Safety and Health at Work 6 (2015) 77–84

Contents lists available at ScienceDirect

Safety and Health at Work

journal homepage: www.e-shaw.org

Original Article

An Efficient Taguchi Approach for the Performance Optimization of Health, Safety, Environment and Ergonomics in Generation Companies

Ali Azadeh [1,*], Mohammad Sheikhalishahi [2,1]

[1] School of Industrial and Systems Engineering and Center of Excellence for Intelligent Based Experimental Mechanics, College of Engineering, University of Tehran, Iran

[2] Centre for Industrial Management/Traffic and Infrastructure, KU Leuven, Heverlee, Belgium

A R T I C L E I N F O

Article history:
Received 24 July 2014
Received in revised form
8 November 2014
Accepted 29 November 2014
Available online 19 December 2014

Keywords:
data envelopment analysis
generation companies
health, safety, environment, and ergonomics
performance optimization
Taguchi methods

A B S T R A C T

Background: A unique framework for performance optimization of generation companies (GENCOs) based on health, safety, environment, and ergonomics (HSEE) indicators is presented.

Methods: To rank this sector of industry, the combination of data envelopment analysis (DEA), principal component analysis (PCA), and Taguchi are used for all branches of GENCOs. These methods are applied in an integrated manner to measure the performance of GENCO. The preferred model between DEA, PCA, and Taguchi is selected based on sensitivity analysis and maximum correlation between rankings. To achieve the stated objectives, noise is introduced into input data.

Results: The results show that Taguchi outperforms other methods. Moreover, a comprehensive experiment is carried out to identify the most influential factor for ranking GENCOs.

Conclusion: The approach developed in this study could be used for continuous assessment and improvement of GENCO's performance in supplying energy with respect to HSEE factors. The results of such studies would help managers to have better understanding of weak and strong points in terms of HSEE factors.

1. Introduction

Health, safety, and environment (HSE) at the operational level will strive to eliminate injuries, adverse health effects, and damage to the environment. Effective application of ergonomics in work-system design can achieve a balance between worker characteristics and task demands. This can enhance worker productivity, provide improved worker safety (physical and mental), and job satisfaction [1]. Several studies have shown positive effects of applying ergonomics principles to the workplace including machine, job, and environmental designs [2–9].

There are many factors in the ergonomics design of a workplace in both micro and macro parts, and therefore, it seems inevitable to consider a model that includes all related factors. Microergonomics consider those factors of machine design and work posture that affect the user interface and working conditions related to the job or task design. In a macroergonomics study, ergonomics factors are considered in parallel to organizational and managerial aspects of working conditions in the context of a total system design. Moreover, it attempts to create equilibrium between organization, operators, and machines. It focuses on total "people-technology" systems and is concerned with the impact of technological systems on organizational, managerial, and personnel subsystems [10,11]. Studies in ergonomics have produced data and instructions for industrial applications [12–14]. Eklund [15] presented the relationships between ergonomics and several factors such as work conditions, product design, ISO 9000, continuous improvements, and total quality management. Azadeh et al [11] described an integrated macroergonomics model for operation and maintenance of power plants. By considering HSE, an organization manages its operations in a manner that places safety and health first. Champoux and Brun [16] gave an overview of the most characteristic occupational health and safety representations and practices in small firms. Chang and Liang [17] developed a model to evaluate the performance of process-safety-management systems of paint-manufacturing facilities based on a three-level multiattribute

* Corresponding author. School of Industrial and Systems Engineering and Center of Excellence for Intelligent Based Experimental Mechanics, College of Engineering, University of Tehran, Iran.

E-mail addresses: aazadeh@ut.ac.ir, ali@azadeh.com (A. Azadeh).

http://dx.doi.org/10.1016/j.shaw.2014.11.001

approach. Singh et al [18] considered the state of the art of understanding the hazards and risks to human health and the environment associated with the use of synthetic chemicals as a basis for developing a risk-assessment procedure for the mining industry. Duijm et al [19] showed that HSE management would benefit greatly from existing management systems and also from the further development of meaningful safety-performance indicators that identify the conditions prior to accidents and incidents. Hassim and Hurme [20] presented an inherent occupational health index for assessing the health risks of various processes. The method considers the hazard from the chemicals and also the potential for the exposure of workers to the chemicals. The certification and implementation of occupational health and safety-management system had become a priority for many organizations. Boughaba et al [21] elucidated the relationship between safety culture maturity and safety performance of a particular company.

HSE and ergonomics (HSEE) have been considered from different points of view [22–24]. A close relationship exists between HSEE factors. Inappropriate design between human and machine could lead to decreased safety. Inappropriate design of system leads to management error. Management error and work-environment-injurious factors could cause human error and safety issues, which consequently would result in environmental risks. It is believed that ergonomics deficiencies in industries are the root cause of workplace health hazards, low levels of safety, and reduced workers' productivity [16].

This study has identified major HSEE indicators, which affect the performance in generation companies (GENCOs). According to the literature, it is realized that HSEE systems require a continual and systematic effort to achieve sustainable success. This paper presents a framework for a comprehensive performance analysis of GENCOs in terms of HSEE factors, which we refer to from this point on to as HSEE.

2. Materials and methods

An integrated Taguchi–data envelopment analysis–principal component analysis (Taguchi–DEA–PCA) approach is proposed for ranking the GENCO's performance based on HSEE indicators. For ranking this sector of industry, the combination of DEA, PCA, and Taguchi is efficiently used for all branches of the GENCO. All of the useful and influential points of these methods are used to measure the GENCO's performance. First, standard indicators are identified and required data are gathered. These indicators are related to HSEE. The structure of the proposed Taguchi–DEA–PCA approach is shown in Fig. 1.

According to the proposed approach, first the standard inputs are determined, collected, and standardized by considering HSEE factors for all branches in GENCO. Then different scenarios are designed by corrupting 5–10% of data to model the complex and vague environment from which data are collected. The DEA, PCA, and Taguchi models are applied for ranking these scenarios. Finally, correlations between rankings for the designed scenarios are calculated and the preferred model is selected based on the maximum correlation. This shows the most consistent model for ranking scenarios in complex, vague, and uncertain environments. In the following sections, the DEA, PCA, and Taguchi models are described.

2.1. Data envelopment analysis

Consistent with DEA terminology, the term "decision-making unit" (DMU) refers to the individuals in the evaluation group. The DEA generates a surface called the "frontier" that follows the peak performers and envelops the remainder [25]. Fig. 2 illustrates the concepts of the empirical and theoretical production frontiers in a two-dimensional surface to generalize the case of a multidimensional surface. The theoretical frontier represents the absolute

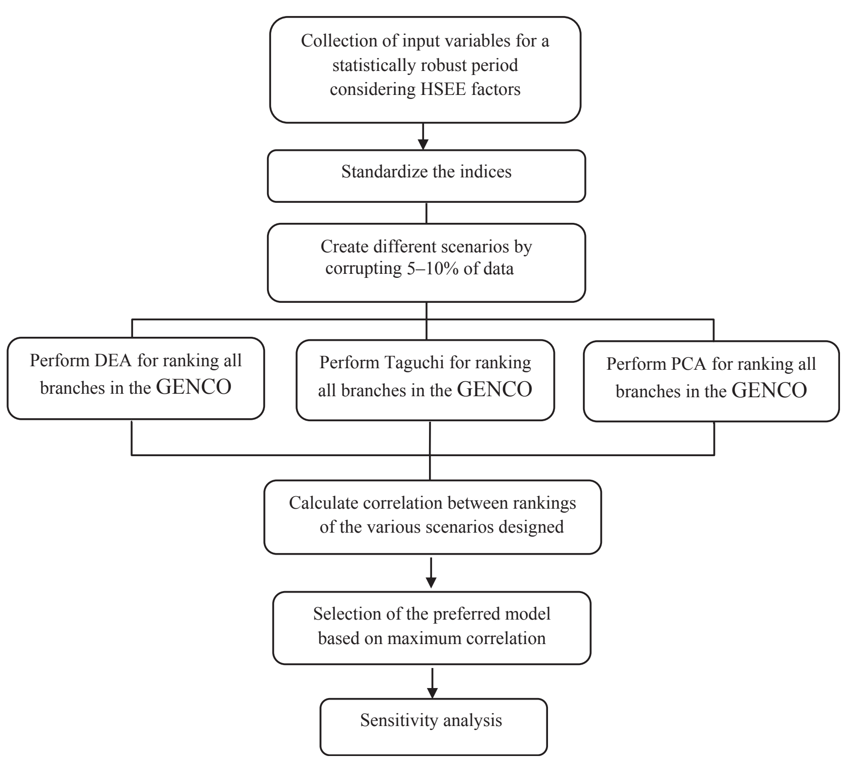

Fig. 1. Structure of the proposed approach. DEA, data envelopment analysis; GENCO, generation companies; HSEE, health, safety, environment and ergonomics; PCA, principal component analysis.

maximum possible production that a DMU can achieve in any level of input. However, the theoretical relationships between input and output parameters of a system are generally difficult to identify and to express mathematically. For this reason, the theoretical frontier is usually unknown. Therefore, the relative or empirical frontier based on real DMU is used. The empirical frontier connects all the relatively best DMUs in the observed population. If the performance of all observed DMUs is generally poor, then the empirical frontier gives only the best of a bad lot. The theoretical frontier would clearly indicate that the poor DMUs were indeed poor [26].

By providing the observed efficiencies of individual DMUs, DEA may help to identify possible benchmarks toward which performance can be targeted. The ability of DEA to identify possible peers or role models as well as simple efficiency scores gives it an edge over other measures. The objective of DEA is to obtain the weights that maximize the efficiency of the DMU under evaluation. It is very important to know that the efficiency values produced by DEA are only valid within that particular group of peers. A DMU that is efficient in one group may be inefficient when compared with another group. In other words, if a group of very poor DMUs was evaluated using DEA, there will still be efficient DMUs. In addition, if the set of DMUs is small, then there is little discrimination between them.

2.2. Principal component analysis

Following the terminology proposed by [35], suppose we have n DMUs, where each unit U_j ($j = 1, 2, \ldots, n$) produces s outputs y_{rj} (1,2, …, s) using m inputs x_{ij} (1,2, …, m). It is possible to look at ratios of individual output to individual input, $d^j_{ir} = y_{rj}/x_{ij}$ ($i = 1, 2, \ldots, m$; $r = 1, 2, \ldots, s$) for each unit U_j ($j = 1, 2, \ldots, n$). The d^j_{ir} gives the ratio between every output and every input. Now let $d^j_k = d^j_{ir}$, where $k = 1$ corresponds to $i = 1$ and $r = 1$, $k = 2$ corresponds to $i = 1$, $r = 2$, etc. Obviously, $k = 1, \ldots, p$ and $p = m \times s$. We need to find some weights that combine those p individual ratios of d^j_k for U_j. Consider the following $n \times p$ data matrix composed by d^j_k:

$$D = (d_1, \ldots, d_2)_{n\times p} \tag{1}$$

Each row represents p individual ratios of d^j_k for each unit and each column represents a specific output-to-input ratio. The PCA is applied to search for a component structure by factoring the sample correlation matrix D and to find out new independent measures, which are respectively different linear combinations of $d_1, \ldots, d_p$. Principal components can be combined by their eigenvalues to obtain a weighted measure of d_j. The PCA process of D is carried out as follows:

Step 1: Calculate the average matrix $\overline{D}$ and the corresponding correlation matrix R.
Step 2: Calculate the eigenvalues λ_k ($k = 1, \ldots, p$) and the related p eigenvectors l^k_i ($k = 1, \ldots, p$) of R.

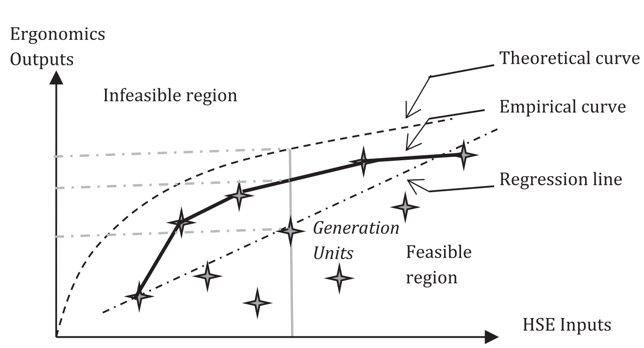

Fig. 2. Frontiers of data envelopment analysis for generation companies with respect to health, safety, and environment (HSE) and ergonomics.

Step 3: Select the principal components by defining:

$$\mathrm{CM} = \frac{\sum_{k=1}^{M}\lambda_k}{\sum_{k=1}^{p}\lambda_k} = \sum_{k=1}^{M}\frac{\lambda_k}{p} \tag{2}$$

There are numerous acceptable criteria for determining the number of M components to be extracted.

Step 4: Evaluation of a single measure z by the first M principal components

$$z = \sum_{k=1}^{M} w_k \times \mathrm{PC}_k = \sum_{q=1}^{p} \tilde{w}_q \times \hat{d}^j_q \tag{3}$$

where $\tilde{w}_q = \sum_{k=1}^{p} w_k l^k_q$ is the aggregate weights and $\hat{d}^j_q$ (q = 1, …, p) represents the standardized d^j_q.

Let $w_k = \lambda_k/p$, if PC_k positively reflects the standardized output-to-input ratios, as measured by the percentage of positive coefficient of all coefficients. Vice versa let $w_k = \lambda_k/p$. The value of z gives a combined measure of various standardized ratios, for each U_j. Based on z, we can evaluate and rank the performance of units using PCA.

2.3. Taguchi

The Taguchi method is a statistical approach, which is mainly used for dealing with the limitation of the factorial and fractional factorial experiments. This method reduces and standardizes the fractional factorial design [27]. In this paper, the Taguchi loss function [28] is used for ranking different scenarios. In this procedure, the Taguchi loss function is used to develop a single objective function in a multicriteria problem [29]. For each criterion, actual loss will be calculated using Equation 4 and will fall between 0% and 100% loss.

$$L = Kx^2 \tag{4}$$

where K is calculated as follows:

$$K = 100\%/(\mathrm{USL})^2 \tag{5}$$

where L is the loss generated for each criterion, x is the characteristic measurement, USL is the upper specification limit, and k is a constant calculated to return 100% loss at the specification limit. This formulation is used for input criteria. For output criteria, the data must be inversed.

3. Results and discussion

3.1. Experiment: The case study

To achieve the objectives of this study, a comprehensive study is conducted to locate all economic and technical indicators (indexes), which influence the performance of the GENCO's branches. These indicators are related to HSEE. Twenty indicators were identified as major indexes affecting the performance of the branches. Table 1 shows these indicators considering HSEE factors [1,18,26,30–32]. The raw data set for these factors is shown in Appendix 1.

The DEA, PCA, and Taguchi are used for ranking GENCOs considering 20 indicators. These parameters were defined as indicators (inputs and outputs) as follows: The reason for determination of these variables as input or output is that in the DEA models, a variable that is desired to be decreased is defined as input (e.g., safety and environment) and, by contrast, a variable that is desired to be increased is defined as output (e.g., health). For more

Table 1
HSEE factors

Category		Factor
Health		1. Periodic examinations from worker with harmful works to total number of workers (%) 2. Pre-employment medical examinations to number of employed people in a given period (%) 3. Periodic examinations from workers 4. pH: water
Safety		1. Accident severity rate 2. Accident frequency rate 3. Fatal accident rate
Environment		1. Energy consumption 2. Input–output fuel gas 3. Emitted NO_x 4. Emitted SO_x 5. Emitted CO 6. Emitted particles
Ergonomics	Microergonomics	1. Light of workplace 2. Skeletal disorder rate 3. Noise level 4. Lifting index 5. PMV_{PPD}
	Macro-ergonomics	1. Availability 2. Reliability

HSEE, health, safety, environment, and ergonomics.

information in this regard, see Charnes et al [25]. Table 2 shows the result of ranking by DEA, PCA, and Taguchi for 60 different GENCOs.

As mentioned earlier, the preferred model is selected based on maximum correlation between the original and corrupted data sets. In order to do so, 10 different scenarios are designed by corrupting 10–20% of data. According to the results (Table 3), the preferred model for ranking GENCOs in complex and uncertain environments is Taguchi.

Table 2
Results of ranking by DEA, PCA, and Taguchi

GENCO	Rank		
DMU	DEA	PCA	Taguchi
1	6	3	30
2	37	6	57
3	22	4	11
4	50	19	51
5	34	12	6
6	11	6	56
7	4	10	28
8	8	8	2
9	18	2	4
10	5	7	5
11	1	1	3
12	49	21	36
13	21	20	12
14	56	43	19
15	9	40	15
16	39	36	33
17	27	11	20
18	33	31	22
19	60	57	58
20	2	27	53
21	20	34	10
22	42	45	13
23	24	54	52
24	15	53	32
25	47	49	40
26	30	37	55
27	59	48	41
28	36	46	49
29	32	28	23
30	57	22	9
31	17	56	37
32	46	50	31
33	7	29	38
34	23	35	14
35	28	58	45
36	25	14	43
37	12	15	8
38	35	41	21
39	55	24	16
40	3	16	7
41	10	30	54
42	31	18	46
43	14	9	17
44	51	52	47
45	45	17	34
46	53	39	26
47	44	42	59
48	26	38	35
49	41	33	18
50	40	32	42
51	13	55	27
52	16	59	25
53	58	23	50
54	19	13	1
55	38	26	48
56	48	51	44
57	43	44	29
58	52	60	60
59	54	25	24
60	29	47	39

DEA, data envelopment analysis; DMU, decision-making unit; GENCO, generation companies; PCA, principal component analysis.

3.2. Sensitivity analysis

A sensitivity analysis is performed to foresee the effect-integrating indicators with the same category. In order to do so, five main categories including health, safety, environment, microergonomics, and macroergonomics are considered. The final score of each category is calculated by average indicator's values. This procedure is also applied for corrupted data sets. The proposed Taguchi–DEA–PCA approach is used to select the preferred method for ranking of GENCOs with respect to five main criteria. As earlier, the preferred method is selected based on maximum correlation between original and corrupted data sets.

According to the results (Table 4), the preferred model for ranking GENCOs is Taguchi. Thus, the preferred model for both 20- and five-indicator cases for ranking GENCOs in complex and uncertain environments is Taguchi.

3.3. Analyzing HSEE factors

To find the most important category for performance optimization of GENCOs, a comprehensive experiment is carried out. In each experiment, four of five categories are considered and one of them is omitted from further calculations. The Taguchi method,

Table 3
Spearman correlation results for 20 indicators

	DEA	PCA	Taguchi
Correlation	0.909157	0.706157	0.925429

DEA, data envelopment analysis; PCA, principal component analysis.

Table 4
Spearman correlation results for 5 indicators

	DEA	PCA	Taguchi
Correlation	0.804079	0.656205	0.853289

DEA, data envelopment analysis; PCA, principal component analysis.

Table 5
Spearman correlation coefficients for categories

Omitted category	Health	Safety	Environment	Microergonomics	Macroergonomics
Correlation coefficient	0.927	0.860	0.802	0.871	0.920

Table 6
Spearman correlation coefficients for environment factors

Factors	Energy consumption	Input—output fuel gas	Emitted NO_x	Emitted SO_x	Emitted CO	Emitted particle
Correlation coefficient	0.964	0.942	0.920	0.884	0.935	0.933

which is selected as the preferred model in the previous section, is applied for ranking GENCOs. The correlation coefficients between these experiments and previous ranking are calculated [33]. It is supposed that if the ranking obtained by eliminating one factor is different from the previous ranking, the factor is important, and correlation coefficient will measure this difference. The values of the correlation coefficient will be calculated by the following formula:

$$\rho = 1 - 6\sum d_i^2 \Big/ n\left(n^2 - 1\right) \tag{6}$$

where ρ is the Spearman correlation coefficient; d_i is the difference between the rank of two criteria; and n is the number of scenarios.

Because five categories for 20 factors are considered, by selecting four of five categories, five different combinations could be formed. The results of correlation coefficient between these five combinations and previous ranking are presented in Table 5.

According to the results, the most important category is environment. The aforementioned procedure could be applied to find the most influential factor in this category. As six factors are considered in the environment category, five of six different combinations could be formed. Table 6 presents the correlation between previous ranking and rankings obtained by omitting each of these factors.

According to the results, emitted SO_x is the most important environmental factor for ranking GENCOs. Thus, in the case study, the most influential category and factor are environment and emitted SO_x, respectively. This procedure may be repeated to prioritize all 20 factors. This would help managers to monitor the most important factors efficiently.

4. Conclusion

In this paper, an integrated Taguchi—DEA—PCA approach is proposed for ranking GENCOs based on HSEE indicators. For ranking this sector of industry, the combination of DEA, PCA, and Taguchi is efficiently used for all GENCOs. All of the useful and influential points of these methods are used to measure the GENCO's performance. To recognize all economic and technical indicators (indices), a comprehensive study is conducted. In the proposed case study, Taguchi was selected as the preferred model for ranking GENCOs. In addition, the sensitivity analysis verifies the results of the proposed approach. Moreover, the most important category and factor are identified, which are environment and SO_x, respectively. The results of such studies would help not only top managers to have a better understanding of weak and strong points in their systems' performance but also help experts and researchers to determine the satisfactory levels of each subsectors' performances in terms of HSEE factors. In addition, the developed approach of this study could be used for continuous assessment and improvement of GENCO's performance in supplying energy with respect to HSEE factors. The proposed approach of this study is also compared with some of the relevant studies to show its advantages over previous ones (Table 7).

Conflicts of interest

All contributing authors declare no conflicts of interest.

Acknowledgments

The authors are grateful for the valuable comments and suggestions by the respected reviewers, which have enhanced the strength and significance of this work. This study was supported by a grant from Iran National Science Foundation (Grant No. 93010029). The authors are grateful for the financial support provided by Iran National Science Foundation.

Table 7
Features of this study versus other studies and methods

Method	Feature					
	HSE factors	Macroergonomics and microergonomics factors	Environmental complexity and nonlinearity	Comprehensive statistical tests	Sensitivity analysis	Robust relative-error-estimation method
The proposed approach	√	√	√	√	√	√
Ebrahimipour et al [30]				√		√
Azadeh et al [1]	√		√			√
Singh et al [18]	√		√			
Otto and Scholl [8]	√					
Fam et al [34]	√		√			√

HSE, health, safety, and environment.

Appendix 1. Raw data for 20 factors

DMU	Health				Safety input			Macroergonomics	
	1	2	3	4	1	2	3	1	2
1	0.620	0.586	0.511	0.591	0.898	0.353	0.720	0.264	0.253
2	0.742	0.751	0.689	0.336	0.694	0.704	0.825	0.905	0.370
3	1.078	1.010	0.639	0.723	0.866	0.640	0.982	0.860	0.501
4	0.794	0.696	0.796	0.562	0.902	0.770	0.785	0.767	0.504
5	0.894	0.585	0.717	0.358	0.563	0.908	0.829	0.635	0.903
6	0.911	0.444	0.084	0.742	0.988	0.577	0.565	0.768	0.316
7	0.883	0.643	1.052	0.443	0.441	0.718	0.998	0.363	0.814
8	0.832	0.516	0.650	0.365	0.607	0.416	0.796	0.607	0.929
9	0.890	0.695	0.696	0.563	0.829	0.899	0.683	0.698	0.366
10	0.512	0.936	1.004	1.025	0.448	0.404	0.758	0.904	0.494
11	1.092	1.021	0.559	0.496	0.588	0.749	0.337	1.248	0.631
12	0.477	0.773	0.713	0.620	0.675	0.736	1.276	0.357	0.607
13	0.790	0.970	0.868	1.067	0.946	0.865	0.940	0.704	0.957
14	0.659	0.675	0.572	0.926	0.851	0.791	0.774	0.769	0.698
15	0.314	0.671	0.725	0.902	0.769	0.990	0.828	0.996	0.942
16	0.724	0.424	0.512	0.632	0.995	0.969	0.864	0.992	0.987
17	0.991	1.073	0.589	0.399	0.774	1.011	1.036	0.681	0.977
18	0.832	0.622	0.587	0.453	0.999	0.863	0.879	0.707	0.843
19	0.526	0.623	0.140	0.244	0.911	0.871	0.979	0.852	0.763
20	0.692	0.913	1.123	0.013	0.842	0.951	0.756	0.663	0.738
21	0.482	0.989	0.622	0.648	0.886	1.033	0.883	0.731	0.753
22	0.485	0.600	1.036	0.745	0.830	0.766	0.836	0.661	0.935
23	0.579	0.366	0.882	0.648	1.038	0.876	1.044	0.664	0.687
24	0.536	0.760	1.252	0.749	0.983	0.763	0.958	0.971	0.697
25	0.397	0.608	1.160	0.841	0.969	0.880	0.770	0.798	0.683
26	0.644	1.041	0.817	0.260	0.980	0.913	0.938	0.819	0.834
27	0.609	0.304	0.415	0.783	0.796	0.879	0.853	0.872	0.825
28	0.734	0.462	0.759	0.294	0.832	0.788	0.837	0.934	0.840
29	0.630	1.064	0.608	0.784	0.893	0.809	1.035	0.750	0.905
30	0.396	0.876	0.437	0.552	0.867	0.887	0.871	0.765	0.661
31	1.018	0.472	0.693	0.637	0.815	0.911	1.021	0.784	0.995
32	0.543	0.199	0.715	0.261	0.812	0.796	0.791	0.945	0.828
33	0.340	0.637	0.659	1.507	0.781	0.765	0.984	0.694	0.871
34	0.589	0.336	0.581	0.676	0.881	0.834	0.881	0.723	0.731
35	0.598	0.673	0.976	0.432	0.870	0.951	1.028	0.713	0.963
36	0.890	0.802	0.619	0.821	0.984	0.824	1.022	0.974	0.945
37	0.482	1.217	0.391	0.921	0.818	0.980	0.963	0.694	0.791
38	0.546	0.622	1.015	0.564	0.887	0.869	0.845	0.683	0.815
39	0.703	0.624	0.911	0.867	0.980	0.816	0.775	0.908	0.778
40	0.614	0.742	0.850	1.249	0.783	0.864	0.859	0.693	0.870
41	1.059	0.318	0.886	0.508	0.800	1.022	0.875	0.862	0.773
42	1.204	0.483	0.895	0.762	0.752	1.014	0.786	0.688	0.886
43	1.222	0.829	0.583	1.001	0.977	0.767	0.754	0.906	0.683
44	0.433	0.617	0.711	0.579	1.050	0.893	1.000	0.714	0.761
45	0.716	0.957	0.755	0.900	0.946	1.048	0.797	0.813	0.906
46	0.611	0.893	0.715	0.514	0.826	0.906	0.962	0.888	0.688
47	0.827	0.678	0.501	0.813	0.990	0.858	0.910	0.757	0.808
48	0.380	0.992	0.465	0.351	0.877	0.863	0.871	0.954	0.888
49	0.560	0.837	1.037	0.924	0.960	0.846	0.835	0.758	0.706
50	0.423	1.019	0.456	1.053	0.928	0.846	0.757	0.920	0.911
51	0.530	0.431	0.688	0.659	0.800	0.881	0.960	0.857	0.664
52	0.447	0.828	0.436	0.753	0.797	0.962	1.031	0.716	0.739
53	0.585	0.611	0.353	0.501	0.971	0.851	1.030	0.918	0.750
54	1.198	0.913	0.487	0.417	0.898	0.763	0.935	0.829	0.804
55	0.569	0.764	0.598	0.568	0.853	0.902	0.910	0.798	0.862
56	0.836	0.570	0.835	0.599	0.933	1.000	0.831	0.827	0.728
57	0.267	0.682	0.699	0.500	0.817	0.932	0.903	0.975	0.693
58	0.413	0.532	0.566	0.755	0.976	0.866	0.983	0.797	0.980
59	0.685	0.656	0.691	0.651	1.009	0.891	0.927	0.843	0.873
60	0.156	0.766	0.160	1.052	0.778	0.887	0.916	0.997	0.836

DMU	Environment input						Microergonomics				
	1	2	3	4	5	6	1	2	3	4	5
1	0.404	0.489	0.429	0.378	0.929	0.427	0.847	0.870	0.930	0.503	0.755
2	0.649	0.689	0.284	0.891	0.322	0.356	0.763	0.696	0.076	0.161	0.432
3	0.908	0.504	0.690	0.970	0.706	0.253	0.944	0.858	0.206	0.674	1.027
4	0.962	1.079	0.161	1.176	0.598	0.448	0.575	0.618	0.496	0.445	0.543
5	0.665	0.498	0.354	0.949	0.344	0.653	0.443	0.787	0.423	0.688	0.534
6	0.744	0.092	0.741	0.476	1.241	0.800	0.351	0.481	0.852	0.749	0.728
7	0.931	1.073	0.625	0.356	1.095	0.162	0.404	0.394	0.668	0.708	1.100
8	0.771	0.612	0.623	0.840	0.422	0.442	0.852	0.899	0.634	0.521	0.917
9	0.586	0.335	0.341	0.589	0.663	0.317	0.762	0.518	0.836	0.819	1.046
10	0.607	0.854	0.477	0.911	0.694	0.428	0.732	0.633	0.404	0.902	0.506
11	0.734	0.734	0.534	0.759	0.607	0.687	0.716	0.721	0.755	0.419	0.961
12	0.682	0.383	0.715	0.949	0.596	0.462	0.344	0.462	0.712	0.632	0.573
13	0.804	0.957	0.373	0.736	0.705	0.427	0.706	0.811	0.982	0.714	0.825
14	0.893	0.959	0.387	0.434	0.599	1.227	0.220	0.739	0.870	0.905	0.833
15	1.011	0.852	0.614	0.417	0.698	0.053	0.526	0.516	0.766	0.998	0.761
16	0.781	0.773	0.318	0.992	0.634	0.730	0.236	0.741	0.898	0.870	0.729
17	0.892	0.752	0.259	0.847	0.881	0.366	0.669	0.392	0.881	0.777	0.979
18	0.850	0.786	0.767	0.427	0.695	0.624	0.882	0.361	0.820	0.951	0.938
19	1.016	0.841	0.934	0.431	0.497	0.747	0.647	0.301	0.719	0.828	0.814
20	0.882	0.919	0.574	0.656	0.732	0.881	1.502	1.125	0.805	0.876	0.764
21	1.008	0.834	0.128	0.124	0.510	0.537	0.573	0.874	0.997	0.827	0.998
22	0.949	0.993	0.610	0.339	0.602	0.617	0.697	1.054	0.709	0.678	0.692
23	0.915	0.952	0.411	0.646	0.858	1.009	0.688	1.183	0.966	0.681	0.879
24	0.853	1.019	0.896	0.703	0.289	0.665	0.461	0.582	0.935	0.987	0.832
25	0.953	1.046	0.622	0.813	0.544	0.605	0.463	0.864	0.912	0.738	0.806
26	1.037	0.780	0.761	0.903	0.211	0.493	0.792	0.233	0.974	0.885	0.938
27	1.050	0.792	0.764	0.892	0.279	0.664	0.810	0.589	0.786	0.852	0.793
28	0.847	0.938	1.093	0.752	0.649	1.050	1.029	0.563	0.887	0.747	0.860
29	0.927	0.958	0.459	0.278	0.862	0.463	0.880	0.411	0.856	0.971	0.832
30	0.861	0.757	0.401	0.477	0.666	0.342	0.965	0.598	0.837	0.688	0.788
31	0.829	1.024	0.848	0.489	0.105	0.889	0.467	0.783	0.685	0.993	0.668
32	0.904	0.821	0.648	0.210	0.671	0.814	0.967	0.812	0.730	0.959	0.761
33	0.895	0.990	0.409	0.321	1.052	0.311	0.723	0.316	0.861	0.782	0.780
34	1.021	0.777	0.579	0.317	0.503	0.134	1.176	0.444	0.922	0.843	0.898
35	0.959	0.894	0.931	0.337	0.602	0.774	0.326	1.347	0.801	0.891	0.925
36	0.966	0.857	0.104	0.431	1.274	0.289	0.765	0.316	0.850	0.882	0.839
37	0.852	0.774	0.391	0.504	0.756	0.176	0.452	1.056	0.843	0.877	0.953
38	0.755	0.877	1.126	0.311	0.327	0.452	0.759	0.388	0.794	0.695	0.855
39	0.845	0.942	0.513	0.872	0.635	0.574	0.395	0.686	0.797	0.924	0.968
40	0.811	0.810	0.183	0.083	0.993	0.655	0.366	1.375	0.863	0.699	0.963
41	1.007	0.842	0.098	0.417	0.731	0.915	1.269	0.245	0.945	0.919	0.734
42	0.912	0.968	0.611	1.045	0.601	0.546	0.753	0.519	0.787	0.679	0.699
43	0.920	0.751	0.373	0.435	1.076	0.492	0.446	0.382	0.801	0.970	0.886
44	0.757	0.784	0.472	0.680	0.243	0.688	0.029	0.812	0.704	0.797	0.809
45	0.828	0.872	0.770	0.766	0.977	0.189	0.448	0.885	0.853	0.770	0.884
46	1.030	0.952	0.578	0.893	0.409	0.569	0.650	0.988	0.859	0.687	0.789
47	0.915	0.910	0.946	0.953	0.740	0.950	1.237	0.344	0.723	0.972	0.835
48	0.954	0.973	0.095	0.517	0.317	0.654	0.609	0.251	0.669	0.661	0.724
49	0.961	0.919	0.665	0.159	0.888	0.543	0.297	0.930	0.751	0.806	0.978
50	0.985	1.045	0.506	1.029	0.640	0.651	0.564	0.515	0.835	0.888	0.992
51	0.929	1.027	0.974	0.122	0.519	0.534	1.383	0.783	0.953	0.965	0.788
52	0.997	0.802	0.718	0.409	0.079	0.998	0.932	1.050	0.849	0.978	0.837
53	0.959	0.807	0.398	0.957	0.816	0.252	0.625	0.286	0.858	0.704	0.961
54	0.797	0.833	0.532	0.856	0.215	0.455	0.660	0.319	0.888	0.727	0.835
55	0.753	0.950	0.169	0.829	0.852	0.967	0.318	0.254	0.704	0.957	0.993
56	0.904	0.768	0.658	0.180	0.679	1.299	0.409	0.579	0.992	0.908	0.855
57	0.884	0.893	0.585	0.505	0.812	0.570	0.509	0.377	0.993	0.977	0.945
58	0.994	0.993	1.070	0.319	0.327	1.243	0.758	0.506	0.748	0.893	0.792
59	0.820	0.757	0.358	0.255	0.630	0.615	0.590	1.111	0.839	0.744	0.974
60	0.893	0.948	0.666	0.367	0.402	0.417	0.393	0.968	0.661	0.867	0.960

DMU, decision-making unit.

References

[1] Azadeh A, Fam IM, Khoshnoud M, Nikafrouz M. Design and implementation of a fuzzy expert system for performance assessment of an integrated health, safety, environment (HSE) and ergonomics system: the case of a gas refinery. Inf Sci 2008;178:4280–300.

[2] Ayoub MA. Ergonomics deficiencies: I. Pain at work. J Occup Med 1990;32:52–7.

[3] Ayoub MA. Ergonomics deficiencies: II. Probable causes. J Occup Med 1990;32:131–6.

[4] Abou-Ali MG, Khamis M. TIREDDX: an integrated intelligent defects diagnostic system for tire production and service. Expert Syst Appl 2003;24:247–59.

[5] Shikdar AA, Sawaqed NM. Ergonomics and occupational health and safety in the oil industry: a managers' response. Comput Ind Eng 2004;47:223–32.

[6] Cimino A, Longo F, Mirabelli G. A multimeasure-based methodology for the ergonomics effective design of manufacturing system workstations. Int J Ind Ergon 2009;39:447–55.

[7] Russ K. Risk assessment in the UK health and safety system: theory and practice. Saf Health Work 2010;1:11–8.

[8] Otto A, Scholl A. Incorporating ergonomics risks into assembly line balancing. Eur J Oper Res 2011;212:277–86.

[9] Zunjic A, Milanovic DD, Milanovic DL, Misita M, Lukic P. Development of a tool for assessment of VDT workplaces—a case study. Int J Ind Ergon 2012;42:581–91.

[10] Hendrick HW. Future directions in macroergonomics. Ergonomics 1995;38:1617–24.

[11] Azadeh A, Keramati A, Fam IM, Jamshidnejad B. Enhancing the availability and reliability of power plants through macroergonomics approach. J Sci Ind Res 2006;65:873–8.

[12] Blanning RW. Management applications of expert systems. Inf Manag 1984;7:311–6.

[13] Bryden R, Hudson PTW. Because we want. Saf Health Pract 2005;23:51–4.

[14] Burri GJ, Helander MG. A field study of productivity improvements in the manufacturing of circuit boards. Int J Ind Ergon 1991;7:207–15.

[15] Eklund J. Ergonomics, quality and continuous improvement-conceptual and empirical relationships in an industrial context. Ergonomics 1997;40:982–1001.

[16] Champoux D, Brun JP. Occupational health and safety management in small size enterprises: an overview of the situation and avenues for intervention and research. Saf Sci 2003;41:301–18.

[17] Chang JI, Liang CL. Performance evaluation of process safety management systems of paint manufacturing facilities. J Loss Prev Process Ind 2009;22:398–402.

[18] Singh K, Ihlenfeld C, Oates C, Plant J, Voulvoulis N. Developing a screening method for the evaluation of environmental and human health risks of synthetic chemicals in the mining industry. Int J Miner Process 2011;101:1–20.

[19] Duijm NJ, Fiévez C, Gerbec M, Hauptmanns U, Konstandinidou M. Management of health, safety and environment in process industry. Saf Sci 2008;46:908–20.

[20] Hassim MH, Hurme M. Inherent occupational health assessment during process research and development stage. J Loss Prev Process Ind 2010;23:127–38.

[21] Boughaba A, Hassane C, Roukia O. Safety culture assessment in petrochemical industry: a comparative study of two Algerian plants. Saf Health Work 2014;5:60–5.

[22] Chen LH. Job satisfaction among information system (IS) personnel. Comput Hum Behav 2008;24:105–18.

[23] Chen CY, Wu GS, Chuang KJ, Ma CM. A comparative analysis of the factors affecting the implementation of occupational health and safety management systems in the printed circuit board industry in Taiwan. J Loss Prev Process Ind 2009;22:210–5.

[24] Einarsson S, Brynjarsson B. Improving human factors, incident and accident reporting and safety management systems in the Seveso industry. J Loss Prev Process Ind 2008;21:550–4.

[25] Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. Eur J Oper Res 1978;2:429–44.

[26] Azadeh A, Rouzbahman M, Saberi M, Fam IM. An adaptive neural network algorithm for assessment and improvement of job satisfaction with respect to HSE and ergonomics program: the case of a gas refinery. J Loss Prev Process Ind 2011;24:361–70.

[27] Yang K, Teo EC, Fuss FK. Application of Taguchi method in optimization of cervical ring cage. J Biomech 2007;40:3251–6.

[28] Taguchi G, Chowdhury S, Taguchi S. Robust engineering. New York: McGraw-Hill; 2000.

[29] Kethley RB. Using Taguchi loss functions to develop a single objective function in a multi-criteria context: a scheduling example. Int J Inf Manag Sci 2008;19:589–600.

[30] Ebrahimipour V, Azadeh A, Rezaie K, Suzuki K. A GA-PCA approach for power sector performance ranking based on machine productivity. Appl Math Comput 2007;186:1205–15.

[31] Azadeh A, Saberi M, Rouzbahman M, Saberi Z. An intelligent algorithm for performance evaluation of job stress and HSE factors in petrochemical plants with noise and uncertainty. J Loss Prev Process Ind 2013;26:140–52.

[32] Morel G, Amalberti R, Chauvin C. How good micro/macro ergonomics may improve resilience, but not necessarily safety. Saf Sci 2009;47:285–94.

[33] Corder GW, Foreman DI. Nonparametric statistics for non-statisticians: a step-by-step approach. Hoboken, New Jersey: John Wiley and Sons; 2009.

[34] Fam IM, Azadeh A, Faridan AM, Mahjoub H. Safety behaviours assessment in process industry: a case in gas refinery. J Chin Inst Ind Eng 2008;25:298–305.

[35] Zhu J. Data envelopment analysis vs principal component analysis: An illustrative study of economic performance of Chinese cities. Journal of Operational Research 1998;111:50–61.