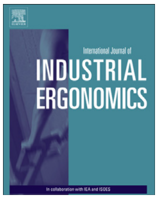
International Journal of Industrial Ergonomics 49 (2015) 68–77

Contents lists available at ScienceDirect

International Journal of Industrial Ergonomics

journal homepage: www.elsevier.com/locate/ergon



A unique algorithm for the assessment and improvement of job satisfaction by resilience engineering: Hazardous labs

A. Azadeh*, N. Alizadeh Bonab, V. Salehi, M. Zarrin

School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

ARTICLE INFO

Article history:
Received 25 April 2014
Received in revised form
14 April 2015
Accepted 4 June 2015
Available online 23 June 2015

Keywords:
Resilience engineering (RE)
Health
Safety and environment (HSE)
Hazardous laboratories
Job satisfaction
Artificial neural network (ANN)
Adaptive network based fuzzy inference system (ANFIS)

ABSTRACT

There are many potential dangers in laboratories of universities. Hence it should be focused on the actions and decisions of the individuals who work in the labs. Resilience Engineering (RE), the ability to recover quickly after an upset, is known as an important feature of a complex system which handles hazardous technical operations. In response to the need for the betterment of health, safety, and environment (HSE) at work; it is felt necessary to study the RE aspects if an unexpected events occurs. The main purpose of this study is to determine the role and effect of RE in improving job satisfaction and occupational safety in laboratories of universities. This study also presents an intelligent algorithm for assessing and improving job satisfaction in laboratories filled with hazardous materials by means of HSE and RE. In doing so, questionnaires related to HSE and RE are filled in by laboratory operators. The average result of each HSE and RE category is considered as input and job satisfaction as output for the proposed algorithm. An integrated neuro-fuzzy algorithm to find optimal solution is developed and tested for the purpose of this study. Also, results are tested and verified by regression analysis. Finally, with the help of Normal probability technique, outlier laboratories will be identified. The results are improved by means of RE as an input. This is one of the first studies introducing an intelligent algorithm for the improvement of job satisfaction by means of RE and HSE in hazardous laboratories.

Practitioner summary

Job satisfaction is an important issue for the safety of hazardous labs. Moreover, HSEs are significant issues in such laboratories. In contrast to HSE programs, RE covers the whole set of results, i.e., the things going right and wrong, where there is little known to deal with. The effect of RE on job satisfaction has not been investigated properly. In this study, job satisfaction is to be evaluated with respect to RE characteristics, HSE and ergonomics concepts in hazardous labs. It is expected that the results will be improve by using both RE, HSE and ergonomics shaping factors.

1. Introduction

Safety is valued as an unsolvable element of all laboratory activities. Moreover a critical element of safety education includes developing and encouraging basic attitudes and habits of cautious behavior in laboratories (Gibson et al., 2014). Accidents in laboratories are often the result of ignorance or carelessness by people who work in the laboratories. The safety precautions will be worthless unless people plan, understand, and think through the consequences of every operation before they do it. The common accidents, which often occur, are fire, explosion, chemical and thermal burns, absorption of toxic and so on. Some of the accidents have occurred in the laboratories of the universities in the world. Below a list of lab safety accidents is presented (www.tinyurl.com/safetyprojectlist):

- 1997, Dartmouth Professor Killed by Spill
- 2005, Ohio State Professor Electrocuted
- 2006, Tufts Toxin Released
- 2006, Texas A&M Gas Explosion
- 2008, UCLA Deadly Fire

---

* Corresponding author.
E-mail address: aazadeh@ut.ac.ir (A. Azadeh).

http://dx.doi.org/10.1016/j.ergon.2015.06.002
0169-8141/

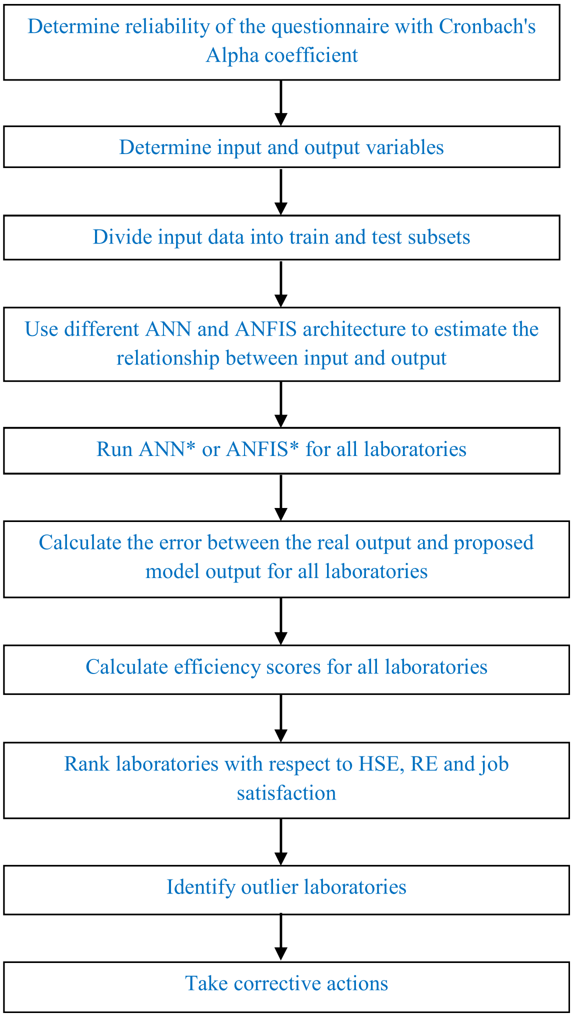


Fig. 1. The algorithm for performance improvement of job satisfaction by RE.

- 2010, Texas Tech Explosion
- 2010, Southern Illinois U. Fire Burns Student
- 2011, Yale Student Killed
- 2011, U. Maryland Explosion and Fire
- 2011, Boston College Student Hurt by Explosion

Therefore occupational safety issue in laboratories of universities is very important.

1.1. *HSE and ergonomics*

The purpose of HSE management system is to anticipate, recognize, and evaluate all health hazards in work environment. Also HSE management systems try to decrease incidents, health problems and environmental damages (Azadeh et al., 2008c). HSE motivates employees and organizations to adopt a healthy and safe lifestyle. It optimizes the relation between the operator, machine and work atmosphere in a way that the operator faces the least level of fatigue and enjoys the most efficiency (Azadeh et al., 2008a; Changchit and Holsapple, 2001; Chen and Yang, 2004). In addition, there is a close relationship among health, safety, environment and ergonomics factors. The precise consideration of human factors might lead to the reduction of the number of incidents, injuries and unsafe behaviors at workplace and improve health and safety (Azadeh et al., 2011).

Table 1
The detailed demographics of respondents.

Demographic factor	Rang	Number of persons
Age (Year)	<18	0
	19–25	24
	26–35	39
	36–45	43
	46–55	20
	>55	10
Gender	Male	101
	Female	35
Experience (Year)	<5	11
	5–10	54
	11–15	40
	16–20	19
	>20	12
Height (Centimeter)	<165	18
	165–170	31
	171–175	39
	176–180	23
	181–185	12
	>185	13
Weight (Kilogram)	<60	21
	60–70	29
	71–80	48
	81–90	23
	>90	15
Marital status	Single	44
	Married	92

Some studies have been conducted in the context of ergonomics that show positive effects of applying ergonomic rules to workplace (Ayoub, 1990; Blanchard and Fabrychy, 1990; Shikdar and Sawaqed, 2004). The effective application of ergonomics in workplace can lead to a balance between human operators and task demands. This can increase worker productivity and lead to efficient workers and job satisfaction (Deng, 1999). Lack of ergonomics rules in a workplace can lead to physical and mental stress, low efficiency and poor quality (Burri and Helander, 1991; Cabrero-Canosa et al., 2003; Caldwell et al., 1998).

1.2. *Resilience engineering*

RE is an important field for safety management in sociotechnical and hazardous environments. Considerable efforts have been made in recent years to specify the essential features of resilient systems (Azadeh et al., 2013). In addition, RE is strongly associated with human factors, control theory, and safety engineering. Henceforth, a typical feature of RE is its focus on understanding how success is obtained, how people learn and adapt themselves to an environment full of faults, hazards and multiple goals by creating safety (Hollnagel and Woods, 2006).

According to several studies (Hollnagel and Woods, 2005; Hale and Heijer, 2006; Wreathall, 2006; Saurin et al., 2008), five principles have been identified that have interfaces with each other and do not possess strictly defined limits. These principles are briefly defined as follows:

a) Top management commitment: The commitment of the management to keep a balance between the pressures of production and the chronic pressures of protection is one of the main measures of RE (Saurin and Carim Júnior, 2011).
b) Reporting: The degree to which the reporting of safety problems is open and encouraged provides an important source of RE in a system (Wreathall, 2006).
c) Learning: RE focuses on learning from the analysis of normal work, while it does not abandon learning from accidents (Saurin and Carim Júnior, 2011).

Table 2
The HSE, ergonomics and RE questions used as input indicators in the algorithm.

Health	Safety	Environment	Ergonomics	RE
Do you have enough free time for resting in your work shift?	Has your safety structure identified work positions required for personal protection equipment?	Does noise bother you in your work area?	Do you feel any backache in your daily work?	Does your supervisor have enough information about your safety issues?
Do hazardous pollutants exist in your work environment?	Is there any procedure for accidents which can occur in your work area?	Is your work area temperature suitable?	Do you feel any headache in your daily work?	Are safety instructions presented to employees manually?
Do you drink enough water in hot days?	Is it necessary to use personal protection items?	Does machine vibration transfer to your body?	Are the heights of chairs adjustable?	Do you have proper trainings about safety issues in your work?
How much ISO 18000 improves your working condition?	Does your work area have a system for reporting accidents to the authorities?	Is there an appointed person responsible for waste management?	Is there enough space for free movement in your work area?	Can you easily report your issues to your supervisor?

d) Awareness: Awareness is required for changing the nature of risks and assessing the trade-off between safety and production (Saurin and Carim Júnior, 2011).
e) Flexibility: The Flexibility principle for RE is to design a more flexible process that is able to work under various disturbances (Dinh et al., 2012).

1.3. Job satisfaction

Job satisfaction is an important field for managers and employees. The evaluation of job satisfaction is not only because of the coexistence of several variables and their interaction, but also it is related to several significant organizational behaviors such as absenteeism, turnover and union activity (Fisher and Locke, 1992). As well, job satisfaction is the main variable in both practice and theory of organizational events from job design to management (Spector, 1997).

Byrd et al. (1996) developed a causal model connecting technical aspects to the staff's job satisfaction. Shikdar and Das (2003) showed that the participative standard with feedback condition performs as the optimum strategy for improving worker satisfaction and job treatments. Calisir and Gumussoy (2007) used an analysis to assess the impact of IT professionals' demographic features, work stress and work characteristics on job satisfaction. Rasmani and Shahari (2007) proposed the use of fuzzy sets to exhibit linguistic terms in Likert-type scale. They also employed the fuzzy conjoint method in job satisfaction assessment.

In this study, in addition to HSEE program, RE is considered as an input for job satisfaction assessment because of its importance in hazardous environments like laboratories with high risk. The purpose of this study is to show the relationship between RE and job satisfaction and also the effect of considering RE factors on improving job satisfaction and occupational safety.

The study is organized as follows. Section 2 provides an introduction to adaptive neural networks. Section 3 includes an introduction to adaptive neuro-fuzzy inference systems. Section 4 introduces the proposed algorithm for assessing efficiency of HSE and RE factors with respect to job satisfaction. Sections 4 and 5 present the experimentation procedure and the case study. Section 6 offers results and analysis. Finally, Section 7 provides the concluding comments.

Table 3
Reliability test of questionnaire with Cronbach's alpha coefficient.

Number of items	Mean	Variance	Std. Deviation	Cronbach's alpha
6	17.8784	9.790	3.1288	0.778

2. Artificial neural network

Simulation meta-modeling is a superior decision support tool that can be utilized to improve the overall effectiveness of the decision making process and decrease costs, time, and amount of effort required during a simulation analysis (Fonseca et al., 2003).

There are many varieties of connections under study; however, only one type of network called Multi-Layer Perception (MLP) was discussed here. Multi-layered feed-forward ANNs are capable of approximating measurable functions according to the desired degrees of accuracy (Hornik et al., 1989). In this network, the data flows forward the output without any feedback. Hidden nodes with suitable non-linear transfer functions are used to process the information received by the input nodes. Back propagation learning is a kind of supervised learning presented by Werbos (1974) and later developed by Rumelhart and McClelland (1986). At the beginning, all weights in the network are initialized to small random values. The algorithm uses a learning set. This set consists of input-desired output pattern pairs. Each input–output pair is gained by the historical data. These pairs are used to modify the weights in the network and to minimize the Sum Squared Error (SSE) for measuring the difference between the real and the wanted values. After computing the back propagation step, the corrections will be applied to the weights.

The advantage of MLP has been described by the ability of the network to learn complex relationships between input and output patterns, which makes it difficult to model with conventional methods.

3. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is a neural-network based on fuzzy approach in which the learning procedures are performed by including the optimization of the prior and conclusion–part parameters (Shoorehdeli et al., 2009). ANFIS uses a feed forward network to search for fuzzy decision rules that perform well. Using a given input–output data set, ANFIS creates an FIS whose membership function parameters are modified by means of a back propagation algorithm alone or by means of the combination of a back-propagation algorithm with the least squares method.

There are different advanced fuzzy inference techniques. In this study, one of them that generates a Sugeno-type FIS structure has been utilized. This is met by using subtractive clustering and requires separate sets of input and output data as input variables. It performs this by extracting a set of rules that models the data behavior. The rule extraction method first uses the subcluster function to determine the number of rules and the antecedent membership function. It then uses linear least squared estimation to determine each rule's equation.

Table 4
Architecture of the 25 ANN-MLP models and their associated relative error (MAPE).

Output 1 (job satisfaction)					
ANN-MLP Model number	Learning method	Number of neurons in first hidden layer	First transfer function	Second transfer function	MAPE
1	LM	4	Logsig	Logsig	0.1461
2	B	1	Logsig	Logsig	0.1429
3	***BFG***	***61***	***Logsig***	***Logsig***	***0.1031***
4	BR	63	Logsig	Logsig	0.1357
5	CGB	24	Logsig	Logsig	0.1332
6	CGF	9	Logsig	Logsig	0.1305
7	CGP	1	Logsig	Logsig	0.1251
8	GD	18	Logsig	Logsig	0.1663
9	GDA	72	Logsig	Logsig	0.1605
10	GDM	32	Logsig	Logsig	0.1339
11	GDX	40	Logsig	Logsig	0.1231
12	OSS	63	Logsig	Logsig	0.1224
13	SCG	80	Logsig	Logsig	0.1231
14	RP	44	Logsig	Logsig	0.1198
15	GDM	28	Tansig	Purelin	0.1905
16	LM	2	Tansig	Purelin	0.1364
17	GDX	30	Tansig	Purelin	0.1346
18	B	5	Tansig	Purelin	0.1662
19	BFG	3	Tansig	Purelin	0.1342
20	BR	21	Tansig	Purelin	0.1345
21	CGB	31	Tansig	Purelin	0.1123
22	CGF	23	Tansig	Purelin	0.1189
23	CGP	66	Tansig	Purelin	0.1232
24	GD	76	Tansig	Purelin	0.1832
25	GDA	51	Tansig	Purelin	0.1184

B: Batch training with weight and bias learning rules; BFG: BFGS quasi-Newton back propagation; BR: Bayesian regularization; C: Cyclical order incremental update; CGB: Powell-Beale conjugate gradient back propagation; CGF: Fletchere-Powell conjugate gradient back propagation; CGP: Polak-Ribiére conjugate gradient back propagation; GD: Gradient descent back propagation; GDA: Gradient descent with adaptive learning rule back propagation; GDM: Gradient descent with momentum back propagation; GDX: Gradient descent with momentum and adaptive learning rule back propagation; LM: Levenberg–Marquardt back propagation; OSS: One step secant back propagation; RP: Resilient back propagation (Rprop); SCG: Scaled conjugate gradient back propagation.

Membership Function (MF) is a curve which defines each point in the input space that is mapped to a membership value between 0 and 1. Different kinds of membership functions are: (a) Triangular membership function, (b) Trapezoid membership function, (c) Gaussian membership function, (d) Bell membership function and (e) Linear membership function.

The default input membership function type in this study is Gaussian, and the default output membership function type is linear.

4. Methodology

4.1. An integrated ANN algorithm and ANFIS algorithm are proposed to measure job satisfaction with respect to HSE program and RE factors as follows

Step 1 Determine the reliability of the questionnaire. In this step, the reliability of the questionnaire is determined with Cronbach's alpha coefficient.

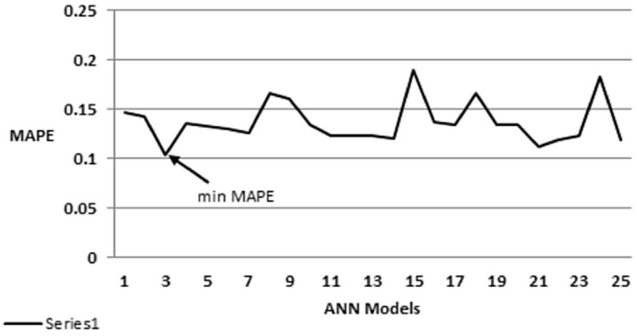


Fig. 2. Relative error estimate for the 25 ANN-MLP models.

Step 2 Determine the input and output variables of the model.

Step 3 Divide input data into two subsets: train and test data.

Step 4 Use the algorithm to estimate the relationship between inputs and outputs:

- Select architecture and training parameters for the ANN algorithm and select membership function and inference methods for the ANFIS.
- Train the model by using the train data.
- Evaluate the model by using the test data.
- Repeat these steps using different architectures and training parameters for ANN algorithm, different membership functions and inference methods for ANFIS.
- Determine the relative error (MAPE[1]) of the learned algorithm.
  If MAPE $\leq$ 0.20, then go to the next step. Otherwise, distribute questionnaires to more laboratories. The max error of 0.20 is defined to allow the extensive variations between laboratories. This is a rational and logical estimate confirmed by experts in the field.
- Select the best architecture (ANN* or ANFIS*) with minimum MAPE on the test data set.

Step 5 Run ANN* or ANFIS* for all laboratories.

Step 6 Calculate the error between the actual output and model output in the selected period to assess the efficiency of laboratories:

$$E_i = P_{real(i)} - P_{ANN^* or ANFIS^*(i)} \quad i = 1, \ldots, n \tag{1}$$

---

[1] Mean Absolute Percentage Error (MAPE) $= \frac{1}{N}\sum_1^N \left|\frac{ActualValue_i - SetPointValue_i}{SetPointValue_i}\right|$
N: the number of rows.

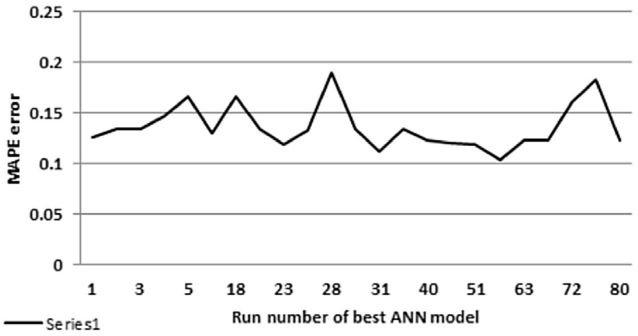


Fig. 3. The comparison of 80 independent runs for the best model (3rd ANN-MLP).

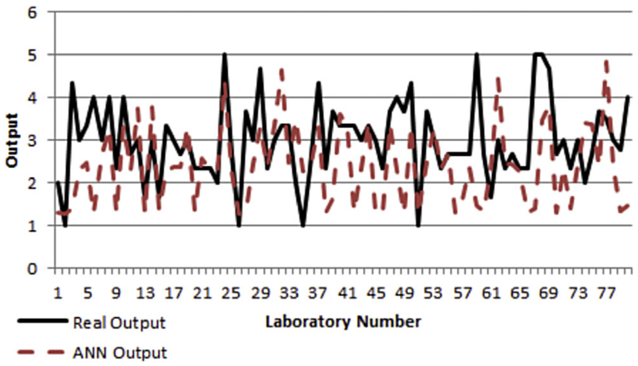


Fig. 4. The results of the selected ANN-MLP and original data for job satisfaction and RE.

Step 7 Shift frontier function from model for obtaining the effect of the largest positive error.

$$E'_i = E_i/P_{ANN^{*}orANFIS^{*}(i)} \quad i = 1, \dots, n \qquad (2)$$

The above formula (2) calculates the largest error by noting the operator scale (Constant Returns to Scale (CRS)). To this end, the largest E'_i which indicates the operator with the best performance is identified. Suppose the *k*th operator has the largest E'_i and hence

$$E'_k = \max\left(E'_i\right) \qquad (3)$$

Thus, the value of the shift for each operator is different and is calculated by

$$Sh_i = E_k * \frac{P_{ANN*orANFIS*(i)}}{P_{ANN*orANFIS*(k)}} \quad i = 1, \dots, n \qquad (4)$$

The effect of the scale of laboratories on their efficiencies is considered. Moreover, the unit used for revision is selected with regard to its scale (CRS) (Azadeh et al., 2007a; Costa and Markellos, 1997; Delgado, 2005).

Step 8 Calculate efficiency scores.

The efficiency scores take values between 0 and 1. This maximum score is assigned to the unit that is used for the correction (Azadeh et al., 2007a).

$$F_i = P_i/(P_{ANN*orANFIS*(i)} + Sh_i) \quad i = 1, \dots, n \qquad (5)$$

Step 9 Plot the Normal probability of efficiency scores by ANN or ANFIS through step 8 for all laboratories to identify outlier laboratories.

Step 10 Perform corrective actions with respect to outlier laboratories.

Fig. 1 shows the steps of proposed algorithm for performance assessment of job satisfaction with respect to HSE and RE.

Table 5
The architecture of the ANFIS models and their MAPE values.

Output1(job satisfaction)								
Structure number	Input membership function	Output membership function	Cluster radius	AND method (T-Norm)	OR method (S-norm)	Implication	Aggregation	MAPE
1	Gaussmf	Linear	0.695	Min	Max	Min	Max	0.3747
2	Gaussmf	Linear	0.695	Min	Probor	Min	Max	0.3747
3	Gaussmf	Linear	0.695	Min	Max	Prod	Max	0.3747
4	Gaussmf	Linear	0.695	Prod	Max	Min	Max	***0.3523***
5	Gaussmf	Linear	0.695	Prod	Probor	Min	Max	***0.3523***
6	Gaussmf	Linear	0.695	Prod	Max	Prod	Max	***0.3523***
7	Gaussmf	Linear	0.695	Min	Probor	Prod	Max	0.3747
8	Gaussmf	Linear	0.695	Prod	Probor	Prod	Max	***0.3523***
9	Gaussmf	Linear	0.695	Min	Max	Min	Sum	0.3747
10	Gaussmf	Linear	0.695	Min	Probor	Min	Sum	0.3747
11	Gaussmf	Linear	0.695	Min	Max	Prod	Sum	0.3747
12	Gaussmf	Linear	0.695	Prod	Max	Min	Sum	***0.3523***
13	Gaussmf	Linear	0.695	Prod	Probor	Min	Sum	***0.3523***
14	Gaussmf	Linear	0.695	Prod	Max	Prod	Sum	***0.3523***
15	Gaussmf	Linear	0.695	Min	Probor	Prod	Sum	0.3747
16	Gaussmf	Linear	0.695	Prod	Probor	Prod	Sum	***0.3523***
17	Gaussmf	Linear	0.695	Min	Max	Min	Probor	0.3747
18	Gaussmf	Linear	0.695	Min	Probor	Min	Probor	0.3747
19	Gaussmf	Linear	0.695	Min	Max	Prod	Probor	0.3747
20	Gaussmf	Linear	0.695	Prod	Max	Min	Probor	***0.3523***
21	Gaussmf	Linear	0.695	Prod	Probor	Min	Probor	***0.3523***
22	Gaussmf	Linear	0.695	Prod	Max	Prod	Probor	0.3523
23	Gaussmf	Linear	0.695	Min	Probor	Prod	Probor	0.3747
24	Gaussmf	Linear	0.695	Prod	Probor	Prod	Probor	***0.3523***

The best structures of ANFIS with the minimum values of MAPE are shown in bold italics font.

Table 6
Estimation of efficiency scores for all laboratories by the proposed algorithm.

Laboratory code	$P_{real(i)}$	$P_{ANN(i)}$	E_i	F_i	Rank	Laboratory code	$P_{real(i)}$	$P_{ANN(i)}$	E_i	F_i	Rank
1	2	1.31	0.69	1	1	41	3.33	3.33	0	0.57	16
2	1	1.27	−0.27	0.36	32	42	3.33	1.32	2.01	0.43	27
3	4.33	1.40	2.93	1	1	43	3	2.32	0.68	0.36	32
4	3	2.29	0.71	1	1	44	3.33	3.41	−0.08	0.48	24
5	3.33	2.45	0.88	1	1	45	3	1.28	1.72	0.32	36
6	4	1.30	2.7	0.65	10	46	2.33	1.29	1.04	0.31	31
7	3	2.68	0.32	0.63	11	47	3.67	3.37	0.3	0.53	20
8	4	3.27	0.73	0.83	3	48	4	2.29	1.71	0.58	15
9	2.33	1.28	1.05	0.32	36	49	3.67	1.28	2.39	0.59	14
10	4	3.34	0.66	0.56	17	50	4.33	3.34	0.99	0.81	5
11	2.67	2.29	0.38	0.54	19	51	1	1.27	−0.27	0.15	46
12	3	3.72	−0.72	0.50	23	52	3.67	2.49	1.18	0.68	8
13	1.67	1.28	0.39	0.21	43	53	3	3.28	−0.28	0.38	31
14	3	3.78	−0.78	0.48	24	54	2.33	2.32	0.01	0.26	42
15	1.67	1.35	0.32	0.50	23	55	2.67	2.65	0.02	0.47	25
16	3.33	2.28	1.05	0.51	22	56	2.67	1.30	1.37	0.29	39
17	3	2.36	0.64	0.50	23	57	2.67	1.60	1.07	0.52	21
18	2.67	2.35	0.32	1	1	58	2.67	2.34	0.33	0.36	32
19	3	3.30	−0.3	0.10	48	59	5	1.47	3.53	0.80	6
20	2.33	1.33	1	0.55	18	60	2.67	1.33	1.34	0.35	33
21	2.33	2.55	−0.22	0.33	35	61	1.67	2.29	−0.62	0.16	45
22	2.33	2.29	0.04	0.38	31	62	3	4.45	−1.45	0.53	20
23	2	2.30	−0.3	0.32	36	63	2.33	2.42	−0.09	0.34	34
24	5	4.36	0.64	1	1	64	2.67	2.42	0.25	0.52	21
25	2.67	2.28	0.39	0.29	39	65	2.33	2.27	0.06	0.47	25
26	1	1.27	−0.27	0.20	44	66	2.33	1.31	1.02	0.39	30
27	3.67	1.33	2.34	0.43	27	67	5	1.40	3.6	0.62	12
28	3	2.42	0.58	0.32	36	68	5	3.46	1.54	0.82	4
29	4.67	3.29	1.38	0.72	7	69	4.67	3.79	0.88	0.60	13
30	2.33	2.38	−0.05	0.27	41	70	2.67	1.30	1.37	0.41	29
31	3	3.32	−0.32	0.51	22	71	3	2.34	0.66	0.02	49
32	3.33	4.65	−1.32	0.51	22	72	2.33	1.39	0.94	0.87	2
33	3.33	2.45	0.88	0.39	30	73	3	2.41	0.59	0.55	18
34	2	3.46	−1.46	0.30	38	74	2	3.40	−1.4	0.21	43
35	1	2.27	−1.27	0.11	47	75	2.67	3.37	−0.7	0.30	38
36	2.33	2.32	0.01	0.28	40	76	3.67	2.41	1.26	0.43	27
37	4.33	3.29	1.04	1	1	77	3.5	4.83	−1.33	0.56	17
38	2.33	1.30	1.03	0.42	28	78	3	2.35	0.65	0.42	28
39	3.67	1.63	2.04	0.42	28	79	2.75	1.32	1.43	0.44	26
40	3.33	3.60	−0.27	0.43	27	80	4	1.45	2.55	0.67	9

5. Experiment

5.1. The laboratories

The laboratories under study are located in the College of Engineering, University of Tehran, Iran. In this study, purposive sampling technique was used and approximately all labs of the engineering college were selected. Some of the studied labs are signal process lab, chemical lab, material lab, robotic lab, microelectronic lab, microprocessor lab, photonic lab, industrial electronic lab, technology lab, design lab, control lab and etc. The questionnaires were distributed among 150 operators and experts of all 80 laboratories. The distribution of the questionnaires lasted about three days. The age range of the respondents was between 30

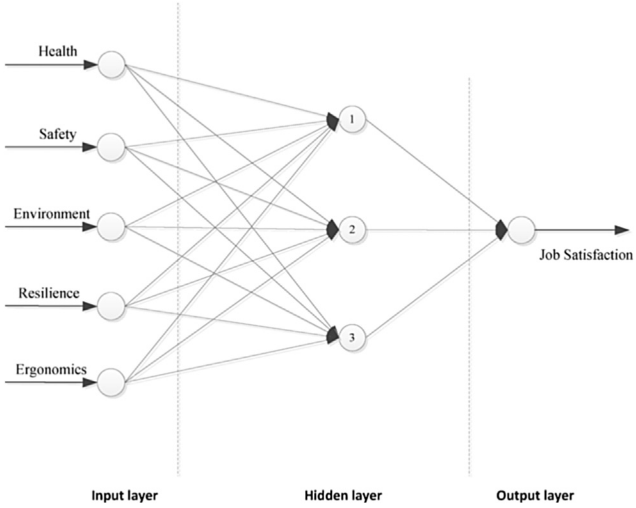


Fig. 5. The architecture of the preferred ANN model for job satisfaction.

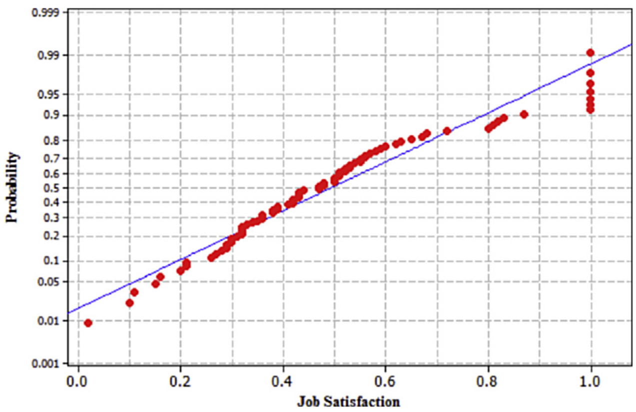


Fig. 6. Normal probability plot for efficiency scores of 80 laboratories.

Table 7
Anderson-Darling normality test for the efficiency scores of all laboratories.

A-squared	1.5
P-value	<0.005

and 55 and all of them had the experience of work at least 5 years in labs. Then, 136 reliable questionnaires were returned. The detailed demographics of respondents are summarized in Table 1. Moreover, job satisfaction in each laboratory with respect to HSEE and RE has been ranked by the proposed algorithm.

5.2. *Data collection*

Six detailed questionnaires containing valuable information related to human factors, safety, environment, health, RE and job satisfaction were developed and distributed among operators and experts. The 5-point Likert-type scale (1 = strongly disagree, 5 = strongly agree) was used in the questionnaires. The first questionnaire includes the items related to the ergonomics factors and machine interface. The second questionnaire contains health and personal protection items. The third questionnaire contains questions related to training, work pressures, organizational structure, occupational safety, and relationship between management and coworkers. The forth questionnaire consists of items about the work, that are, temperature, ventilation, lighting, and noise. The fifth questionnaire includes questions about RE and its features such as top management commitment, reporting culture, learning, awareness and flexibility. The sixth questionnaire investigates operator's revenue and total job satisfaction. The structured questionnaires of HSE, ergonomics and job satisfaction concepts were developed based on previous studies (Azadeh et al., 2011, 2013). Also the structured questionnaire of RE was developed based on previous studies (Huber et al., 2009; Azadeh et al., 2013). The input indicators are divided to 5 main categories, i.e. ergonomics, health, safety, environment and RE, and job satisfaction defined. Besides, the average score for each indicator is computed by referring to the related questions in Table 2.

5.3. *The intelligent algorithm*

The applicability of the proposed algorithm is experimented in actual laboratories. It is shown the way each step is applied to evaluate the relationship of HSEE and RE with job satisfaction in hazardous labs. Moreover, the efficiency of the proposed algorithm is shown by MAPE.

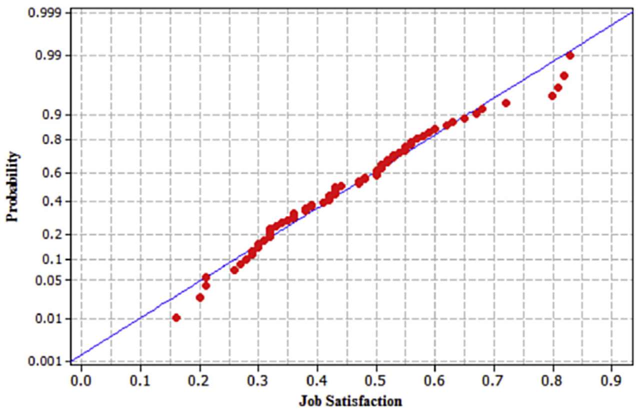


Fig. 7. Normal probability plot for efficiency scores of non-outlier laboratories.

Table 8
Results of linear regression.

Operator number	Real output (job satisfaction)	Conventional regression
73	3.00	2.66
74	5.00	4.57
75	2.67	3.25
76	1.67	3.67
77	3.00	2.83
78	2.33	2.70
79	2.67	2.74
80	2.33	1.24
MAPE = 0.29		

Table 9
Results of second order regression.

Operator number	Real output (job satisfaction)	Conventional regression
73	3.00	1.73
74	5.00	3.03
75	2.67	2.31
76	1.67	2.62
77	3.00	1.73
78	2.33	1.62
79	2.67	1.79
80	2.33	1.16
MAPE = 0.347		

6. Computational results and analysis

Step 1 The reliability of the questionnaire was determined through Cronbach's alpha coefficient for the six categories of ergonomics, health, safety, and environment and RE, and job satisfaction. The result of reliability test is shown in Table 3 and Cronbach's alpha coefficient value is acceptable (Cronbach, 1951; Raykov, 1997; Santos, 1999).

Step 2 The next step involves the determination of input and output variables for the algorithm. There are 5 main categories (health, safety, environment, ergonomics and RE) as input variables and one output category (job satisfaction). Then, for each category, the average score is used in the proposed algorithm. The accumulated data is shown in Appendix A.

Step 3 Data includes 65 rows of train data and 15 rows of test data.

Step 4.1 To locate the optimum structure for this study, we tested 25 distinct ANN models. The maximum number of neurons in the first hidden layer is set to 80. Each model is replicated 80 times to take care of the possible degree of bias or noise. The architecture of the ANN-MLP models and their MAPE values are shown in Table 4.

It seems that the third ANN-MLP model for job satisfaction has the lowest MAPE; therefore, it is chosen as the optimum model.

Table 10
Results of logarithmic regression.

Operator number	Real output (job satisfaction)	Conventional regression
73	3.00	2.80
74	5.00	4.28
75	2.67	3.32
76	1.67	3.64
77	3.00	2.95
78	2.33	2.83
79	2.67	2.86
80	2.33	0.78
MAPE = 0.281		

Table 11
Comparison of ANN and conventional regression.

Models	Linear regression	Second order regression	Logarithmic regression	ANN algorithm
MAPE	0.29	0.347	0.281	0.1031

This is also shown graphically in Fig. 2. Fig. 3 shows the result of 80 independent times of running the preferred model (3rd ANN-MLP). It can be seen that the instabilities lie within a narrow range.

Step 4.2 Several ANFIS models are tested (randomly) to find the optimum model for the output. Moreover, the preferred (optimum) ANFIS model is identified for the output. The architecture of the ANFIS models and their MAPE values are shown in Table 5. It seems that half of these models have similar MAPE values while the rest have different values.

Step 5 Therefore, the 3rd ANN-MLP is selected for estimating the performance assessment of HSEE and RE versus job satisfaction. To identify an ANN output for each operator, the preferred model is tested for all laboratories. Fig. 4 presents the distance between the results of the preferred ANN and original data. This figure validates that the preferred model is relatively close to actual data.

Steps 6–8 The results of these steps are shown in Table 6. This table shows the efficiency scores for all laboratories by the proposed algorithm. Moreover, all laboratories are ranked according to their efficiency scores. Fig. 5 presents the ANN architecture of the preferred network with respect to HSSE and job satisfaction (23rd Model in Table 4).

Steps 9 and 10 The normal probability plot for all laboratories are shown in Fig. 6. This is to identify the outlier laboratories. As shown in this figure, several laboratories are identified as outliers. Management should take proper corrective actions with respect to these laboratories. This may be done through proper on-the-job training, simulator classes, etc. The result of Normality test is shown in Table 7.

As shown in Table 7, the normality assumption was rejected among 80 laboratories. The outlier laboratories should be found and management should take proper corrective actions with respect to these laboratories. Fig. 7 shows normal probability plot for non-outlier laboratories. The assumption of normality for non-outlier laboratories is not rejected because of the p-value of 0.286. There are several reasons for the existence of outlier laboratories. Operators

Table 12
The features of the integrated algorithm versus other studies.

Feature Study	HSE modeling	Ergonomic modeling	RE modeling	Job satisfaction evaluation	Integrated HSE-ergonomics versus job satisfaction	Data complexity and non-linearity	An integrated ANN algorithm	An ANFIS algorithm	High precision and reliability	Data pre-processing and post-processing
The framework of this study	√	√	√	√	√	√	√	√	√	√
Delphi Methods	√	√							?	
Statistical Methods	√	√							?	
Edosomwan (1986)										
Byrd et al. (1996)		√		√					?	
Saksvik and Nytr (1996)		√		√						
Trop and Moen (2006)	√	√							?	
Azadeh et al. (2006)		√							?	
Rasmani and Shahari (2007)				√					√	
Calisir and Gumussoy (2007)		√		√					?	
Mohammad Fam et al. (2007)		√							?	
Mohammad Fam et al. (2008)		√							?	
Baradaran et al. (2008)		√		√					?	
Azadeh et al. (2008b)	√	√							?	
Azadeh et al. (2011)	√	√		√	√	√	√		√	√

of some of these laboratories might not have good knowledge of HSE and, as a result, they need to have on-the-job training courses. A few might have answered the questions incorrectly due to job insecurity. Management should provide the means to investigate assignable causes that have brought about this inefficiency. Laboratories 1, 3, 5, 18, 19, 24, 35, 37, 51, 71 and 72 are considered as outlier laboratories. Therefore, 12 operators who worked in these laboratories were not satisfied with their jobs with respect to HSE and ergonomic factors. As mentioned, proper corrective actions should be taken by the management to resolve this issue.

6.1. Comparison of ANN with conventional regression

Conventional regression analysis is the most frequently used statistical tool to explain the variation of a dependent variable Y in terms of the variation of explanatory variables X as: $Y = f(X)$ where $f(X)$. This analysis is used for the prediction of job satisfaction among laboratories and the experts of the laboratories under study. Thereafter, 72 laboratories are used to find the best regression model and job satisfaction is estimated for the remaining 8 laboratories. The results of forecasting by linear, second order and logarithmic regressions are shown in Tables 8–10, respectively. The results of the ANN algorithm are compared with the above-mentioned methods with respect to mean absolute percentage error (MAPE) (Table 11). Obviously, the adaptive algorithm provides better solutions (lower relative error) than conventional regression approaches. These results also showed that better solutions are possible by considering RE as an input.

7. Conclusion

In this study, an intelligent algorithm was proposed to measure and rank job satisfaction scores with respect to RE factors in addition to HSE and ergonomic concepts in laboratories of a university. HSE and RE factors were considered as input variables while job satisfaction was considered as an output variable. This algorithm was chosen between ANN and ANFIS algorithms. To show its applicability and superiority, we applied it to laboratories. The efficiency score between 1 and 5 was devised to show job satisfaction with respect to the performance of HSE, ergonomic concepts, and RE factors. The laboratories were then ranked by the algorithm. Then, the normal probability plot for all laboratories was plotted to identify outlier laboratories. The existence of outlier laboratories suggests that they are not satisfied with existing programs. Management should provide necessary means to investigate assignable causes that might have brought about this inefficiency among several operators. The results of the intelligent algorithm were compared with conventional regression methods with respect to MAPE (Table 11). Moreover, it was shown that the adaptive algorithm provided better solutions than conventional regression approaches. It can be claimed that the results of RE are much better than conventional approaches.

Table 12 presents the features of the proposed algorithm of this study. It is capable of the integrative assessment of HSE and RE factors with respect to job satisfaction whereas RE characteristic has not yet been considered in job satisfaction assessment. It is also capable of handling non-linearity and complexity data. The algorithm pre-processes and post-processes the data to eliminate non-normalized behavior. It also provides high reliability and accuracy because it identifies the best ANN or ANFIS architecture with the lowest relative error.

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.

Appendix A. The accumulated data used in the intelligent algorithm

Operator code	Health	Safety	Environment	Ergonomics	RE	Job satisfaction	Operator code	Health	Safety	Environment	Ergonomics	RE	Job satisfaction
1	2.75	3.00	2.25	2.67	2.17	2.00	41	2.67	2.50	3.13	2.88	2.83	2.75
2	3.42	1.25	1.75	2.00	1.67	1.00	42	4.25	4.50	2.88	4.17	3.33	4.00
3	4.50	2.33	2.00	3.50	4.17	4.33	43	2.83	3.00	1.88	2.83	2.17	2.33
4	4.50	1.50	2.50	3.17	3.67	3.00	44	4.08	3.75	3.50	4.17	3.83	5.00
5	3.83	2.25	2.75	3.33	2.83	3.33	45	3.17	2.00	1.50	2.50	1.83	3.00
6	4.25	2.75	2.88	3.50	3.00	4.00	46	3.58	2.25	2.88	3.17	2.83	2.33
7	3.67	3.25	3.75	3.17	4.00	3.00	47	3.00	2.75	2.63	2.67	3.00	3.67
8	4.25	2.50	2.88	3.17	1.50	4.00	48	4.17	2.50	2.88	2.67	2.67	4.00
9	4.42	2.75	3.25	2.50	1.50	2.33	49	4.17	2.25	2.86	2.83	2.50	3.67
10	2.58	2.75	2.38	3.33	2.83	4.00	50	4.17	3.00	3.25	3.00	3.00	4.33
11	3.64	2.67	3.75	3.33	2.67	2.67	51	3.00	1.75	3.00	3.33	1.83	1.00
12	2.92	3.50	3.25	2.83	4.00	3.00	52	3.17	2.75	3.13	2.17	3.33	3.67
13	3.17	2.50	2.25	2.00	1.83	1.67	53	2.92	2.00	2.75	2.00	2.00	3.00
14	2.83	3.50	2.75	2.00	3.83	3.00	54	3.86	2.25	4.00	3.50	3.33	2.33
15	2.25	3.25	3.00	2.83	2.50	1.67	55	3.83	3.00	3.38	3.33	3.83	2.67
16	2.27	1.50	1.63	3.00	1.67	3.33	56	3.58	4.00	4.13	4.33	3.83	3.33
17	2.25	2.25	2.25	1.50	2.67	3.00	57	2.73	3.50	2.43	1.67	2.80	2.00
18	1.50	3.00	3.67	2.67	2.67	2.67	58	2.67	1.50	2.38	2.33	1.00	1.00
19	3.75	3.50	2.25	2.00	2.00	3.00	59	3.00	2.75	2.63	2.17	2.67	2.33
20	4.00	3.50	2.88	3.00	1.83	2.33	60	4.50	2.50	3.71	3.33	2.67	4.33
21	2.58	3.00	2.25	2.50	3.50	2.33	61	2.25	3.00	3.13	2.00	1.67	2.33
22	3.50	2.25	2.09	3.00	2.17	2.33	62	3.75	3.50	3.63	3.00	3.50	3.67
23	3.67	2.50	3.13	2.83	2.83	2.00	63	5.00	4.00	3.00	3.83	3.50	3.33
24	4.33	2.00	2.50	3.67	4.33	5.00	64	3.50	2.75	2.63	3.17	2.83	3.33
25	3.33	1.00	2.63	2.00	2.00	2.67	65	3.33	2.25	1.75	3.17	2.33	3.33
26	3.33	1.25	2.25	2.17	1.00	1.00	66	3.17	3.50	3.38	4.17	2.83	3.00
27	3.17	1.75	2.29	2.33	3.17	3.67	67	3.08	3.75	2.38	3.17	2.67	3.33
28	3.73	2.75	3.00	2.50	3.33	3.00	68	3.75	2.50	3.38	4.33	4.67	5.00
29	4.00	2.00	2.75	3.50	3.17	4.67	69	4.58	2.75	4.50	3.50	4.33	4.67
30	3.08	3.00	2.75	3.33	3.33	2.33	70	3.25	2.50	3.13	2.83	2.83	2.67

(*continued*)

Operator code	Health	Safety	Environment	Ergonomics	RE	Job satisfaction	Operator code	Health	Safety	Environment	Ergonomics	RE	Job satisfaction
31	2.92	2.50	2.63	2.83	2.83	3.00	71	3.08	3.00	3.13	3.00	2.67	3.00
32	3.67	4.75	4.50	3.83	3.67	3.33	72	2.92	3.00	2.88	3.00	3.00	2.33
33	3.91	2.75	2.63	2.83	2.50	2.67	73	3.00	3.25	3.00	2.83	2.83	3.00
34	3.17	3.75	3.63	2.33	3.00	2.67	74	5.00	3.50	3.00	4.33	4.33	5.00
35	3.75	3.25	5.00	3.00	2.67	2.67	75	3.75	3.25	3.00	3.67	3.00	2.67
36	2.33	2.50	3.38	2.00	3.33	2.00	76	4.33	2.25	3.00	4.00	3.17	1.67
37	2.50	3.25	2.88	3.00	2.67	2.67	77	3.58	3.25	3.13	2.50	3.00	3.00
38	2.67	3.50	2.75	2.83	2.67	3.67	78	3.17	3.25	2.88	2.67	2.83	2.33
39	4.17	4.25	2.75	3.00	4.33	3.50	79	2.83	3.25	3.00	3.00	3.00	2.67
40	3.17	3.50	1.88	4.17	2.67	3.00	80	2.33	1.50	2.88	1.83	1.00	2.33

References

Ayoub, M.A., 1990. Ergonomic deficiencies: I. Pain at work. J. Occup. Environ. Med. 32 (1), 52–57.

Azadeh, A., Fam, I.M., Khoshnoud, M., Nikafrouz, M., 2008a. 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. 178 (22), 4280–4300.

Azadeh, A., Fam, I.M., Nouri, J., Azadeh, M.A., 2008b. Integrated health, safety, environment and ergonomics management system (HSE-MS): an efficient substitution for conventional HSE-MS. J. Sci. Indus. Res. 67, 403–411.

Azadeh, A., Ghaderi, S., Anvari, M., Saberi, M., 2007a. Performance assessment of electric power generations using an adaptive neural network algorithm. Energy Policy 35 (6), 3155–3166.

Azadeh, A., Mohammad Fam, I., Sadjadi, M., Hamidi, Y., Kianfar, A., 2008c. An integrated and multivariate model along with designing experiments approach for assessment of micro-and macro-ergonomic factors: the case of a gas refinery. J. Res. Health Sci. 8 (2), 28–39.

Azadeh, A., Rouzbahman, M., Saberi, M., Fam, I.M., 2011. 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 Industries 24 (4), 361–370.

Azadeh, A., Saberi, M., Rouzbahman, M., Saberi, Z., 2013. An intelligent algorithm for performance evaluation of job stress and HSE factors in petrochemical plants with noise and uncertainty. J. Loss Prev. Process Indus. 26 (1), 140–152.

Azadeh, M., Keramati, A., Mohammadfam, I., Jamshidnedjad, B., 2006. Enhancing the availability and reliability of power plants through macroergonomics approach. J. Sci. Indus. Res. 65 (11), 873.

Baradaran, V., Ghadami, S., Malihi, S.E., 2008. A multi objective approach for selecting solutions to improve job satisfaction an empirical case analysis. In: Proceedings Industrial Engineering and Engineering Management. IEEE, pp. 1945–1948. IEEM 2008. IEEE International Conference on 2008.

Blanchard, B.S., Fabrycky, W.J., 1990. Systems Engineering and Analysis. Prentice Hall Englewood Cliffs, New Jersey.

Burri, G.J., Helander, M.G., 1991. A field study of productivity improvements in the manufacturing of circuit boards. Int. J. Industrial Ergonomics 7 (3), 207–215.

Byrd, T., Sankar, C., Loh, L., 1996. Strategies to Improve Job Satisfaction of US Technical Personnel.

Cabrero-Canosa, M., Castro-Pereiro, M., Graña-Ramos, M., Hernández-Pereira, E., Moret-Bonillo, V., Martin-Egana, M., Verea-Hernando, H., 2003. An intelligent system for the detection and interpretation of sleep apneas. Expert Syst. Appl. 24 (4), 335–349.

Caldwell, N.H., Breton, B.C., Holburn, D.M., 1998. Remote instrument diagnosis on the Internet. IEEE Intell. Syst. 13 (3), 70–76.

Calisir, F., Gumussoy, C., 2007. Determinants of job satisfaction in the it industry. In: Proceedings Industrial Engineering and Engineering Management. IEEE, pp. 1960–1964. IEEE International Conference on 2007.

Changchit, C., Holsapple, C.W., Madden, D.L., 2001. Supporting managers' internal control evaluations: an expert system and experimental results. Decis. Support Syst. 30 (4), 437–449.

Chen, J.-R., Yang, Y.-T., 2004. A predictive risk index for safety performance in process industries. J. Loss Prev. Process Industries 17 (3), 233–242.

Costa, Á., Markellos, R.N., 1997. Evaluating public transport efficiency with neural network models: transportation research Part C. Emerg. Technol. 5 (5), 301–312.

Cronbach, L.J., 1951. Coefficient alpha and the internal structure of tests. Psychometrika 16 (3), 297–334.

Delgado, F.J., 2005. Measuring efficiency with neural networks, an application to the public sector. Econ. Bull. 3 (15), 1–10.

Deng, H., 1999. Multicriteria analysis with fuzzy pairwise comparison. Int. J. Approx. Reason. 21 (3), 215–231.

Dinh, L.T., Pasman, H., Gao, X., Mannan, M.S., 2012. Resilience engineering of industrial processes: principles and contributing factors. J. Loss Prev. Process Industries 25 (2), 233–241.

Edosomwan, J., 1986. The role of ergonomics in improving productivity and job satisfaction in computer-aided assembly tasks. In: Proceedings International Industrial Engineering Conference, pp. 378–381.

Fisher, C.D., Locke, E.A., Henne, D., 1992. The New Look in Job Satisfaction Theory and Research.

Fonseca, D., Navaresse, D., Moynihan, G., 2003. Simulation metamodeling through artificial neural networks. Eng. Appl. Artif. Intell. 16 (3), 177–183.

Gibson, J.H., Schröder, I., Wayne, N.L., 2014. A research university's rapid response to a fatal chemistry accident: safety changes and outcomes. J. Chem. Health Saf. 21 (4), 18–26.

Hale, A., Heijer, T., 2006. Is Resilience Really Necessary? the Case of Railways: Resilience Engineering: Concepts and Precepts, pp. 125–148.

Hollnagel, E., 2006. Resilience: the Challenge of the Unstable.

Hollnagel, E., Woods, D.D., 2005. Joint Cognitive Systems: Foundations of Cognitive Systems Engineering. CRC Press.

Hornik, K., Stinchcombe, M., White, H., 1989. Multilayer feedforward networks are universal approximators. Neural Netw. 2 (5), 359–366.

Huber, S., van Wijgerden, I., de Witt, A., Dekker, S.W., 2009. Learning from organizational incidents: resilience engineering for high-risk process environments. Process Saf. Prog. 28 (1), 90–95.

Mohammad Fam, I., Azadeh, A., Azam Azadeh, M., 2007. Modeling an integrated health, safety and ergonomics management system: application to power plants. J. Res. Health Sci. 7 (2), 1–10.

Mohammad Fam, I., Azadeh, A., Faridan, M., Mahjub, H., 2008. Safety behaviors assessment in process industry: a case study in gas refinery. J. Chin. Inst. Indus. Eng. 25 (4), 298–305.

Rasmani, K.A., Shahari, N.A., 2007. Job satisfaction evaluation using fuzzy approach. In: Proceedings Natural Computation, vol. 4. IEEE, pp. 544–548. ICNC 2007. Third International Conference on2007.

Raykov, T., 1997. Scale reliability, Cronbach's coefficient alpha, and violations of essential tau-equivalence with fixed congeneric components. Multivar. Behav. Res. 32 (4), 329–353.

Rumelhart, D.E., McClelland, J.L., Group, P.R., 1986. Parallel Distributed Processing: Explorations in the Microstructures of Cognition, vol. 1. Foundations: MIT Press, Cambridge, MA, pp. 560–567 v. 2.

Saksvik, P.Ø., Nytrø, K., 1996. Implementation of internal control (IC) of health, environment and safety (HES) in Norwegian enterprises. Saf. Sci. 23 (1), 53–61.

Santos, J.R.A., 1999. Cronbach's alpha: a tool for assessing the reliability of scales. J. Ext. 37 (2), 1–5.

Saurin, T.A., Formoso, C.T., Cambraia, F.B., 2008. An analysis of construction safety best practices from a cognitive systems engineering perspective. Saf. Sci. 46 (8), 1169–1183.

Saurin, T.A., Júnior, G.C.C., 2011. Evaluation and improvement of a method for assessing HSMS from the resilience engineering perspective: a case study of an electricity distributor. Saf. Sci. 49 (2), 355–368.

Shikdar, A., Das, B., 2003. A strategy for improving worker satisfaction and job attitudes in a repetitive industrial task: application of production standards and performance feedback. Ergonomics 46 (5), 466–481.

Shikdar, A.A., Sawaqed, N.M., 2004. Ergonomics, and occupational health and safety in the oil industry: a managers' response. Comput. Indus. Eng. 47 (2), 223–232.

Shoorehdeli, M.A., Teshnehlab, M., Sedigh, A.K., Khanesar, M.A., 2009. Identification using ANFIS with intelligent hybrid stable learning algorithm approaches and stability analysis of training methods. Appl. Soft Comput. 9 (2), 833–850.

Spector, P.E., 1997. Job Satisfaction: Application, Assessment, Causes, and Consequences. Sage Publications.

Torp, S., Moen, B., 2006. The effects of occupational health and safety management on work environment and health: a prospective study. Appl. Ergon. 37 (6), 775–783.

Werbos, P., 1974. Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences.

Wreathall, J., 2006. Ashgate, Burlington, VT. www.tinyurl.com/safetyprojectlist (accessed 21.04.14.).