1.239	0.204
0.1	80	0.985	0.043	1.214	0.170	0.968	0.029	1.335	0.160
0.2	80	0.988	0.049	1.165	0.164	0.973	0.034	1.083	0.244
0.3	80	0.979	0.043	1.118	0.157	0.966	0.047	1.084	0.167
0.4	*80*	*0.986*	*0.081*	*1.073*	*0.151*	0.960	0.047	1.148	0.151
0.5	80	0.981	0.045	1.031	0.145	0.963	0.043	1.072	0.155
0.6	80	0.993	0.032	0.990	0.139	0.991	0.047	1.040	0.159
0.7	80	0.977	0.035	0.951	0.134	0.965	0.032	1.046	0.034
0.8	80	0.985	0.040	0.914	0.128	0.971	0.035	0.859	0.058
0.9	80	0.992	0.038	0.878	0.123	0.978	0.035	0.913	0.193
0.95	80	0.979	0.037	0.860	0.121	0.976	0.035	0.869	0.151
0.99	80	0.985	0.034	0.847	0.119	0.977	0.027	0.898	0.169
1	80	0.977	0.037	0.843	0.118	0.962	0.038	0.776	0.088

Note: The preferred FDEA model with the best α-cut is shown in italic font

Table IV. Normality test results of FDEA models

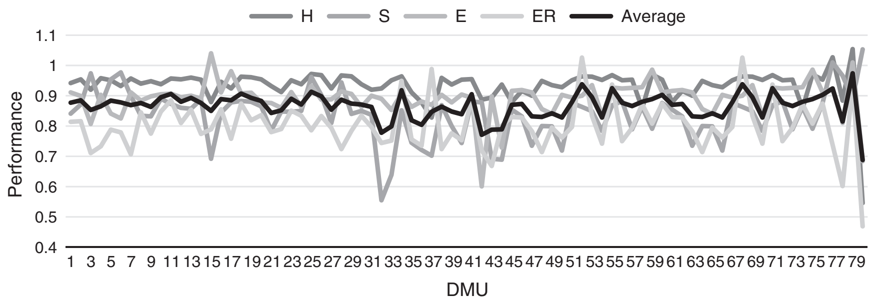

Figure 2. Performance scores calculated by ANFIS-based algorithm

Referring to results provided in Table IV, upper bound model with the α-cut of 0.4 is normally distributed; therefore, it is selected as the preferred model in this study. Given the α-cut, the assumption based on the uncertainty in the data is confirmed and the data takes up to 60 percent uncertainty. Therefore, the results obtained in previous steps are approved. After selecting the appropriate model, the efficiencies and ranks of DMUs have been calculated. The results of performance scores with associated ranks of DMUs are presented in Figure 3.

In order to achieve more reliable results, between FDEA and ANFIS-based algorithm the method with the highest robustness to noise is selected as the preferred method. To do so,

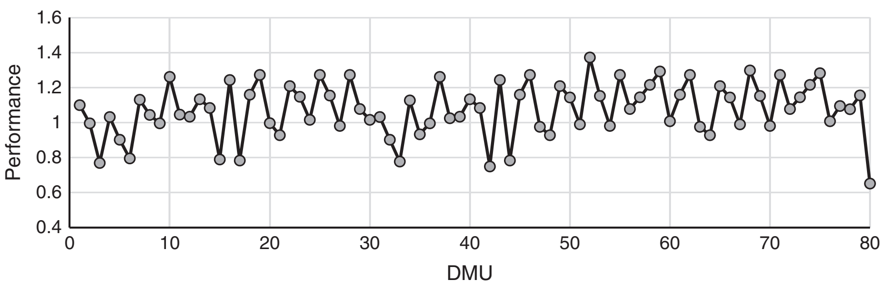

Figure 3. Results of performance scores with associated ranks of DMUs

a noise (20 percent of data set is randomly selected and multiplied by 50) is inserted into the data set, and then Spearman's correlation test is conducted between the results obtained before noise insertion and those of after doing so. The method with the highest correlation coefficient is selected as the preferred one, by means of which the sensitivity analysis is conducted to determine the impact of indices (HSEE factors and EFQM criteria) on the system's performance. The results of Spearman's correlation coefficients are presented in Table V. The results indicate that FDEA is selected as the preferred model due to the robustness in dealing with the inserted noise.

Sensitivity analysis

In this step, the impact of indices on the system's performance is determined. For this purpose, several experiments are designed. In each experiment, one of the indices is eliminated and FDEA model is carried out and performance of the system is recalculated. Then, two-way paired t test is carried out to analyze the results. The null hypothesis in this test is $\mu_{\text{main}} = \mu_i$, where μ_{main} denotes the average efficiency before omitting index and μ_i is the average efficiency after eliminating ith indicator. The alternative hypothesis is $\mu_{\text{main}} \neq \mu_i$. The significance level in the tests is 5 percent. If the null hypothesis is rejected, average efficiency before and after eliminating indices would be different. Thus, it is concluded that the eliminated factor/indicator has an effect on system's performance.

In order to specify the impact degree of the omitted factor on system's performance in the company from the view point of the staff, we conduct one-way t test with the alternative hypothesis of $\mu_{\text{main}} > \mu_i$, to indicate how the null hypothesis of the two-way t test is rejected. If the one-way test is rejected, it can be concluded that the factor has positive effect and, in other words, has been appropriately implemented within the HRs (DMUs), since its elimination has reduced the average performance. Spearman's rank correlation coefficient is also calculated to determine the degree to which the performance scores before and after omitting factor i are associated. A similar sensitivity analysis can be performed to indicate the impacts of each concept on the system's performance from HRs perspective. To this end, each of concepts (i.e. HSEE and EFQM) is omitted and the performance scores are recalculated and then the analyses are performed. The results obtained from these tests are shown in Table VI.

As can be seen in Table VI, environment and ergonomics among HSEE factors and leadership, policy and strategy, people, partnerships and resource, customer results, people results and key performance results from EFQM model have positive impact on the performance, while the remaining factors do not have a significant effect on the company's performance statistically. In other words, according to the results, it is realized that the factors with positive impact require more attention and planning for improving HR performance. For the factors with no significant impact, it can be concluded that they have been appropriately implemented in the company from the HR's standpoints. Overall, the results show that both concepts HSEEMS and EFQM have significant effect on the system's performance and also, they are not well implemented in the company because

Table V. Spearman's correlation coefficients

Method	Mean	SD	Correlation
FDEA			
Without noise	1.0733	0.1507	0.801
With noise	1.0096	0.2102	
ANFIS-based algorithm			
Without noise	0.8663	0.0427	0.496
With noise	0.5206	0.1571	

i	Omitted factor	Average performance	Two-way paired t test result (p-value)	One-way paired t test result	Type of impact	Correlation coefficient
Factors						
1	Health	1.0733	Accepted (0.182)	$\mu_{\text{main}} = \mu_1$	No sig. imp.	0.997
2	Safety	1.0731	Accepted (0.237)	$\mu_{\text{main}} = \mu_2$	No sig. imp.	0.997
3	Environment	1.0735	Rejected (0.027)	$\mu_{\text{main}} > \mu_3$	Positive	0.970
4	Ergonomics	1.0698	Rejected (0.029)	$\mu_{\text{main}} > \mu_4$	Positive	0.930
5	Leadership	1.0472	Rejected (0.000)	$\mu_{\text{main}} > \mu_5$	Positive	0.977
6	Policy and strategy	1.0687	Rejected (0.002)	$\mu_{\text{main}} > \mu_6$	Positive	0.940
7	People	1.0655	Rejected (0.008)	$\mu_{\text{main}} > \mu_7$	Positive	0.930
8	Partnerships and resources	1.0727	Rejected (0.016)	$\mu_{\text{main}} > \mu_8$	Positive	0.908
9	Processes	1.0732	Accepted (0.101)	$\mu_{\text{main}} = \mu_9$	No sig. imp.	0.998
10	Customer results	1.0675	Rejected (0.000)	$\mu_{\text{main}} > \mu_{10}$	Positive	0.907
11	People results	1.0551	Rejected (0.001)	$\mu_{\text{main}} > \mu_{11}$	Positive	0.901
12	Society results	1.0723	Accepted (0.134)	$\mu_{\text{main}} = \mu_{12}$	No sig. imp.	0.988
13	Key performance results	1.0342	Rejected (0.000)	$\mu_{\text{main}} > \mu_{13}$	Positive	0.872
Concept						
1	HSEE	1.0690	Rejected (0.022)	$\mu_{\text{main}} > \mu_1$	Positive	0.897
2	EFQM	0.9127	Rejected (0.000)	$\mu_{\text{main}} > \mu_2$	Positive	0.698

Note: No sig. imp., no significance impact

Table VI. Results of sensitivity analysis conducting on factors

some of their factors and criteria need more attention and planning. Once the way that each factor impacts the performance has been determined, the factors are ranked based on their importance in the HSEE-EFQM and the most effective factor in our case study is identified. In order to achieve this goal, a weight is assigned to each index based on the difference between the average performance before and after eliminating the factor. Larger difference reflects more amount of influence and thus, greater weight. The weights assigned to each factor and concept of HSEE and EFQM are presented in Figures 4 and 5, respectively.

As can be seen, the three criteria "key performance results," "leadership" and "people results" are the most effective ones with the highest impacts on the system performance. These three factors account for 0.67 of the weights. Furthermore, the analyses show the higher degree of importance of EFQM model compared to HSEE. However, both HSEE and

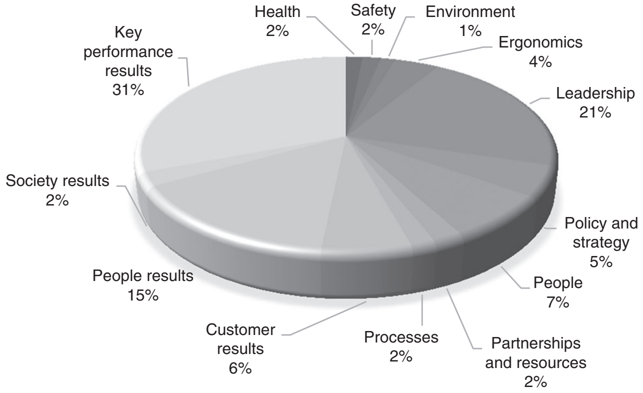

Figure 4. Weights calculated for each factor of HSEE and EFQM

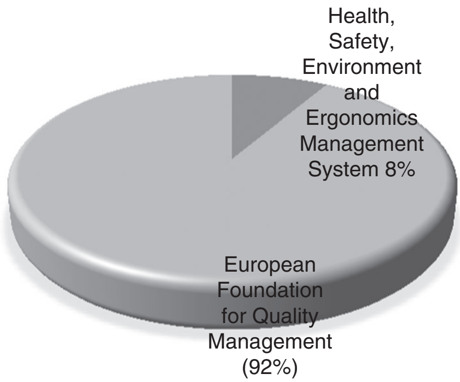

Figure 5.
Weights calculated for HSEE and EFQM

EFQM have positive impact on the system's performance. As a result, performance evaluation by integration of them, specialists' participation in analyzing operational safety, preventing injuries, improving employee engagement, creating and developing a better health and safety culture and reducing significant aviation environmental impacts to help operators better manage human error. Based on these analyses, omitting EFQM factors lead to the greatest change (or decrease) in the values of the performance of the DMUs. As a result, by focusing more on the EFQM standards, the managers are enabled to increase their HRs performance which in turn leads to a significant increase in the productivity of the whole company.

In excellent organizations, key performance results are associated with the organization's basic role as determined in its policy and strategy and the objectives set for it. Therefore, the managers of the aviation company can develop a clear set of key performance indicators based on the expectations and requirements of their stakeholders and in harmony with their chosen strategy. The leaders of the company should also focus more on achieving objectives through people since, according to the obtained results, they play an important role in performance improvement. They are definitely agents for motivation, inspiration and change. Furthermore, they are role models for social responsibility, ethical behavior and integrity, both externally and internally, guaranteeing their personnel adopt the highest standards of ethical activities. In addition, they need to take into consideration their customers, partners and the environment in which they operate in order to succeed in accomplishing the mission and vision. The results obtained from the proposed framework are useful for planning since the managers can employ them to make links between what an organization does and the results it achieves, highlighting how they are attained.

Conclusions

In this study, a novel intelligent framework was presented for performance evaluation with respect to the integrated HSEE and EFQM management system from HRs' viewpoints. For this purpose, a standard questionnaire was designed and handed out among the HRs of two departments of an aviation industry. The reliability and validity of the collected dada were confirmed by conducting suitable statistical analyses. Subsequently, an ANFIS-based algorithm together with fuzzy DEA model were developed and employed to assess the performance of the operators as DMUs. The best performance evaluation method was selected by inserting noise to the data. The model with the highest coefficient was the most resistant model to the noise and thus was selected as the preferred method. The impact of the factors on the performance was identified by performing sensitivity analysis.

Then, a weight was assigned to each factor of HSEE and EFQM based on their importance and influence on the performance.

The empirical results of sensitivity analysis showed that environment and ergonomics among HSEEMS factors and leadership, policy and strategy, people, partnerships and resource, customer results, people results and key performance results from EFQM model were the most significant factors (criteria). From the viewpoints of the company's HRs, the criteria of EFQM model had a far greater impact on the company's performance compared to HSEE management system.

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