Performance Optimization of Integrated Resilience Engineering and Lean Production Principles

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Abstract

This paper conducts performance assessment from integrated resilience engineering (IRE) and lean production points of view. This is the first study that evaluates the impact of integrated resilience engineering (IRE) on lean production principles. Second, this study considers integrated impact of lean production by a unique intelligent algorithm. The proposed algorithm is composed of radial basis function (RBF), multi-layer perceptron (MLP) and adaptive neuro-fuzzy inference system (ANFIS). Moreover, the algorithm is capable of handling both crisp and fuzzy data due to the existence of intelligent approach. The proposed algorithm is equipped with verification and validation mechanism through conventional regression, statistical methods and data envelopment analysis. To demonstrate the applicability of the study, a real-world pipe manufacturer is considered as our case study. The results showed that “pull system” and “fault tolerant” among lean and IRE factors,

respectively have been implemented inappropriately, while other factors are either suitably executed or ineffective.

Keywords: Integrated resilience engineering (IRE); Lean production; Artificial neural networks (ANNs); Adaptive neuro-fuzzy inference system (ANFIS); Data envelopment analysis (DEA)

1. Introduction

Resilience engineering (RE) and lean production are two critical concepts that have rarely been discussed concurrently, particularly in the production context. This is surprising given that they have a similar motivation for improvement of processes and service delivery. There has certainly been a growing interest in both RE and lean production in recent years due to the focus on the efficiency of production systems. In this paper, we investigate how they could work together in order to achieve mutual benefits.

1.1. Definition and key assumptions of lean

Lean manufacturing/ production derived mostly from the Toyota Production System (TPS). It has been defined in many ways according to the suitability of the research context. However, it is still based on the original goal of TPS which is “to do more with less”. In the definition of lean, three concepts of Muda, Muri and Mura have been introduced. Muda is waste on the scope of lean or non-value adding activities. Muri refers to a poor work condition and Mura represents unevenness in demand.

The philosophy of this theory is to remove non-value adding steps (wastes). The initial manufacturing wastes were defined by Ōno (1988) as follows:

- **Transport:** Moving products that are not actually required to perform the processing;
- **Inventory:** All components, works-in-process, and finished products not being processed;
- **Motion:** People or equipment moving or walking more than is required to perform the processing;
- **Waiting:** Waiting for the next production step, interruptions of production during shift change;
- **Overproduction:** Production ahead of demand;
- **Over Processing:** Resulting from poor tool or product design creating activity;
- **Defects:** Effort involved in inspecting for and fixing defects.

It is possible to define lean through five ‘lean principles’ as follows (Womack & Jones, 2010):

- **Customer orientation:** Determining what customer exactly expects and wants;
- **Reduce waste:** Investigating each product value stream and then determining all non-value added steps;
- **Standard product:** Standardizing all the processes after designing the most efficient product flow;
- **Pull system:** This principle is used when continuous flow is impossible in a product flow. It is employed by considering product demand and by enabling backwards in product value chain;
- **Task management:** This factor seeks to remove non-value adding steps and use resources such as time and information efficiently.

Lean concept is well accepted for improving efficiency and eliminating wastes in production systems (Flidner, 2008). Over the last decade there has been a quick and sudden increase in the use of lean (Brandao de Souza, 2009). It is important to know that lean principles are not designed just for waste reduction. Besides reducing wastes, and consequently costs, lean seeks to improve the efficiency of production system by increasing value-adding activities in product flow (Govindan, Azevedo, Carvalho, & Cruz-Machado, 2015; Hines, Holweg, & Rich, 2004). Ng, Vail, Thomas, and Schmidt (2010) used lean principles in order to improve the quality of care in an emergency department without any additional resources. Hicks, McGovern, Prior, and Smith (2015) applied lean principles to the design of healthcare facilities and demonstrated the applicability and efficiency of the lean principles. Lunardini et al. (2014) optimized instruments’ utilization in a spine surgery medical center by employing lean principles. Aqlan and Ali (2014) integrated lean principles, failure mode and effects analysis (FMEA), and fuzzy analysis for improving risk assessment process in a chemical plant. FMEA is one of the first highly structured, systematic techniques for failure analysis. Min (2014) investigated the impact of lean implementation on performance of healthcare systems. Susilawati, Tan, Bell, and Sarwar (2015) performed lean assessment in manufacturing systems in Indonesia. They identified 66 effective parameters in lean assessment, and used standard questionnaire and fuzzy based method for measuring the leanness of manufactories. Sharma, Dixit, and Qadri (2015) investigated the impact of lean production on performance of machine tool companies by determining lean criteria and using

factor analysis and multiple regression analysis. At the end, they determined criteria with significant positive and negative impact on companies' performance.

Although lean principles have served as an improvement tool for manufacturing and service systems, many researchers have shown that companies' tendencies to find low-cost solutions may have led them to leaner but more vulnerable environment (Azevedo et al., 2008; Peck, 2005). Besides, turbulence and volatility are main characters of today's market and manufacturing systems. Therefore, manufacturing systems need to be resilient in order to survive (Carvalho et al., 2011). Therefore, considering resilience engineering (RE) along with lean production principles is required for high volume and low cost productions.

1.2. Resilience Engineering

Resilience engineering (RE) is a new concept which seeks safety and performance improvement in organizations (Wreathall, 2006). It helps organizations to make their system much more reliable and sustainable in case of any disturbance. According to Nemeth et al. (2008), a resilient organization can predict, deal with, recover and learn from unanticipated threats. Therefore, the advantages of RE is twofold: (1) it precludes failures, losses and damages, and (2) it is capable of reacting efficiently soon after these phenomena took place (Nemeth, Wears, Woods, Hollnagel, & Cook, 2008).

Resilient organizations function proactively. It means that they don't only have high levels of immunity but also are able to react to any changes which deflect system's performance from the planned one (Haimes, 2009)(Hollnagel, Braithwaite, & Wears, 2013). The classical factors of RE are as follows: (Hollnagel, Woods, & Leveson, 2007; Woods & Hollnagel, 2006; Wreathall, 2006).

- ***Top management commitment:*** This principle indicates management's willingness to invest, assign resources and a devotion to improve RE above or to the same degree as the organization's other goals.
- ***Reporting culture:*** Without a just culture of reporting, the willingness of the staff to report problems and subjects will be much decreased. Hence, the ability of the association is limited to learn about weaknesses in its late defenses.
- ***Learning:*** System should be able to learn from past events in order to respond effectively. It is a culture which should be implemented in system's structure.
- ***Awareness:*** Management should allow the personnel to participate in system's information regarding failures, so they can be aware of what happened, why happened

and what the consequences are. Keeping this kind of information in a black box and prevent systems' components to determine new vulnerabilities.

- **Preparedness:** The association or system actively predicts the problems of human activity in human-machine systems and prepares to deal with them.
- **Flexibility:** Systems' components should be allowed to deal with failures using their natural instincts, abilities and experiences. This confidence help the personnel to improve their abilities in case of any new failure and disturbance happened, so they can deal with it better. Without flexibility, it is not possible to prepare the system to deal with any new disturbance or failure (Clegg, 2000).

Azadeh, Salehi, Ashjari, and Saberi (2014) incorporated four additional principles into classic RE and called it integrated RE (IRE) as follows:

- **Self-organization:** In self-organization systems, arrangements come from the performances of interdependent agents who change data, take actions, and non-stop adjust to react about others' activities more than from the imposition of an overall plan by a main authority (Plowman et al., 2007).
- **Teamwork:** It is one of the most important facilitators in obtaining positive, cost-effective results in different organizational and adaptability and productivity. When the workload of system is high, this feature can mitigate the pressure on individuals and organizations(Rasmussen, Pejtersen, & Goodstein, 1994).
- **Redundancy:** Based on this factor, there should be a replacement plan for each critical resource such as staff or equipment in case of failure, breakdown or absence (Frangopol & Curley, 1987).
- **Fault-tolerant:** This factor is one of the most promising ways of increasing system immunity and reliability. It helps the system to preserve the specified function in the presence of mistakes (Ling-Ling & Yong-Duan, 2010).

In the past decade, several studies have focused on concept and applicability of RE in different industries. Shirali, Motamedzade, Mohammadfam, Ebrahimipour, and Moghimbeigi (2015) assessed RE factors in a process industry. They employed some other concepts such as risk management to determine poor indicators for process improvement. Hegde et al. (2014)analyzed RE in a healthcaresystem by employing the critical incident interviewing method. Ross et al. (2014) presented a study on a healthcare system by considering resilience and quality of care, they demonstrated that possible failures can cause delay in patient treatment. Jeffcott, Ibrahim, and Cameron (2009) studied RE concept in health care systems

and proved its effectiveness in safety improvement. Dinh, Pasman, Gao, and Mannan (2012) identified six effective principles in employing RE and resilience of a process by studying related literature and experts' judgment. Hansson, Herrera, Kongsvik, and Solberg (2009) demonstrated the application of RE for occupational hazards and injuries reduction, and safety improvement. Azadeh, Salehi, Ashjari, et al. (2014) assessed performance of IRE factors in a petrochemical plant using standard questionnaire and data envelopment analysis approach. Azadeh, Salehi, Arvan, and Dolatkhah (2014) evaluated the performance of RE factors in a petrochemical plant. They evaluated the performance of RE factors in safety improvement in high risk environments.

This paper aims to conduct performance assessment from IRE and lean points of view by an intelligent algorithm based on artificial neural networks (ANNs). To the best of our knowledge, this is the first study that conducts a comprehensive performance assessment from the viewpoints of RE and lean production in a real-world case.

The plan for the remainder of the paper is as follows. Section 2 presents a description of the algorithm used. Implementation of the algorithm on a real-world case study is explained in Section 3. Section 4 provides the results obtained together with some fruitful analyses on them. Lastly, Section 5 is dedicated to concluding remarks and directions for future research.

2. The proposed algorithm

Performance assessment of production and service-oriented systems has been a very important issue in past decades. Many efficiency frontier analysis approaches have been presented, however, the restrictive assumptions have been made. Most of the presented approaches have considered deterministic frontier, which is sensitive to outliers. Azadeh et al. (2007) presented a non-parametric efficiency frontier analysis approach based on neural networks. The presented algorithm is been used as a base approach for performance assessment of various industrial systems. Estimating efficiency scores using neural networks empower the approach to deal with stochastic frontier, which makes the results more reliable. The previous algorithm by Azadeh et al. (2007) has been modified with new features in order to provide better performance evaluations. In this paper, an adaptive intelligent algorithm proposed by Azadeh, Ghaderi, Anvari, and Saberi (2007) is employed to assess performance from RE and lean points of view. The algorithm is based on ANNs and statistical methods. In this study, three well-known ANN models namely multilayer perceptron (MLP), radial basis function (RBF), and adaptive neuro-fuzzy inference system (ANFIS) are considered. Data envelopment analysis is also employed for verification and validation of obtained results,

while perturbation tests are used for determining the optimal DEA model. The main contribution of this study is the presented conceptual model which considers combined resilience engineering factors and lean principles to improve both performance and sustainability. Also, a real world case study is evaluated and the effectiveness of the proposed algorithm is shown. The proposed package for evaluating both RE and lean philosophy is applicable and easy to use and can help managers to improve the resiliency and performance similar manufacturing systems. The flowchart of the presented algorithm in this study for evaluating integrated resilience engineering (IRE) and lean production principles is demonstrated in Figure 1.

Figure 1.The flowchart of the proposed algorithm in this study

3.1. Implementation of the algorithm

The steps of the presented intelligent algorithm along with the nomenclature used in this paper are as follows:

Indices

i The index of considered input variables ($i = 1, 2, \dots, m$)

r The index of considered output variables ($r = 1, 2, \dots, s$)

j	The index of operators ($j = 1, 2, \dots, n$)
v	The index of the DMU with the maximum frontier function shift value
Parameters	
x_{ij}	The observed value for input variable i and operator j
y_{rj}	The observed value for output variable r and operator j
Variables	
Z_{rj}	The normalized value of output variable r for operator j
Z_{ij}	The normalized value of input variable i for operator j
T_{rj}	The estimated value for output variable r and DMU j using optimum ANN model
E_{rj}	The error between the observed output value and estimated output value using ANN for each output variable r and operator j
E'_{rj}	The frontier function shift for output r and operator j
E_v	The maximum value for frontier function shift among all DMUs
T_{rv}	The estimated value for DMU v (the DMU with the maximum value of frontier function shift)
Sh_{rj}	The shift value for output variable r and operator j
F_{rj}	The efficiency score of output variable r and operator j
λ_j	The degree of benchmarking for j th DMU
θ	The obtained efficiency score using DEA

Step 1. Data Collection: For collecting the required data, standard questionnaires are designed and distributed among operators of the system being studied. In order to employ an integrated evaluation and optimization scheme, a conceptual model based on IRE factors and lean production principles is presented. In the presented model, IRE factors are considered as inputs of the model and lean production principles are considered as outputs. The conceptual model of the presented study is explained as follows:

In efficiency frontier analysis, efficiency score is obtained by maximizing outputs while minimizing inputs. Although the concept of considered factors indicates that both IRE and lean factors should be considered as output variables, it appears (mathematically) that IRE factors as inputs provide better efficiency scores. Therefore, Equations 1 and 2 are presented to arrange inputs (IRE) and outputs (lean production) correctly. Since, input variables should be smaller the better (STB) type while outputs should be larger the better (LTB) type. The

following equations are presented to range the values between 0 to 1 (normalization), and fix their types simultaneously (Bashiri, Farshbaf-Geranmayeh, & Mogouie, 2013). Equation (2) is applicable for lean production principles, while Equation (1) changes the type of the data along with its scale. Therefore, IRE factors are changed into STB type using Equation (1).

$$Z_{ij} = \frac{Max(x_{ij}) - x_{rj}}{Max(x_{rj}) - Min(x_{rj})} \quad j = 1, 2, \dots, n; \quad i = 1, 2, \dots, m \quad (1)$$

$$Z_{rj} = \frac{y_{rj} - Min(y_{rj})}{Max(y_{rj}) - Min(y_{rj})} \quad j = 1, 2, \dots, n; \quad r = 1, 2, \dots, s \quad (2)$$

Where Z_{rj} is the normalized value of the output variable r for operator (DMU) j , while Z_{ij} is the normalized value of the input variable i for operator (DMU) j . The observed value for output variable i and operator j is indicated by x_{ij} , while y_{rj} represents the observed value for output variable r and operator j .

Step 2. Reliability and validity: Determine the reliability and validity of the questionnaire by Cronbach's Alpha and factor analysis, respectively.

Step 3. Data preparation: In this study IRE factors are considered as inputs and lean principles are outputs of the model. Since ANN is used in this study, after gathering required data regarding inputs and outputs of the model, we have to determine a set of data for training and testing of ANN. In this study 30% (15% each) of gathered data is considered for test and validation of the model.

Step 4. Determining the best ANN structure for function estimation: In order to find the best structure for estimating outputs of the model and calculating efficiencies, three different artificial neural networks are used. The considered ANN models are compared to each other based on their related mean absolute error (MAE). Different structures have been considered for each model. At the end, the best estimation function is determined. It should be mentioned that the number of training data is changed from 70 to 90 percent of the data set to prevent overtraining (overfitting). Also, each architecture is run 100 times with random data sets to handle possible noise and prevent overfitting. Thus, the obtained MAE value for each model would be the average of MAEs for all the runs with 10 to 30 percent of the data as test data for 100 times.

Step 5. Evaluating the superiority of the optimum model: In order to evaluate the performance of the optimum model and validate its superiority, it is compared to other forecasting tools such as different conventional regression models in terms of MAE.

Step 6. Efficiency estimation: Use the determined best ANN structure to model relation between inputs (IRE) and outputs (lean principles). In order to calculate efficiency scores, we have used the presented steps by Azadeh, Rouzbahman, Saberi, Valianpour, and Keramati (2013):

- Calculate the error between the observed output value Z_{rj} and optimum model output T_{rj} for each output variable r and operator j using Equation (3).

$$E_{rj} = Z_{rj} - T_{rj} \quad j = 1, 2, \dots, n; r = 1, 2, \dots, 5 \quad (3)$$

- Calculate frontier function shift (E'_{rj}) for obtaining the effect of the largest positive error using Equation (4).

$$E'_{rj} = \frac{E_{rj}}{T_{rj}} \quad j = 1, 2, \dots, n; r = 1, 2, \dots, 5 \quad (4)$$

- Calculate the maximum value for frontier function shift (E'_v) among operators (DMUs):

$$E_v = \text{Max}(E'_{rj}) \quad j = 1, 2, \dots, n; r = 1, 2, \dots, 5 \quad (5)$$

- Calculate shift (Sh_{rj}) for each operator j and output r as follows:

$$Sh_{rj} = \frac{E_v * T_{rj}}{T_{rv}} \quad j = 1, 2, \dots, n; r = 1, 2, \dots, 5 \quad (6)$$

Where T_{rj} represents the optimum model value for output r and DMU j . Also, the optimum model value for output r and DMU v (which is the DMU with the maximum frontier function shift value) is represented by T_{rv} .

- Calculate the efficiency score (F_{rj}) for output r operator j using Equation (7).

$$F_{rj} = \frac{Z_{rj}}{T_{rj} + Sh_{rj}} \quad j = 1, 2, \dots, n; r = 1, 2, \dots, 5 \quad (7)$$

Step 7. Sensitivity analysis: Once the efficiency scores are calculated for the conceptual model, it is possible to evaluate each factor's importance and effect by omitting it from the conceptual model and recalculating the efficiency scores. In other words, input and output variables are left out of the calculations one by one, and the efficiency scores are measured anew. The results obtained before factor elimination are compared to those yielded after elimination to find out how the factor has affected the efficiency scores. This comparison is done by using paired t-test between efficiency scores obtained before elimination of each factor and efficiency scores of after elimination.

Step 8. Validation of obtained results: Here, the efficiency scores of the DMUs are calculated by data envelopment analysis (DEA) method, and the results obtained by the intelligent algorithm are compared to those yielded by DEA. The results attained by the algorithm are validated in case they are consistent with those of DEA. To this end, first the optimum DEA model should be selected. To do so, first, different DEA models are run and compared with each other to see if model selection influences the results. In this study, CCR input-oriented, CCR output-oriented, BCC input-oriented, and BCC output-oriented model are run. Spearman's rank-order correlation is calculated between each pair of the models. Rejection of the null hypothesis for correlation with a large coefficient shows that the results obtained by different models are similar and thus model selection does not affect the results. However, to choose a single model, a noise is inserted to the data, and the model with the lowest sensitivity to this noise is selected as the optimum model. This is also examined by Spearman's correlation test between the results related to each model before and after noise insertion. The model with the highest coefficient is selected as the preferred DEA model. Mathematical programming model of considered DEA models including BCC-Input oriented, BCC-Output oriented, CCR-Output oriented and CCR-Input oriented are presented as follows:

- CCR (Charnes, Cooper and Rhodes, 1978) DEA model

Presented mathematical model evaluates the relative efficiencies of n DMUs ($j = 1, 2, \dots, n$) by minimizing the input variables while the outputs are considered constant. Each DMU contains m input variables ($x_{1j}, x_{2j}, \dots, x_{mj}$) and s output variables ($y_{1j}, y_{2j}, \dots, y_{sj}$). The input-oriented CCR model is presented in Equation 8.

$$\begin{aligned}
 & \text{Min } \theta \\
 & \text{s. t. } \theta x_{i0} \geq \sum_{j=1}^n \lambda_j x_{ij}, \quad i = 1, \dots, m \\
 & \quad y_{r0} \leq \sum_{j=1}^n \lambda_j y_{rj}, \quad r = 1, \dots, s \\
 & \quad \lambda_j \geq 0, j = 1, \dots, n
 \end{aligned} \tag{8}$$

- The output-oriented model is obtained by maximizing output variables while input variables are considered constant. The output-oriented CCR model is presented in Equation 9.

Max θ

$$s.t. \quad x_{i0} \geq \sum_{j=1}^n \lambda_j x_{ij}, \quad i = 1, \dots, m$$

$$\theta y_{r0} \leq \sum_{j=1}^n \lambda_j y_{rj}, \quad r = 1, \dots, s$$

$$\lambda_j \geq 0 \quad j = 1, \dots, n$$

9

- BCC (Banker et al. 1984) DEA model

BCC model is similar to CCR model while one more constraint is added, which ensures that the summation of λ_j is equal to 1. Output-oriented BCC model is presented in Equation 10.

Max θ

$$s.t. \quad x_{i0} \geq \sum_{j=1}^n \lambda_j x_{ij}, \quad i = 1, \dots, m$$

$$\theta y_{r0} \leq \sum_{j=1}^n \lambda_j y_{rj}, \quad r = 1, \dots, s$$

$$\sum_{j=1}^n \lambda_j = 1$$

$$\lambda_j \geq 0, \quad j = 1, \dots, n$$

10

- Input-oriented BCC model is presented in Equation 11.

Min θ

$$s.t. \quad \theta x_{i0} \geq \sum_{j=1}^n \lambda_j x_{ij}, \quad i = 1, \dots, m$$

$$y_{r0} \leq \sum_{j=1}^n \lambda_j y_{rj}, \quad r = 1, \dots, s$$

$$\sum_{j=1}^n \lambda_j = 1$$

$$\lambda_j \geq 0, \quad j = 1, \dots, n$$

11

After determination of the optimum DEA model, the model is run based on the conceptual model, and the efficiency scores are calculated. The high consistency between efficiency scores yielded by optimum DEA model and those yielded by proposed algorithm, validates the algorithm results.

4. Case study

In this section, we apply the algorithm to a pipe manufacturer in Iran as our real-world case study with the aim of investigating its performance from the viewpoints of IRE and lean.

4.1. Data collection

Step 1. IRE factors are considered as inputs and lean factors as outputs of the conceptual model. Required data collected by questionnaires which are designed and divided among staff of pipe factory, 75 operators answered the questionnaire. The respondents could select a number from among 1 to 10 for answering the questionnaire. The questionnaire designed and used in this study is presented in Table I in Appendix I.

4.2. Reliability and validity of the questionnaire

Step 2. The reliability of gathered data from questionnaire was analyzed by calculating Cronbach's alpha using SPSS software, related results are presented in Table 1. First, standard questionnaires which contained queries about the factors of both IRE and lean were distributed among personnel.

Table 1. Reliability of the collected data

	Factors	Cronbach's Alpha
Resilience Engineering Factors	"Reporting culture"	0.842
	"Learning"	0.742
	"Awareness"	0.647
	"Top management commitment"	0.842
	"Flexibility"	0.727
	"Self-organization"	0.694
	"Preparedness"	0.801
	"Teamwork"	0.783
	"Redundancy"	0.728
Lean Factors	"Fault-tolerant"	0.786
	"Customer orientation"	0.942
	"Reduce waste"	0.762
	"Standard product"	0.862
	"Pull system"	0.941
	"Task management"	0.883

4.3. Efficiency score estimation using ANN

Step 3 and 4. In this paper we have used three different ANN models for function estimation. In order to find the best prediction structure of ANN models, different structures of estimation networks including ANN-MLP, RBF and ANFIS models are considered, and their related MAE is calculated. Since there might be a noise in ANN results, each model has been run 20 times and the average of gathered MAE is considered for models' comparison. The architecture of the ANN-RBF, ANN-MLP and ANFIS models and their related MAE values are presented in Tables 2, 3 and 4 respectively.

Table 2. Different structures of RBF considered for comparison, and their related MAE

Model No.	Spread	Maximum Number of Neurons	Customer Orientation	Reduce Waste	Standard Product	Pull System	Task Management
1	2	25	0.130	0.118	0.142	0.186	0.102
2	4	25	0.111	0.134	0.148	0.144	0.138
3	0.5	30	0.186	0.184	0.204	0.228	0.182
4	2	15	0.193	0.157	0.166	0.155	0.153
5	4	12	0.119	0.194	0.152	0.164	0.133
6	3	20	0.084	0.157	0.129	0.131	0.127
7	5	10	0.227	0.194	0.177	0.188	0.163
8	5	20	0.112	0.167	0.164	0.170	0.148
9	4	20	0.148	0.133	0.140	0.140	0.117
10	3	15	0.126	0.172	0.138	0.159	0.123

Table 3. Different structures of ANN-MLP considered for comparison, and related MAE

N	Tr. F	TF of HL	TO of OL	Number of neurons in HL	MAE				
					Customer Orientation	Reduce Waste	Standard Product	Pull System	Task Management
1	LM	Logsig	Pureline	5	0.2493	0.2028	0.2074	0.2614	0.2153
2	OSS	Logsig	Pureline	12	0.2184	0.2114	0.2284	0.2556	0.2405
3	GD	Logsig	Pureline	15	0.2008	0.1925	0.2243	0.2694	0.1922
4	BFG	Logsig	Pureline	8	0.1966	0.1875	0.1861	0.2484	0.1942
5	LM	Logsig	Pureline	30	0.2189	0.1677	0.2050	0.2433	0.1566
6	GDX	Logsig	Pureline	35	0.2107	0.1994	0.1993	0.2620	0.2242
7	GDA	Logsig	Pureline	45	0.2213	0.2195	0.2097	0.2598	0.2070
8	OSS	Logsig	Pureline	10	0.1692	0.2114	0.2114	0.2584	0.2021
9	GD	tansig	Pureline	35	0.1738	0.1922	0.2198	0.2892	0.1984
10	OSS	tansig	Pureline	5	0.2235	0.1972	0.2052	0.2679	0.1866
11	BFG	tansig	Pureline	7	0.2196	0.1931	0.1974	0.2393	0.2188
12	LM	tansig	Pureline	10	0.1858	0.2057	0.2104	0.2453	0.2216
13	GDM	tansig	Pureline	9	0.2184	0.1846	0.2174	0.2568	0.2183
14	OSS	tansig	Pureline	38	0.2334	0.1805	0.2248	0.2686	0.2182

Note. Tr. F: Training function; TF: Transfer function; HL: hidden layer; OL: Output layer; LM: Levenberg-Marquardt back propagation; BFG: quasi-Newton back propagation; GD: Gradient descent back propagation; GDA: Gradient descent with adaptive learning rule back propagation; OSS: One step secant back propagation; GDX: Gradient descent with momentum and adaptive learning rule back propagation

Table 4. Different structures of ANFIS considered for comparison and related MAE

N	Initial FIS	Radius	N of MF	N of Clusters	Optimization method	And	Or	Implication method	Aggregation method	Customer Orientation	Reduce Waste	Standard Product	Pull System	Task Management
1	FC	-	-	3	H	prod	max	min	max	0.100	0.127	0.142	0.153	0.113
2	FC	-	-	6	BP	min	probor	prod	sum	0.116	0.113	0.157	0.186	0.097
3	FC	-	-	7	H	prod	probor	prod	max	0.139	0.109	0.138	0.201	0.103
4	FC	-	-	5	BP	min	max	prod	sum	0.162	0.080	0.162	0.190	0.121
5	GP	-	3	-	BP	min	probor	min	sum	0.113	0.132	0.137	0.163	0.100

6	GP	-	2	-	H	prod	probor	prod	max	0.148	0.141	0.152	0.188	0.131
7	GP	-	2	-	BP	min	max	min	sum	0.114	0.125	0.169	0.164	0.114
8	GP	-	3	-	H	prod	probor	min	max	0.124	0.108	0.182	0.188	0.102
9	SC	0.6	-	-	H	prod	max	prod	sum	0.153	0.110	0.153	0.169	0.120
10	SC	0.5	-	-	BP	min	max	prod	max	0.147	0.124	0.148	0.155	0.099
11	SC	0.3	-	-	H	min	probor	min	sum	0.121	0.142	0.143	0.166	0.121
12	SC	0.4	-	-	BP	prod	probor	prod	max	0.137	0.100	0.151	0.180	0.116

Note: Input membership function for all structures: Gaussmf; Output member ship function for all structures: Linear; FIS: Fuzzy inference system; H: Hybrid; BP: Back-Propagation; N: Number; MF: Membership function; FC: Fuzzy c-means (FCM) clustering; GP: Grid partition; SC: Subtractive clustering

Step 5. Once the best model has been determined for each output, in order to examine their estimation efficiency, they are compared to three regression models, namely linear, quadratic and exponential regressions. The results are given in Table 5. Moreover, it is shown that the intelligent methods of the algorithm such as ANN-MLP, ANN-RBF and ANFIS provide better solution than conventional regression methods. This may be considered as structural validation of the proposed algorithm.

Table 5. Comparison of the best intelligent model to conventional regression methods

Model	Mean absolute error (MAE)				
	Customer Orientation	Reduce Waste	Standard Product	Pull System	Task Management
Linear regression	0.119	0.102	0.142	0.141	0.112
Quadratic regression	0.112	0.108	0.138	0.136	0.116
Exponential regression	0.119	0.111	0.151	0.139	0.109
Optimum model	0.100	0.080	0.129	0.131	0.097
Corresponding intelligent model	ANFIS	ANFIS	ANN-RBF	ANN-RBF	ANFIS
Corresponding structure	Number 1	Number 4	Number 6	Number 6	Number 2

Step 6. Table 5 shows that the optimum models enjoy the minimum MAE values and thus remain optimum. These models are then employed for measuring efficiency scores of DMUs according to the algorithm steps. The results are presented in Appendix III.

4.4. Sensitivity analysis

Step 7. In this step, the way each factor of IRE and lean affect the performance is analyzed through statistical techniques. For this purpose, as mentioned in the methodology section, each factor is eliminated from the calculations, and the efficiency scores are measured anew. After obtaining the efficiency scores related to elimination of each factor, it is possible to compare mean of efficiencies before factor's elimination with related efficiency scores to elimination of each factor. Since the decision making units (DMUs) are similar in both experiments, paired t-test is employed. Paired t-test is then used to compare the results related to the original situation to those obtained after eliminating each factor. In this test, null hypothesis is $\mu_1 = \mu_2$ and alternative is $\mu_1 > \mu_2$ or $\mu_1 < \mu_2$ which indicates that after elimination of each factor, the efficiency scores are significantly changed or not. The related results for sensitivity analysis are presented in Table 6.

Table 6. Analysis of the factors' effects

	Factors	Two-tailed paired t-test p- value	One-tailed paired t-test result	Effect
Lean Production Principles	No Customer Orientation	0.076	-	Ineffective
	No Reduce Waste	0.300	-	Ineffective
	No Standard Product	0.082	-	Ineffective
	No Pull System	0.000	$\mu_i > \mu_F$	Negative
	No Task Management	0.000	$\mu_i < \mu_F$	Positive
	No Reporting culture	0.000	$\mu_i < \mu_F$	Positive
	No Learning	0.000	$\mu_i < \mu_F$	Positive
Integrated Resilience Engineering Factors	No Awareness	0.000	$\mu_i < \mu_F$	Positive
	No Top management commitment	0.000	$\mu_i < \mu_F$	Positive
	No Flexibility	0.067	-	Ineffective
	No Self-organization	0.083	-	Ineffective
	No Preparedness	0.000	$\mu_i < \mu_F$	Positive
	No Teamwork	0.000	$\mu_i < \mu_F$	Positive
	No Redundancy	0.220	-	Ineffective
	No Fault-tolerant	0.000	$\mu_i > \mu_F$	Negative

The obtained results in Table 6 determine the current state of each factor in the considered system. Thus, system weaknesses and strengths from the integrated IRE and Lean production are identified and addressed. The hypothesis of equal means has been accepted for certain factors including “customer orientation”, “reduce waste”, “flexibility”, “Standard Product”, “Self-Organization” and “Redundancy”. Therefore, the stated factors are implemented effectively in the system. However, they should not be considered as strength or weakness of the system under study (ineffective). The null hypothesis is rejected for the rest of considered factors. This shows eliminating these factors make significant changes on efficiency scores. Mean efficiencies are compared before and after factor elimination to find out if the impact of the interested factor is positive or negative? It shows the negative impact of the factor if mean efficiency has been increased such as “pull system” and “fault-tolerant”. It shows the positive impact of the factor if mean efficiency has been decreased such as “task management”, “reporting culture”, “learning”, “awareness”, “top management commitment”, “preparedness” and “teamwork”. According to Table 6, among the factors of lean production, “pull system” and “task management” have the most negative and positive effects on performance.

The results of this study can be extended to similar manufacturing environments. Moreover, the same approach and analogy may be used for performance improvement of integrated lean production and resilience engineering. It is an intelligent practical approach for decision-makers and managers of identical manufacturing and production units.

4.4.1. Weight calculation

Weights of each factor is calculated based on results of sensitivity analysis. In order to calculate weights, the percentage difference between correlation of omitted factors and full factor condition is computed. Figure 2 presents the calculated weights of IRE and lean production factors. Management can use the results of this section to prioritize the continuous improvement plans.

Figure 2. Weight of each considered factor in the evaluation

4.5. Verification and validation

Step 8. In order to validate the results obtained by the algorithm, DEA method is used to measure the efficiency scores as well, and the results yielded by the two approaches are compared with each other. As mentioned in the methodology, first the optimum DEA should be selected. For this purpose, 20% noise is employed on five random DMUs. Spearman's correlation results between efficiency scores before and after noise are presented in Table 7.

Table 7. Noise test results for determining the optimum DEA model

BCC-output oriented		BCC-input oriented		CCR-output oriented		CCR-input oriented	
Before noise	After noise	Before noise	After noise	Before noise	After noise	Before noise	After noise
1	1	1	1	0.96717423	0.9715926	1.033939873	1.029238
0.819499061	0.8194991	1.031926864	1.03192686	0.81047607	0.8104761	1.233842725	1.23384272
1	1	0.999999999	1	0.91351142	0.9135114	1.094677067	1.09467707
1.003900988	1	0.99826017	1	1.00174286	1	0.99826017	0.97346738
0.931657851	0.9316578	1.147838495	1.14778486	0.85723185	0.8572318	1.166545547	1.16654555
1	1	1	1	1	1	1	1
0.989349912	0.9902381	0.973473483	0.98374375	0.97980137	0.9798014	1.020615029	1.02061503
0.874722975	0.8858508	1.019268173	1.01124239	0.81115676	0.8111568	1.232807336	1.23280734
1.000000001	1	1	1	1	1	1	1
1	1	0.999999995	1.01380859	0.86887611	0.8688761	1.150912069	1.15091207
0.785377354	0.7868349	1.091350022	1.09135002	0.78210313	0.7821031	1.278603754	1.27860375
0.869816582	0.8698166	1.084181422	1.08418142	0.85279803	0.852798	1.172610587	1.17261059
0.9375	0.9375	1.037070048	1.03707005	0.92298684	0.9229868	1.08343907	1.08343907
0.911221956	0.911222	1.08830439	1.08830439	0.90198844	0.9019884	1.108661664	1.10866166
0.808367356	0.8083674	1.097569515	1.09756951	0.80422859	0.8042286	1.243427572	1.24342757
0.76680353	0.7668035	1.108108108	1.10810811	0.73578208	0.7357821	1.359098059	1.35909806
1	1	1	0.95454545	0.8867596	0.8867596	1.127701348	1.12770136
0.882142616	0.8821426	1.00613497	1.00613497	0.8549964	0.8549964	1.16959557	1.16959557
1.098934634	1.084585	0.998723954	0.90338828	1	1.0754582	1	0.9298362
1.000000001	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1
1	1	1	0.99999999	0.8943591	0.8943591	1.118119099	1.1181191
0.832318013	0.7272194	1.065761717	1.06576172	0.82930904	0.6653477	1.2058231	1.50297366
1	1	1	1	1	1	0.999999994	1
0.792835236	0.7942851	1.086209084	1.0860265	0.79264303	0.7937465	1.261601956	1.25984812
1	1	1	1	1	1	1	1
1	0.9742176	1	1.0060717	1	0.8820924	1	1.13366802
0.981649218	0.9816492	1.019422395	1.01942239	0.9788315	0.9788315	1.021626295	1.0216263
1	1	1	1	0.92554648	0.9257018	1.080442762	1.08026148
1	1	0.999999997	1.00289491	1	1	1	1
1.000000005	1	1	1	1.00000001	1	0.999999996	1.01384921
1.000000001	1	1	1	1	1	1	1
0.844601525	0.8446015	1.086905951	1.08642385	0.83056137	0.8305614	1.204004956	1.20400496
0.889976233	0.8899762	1.097527019	1.09703056	0.8607552	0.8607552	1.161770503	1.1617705
1.000000001	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1
0.822851317	0.8228513	1.069284331	1.05037826	0.81988811	0.8198881	1.219678626	1.21967863
1	1	1	1	0.97542743	0.9754274	1.025191592	1.02519159
0.926339542	0.9299844	1.043024772	1.04302477	0.91055169	0.9207083	1.098235292	1.08612031
0.756075475	0.7560755	1.13330244	1.13330244	0.74617586	0.7461759	1.340166636	1.34016664
0.923003709	0.9230037	1.027197669	1.01973684	0.87962436	0.8796244	1.136848916	1.13684892
1	1	1.147633936	1.14763394	0.87135799	0.871358	1.147633936	1.14763393
0.956971256	0.9569713	1.031791763	1.03179176	0.95636824	0.9563682	1.045622342	1.04562234

1	1	1	1	1	1	1	1
1.001546391	1.0015464	0.99867021	0.99867021	0.99766053	0.9976605	1.002344965	1.00234496
0.770384727	0.771287	1.093838642	1.09383864	0.76316855	0.763705	1.310326534	1.30940615
0.916836142	0.9168361	1.159720512	1.15972052	0.82932174	0.8293217	1.205804641	1.20580463
0.76303681	0.7630368	1.131240521	1.13060786	0.73943235	0.7394324	1.352388767	1.35238877
0.843516593	0.8435166	1.029939347	1.02993935	0.83749764	0.8397834	1.194033216	1.19078331
0.895523697	0.8955237	1.043750263	1.04375026	0.89023053	0.8906014	1.123304545	1.12283676
1	1	1	1	1	1	1	1
1	1	1	1	0.99746127	0.9974613	1.002545192	1.0025452
0.8258185	0.8258185	1.048917906	1.04891791	0.82047628	0.8204763	1.218804273	1.21880427
0.772525486	0.7725255	1.078947368	1.07894737	0.75515594	0.7551559	1.324229801	1.3242298
0.947392847	0.9572381	1.012390483	1.0129394	0.91226158	0.9122616	1.096176824	1.09617682
1	1	1	1	0.83675568	0.8367557	1.195637179	1.19509198
1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1
1	1	0.999999997	1	0.9721992	0.976701	1.028595785	1.02445405
0.801400168	0.8014002	1.108019103	1.1080191	0.79911726	0.7991173	1.251380811	1.25138081
0.770825373	0.7708254	1.163280111	1.16328012	0.76063997	0.76064	1.314682429	1.31468243
1	1	1	0.999999999	0.94696965	0.9469697	1.056000051	1.05600005
0.771471247	0.7714712	1.117250439	1.11714543	0.74514503	0.7459164	1.34202062	1.34063287
1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1
0.901711912	0.9017119	1.039257105	1.0392571	0.89605832	0.8960583	1.115998785	1.11599879
1	1	0.999999999	0.999999999	1	1	1	1
0.893453771	0.8934538	1.068062591	1.06806259	0.89170635	0.8917063	1.121445426	1.12144543
1	1	1	1	1	1	1	1
0.86040725	0.8604072	1.08345153	1.08079763	0.85875323	0.8587532	1.164478878	1.16447888
0.893750874	0.8937509	1.108108113	1.10810811	0.83204236	0.8320424	1.201861883	1.20186188
1	1	1	1	1	1	1	1
0.941157759	0.9411578	1.073824713	1.07382471	0.90723439	0.9072344	1.102250986	1.10225099
0.892547852	0.8926603	1.022891514	1.02289151	0.86121911	0.8612191	1.161144693	1.1611447
Spearman's Correlation Coefficient							
0.9895181		0.9706354		0.9626219		0.94783941	

As indicated in Table 7, BCC-Input oriented model has the least sensitivity to created noise. Therefore, it is selected as the optimum DEA model to validate the obtained results. After determination of the optimum DEA model, the model is run based on the conceptual model, and the efficiency scores are calculated. The high consistency between efficiency scores yielded by optimum DEA model and those yielded by proposed algorithm, validates the algorithm results. The value of Spearman correlation coefficient between the ranks of DMUs obtained by the algorithm and those by DEA optimum model is equal to 0.873 (p-value=0.012) which shows that the results are similar, and thus the results obtained

by the algorithm are valid. The efficiency scores obtained by the optimum DEA model and the proposed algorithm are presented in Table 8.

Table 8. Verification and validation results

DMU	Efficiency Score	
	Proposed Algorithm	Optimum DEA
1	0.78204	1
2	0.68031	0.8194991
3	0.79237	1
4	0.83238	1.003901
5	0.74238	0.9316579
6	0.79576	1
7	0.74894	0.9893499
8	0.68031	0.874723
9	0.76397	1
10	0.78267	1
11	0.59845	0.7853774
12	0.54724	0.8698166
13	0.69458	0.9375
14	0.66830	0.911222
15	0.56545	0.8083674
16	0.52388	0.7668035
17	0.82723	1
18	0.63483	0.8821426
19	0.83746	1.0989346
20	0.82373	1
21	0.67834	1
22	0.78347	1
23	0.58940	0.832318
24	0.72383	1
25	0.54992	0.7928352
26	0.90273	1
27	0.89294	1
28	0.73873	0.9816492
29	0.82738	1
30	0.79835	1
31	0.74382	1
32	0.80237	1
33	0.60168	0.8446015
34	0.64706	0.8899762
35	0.74347	1
36	0.81273	1
37	0.57993	0.8228513
38	0.68349	1
39	0.68342	0.9263395

40	0.60347	0.7560755
41	0.72035	0.9230037
42	0.77348	1
43	0.65348	0.9569713
44	0.75348	1
45	0.86835	1.0015464
46	0.52746	0.7703847
47	0.69348	0.9168361
48	0.58348	0.7630368
49	0.64238	0.8435166
50	0.67348	0.8955237
51	0.76348	1
52	0.79347	1
53	0.69343	0.8258185
54	0.63482	0.7725255
55	0.70447	0.9473928
56	0.68350	1
57	0.70238	1
58	0.79349	1
59	0.72383	1
60	0.55848	0.8014002
61	0.52791	0.7708254
62	0.75708	1
63	0.52855	0.7714712
64	0.76348	1
65	0.79835	1
66	0.75708	1
67	0.67835	0.9017119
68	0.78744	1
69	0.65053	0.8934538
70	0.75708	1
71	0.61749	0.8604073
72	0.65083	0.8937509
73	0.75708	1
74	0.69824	0.9411578
75	0.64963	0.8925479
Spearman's Correlation Coefficient	0.873	

In order to indicate the effectiveness of the proposed algorithm considering RE and lean production concepts together, the efficiency scores of RE and lean principles factors are calculated separately, and the results are compared to the conceptual model of the presented study (RE combined with lean principles). The results are presented in Table 9.

Table 9. Superiority of combined RE and lean production versus each one separately

Factors	Mean of Efficiencies	T-test Result	Comparison between mean of efficiencies
Combined RE and Lean Principles	$\mu_{Combined} = 0.7070$	-	-
RE Factors	$\mu_{RE} = 0.6947$	P-Value = 0.327	$\mu_{Combined} > \mu_{RE}$
Lean Principles	$\mu_{Lean} = 0.6583$	P-Value = 0.000	$\mu_{Combined} > \mu_{Lean}$

As shown in Table 9, considering both concepts together provide higher efficiency scores for DMUs which validates the conceptual model of the presented study.

6. Conclusions and directions for future research

The goal of this paper was to conduct performance assessment from RE and lean points of view points in a pipe factory. Required data were gathered by distributing standard questionnaires among the staff. Thereafter, an adaptive intelligent flexible algorithm composed of various artificial neural networks including MLP, RBF and ANFIS as well as robust mathematical and statistical methods was used for performance assessment of the organization. IRE and lean factors were considered as input and output variables of the model, respectively. After determining the best estimation structure for each output, they were used in the algorithm to calculate decision making units (DMUs) efficiency scores. Subsequently, data envelopment analysis (DEA) method was used to validate the results obtained by the algorithm. In a significant phase of the algorithm, the way each factor of IRE and lean production affected the performance were analyzed statistically. For this purpose, each of the input and output factors were eliminated from the calculations and the efficiency scores were measure anew. The results were then compared to each other by paired t-test. According to the results obtained, after elimination of customer orientation, reduce waste and standard product, and also flexibility, self-organization and redundancy average efficiency gains (μ_2) is equal to the average efficiency (μ_1) before elimination of the stated factors ($\mu_1 = \mu_2$). Therefore, these factors have not a significant impact on organizational efficiency. On the other hand, by eliminating reporting culture, learning, awareness, top management commitment, preparedness, and teamwork, and also task management, average efficiency (μ_2) is less than the average efficiency (μ_1) before elimination of the stated factors ($\mu_1 > \mu_2$). This means, with elimination of these factors organizational efficiency diminishes, and thus these factors have positive impact on organizational efficiency. Also, according to the results, with elimination of pull system and Fault-tolerant, efficiency increases ($\mu_1 < \mu_2$), since the

elimination of these two factors increased efficiency, so these two factors have negative impact on organizational efficiency. The management could use these results to perform corrective actions on negative factors as well as use positive factors for benchmarking. MATLAB V.2015 is used and executed for determining the optimal structures of neural networks (parameter tuning). The codes used for RBF, MLP and ANFIS are presented in Appendix II. Microsoft Excel is used for calculating efficiency scores using mathematical algorithm. Statistical methods such as paired t-test and Cronbach's Alpha are accomplished by SPSS v. 21. DEA is executed and solved by Auto Assess (Azadeh et al, 2014). Auto Assess is capable of executing and solving various DEA, fuzzy DEA, principle component analysis (PCA) and numerical taxonomy (NT).

Acknowledgements

This study was supported by a grant from University of Tehran (No. 8106013/1/20). The authors are grateful for the support provided by the College of Engineering, University of Tehran, Tehran, Iran. This study was also supported by a grant from the Iran National Science Foundation (No. 94002128). The authors are grateful for the financial support provided by the Iran National Science Foundation.

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Appendix I:

Table I. The questionnaire used for collecting required data

Main Question	Factor
How do you assess management's willingness to invest, assign and devote resources to improve safety precautions?	Top Management Commitment
How do you assess the willingness of the staff to report problems and subjects in your organization?	Reporting Culture
Does your work environment encourage you to learn from past events in order to respond effectively in future?	Learning
Does management allow you to be aware of system failures and its consequences?	Awareness
Do you feel the system is actively preparing and predicting problems and issues of human-machine systems?	Preparedness
Do you feel you are allowed to deal with failures using your natural instincts, abilities and experiences?	Flexibility
Do arrangements come from the performances of interdependent agents who change data, take actions, and adjust to react about other activities?	Self-organization
How do you assess teamwork in your working environment?	Teamwork
Is there a replacement plan for each critical resource such as staff or equipment in case of failure, breakdown or absence?	Redundancy
Do you feel the system is preserving to the specified function in the presence of mistakes and faults?	Fault-tolerant
How do you assess customer orientation in your organization?	Customer Orientation
Does your organization investigate each product value stream and determine all non-value added steps?	Reduce Waste
Does your organization standardize all processes after designing most efficient product flow?	Standard Product
Does your production system control flow of resources by replacing only what has been consumed?	Pull System
How do you assess the ability of your organization to utilize resources (such as time and information) efficiently?	Task Management
The respondents can answer the question by continuous values between 1 to 10: 1 stands for completely disagree while 10 is vice versa.	

Appendix II: MatLab Codes

Table II. Multi-layer perceptron MatLab code

<pre>x = xlsread('Inputs'); t = xlsread('Outputs');</pre>

```

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. NFOOTOL falls back to this in low memory situations.
trainFcn = 'trainlm'; % Levenberg-Marquardt
% Create a Fitting Network
hiddenLayerSize = [15 15];
TF = {'logsig','tansig','purelin'}
net = newff(x,t,hiddenLayerSize,TF);
% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};
% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse'; % Mean squared error
% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
'plotregression','plotfit'};
net.trainparam.max_fail = 10
net.trainparam.min_grad = 1e-12
% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)
z = abs(e)
k = mean(z)
MAPE = mse(k)
% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)
figure;
plot(x,'k');
hold on;
plot(t,'r');
legend('x','t');
title('All Data');
% View the Network
view(net)
% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotfit(net,x,t)
%figure, plotregression(t,y)
%figure, ploterrhist(e)
% Deployment
% Change the (false) values to (true) to enable the following code blocks.
if (false)
% Generate MATLAB function for neural network for application deployment
% in MATLAB scripts or with MATLAB Compiler and Builder tools, or simply
% to examine the calculations your trained neural network performs.
genFunction(net,'myNeuralNetworkFunction');
y = myNeuralNetworkFunction(x);
end
if (false)
% Generate a matrix-only MATLAB function for neural network code
% generation with MATLAB Coder tools.
genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
y = myNeuralNetworkFunction(x);
end
if (false)
% Generate a Simulink diagram for simulation or deployment with.
% Simulink Coder tools.
gensim(net);
end

```

Table III. Radial basis function MatLab code

```

X = xlsread('Inputs');
Y = xlsread('Outputs');
inputs = X';
targets = Y';
nData=size(inputs,2);
Perm=randperm(nData);
pTrainData=0.7;
nTrainData=round(pTrainData*nData);
trainInd=Perm(1:nTrainData);
Perm(1:nTrainData)=[];
trainInputs = inputs(:,trainInd);
trainTargets = targets(:,trainInd);

pTestData=1-pTrainData;
nTestData=nData-nTrainData;
testInd=Perm;
testInputs = inputs(:,testInd);
testTargets = targets(:,testInd);
% Create and Train RBF Network
Goal=0;
Spread=2;
MaxNeuron=15;
DisplayAt=1;
for i=1:5
net = newrb(trainInputs,trainTargets,Goal,Spread,MaxNeuron,DisplayAt);
% Test the Network
outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs);
% Recalculate Training, Validation and Test Performance
trainOutputs = outputs(:,trainInd);
trainErrors = trainTargets-trainOutputs;
trainPerformance = perform(net,trainTargets,trainOutputs);

testOutputs = outputs(:,testInd);
testError = testTargets-testOutputs;
testPerformance = perform(net,testTargets,testOutputs);
% PlotResults(targets,outputs,'All Data');
% PlotResults(trainTargets,trainOutputs,'Train Data');
% PlotResults(testTargets,testOutputs,'Test Data');
MAPE(i)=sum(abs(((testTargets-testOutputs)./testOutputs)))/size(testOutputs,2);
end
MAPE=mean(MAPE);
% View the Network
% view(net);

```

Table IV. Adaptive neuro-fuzzy inference system MatLab code

```

% this program is for calculate MAPE with different architectures
clc;
clear;
close all;

%% Load Data

x=xlsread('TrainDataInputs');
y1=xlsread('TrainDataOutputs');
y=y1(:,1);
% y=y1(:,2);
% y=y1(:,3);
% y=y1(:,4);
% y=y1(:,5);

xx=xlsread('TestDataInputs');
yy1=xlsread('TestDataOutputs');
yy=yy1(:,1);
% yy=yy1(:,2);
% yy=yy1(:,3);
% yy=yy1(:,4);
% yy=yy1(:,5);

TrainInputs=x;
TrainTargets=y;
TrainData=[TrainInputs TrainTargets];

TestInputs=xx;
TestTargets=yy;
TestData=[TestInputs TestTargets];

%% Design ANFIS

```

```

ItNum=10;
for i=1:ItNum
%% Fis Type
%Grid Partitioning
% nMFs=2;
% InputMF='gaussmf';
% OutputMF='linear';
% fis=genfis1(TrainData,nMFs,InputMF,OutputMF);

%Sub. Clustering
Xin=x;
Xout=y;
r=0.5;
fis=genfis2(Xin,Xout,r);

%FCM
% Xin=x;
% Xout=y;
% fis=genfis3(Xin,Xout,'sugeno');

%% FIS Option

fis.andMethod='prod';
fis.orMethod='probor';
fis.impMethod='prod';
fis.aggMethod='max';

%ANFIS Train Option
MaxEpoch=100;
ErrorGoal=0;
InitialStepSize=0.01;
StepSizeDecreaseRate=0.9;
StepSizeIncreaseRate=1.1;
TrainOptions=[MaxEpoch ...
              ErrorGoal ...
              InitialStepSize ...
              StepSizeDecreaseRate ...
              StepSizeIncreaseRate];

fis=anfis(TrainData,fis,TrainOptions);
%% Apply ANFIS
TrainOutputs=evalfis(TrainInputs,fis);
TestOutputs=evalfis(TestInputs,fis);

MAPE(i)=sum(abs((TestTargets-TestOutputs)./TestOutputs)))/size(TestOutputs,1);
end
MAPE=sum(MAPE)/ItNum;

% Errors=Targets-Outputs;

figure;
PlotResults(TrainTargets,TrainOutputs,'Train Data');

figure;
PlotResults(TestTargets,TestOutputs,'Test Data');

```

Appendix III:

Table V. Efficiency scores obtained by the algorithm for full factor condition

Operator	Customer Orientation (F ₁)	Reduce Waste (F ₂)	Standard Product (F ₃)	Pull System (F ₄)	Task Management (F ₅)	Efficiency Score	Ranking
1	0.82205	0.80298	0.79634	0.55207	0.93673	0.78204	7
2	0.70898	0.66624	0.56942	0.98127	0.76678	0.68031	22
3	0.64898	0.48999	0.88049	0.53331	0.84876	0.79237	54
4	0.82626	0.69364	0.78316	0.59392	0.74870	0.83238	24
5	0.56776	0.65784	0.53428	0.67231	0.80051	0.74238	64
6	0.81119	0.63195	0.50240	0.46978	0.99772	0.79576	51
7	0.48846	0.60393	0.63427	0.44182	0.82377	0.74894	73
8	0.88120	0.73982	0.70552	0.77403	0.89796	0.68031	3
9	0.65786	0.68519	0.72085	0.85729	0.89866	0.76397	12
10	1.00000	0.73952	0.82644	0.77865	0.79113	0.78267	1
11	0.83345	1.00000	0.82307	0.52995	0.76366	0.59845	5

12	0.81329	0.65090	0.63853	0.73542	0.62844	0.54724	40
13	0.66039	0.75170	0.65636	0.68757	0.82466	0.69458	28
14	0.67479	0.66858	0.47501	0.62355	0.64278	0.66830	68
15	0.78009	0.73089	0.70476	0.50087	0.47542	0.56545	65
16	0.67064	0.74299	0.74563	0.61535	0.73957	0.52388	36
17	0.56485	0.85801	0.82609	0.46934	1.00000	0.82723	20
18	0.87582	0.63147	0.45059	0.60798	0.93003	0.63483	39
19	0.42949	0.80270	0.46652	0.46931	0.78062	0.83746	74
20	0.44328	0.82156	1.00000	0.57071	0.69863	0.82373	32
21	0.82209	0.71639	0.94785	0.48704	0.86596	0.67834	11
22	0.92350	0.83258	0.68222	0.57020	0.92033	0.78347	6
23	0.72160	0.84300	0.57118	0.72008	0.69954	0.58940	30
24	0.66403	0.54075	0.85902	0.45195	0.90591	0.72383	46
25	0.83473	0.40512	0.85071	0.46625	0.85832	0.54992	50
26	0.28842	0.43552	0.86480	0.93963	0.74778	0.90273	62
27	0.75293	0.69005	0.77438	0.45571	0.85145	0.89294	35
28	0.58735	0.60873	0.50455	0.71057	0.86517	0.73873	61
29	0.80466	0.59851	0.90985	0.56664	0.79705	0.82738	23
30	0.76296	0.76508	0.73643	1.00000	0.60725	0.79835	9
31	0.57417	0.69837	0.75381	0.88642	0.86761	0.74382	16
32	0.47364	0.78064	0.83583	0.53479	0.78493	0.80237	53
33	0.82461	0.67240	0.77503	0.41254	0.86607	0.60168	31
34	0.69773	0.66853	0.67469	0.50049	0.92505	0.64706	41
35	0.22824	0.80602	0.79423	0.69832	0.73567	0.74347	63
36	0.79014	0.63040	0.83541	0.63965	0.97759	0.81273	8
37	0.78685	0.57422	0.61051	0.43637	0.95113	0.57993	57
38	0.78330	0.64888	0.97328	0.72668	0.86899	0.68349	2
39	0.82205	0.76773	0.76571	0.51264	0.84306	0.68342	21
40	0.79738	0.68114	0.52620	0.65225	0.74237	0.60347	55
41	0.58896	0.42547	0.81213	0.39350	0.82651	0.72035	70
42	0.76864	0.50403	0.69479	0.48779	0.64815	0.77348	67
43	0.68182	0.69551	0.77584	0.46894	0.74592	0.65348	56
44	0.81119	0.68184	0.73791	0.43364	0.89795	0.75348	29
45	0.48846	0.62463	0.73713	0.40080	0.74139	0.86835	72
46	0.88120	0.71310	0.82982	0.60984	0.77051	0.52746	13
47	0.67428	0.61553	0.71334	0.69937	0.70883	0.69348	52
48	0.94385	0.66717	0.67359	0.53139	0.82017	0.58348	25
49	0.83345	0.95041	0.93830	0.45424	0.79838	0.64238	4
50	0.81329	0.66849	0.76686	0.44194	0.72767	0.67348	48
51	0.66039	0.73192	0.84149	0.51568	0.97738	0.76348	18
52	0.77014	0.73265	0.40426	0.60852	0.61330	0.79347	66
53	0.73359	0.71831	0.79230	0.58891	0.48730	0.69343	59
54	0.67064	0.76307	0.71173	0.59777	0.78781	0.63482	34
55	0.56485	0.91844	0.82609	0.48739	0.95455	0.70447	17
56	0.78040	0.83016	0.56531	0.62253	0.99209	0.68350	15
57	0.42949	0.71831	0.48380	0.48736	0.79363	0.70238	75
58	0.44328	0.77425	1.00000	0.53418	0.78247	0.79349	33
59	0.77435	0.68476	0.85905	0.51637	0.95992	0.72383	14
60	0.92350	0.71810	0.71633	0.59213	0.77189	0.55848	19
61	0.80892	0.74356	0.61162	0.62471	0.66261	0.52791	42
62	0.66403	0.55877	0.77480	0.42704	0.85280	0.75708	60
63	0.83473	0.52260	0.73619	0.44960	0.87393	0.52855	49
64	0.35995	0.45891	0.72502	0.67886	0.79569	0.76348	71
65	0.75293	0.71694	0.69694	0.59441	0.85145	0.79835	26
66	0.58735	0.66407	0.53462	0.71057	0.93047	0.75708	44
67	0.77241	0.58805	0.68221	0.65387	0.81592	0.67835	37
68	0.76296	0.76508	0.80046	0.75862	0.76919	0.78744	10
69	0.57417	0.65181	0.75381	0.69302	0.76639	0.65053	43
70	0.47364	0.66640	0.86369	0.55262	0.79894	0.75708	58
71	0.73729	0.70766	0.70034	0.47206	0.88096	0.61749	38

72	0.69773	0.69678	0.68433	0.55053	0.79290	0.65083	45
73	0.35188	0.79710	0.77609	0.38854	0.76713	0.75708	69
74	0.79014	0.69435	0.68071	0.60251	0.65071	0.69824	47
75	0.78685	0.63560	0.75511	0.45383	0.95113	0.64963	27