Environmental Science and Pollution Research (2021) 28:29394–29411
https://doi.org/10.1007/s11356-021-12595-5

RESEARCH ARTICLE

Selection and performance estimation of Green Lean Six Sigma Projects: a hybrid approach of technology readiness level, data envelopment analysis, and ANFIS

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Received: 2 September 2020 / Accepted: 18 January 2021 / Published online: 8 February 2021

Abstract

Nowadays budget and schedule constraints have forced organizations to select six sigma projects based on pre-defined success criteria. Also, progressive approaches based on green and lean paradigm are vital for companies to enhance their social and environmental performance. Then, Green Lean Six Sigma (GLS) projects play the main role in improving the performance of an organization while augmenting its sustainability. Accordingly in this paper, past studies were reviewed, and GLS projects' indicators and performance evaluation criteria were identified. Data envelopment analysis (DEA) was employed for the appropriate selection of GLS projects. Next, the ranking and performance weight of each project were investigated, and also the projects were categorized based on the technology readiness level (TRL). Additionally, an adaptive neuro-fuzzy inference system (ANFIS) method was applied for the successful prediction of selected GLS projects. Twenty-eight inputs and 9 outputs for the first project category (with TRL 9) and 28 inputs and 6 outputs for the second project category (with TRL 8) were entered into the model. The statistical assessment measures such as Nash–Sutcliffe efficiency (NSE), root mean squared of error (RMSE), mean absolute error (MAE), and R^2 were employed for capability appraisal of ANFIS model. Results of NSE and R^2 indicators for both project categories were 1.00 that proved the efficiency of the ANFIS model for success prediction of GLS projects. Also, RMSE and MAE indicators for category 1 were 0.01 and 0.02 respectively. Similarly, these measures for category 2 were 0.02 and 0.02. The results advocate a proper approximation for observed values by the ANFIS model. Also, the results indicated that TRL as an important enabler of the GLS project has a meaningful role in the performance of GLS projects.

Keywords Green Lean Six Sigma (GLS) project · Data envelopment analysis (DEA) · Technology readiness level (TRL) · Adaptive neuro-fuzzy inference system (ANFIS)

Introduction

Over recent years, there has been a growing interest in the use of Six Sigma (SS) techniques. Many organizations such as Toyota and General Electric have properly tested and implemented SS projects in their daily activities. The fundamental goal of SS is to execute a strategy based on performance assessment and implementation of SS projects, and eventually to decrease fluctuations of processes (Su and Yang 2015; Sagnak and Kazancoglu 2016; Erdil et al. 2018). In recent years, alongside emerging quality augmentation methodologies such as SS, social and environmental concerns for responding to dynamic business ecosystems have been increased (Cherrafi et al. 2017). Traditional production performance criteria such as efficiency and profitability have been expanded to modern measures like customer satisfaction, resilience, and compliance (Eslami et al. 2020; Garza-Reyes et al. 2018; Ershadi and Omidzadeh 2018). Bergmiller and McCright (2009) indicated that businesses for surviving in a current competitive environment need careful consideration of social, economical, and environmental factors simultaneously. The negative impact of industries on climate such as

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supplying a considerable part of global Green House Gases (GHGs) radiation (about one third) that caused the temperature of the earth is increased has compelled the organizations to confront environmental laws (Shakoor et al. 2020; Kaswan and Rathi 2019). In this scheme, corporations were required to balance economic and internal performance indicators while achieving sustainability goals.

To achieve this aim, Green and Lean approaches have been developed to help organizations for attaining achievable economic performance besides maintaining sustainability. Lean Six Sigma (LSS) approach is a combination of two concepts: lean production to reduce wastes and SS that helps companies reduce their process variations and failures. LSS is more than just improvement projects (Raja Sreedharan et al. 2020; Dües et al. 2013). Green Six Sigma (GSS) can be characterized as the evaluation of the explicit environmental impacts of all processes and products in any organization. These activities include regular use of infrastructure and human resources and the optimal utilization of technology. An extensive review of studies performed in the SS field reveals that researchers explored SS programs. The majority of their focus was on identifying the critical success factors (CSFs) of SS (Yazdi et al. 2018).

Recent researches show that lean, SS, and Green approaches contribute to the improvement of sustainability on organizational achievement (Bai et al. 2020; Sreedharan et al. 2019). Also, the combination of SS and Green approaches helps organizations to reduce their energy use while improving the quality of their products or services (Antony 2014). These approaches must be gradual, meaning that companies must evaluate their strengths and weaknesses, determine priorities, and choose targets for successful implementation (Erdil et al. 2018). Furthermore, an integrated GSS and LSS methodology called green lean six sigma (GLS), helps organizations to improve their quality and reduce the wastes while decreasing the negative environmental impact (Antony 2014). Thus, to match aggressive schedules and inflexible budget restraints, selecting GLS projects among all options based on appropriate criteria is inevitable.

The maturity of the technology, called the technology readiness level (TRL), has the main impact on the success of organizations in implementing GLS projects (Rybicka et al. 2016). Kandiero et al. (2014) analyzed some industrial cases to assert technology facilitates improving quality and productivity. Also, the role of technology as a critical factor in implementing quality augmentation programs has been mentioned by Siegel et al. (2019), Ruben et al. (2018), and Garza-Reyes et al. (2018). In GLS, all activities which are defined for improvement of quality are characterized as projects (Saghaei and Didehkhani 2011). The social and environmental impact of GLS projects besides the effect of technology implementation has forced managers to select appropriate GLS projects. Thus, a selection mechanism is an inevitable factor in early success and continuing admission of GLS projects (Saghaei and Didehkhani 2011).

Adaptive neuro-fuzzy inference system (ANFIS) is a well-known framework for predicting the utility of projects. This technique has been developed based on three different concepts of fuzzy set theory (Lam and Tai 2018), fuzzy reasoning, and fuzzy if-then rules. ANFIS method was firstly developed in a network-based framework of the inference system to be trained from a previous data set. Although this technique individually is applicable in a wide domain of industries, recently, it has been empowered by different meta-heuristics or intelligent methodologies.

In GLS projects, deriving utility and predicting the success rate are vital stages that in previous studies have been achieved by methods such as multiple-criteria-decision-making (MCDM) approach or goal programming (Saghaei and Didehkhani 2011). In this paper, an ANFIS is developed to concurrently handle interrelations among pre-defined success criteria and finally is applied to plastic industries as a case.

The plastic injection process is one of the fastest and most useful plastic part production processes that can be utilized to mass-produce plastic parts. The requirement for the implementation of this process is having a plastic injection mold. General purpose polystyrene (GPPS), polycarbonate (PC), acrylonitrile butadiene styrene (ABS), and polypropylene (PP) are some of the materials utilized in this type of process. Sapel Company is one of the largest plastic injection factories in Iran that manufactures different plastic containers. The company uses various machines such as Chinese and Iranian blow molding machines and injection molding machines for the production of plastic containers. The quality problems of these types of machinery are categorized into three types of processing and device, mold, and materials. Inattention to these problems can increase the final cost of the company's products. This increasing in cost may lead to the reduction of the company's market share. Also, the existence of some problems and wastes contradicts the company's environmental and social goals.

In Iran, the production of plastic and its products is welcomed by many producers due to the country's high population. This is particularly because plastic containers known as polyethylene terephthalate (PET) are widely used in the packaging of various beverages and other edibles, and there is a high demand for their production. Sapel Company is a pioneer in the production of blow and injection molded plastic containers with volumes ranging from 8 cc to 60 liters and also injection and blows molded parts up to 1 kg. Primary petrochemical materials are brought into the factory, carried over to the warehouse, and then placed inside devices via suction machines. Next, operators package them and transfer them to the warehouse. However, there are quality issues in the production process of plastic products which can variate from slight cracks on the surface to major flaws that can affect the function of the product. Some defects may be challenging and others can be prevented by modifying the process. Furthermore, according to a report of the Community Research and Development Information Service (CORDIS) in 2013 entitled “Mold for Productivity Enhancement,” international concerns about chemicals in plastic products have led to tightened environmental regulations, and there is a push to improving the quality of these products. Hence, the aforementioned problems and defects endanger society’s environmental standards that may cause socio-environmental impacts.

Although recently a few kinds of researches have been conducted to analyze the interaction among SS, green, and lean approaches (Siegel et al. 2019; Hussain et al. 2019), the selection of GLS projects is the main problem that has not been considered in the literature. Besides, GLS projects play the main role in the aggressive strategy of organizations (Garza-Reyes et al. 2018). Also, lack of readiness in technology and consequently the fear of failure have forced companies to be reluctant in selecting appropriate GLS projects (Kaswan and Rathi 2019).

As a result, the said literature gaps have provided the direction for the present study. Thus, the novelty of this research is incorporating the TRL framework into the ANFIS model for performance appraisal of GLS projects besides efficiency evaluation employing DEA methodology. Hence, the main questions of this research are defined as follows. What are the uses of GLSS projects via DEA for improving quality? What effect does each project have on the performance of machinery in the factory? The latter will be determined via ANFIS.

The main objective of this study is to design a mathematical model to select such that results in the maximum gain to the organization. As a case, a company of production of plastic containers is studied to show the results of the developed model. It is assumed that in this company, a DMAIC methodology has been implemented which led to some options for GLS projects to improve the quality of process or product. In the developed model, maturity of the technology is considered using the technology readiness level (TRL) factor. Previous studies generally cover many important dimensions such as leadership, resources, customer focus, and so on (Yousefi and Hadi-Vencheh 2016; Wei and Cheng 2018), but are deficient in relation to integrating technology readiness of projects. Besides, for the appropriate selection of projects, a data envelopment analysis (DEA) was employed as a well-known mechanism for benchmarking in operations management, where a set of measures is selected to assess the performance of manufacturing and service operations. Additionally, an ANFIS is applied for the successful prediction of selected GLS projects. In the next section, the background of this research is investigated.

Theoretical framework and research background

Green Lean Six Sigma

The idea of sustainability for the first time was initiated by the World Commission on Environment and Development as an answer to the accelerated environmental and social impact of nature damages caused by human intervention (Saieg et al. 2018). Improvements on the application of lean paradigm such as consuming fewer resources, implementing quality improvement programs, and reducing rework, waste, and energy utilizing, provided a framework for improving sustainability in organizations (Zu and Zeng 2020; Qamar et al. 2020; Piercy and Rich 2015). Today, lean SS (LSS), and Green attitudes contribute to the improvement of economic, cultural, and environmental dimensions of organizational performance (Dieste et al. 2020; Cherrafi et al. 2017). The GSS approach helps organizations significantly to reduce their energy use (Kaswan and Rathi 2019). These approaches must be gradual, meaning that companies must evaluate their strengths and weaknesses, determine priorities, and choose targets for successful implementation (Nedeliaková et al. 2017). Three different dimensions of sustainability such as environmental, economic, and social are vital factors to be considered by any organization (Bergmiller and McCright 2009). In this regard, the competitiveness of organizations forced them to cover all their stakeholder’s requirements via achieving positive efficiency while finding a balanced state on three dimensions of sustainability.

In recent years, green approaches have been emerged to assess the environmental impact of all products and processes of a company (Sreedharan et al. 2019). The GLS helps organizations to define SS projects based on green approaches such as landfill waste, reducing energy requirements, or systematically conservation of natural resources (Chen et al. 2019). The advantages of GLS can be summarized as follows.

- Reduces general costs and consequently increases profit.
- Decreases greenhouse gases
- Encourages green energy conservation in companies
- Popularize cost-effective technology and green applications
- Improves green vision
- Increases both employee and customer satisfaction (Nedeliaková et al. 2017).

Prosperous deployment of GLS projects in any company needs suitable enablers for reducing failure risks. As was discussed in the “Introduction” section, nowadays TRL plays an important role not only in manufacturing industries but also as an enabler should be appropriately evaluated. In the following sub-section, the basic definition of this concept is presented.

Technology readiness levels

Technology consists of the ability to utilize knowledge, skills, equipment, and facilities to produce and develop products and services (Rybicka et al. 2016). One of the criteria that has been employed to evaluate the readiness and maturity of technologies is TRL (Mont 2002). TRL is an analytical tool for the assessment of the level of readiness and maturity of the technology while appraising the risk of using one technology in developing a product. TRL was first introduced by the National Aeronautics and Space Administration (NASA). Over time in 1995, Mankins described the stages of this model up to 9 levels. In a paper titled "technology readiness levels in NASA," he proposed the use of these levels in different industries and technologies. Subsequently, the US Government Accountability Office (US GAO) issued an instruction for the utilization of TRLs in industries and the private sector. These levels include the following definitions (Carmack et al. 2017).

TRL1: basic scientific principles observed, understood, and reported
TRL2: technology concept and/or application modeled.
TRL3: proof of concept at the level of the mathematical model established and initial experiments performed.
TRL4: obtaining an efficient laboratory prototype in a laboratory environment.
TRL5: obtaining an efficient laboratory prototype in an environment that is similar to real life.
TRL6: obtaining an efficient primary laboratory prototype in an environment that is similar to real life.
TRL7: proving the functionality of the prototype in a real environment.
TRL8: completing the final system and acquiring the required conditions for operational application/increasing the production scale up to the pilot production level.
TRL9: launching the final system in the real environment/launching the production line.

Jafari Khanshir et al. (2015) in a study tried to identify TRLs based on technical documents. They utilized the experiences of experts from a design office associated with the design and development of complex systems. After reviewing the literature about how to evaluate and determine TRLs, they used expert analysis and creation engineering and also TRL tools for the evaluation of technology readiness. Next, proportionate to each TRL, standard technical documents and evidence as the criterion for the validation of a TRL level through expert opinion were identified.

Yazdi et al. (2018) conducted a study titled "fuzzy integration and data envelopment analysis and fuzzy neural network for the measurement of the effect of the success of human resource spirituality." The purpose of their research was to investigate the effect of human resource spirituality on the success of the strategic change projects of organizations. This paper offers a combined algorithm of fuzzy DEA (FDEA) and ANFIS for the measurement of the pure effect of human resource spirituality in the electric power industry. In this study, ANFIS could properly model nonlinear and complicated relations in ambiguous fuzzy modeling environments. Furthermore, the determination of success indicators for GLS projects is the main problem for each organization. Then these indicators are introduced in the following subsection of this paper.

Six Sigma characteristics

Based on past studies and according to Yousefi and Hadi-Vencheh (2016), Sagnak and Kazancoglu (2016), Nedeliaková et al. (2017), Dinesh Kumar et al. (2007), and Erdil et al. (2018), GLS characteristics are displayed in the following table.

Also, in the following table, project success evaluation criteria were identified using the research of Yazdi et al. (2018).

After introducing the main technical applied concepts and their literature, a developed framework for the selection of GLS projects is discussed in the "Methodology" section.

Methodology

In several previous studies such as Siegel et al. (2019), Ruben et al. (2018), and Garza-Reyes et al. (2018), the readiness of technology in an organization has been considered for success criteria on green lean projects. On the other hand, GLS projects are recently known as the most important paradigm for sustainability improvement of organizations (Ruben et al. 2018). Thus, in this paper, TRL is used for project categorization as a measure for selecting and evaluating GLS projects. Also, the impact of these criteria on the successful evaluation and decision-making on the GLS projects is investigated based on obtained results from the studied case.

This research, in terms of its orientation, is an applied research, and in terms of its objectives, is a descriptive study, and, in terms of its strategy, is a survey study. The research process is as follows (Fig. 1).

Data acquisition was performed via library research. In this regard, papers, studies, and theses relating to the subject of the present research were collected. Furthermore, GLS projects and the characteristics of each one were collected using past studies. The required data were collected through field survey and document reviews. Therefore, the evaluation of projects was conducted based on a researcher-made questionnaire, and the data related to the performance of each machine was collected by utilizing the factory's documents.

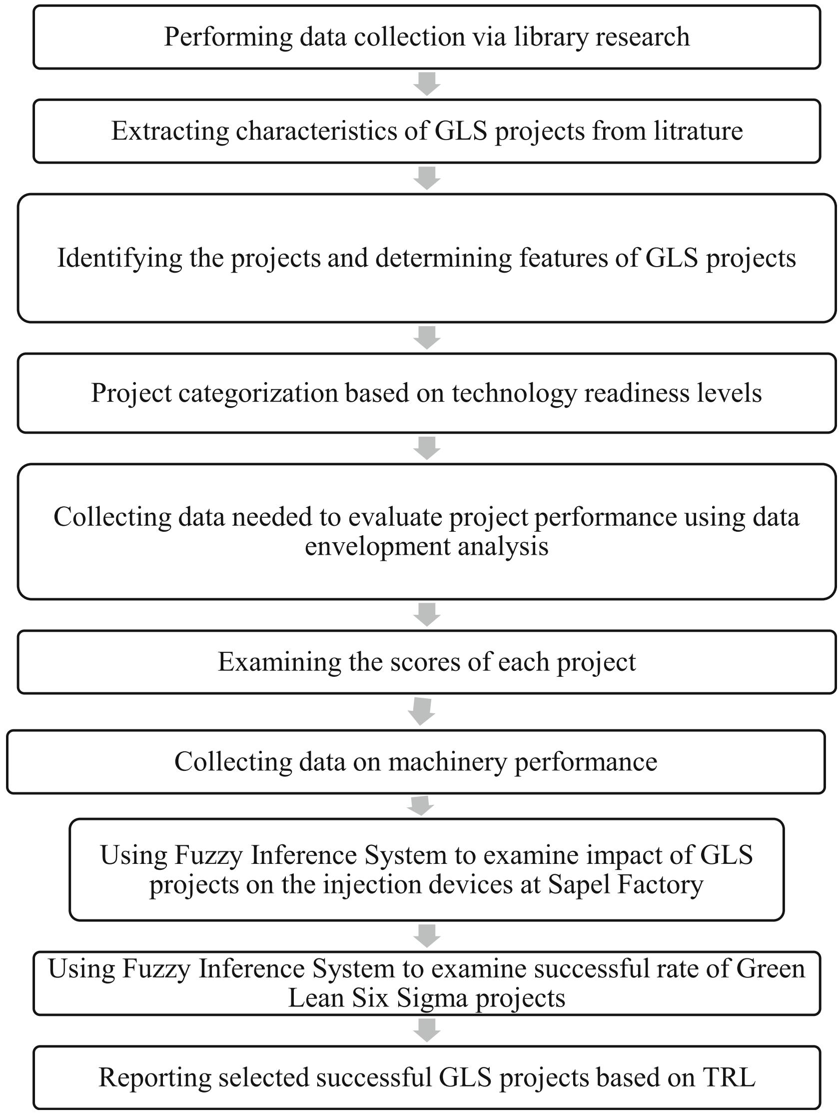


Fig. 1 Main steps of the research process

In the proposed methodology, as is shown in Fig. 1, DEA is applied for efficiency assessment of GLS projects based on inputs and outputs of each project. Moreover, gathered data are imported to the ANFIS system for predicting the success of GLS projects. Thus, DEA and ANFIS are two main methods for data analysis in the current study which are introduced in the "DEA" and "ANFIS method" sections respectively.

DEA

DEA is a mathematical optimization approach for the appraisal of decision-making units (DMUs) that employs several inputs for the production of several outputs. DEA technique is the main type of MCDM techniques. Most well-known tools available in MCDM such as TOPSIS, analytic hierarchy process (AHP) (Singh and Nachtnebel 2016), or Best-Worth Method (BWM) (Rezaei 2015) assign priori weights to the parameters of the projects. Hence, the obtained solutions by these methods are so sensitive to the preceding weights. In DEA, there is no need for the allocation of weights to inputs and outputs. This method introduces some units as the reference ones and virtual units are constructed considering the weights of these reference units (λ) to identify the inefficient DMUs. The weights of the reference units (λ) are a ratio of the inputs and outputs of all units that are combined to form a virtual unit (Yazdi et al. 2018). One of the most applicable models was the CCR multiplier form that can be applied either output-oriented or input-oriented. In this paper, the input-oriented CCR is selected. Because the input-oriented is more straightforward to model the selection of GLS projects than the output-oriented. The input-oriented model known as the envelopment form is as follows.

$$\begin{aligned}
&\mathrm{Min}\ y_0 = \theta - \sum_{r=1}^{s} \varepsilon\, s_r^+ - \sum_{i=1}^{m} \varepsilon s_i^- \\
&\mathrm{St}: \\
&\quad \sum_{j=1}^{n} \lambda_j y_{r_0} - s_r^+ = y_{r_0}\ (r = 1.2.\ldots.n) \\
&\quad x_{i_0}\theta - \sum_{j=1}^{n} x_{ij}\lambda_j - s_i^- = 0\ (i = 1.2.\ldots.n) \\
&\quad \lambda_j`s_r^+`s_i^- \geq 0 \\
&\quad \forall j.r.i_0
\end{aligned} \tag{1}$$

$$\begin{aligned}
&\mathrm{Min}\ y_0 = \theta - \varepsilon\left(\sum_{r=1}^{s} s_r^+ + \sum_{i=1}^{m} s_i^-\right) \\
&\mathrm{St}: \\
&\quad \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r_0}\ (r = 1.2.\ldots.s) \\
&\quad \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{i_0}\ (i = 1.2.\ldots.m) \\
&\quad \theta, \lambda_j, s_r^+`s_i^- \geq 0\ (j = 1.2.\ldots.n) \\
&\quad \forall j.r.i_0
\end{aligned} \tag{2}$$

Model 1 The input-oriented CCR Model

The definition of nomenclature in Eqs. (1) and (2) is as follows.

$\mathbf{s_r^+}$ shows the surplus of the auxiliary variable of deficiency in the amount of production output for the r specified output.

$\mathbf{s_i^-}$ demonstrates another auxiliary variable that states the input i used from it.

x_{ij} denotes the amount of ith input consumed by the jth DMU where $i = 1,\ldots,m$ and $j = 1,\ldots,n$.

y_{rj} denotes the amount of rth output produced by the jth DMU where $r = 1,\ldots,s$ and $j = 1,\ldots,n$.

$\boldsymbol{\theta}$ is the efficiency of each project.

λ is the weight of the reference unit.

A DMU is efficient when $\boldsymbol{\theta^* = 1}$ and $\mathbf{s_r^+} = \mathbf{s_i^-} = 0$ (Yazdi et al. 2018). Also, in the proposed CCR model Eqs. 1 and 2 are applied on each GLS project. Then, the projects with a higher value of θ would be more efficient. The outputs of each GLS project are estimated using criteria of Table 2 which are assessed by experts using a questionnaire. Furthermore, inputs for each project are measured based on Table 1 indexes. The identified criteria which are demonstrated in Tables 1 and 2 are generally applicable in all industrial domains.

In Eqs. (1) and (2), it is assumed that there are n identified GLS projects in which their efficiencies should be assessed. x_{ij} and y_{rj} are GLS indexes and project success indicators respectively while they could be obtained using the questionnaire. These two parameters could be gathered for each GLS project in another industry or corporation using the presented questionnaire and each organization would be capable to evaluate its own GLS projects based on gathered data.

As previously mentioned, after selecting GLS projects, forecasting the success of each project is another problem that is responded to using the ANFIS tool as is introduced in the next sub-section.

ANFIS method

ANFIS is a popular computing framework that has been developed based on the combination of two powerful techniques called Artificial neural network (ANN) and fuzzy logic to employ the strengths of both approaches. The main aim of ANFIS is determining the optimum values for parameters of an identical fuzzy inference system by employing a learning algorithm. ANFIS can be composed of three different methods, namely Genfis 1, Genfis 2, and Genfis 3. Because of input limitation in Genfis 1, Genfis 2 was employed in this research for analyzing the data.

In this paper, to demonstrate ANFIS two fuzzy IF-THEN rules are applied (Eqs. 3 and 4). In these equations x and y are the inputs, while A_i and B_i are the fuzzy sets. Also, f_i are the outputs inside the fuzzy neighborhood established by the fuzzy rule while p_i and q_i are parameters which are tuned during the training process (Al-Hmouz et al. 2011).

Rule (1): IF x is A_1 AND y is B_1 THEN

$$f_1 = p_1 x + q_1 y + r_1 \tag{3}$$

Rule (2): IF x is A_2 AND y is B_2 THEN

$$f_2 = p_2 x + q_2 y + r_2. \tag{4}$$

ANFIS architecture

In ANFIS architecture as is shown in Fig. 2, the circular nodes represent fixed nodes while square nodes represent adaptive nodes. ANFIS structure consists of five different layers called the fuzzification layer, the product layer, the normalized layer, the defuzzification layer, and the output layer (Nguyen et al. 2020).

The fuzzification layer (layer 1) consists of adaptive nodes, and its outputs are fuzzy membership grades of the inputs as are shown below.

$$O_{1,i} = \mu_{Ai}(x), i = 1, 2, \tag{5}$$

Table 1 Features of GLS projects

Dimension	Row	Features	Reference
Leadership and perspectives	1	Leader/senior manager support at different levels of a company	Yousefi and Hadi-Vencheh (2016)
	2	Providing support, guidance, and reward for staff by senior manager/leader	Erdil et al. (2018)
	3	Making the relationship between improvements made from Six Sigma projects with the needs of the company	Nedeliaková et al. (2017)
	4	Perception and acceptance of senior manager/leader that Six Sigma needs a long-term commitment	Yousefi and Hadi-Vencheh (2016)
	5	Commitment of senior management/company leader to implement Six Sigma	Dinesh Kumar et al. (2007)
	6	Leader/leader's ability and desire to maintain Six Sigma principles	Sagnak and Kazancoglu (2016)
Management commitment and resources	1	Senior manager/leader's familiarity with the Six Sigma process	Yousefi and Hadi-Vencheh (2016)
	2	Associating SS principles with goals of the company	
	3	Applying criteria to highlight the benefits of SS for shareholders	Erdil et al. (2018)
	4	Active senior manager/leader presence in Six Sigma projects	Yousefi and Hadi-Vencheh (2016)
	5	The human resource management system should be able to provide a motivation mechanism related to the needs of employees	Dinesh Kumar et al. (2007)
	6	The ability to participate in financial support to improve the project	Erdil et al. (2018)
Focusing on customer	1	Identifying customer expectations and put them at the analytical center	Yousefi and Hadi-Vencheh (2016)
	2	Customer-oriented relationship with company policy, employee development plan, and training programs	Dinesh Kumar et al. (2007)
Selecting the right people	1	Understanding the logic behind Six Sigma by people who are supposed to work on the project	Yousefi and Hadi-Vencheh (2016)
	2	Using the criteria for selecting the right people to teach and implement the project	Erdil et al. (2018)
	3	The flexibility of open-minded people who are supposed to work on the project	
	4	Good perception of people who are supposed to work on the project using Six Sigma tools	Sagnak and Kazancoglu (2016)
Management and process improvement	1	Company's use of a reliable methodology for improvement outcomes	Yousefi and Hadi-Vencheh (2016)
	2	Regular use of SPC tools (process maps, control charts, Pareto graphs)	Dinesh Kumar et al. (2007)
	3	Data collection for key process functions	Sagnak and Kazancoglu (2016)
	4	Accuracy of collected data	
	5	Controlling processing costs	Yousefi and Hadi-Vencheh (2016)
	6	Senior Manager/leader's desire to invest in employee training and decision-making permission	Erdil et al. (2018)
Company strategy	1	The company should have a well-defined, stable strategy	
	2	Employee perception that strategy is the key to company success	Sagnak and Kazancoglu (2016)
	3	Taking into account the process improvement approach to achieve the strategy	Erdil et al. (2018)
	4	The existence of criteria for measuring the extent to which a company's strategy is achieved	Yousefi and Hadi-Vencheh (2016)

$$O_{1,i} = \mu_{Bi-2}(y), i = 3, 4 \tag{6}$$

In Eqs. 5 and 6, x and y are the inputs to the node i respectively and A_i and B_i are the linguistic variables related to each node. Beside, $\mu_{Ai}(x)$ and $\mu_{Bi-2}(y)$ are the fuzzy membership functions.

In layer 2, all nodes are fixed. Fuzzification of inputs is executed in this layer using AND operator. Labels π in this layer indicates a simple multiplier. The output of this layer is shown in Eq. 7.

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y), i = 1, 2, \tag{7}$$

Table 2 Project success evaluation criteria

Row	Criteria	Row	Criteria	Row	Criteria
1	Project performing cost	5	Market share	9	Technology
2	The time of performing project	6	Observe the defined project constraints	10	Proper system
3	Customer satisfaction	7	Safety	11	Environment
4	Achieving production quality standards	8	Fame		

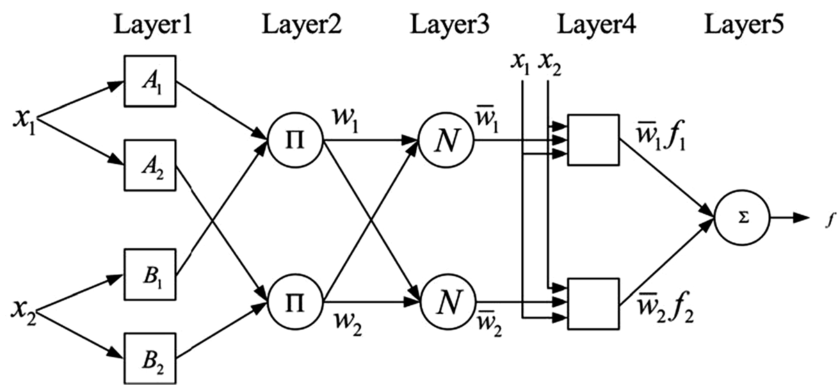


Fig. 2 The basic model of ANFIS (Jang 1993)

In layer 3, the normalization process for the outputs of layer 2 is executed. This normalization is shown in the following equation.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1, 2, \tag{8}$$

The nodes in layer 4 are adaptive. This means that the output of every node in this layer is obtained by multiplying the output of the previous layer by a first-order polynomial. Equation 9 shows the outputs of this layer. Also, the coefficients of this function are adjusted via a combination of least squares approximation and backpropagation approach.

$$O_{4,i} = \overline{w}_i \times f_i = \overline{w}_i \times (p_i x + q_i y + r_i), i = 1, 2, \tag{9}$$

Layer 5 acts as a summation of all incoming signals. Equation 10 shows the calculation method for obtaining the output of this layer.

$$O_{5,i} = \sum_{i=1}^{2} \left(\overline{w}_i \times f_i\right) = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=1}^{2} w_i} \tag{10}$$

In this paper based on 5 previous layers, the ANFIS model is executed. Inputs and outputs of the ANFIS model are GLS indicators and performance rate of the projects respectively. Also, 70 IF-THEN rules were used in the design of fuzzy inference system model. As has been shown in Eqs. 3 and 4, A_1, A_2, B_1, and B_2 are four different nonlinear parameters, while p_1, p_2, q_1, q_2, r_1, and r_2 are six linear parameters of the ANFIS model.

In the next sub-section, some indicators for performance evaluation of proposed ANFIS are provided.

Evaluation metrics for ANFIS performance

The main indicators for performance assessment of ANFIS are Nash–Sutcliffe efficiency (NSE), root mean squared of error (RMSE), mean absolute error (MAE), and R^2 (Nguyen et al. 2020; Adnan et al. 2019). The consistency among predicted values and measured values based on a regression relationships is calculated using the R^2 statistic (Eq. 11). In this equation Y_i represents the prediction of the model, Y_{1i} indicates the prediction of the regression line and $\overline{Y}$ shows the average of regression values.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - Y_{1i})^2}{\sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2} \tag{11}$$

Another statistical measures for performance appraisal of the predictive model are RMSE and MAE. These two indicators demonstrate the mean of errors per each output variable (Nguyen et al. 2020). These two metrics are shown in Eqs. 12 and 13 respectively.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left(Y_i - Y_{2i}\right)^2}{n}} \tag{12}$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left| \left(Y_i - Y_{2i}\right| \right. \tag{13}$$

where represents the value of the 1:1 line and n is the sample number.

The last measure for the assessment of the model is NSE which operates as a normalized parameter. This parameter indicates the proportionate significance of the residual variance compared to the measured data variance. Equation 14 shows the mathematical formula for calculating NSE. In this equation, $\overline{X}$ and X are observed value and average of observed values respectively.

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (Y_i - Y_{2i})^2}{\sum_{i=1}^{n} \left(X_i - \overline{X}\right)^2} \tag{14}$$

In the "Implementation of the proposed framework to the case" section, the implementation process of the proposed framework to a real case is briefly introduced.

Implementation of the proposed framework to the case

Sapel Company is a pioneer company in the field of blowing and injecting polymer packages. The main goal of this company is implementing GLS projects to increase productivity besides considering environmental impacts and socio-technical issues. The selected GLS projects describe in Table 3 of the "Research findings" section. For an appraisal of the inputs and outputs of each GLS project, a questionnaire was designed and validated. For validity appraisal, the questionnaire was distributed among 5 elites of the GLS approach that were completely familiar with the plastic industry. After gathering their results and making the suggested amendments, the questionnaire was validated. For assessment of each GLS project, the questionnaires were distributed to 15 elites. Thirty-three percent of respondents were with the upper 20 years' experience, 47% between 10 and 20 years, and 20% lower 10 years' experience. The next section presents the main finding of this research based on the gathered data.

Research findings

The primary model of the DEA consists of 28 GLS indicators for project success which were taken from Tables 1 and 2. A committee for selecting GLS projects was established. The members of this committee were managers who have been educated as Six Sigma Black Belts or Master Black Belts. These members selected 15 GLS projects based on opportunities and frustrations inside the organization. These 15 GLS projects have been described in Table 3.

Accordingly, the DEA was formed as follows (Fig. 3).

Each project was considered to be a DMU. Next, the collected data were entered into the DEA Solver, and the following results were obtained (Table 4).

As is shown in Table 4, only projects 7 and 11 are efficient with the highest performance, because the obtained value of parameter θ after solving model 1 is equal to one. Other projects are inefficient and could not be selected for implementation. These results indicate that selecting these two GLS projects enables organizations to achieve the desired results (like quality improvement, sustainability) by consuming minimum resources such as materials, energy, and efforts. Hence, because of resource constraints, the executive manager must prefer these two projects for capital investment and constituting teamwork for implementation.

The other main factor which has been previously investigated for the success of GLS projects is TRL (the "Technology readiness levels" section). The next sub-section shows how project classification is taken place using this factor.

Project categorization based on TRLs

In this research, because the TRL of each GLS project has the main impact on forecasting its success, before initiating the ANFIS stage, the projects were categorized based on TRLs. Hence, as was discussed in the "Methodology" section, experts were asked to categorize 15 projects according to 9 different TRLs. Discriminations and characteristics of these 9 different levels of TRLs were explained in the "Technology readiness levels" section. The obtained results based on the expert's judgment have been shown in Table 5.

Results of technology levels categorization indicated that the projects could be placed inside two categories. Nine projects were placed in the category of launching the final system in a realistic environment/launching a production line. Six projects were placed inside the category of completing the final system and acquiring the required conditions for

Table 3 Fifteen GLS projects in Sapel Company

Index	The GLS project name	Index	The GLS project name
DMU1	Waste reduction of machine BM01	DMU9	Increasing customer satisfaction for product #10
DMU2	Reducing nonconformities of product #1	DMU10	Waste reduction of machine BM10
DMU3	Improving defects of product #2	DMU11	Improving defects of product #10
DMU4	Increasing customer satisfaction for product #3	DMU12	Increasing capability of process (Cp) for product #11
DMU5	Waste reduction of machine BM03	DMU13	Improving defects of product #12
DMU6	Improving defects of product #4	DMU14	Increasing customer satisfaction for product #14
DMU7	Waste reduction of machine BM06	DMU15	Waste reduction of machine BM15
DMU8	Improving defects of product #6		

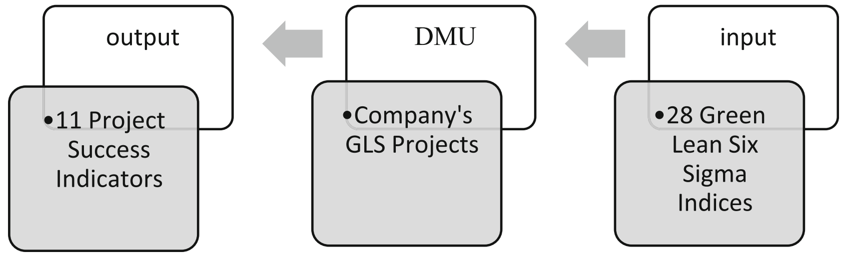


Fig. 3 Data envelopment analysis model

operational application/increasing production scale to the level of pilot production. Therefore, two project categories were formed as is shown in Table 6.

After categorizing the projects, a predictive model is proposed for each category by using a neural network and applying a fuzzy inference system.

Presenting a predictive model based on the ANFIS method

In this section, using the ANFIS method, we offered a predictive model to forecast the success rate for GLS projects. Also, data relating to the inputs and outputs of the neural network were entered into the MATLAB software. As was shown in the previous section, a partitioning for GLS projects needs to be implemented based on TRL values. In other words, the ANFIS method is independently customized and implemented for two categories of GLS projects. Consequently, the performance evaluation of applied ANFIS for each category was carried out. The structure of this section is as follows. In the "Performance assessment of predictive model" section, the results of performance evaluation metrics are provided. Then, in the "Customized ANFIS for successful rate approximation" section, the customized structure of ANFIS for determining the successful rate of GLS projects is presented. Finally, in the "Results of ANFIS execution on the model" section, the obtained results of ANFIS implementation are described.

Performance assessment of predictive model

Table 7 demonstrates the computed performance evaluation indicators such as R^2, NSE, RMSE, and MAE for each category of GLS projects. Among these four indicators, R^2 and NSE have been used in previous studies to show the predictive performance of the model (Nguyen et al. 2020). The higher obtained values for these two metrics indicate the goodness of the model for simulating the results.

As is shown in Table 7, obtained values of NSE and R^2 based on training data are 1.00 in both categories 1 and 2. These calculated values prove that applied ANFIS has the appropriate capability for determining the success rate of GLS projects. Furthermore, smaller values for RMSE and MAE advocate a better approximation for observed values in the ANFIS model (Nguyen et al. 2020). Hence, the results of Table 7 through these two indicators approve the accuracy of the model for predicting the observed values.

Customized ANFIS for successful rate approximation

In this sub-section, the ANFIS structure for modeling the first category of projects (TRL 9) is represented. In the applied ANFIS model the inputs included 28 GLS indicators and output was the performance weight of the projects. Next, the fuzzy inference system (FIS) relations based on the questionnaire data and the output acquired for each project were entered into the software.

Table 4 Performance results for company's 15 projects

Sapel company projects	Performance	Performance rating	Sapel company projects	Performance	Performance rating	Sapel company projects	Performance	Performance rating
DMU1	0.873032	3	DMU6	0.807988	5	DMU11	1	1
DMU2	0.742722	9	DMU7	1	1	DMU12	0.742722	9
DMU3	0.797853	7	DMU8	0.742722	9	DMU13	0.824298	4
DMU4	0.742722	9	DMU9	0.787008	8	DMU14	0.742722	9
DMU5	0.876506	2	DMU10	0.742722	10	DMU15	0.802094	6

Table 5 Classification of the 15 projects based on the stages of technology readiness levels

Project number	TRL1: Viewing and understanding basic science principles and reporting them	TRL2: Modeling core idea of technology and its application	TRL3: Proof of performance at the level of mathematical model and initial experiments	TRL4: Achieving an efficient laboratory sample in a laboratory environment	TRL5: Achieving an efficient laboratory sample in an environment that is similar to the actual performance environment	TRL6: Achieving an efficient prototype in an environment that is similar to the actual operating environment	TRL7: Proof of prototype performance in a real environment	TRL8: Completion of the final system and achieving the operational requirements / Increasing the production scale to the production level of the pilot	TRL9: Launching the final system in the real environment / Launch the production line
1									
2									
3									
4									
5									
6									
7									
8									
9									
10									
11									
12									
13									
14									
15									

The following figure shows 28 inputs (left side) and 9 projects (middle section) and 9 model outputs (right side) which are performance weights. Fig. 4

Beside, the relations between the inputs and outputs in the FIS are demonstrated in Fig. 5.

After running the model, the trained data and the real data are shown in the model. If the trained data are close to the real result data, this would mean that the model has a good inference capability. In Fig. 6, the results of this test are given.

As is shown in Fig. 6, the trained data match the real data, and the software approximation is very high.

For ANFIS implementation in the second category of projects (TRL 8), there were 6 projects to predict their performance rate. Then, FIS relations based on the questionnaire data and the acquired output of each project were entered into the software. The following figure shows 28 inputs (left side) and 6 projects (middle section) and 6 model outputs (right side) which are performance weights. The structure of rules and relationships among inputs and outputs in the second

Table 6 Groups formed in the research

First category projects	Second category projects
Project 1	Project 3
Project 2	Project 8
Project 4	Project 10
Project 5	Project 11
Project 6	Project 12
Project 7	Project 15
Project 9	
Project 13	
Project 14	

Table 7 Performance evaluation of ANFIS

Stage	Category #1				Category #2			
	R^2	NSE	RMSE	MAE	R^2	NSE	RMSE	MAE
Training	1.00	1.00	0.01	0.02	1.00	1.00	0.02	0.02
Testing	0.90	0.53	1.01	1.64	0.98	0.49	1.03	1.62

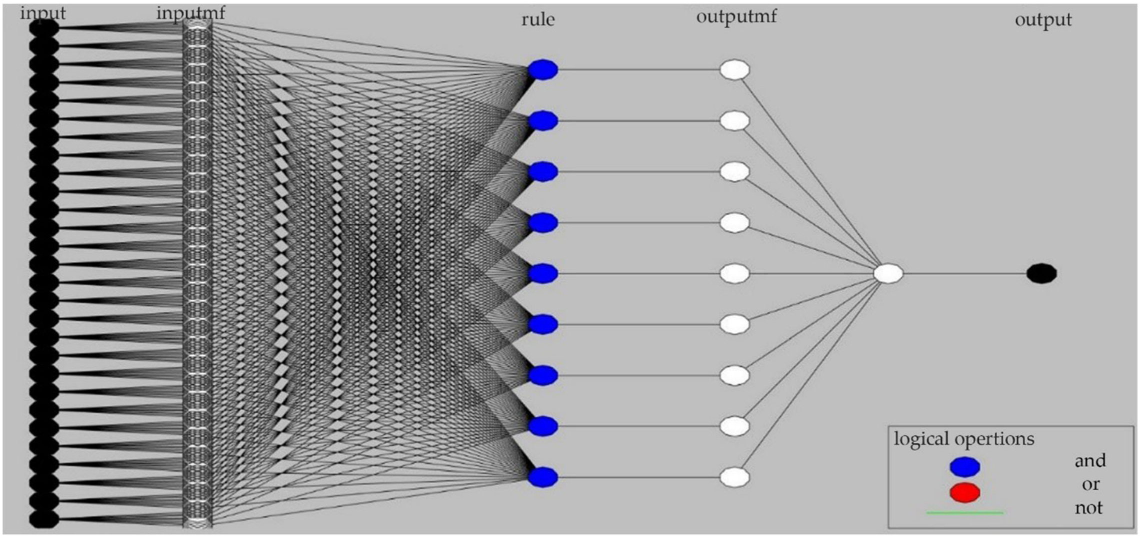


Fig. 4 Input and output structure in the MATLAB software for the first category of projects

category of the projects are quite similar to that of the first category of the project Fig. 7

The next sub-section provides the results of applied ANFIS for the prediction of success rate of GLS projects.

Results of ANFIS execution on the model

Based on the approved capability of the model for performance assessment of GLS projects (the "Performance assessment of predictive model" sub-section) and the structure of the customized model (the "Customized ANFIS for successful rate approximation" sub-section) in this section the results of ANFIS execution for two categories of GLS projects are presented. The level of matching between the estimates and the actual values in both categories 1 and 2 is separately given in the following figures and tables. Table 8 indicates that the results of the estimation of the designed model for category 1 are very close to the real calculated performance of the projects, and also the approximation for 4 items was close to 100%. For other items, the model approximation was no less than 0.97. This means that if the model inputs which are 28 GLS indicators of the project are available, it will be possible to predict, with an approximation that is close to 99%, whether a project will succeed or not. Therefore, it is possible to predict the success of plastic injection projects in Sapel Company based on the characteristics of GLS and also the categorization of TRLs.

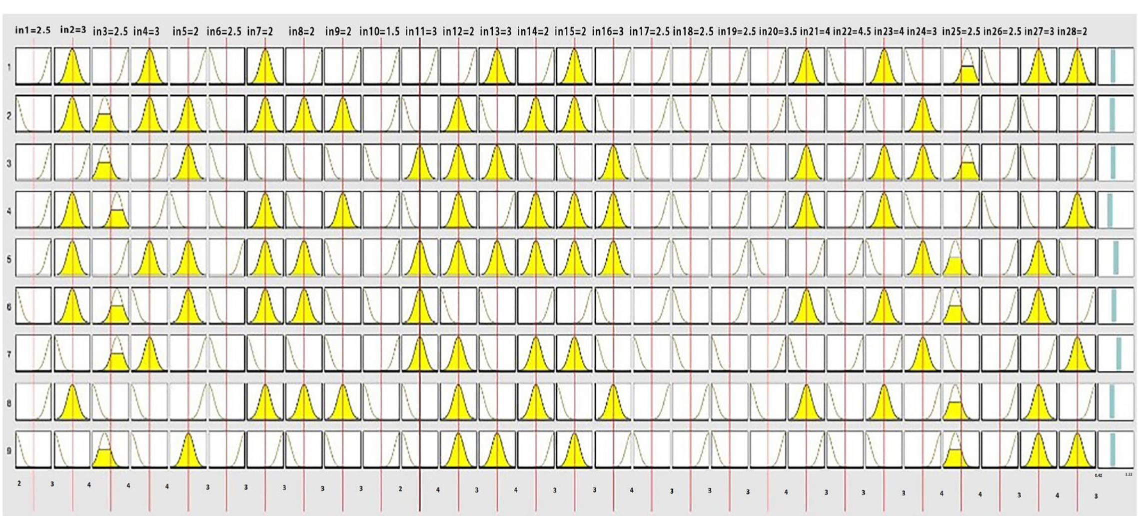


Fig. 5 Input and output relationships in FIS

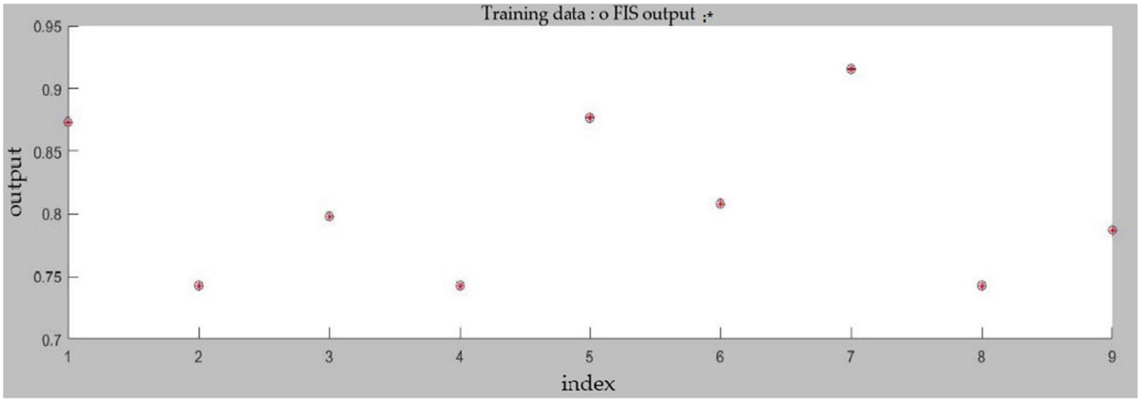


Fig. 6 Real data and data trained in MATLAB software

Figure 8 illustrates the comparison of the estimated amount and actual performance of GLS projects. Also, Fig. 9 demonstrates a scatter plot for the results of the ANFIS model in both estimated and actual performance of GLS projects.

The capability of the ANFIS model for the performance prediction of the second category of projects is discussed in the following this section. As is shown in Table 9, the results of the estimation of the designed ANFIS model are very close to the real calculated performance of the projects and for 5 items the approximation was close to 100%. For other items, the model approximation was 0.97.

Figure 10 depicts the comparison of the estimated amount and actual performance of the second category of GLS projects. Also, Fig. 11 illustrates a scatter plot for the results of the ANFIS model in both estimated and actual performance of GLS projects. This means that if the model inputs which are 28 GLS indicators of the project are available, it will be possible to predict, with an approximation close to 99%, whether a project will succeed or not.

The obtained results through the provided model are discussed in the "Discussion" section as follows.

Discussion

In this paper, the DEA method was applied for GLS projects to evaluate the efficiency of projects. Although previous studies such as Vinodh and Swarnakar (2015), Wei and Cheng (2018) have been conducted for selecting SS projects based on other MCDM approaches, these studies are deficient in relation to considering the efficiency of resource-consuming in succeeding SS projects. Also, in the scope of GLS projects, recently, the researchers have focused on their importance and barriers to implementation. For more information about this subject, researches of Hussain et al. (2019), Kaswan and Rathi (2019), and Siegel et al. (2019) could be studied. This project is in alignment with the researches of Lagrosen et al. (2011), Laureani and Antony (2012), and Antony (2014) in terms of

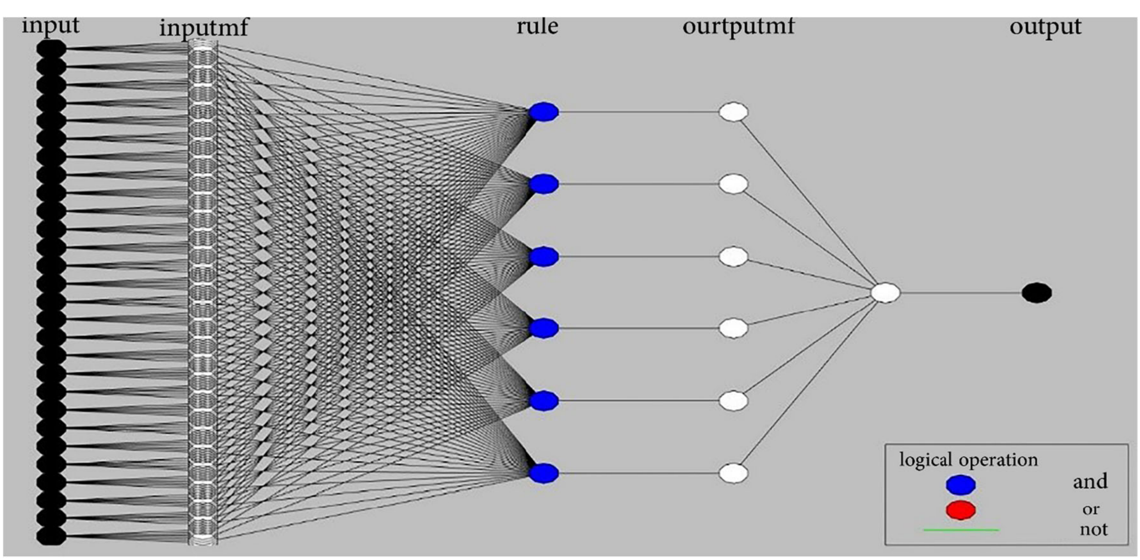


Fig. 7 Input and output structure in the MATLAB software for the second category

Table 8 Results of the prediction model for evaluating the success of the first category of projects

Estimated amount	Real performance	Project number
0.864301	0.873032	1
0.727868	0.742722	2
0.727868	0.742722	4
0.867741	0.876506	5
0.783748	0.807988	6
0.906562	0.915719	7
0.779137	0.787008	9
0.799569	0.824298	13
0.727868	0.742722	14

the identified GLS indicators. In this research, a set of the characteristics mentioned in the above studies was customized in GLS projects.

On the other hand, the readiness of an organization especially in technology is a main effective factor for each SS project. Then, in this paper, the TRL approach was employed and the proposed 15 projects were categorized based on TRL indicators as were shown in the "Project categorization based on TRLs" section. The results of predicting the performance of projects within each TRL category as were shown in the "Presenting a predictive model based on the ANFIS method" sub-section indicate that the performance of the first category is higher than the second category. This result shows that technology readiness has the main effect on the success of GLS projects. This result is in line with the researches of Siegel et al. (2019), Ruben et al. (2018), and Garza-Reyes et al. (2018). Additionally, the performance measures of tuned ANFIS showed enough capabilities for deriving GLS projects. These results are consistent with other case studies in some quality improvement projects such as Saghaei and Didehkhani (2011).

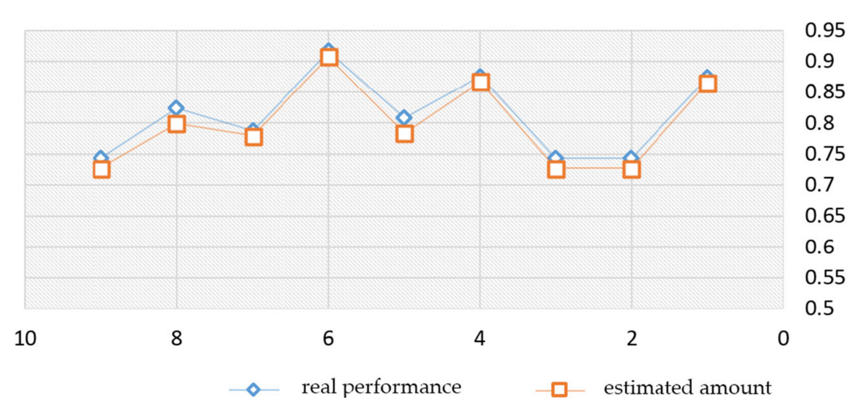
In plastic manufacturing industries, it is estimated that from 4 to 8% of total global oil production is assigned to producing plastic goods (British Plastics Federation 2017). Although replacing natural substances with plastic goods has beneficiated many, it has also caused human dependencies on plastic that has resulted in extremely high levels of inert waste and logistical problems of substitution (Durant and Lucas 2018). Unfortunately, most of the raw materials in plastic production factories are processed by low-tech, family-run businesses, and little or no occupational health and safety measures or environmental controls. Then, there are compelling reasons for factories to radically reduce the percentage of wasted plastic products ending up as ocean pollution. Quality improvement through implementing GLS projects causes waste reduction and finally reduces the socio-environmental impact of accelerated growth of plastic usage in the world. The next section is devoted to the conclusion of this research.

Conclusion

Although many process improvement tools have been emerged in the past six decades and these techniques certainly improve the quality and productivity of processes, some companies may fail to obtain appropriate results from these tools and techniques. On the other hand, environmental, economic, and social sustainability has recently become a strategic requirement of any organization. Merging these concepts into a lean paradigm is vital for any continuous improvement program such as GLS projects. So the main goals of the current research were constructing a framework for selecting appropriate GLS projects among all candidates and then developing a prediction model to respond to the question that if a GLS project would yield successful performance results if properly implemented in a company. Finally, the TRL of the company's machinery because of its importance, as the main factor, was added to the prediction model for performance evaluation of GLS projects.

Results of applied DEA indicated that among 15 identified projects, 7 projects have efficiency higher than 0.8. Then, based on a comprehensive TRL assessment for all GLS projects, these projects were categorized into two independent groups consisting of TRLs 8 and 9. After that, 28 inputs and

Fig. 8 ANFIS model estimation results of GLS projects (group #1)



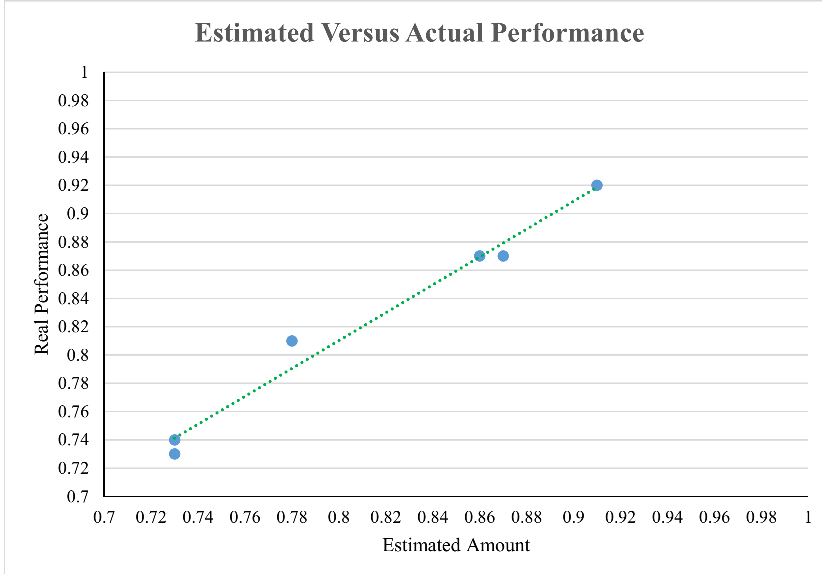


Fig. 9 Comparison between estimated and actual performance of GLS projects (group #1)

9 outputs were assigned for the first project category, and then 28 inputs and 6 outputs were allocated for the second project category. GLS project modeling was carried out based on the collected data, and the calculated performance weight and then the analyses were performed. The results indicated that the reliability of estimated approximations by ANFIS for projects with TRLs 8 and 9 was 0.99 and 0.98 respectively. Furthermore, the estimated amount of performance for projects with TRL 8 was 75%, while for projects with TRL 9 was 80%. These results showed that the provided framework has enough capability for selecting efficient GLS projects and evaluating their success. Also, TRL as an important enabler of the GLS project has a meaningful role in the performance of these projects.

The main implication of the current research for practitioners is to consider the technology readiness of the organization as the main factor in selecting any process improvement project. Moving toward zero defects as an impact of implementing selected GLS projects by recycling plastic commodities certainly needs a thorough readiness of technology. Reducing energy consumption of plastics injection as a main consequence of this movement is just one small part of an overall sustainability initiative. This approach definitely reduces the dependency on fossil fuels and makes feasible the usage of clean energy such as solar and wind. Also, a thorough implementation of GLS in any organization results in reducing the destructive impact of wasted plastics on the ecological environment and would cause social benefit through symbiotic relationships with the planet. Reduced wastes of PP- or PE-formed plastic parts certainly result in lesser environmental degradation because humans are particular victims of negative impacts of wasted parts. Another implication of current research is for industrial managers who need a framework for performance evaluation and selection of GLS projects. The ANFIS method which has been developed in this study, in spite of other MCDM methods, includes complicated relationships among success criteria of GLS projects and has appropriate flexibilities to be tuned in a wide range of GLS projects. All successful measures of GLS projects such as execution time, customer satisfaction, and technology have correlations with each other, and using ANFIS could be so helpful for their analysis and converging to appropriate performance estimation.

The main limitation of this research is estimating measures that are used for the assessment of success in GLS projects. Data which were obtained by factory documents and information were gathered using a questionnaire have the main impact on the validity of results. Selecting the elites of an organization that validates the input and output results and also analyzing trends of data based on appropriate statistical analysis are useful for reducing this limitation. Also, the main criticism of the implementation of GLS projects to any company is that no standard methodology available for the execution of these programs. Other methodologies such as ISO 9001 or EFQM model define a complete assessment structure as guidelines

Table 9 Results of the forecast model for evaluating the success of second category projects

Estimated amount	Real performance	Project number
0.789875	0.797853	3
0.72044	0.742722	8
0.735295	0.742722	10
0.99	1	11
0.735295	0.742722	12
0.794073	0.802094	15

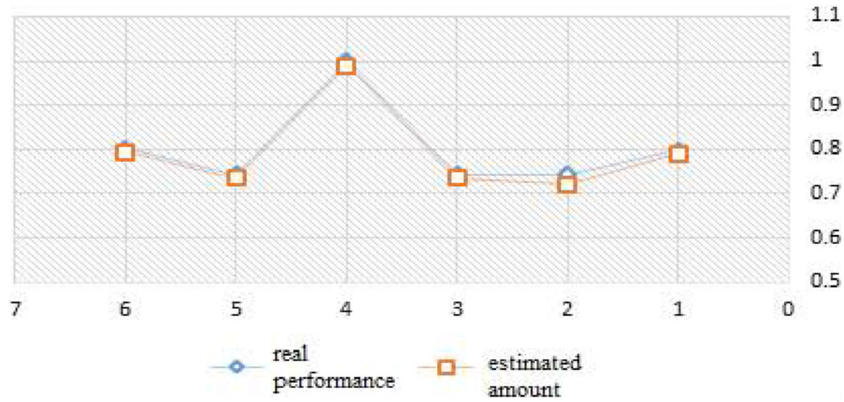


Fig. 10 ANFIS model estimation results of GLS projects (group #2)

for implementation (Moosa and Sajid 2010). But companies feel difficulty when GLS projects come to the implementation phase.

Besides, some recommendations are offered to the authorities of Sapel Company similar to other plastic manufacturing companies as follows.

– Company managers should strengthen the dimensions of leadership and vision in their projects. This is possible by increasing the support of the senior manager/leader across different levels of the company. Also, organizational managers must support, guide, and reward employees based on the success rate of GLS projects. This approach will cause motivation of employees and their realization that their efforts yielded success.
– Company managers are recommended to increase their commitment to the implementation of GLS and include it in the work plan of the operators.
– The proposed practical framework of this paper (especially applied DEA) could be considered a guideline for managers for the selection of efficient GLS projects. This approach would lead the managers to select GLS projects which have enough capability for achieving the pre-defined outputs by consuming determined inputs.
– Company managers are suggested to strengthen the human resource system to allow a motivation mechanism relevant to the needs of employees, so the employees will have a high motivation when working across a GLS project.
– Managers are recommended to consider satisfactory financial support for the implementation of a GLS project.
– Given the approximation of the predictive model, it can be suggested that the support of managers for the successful implementation of GLS projects will only result in project success individually. The managers are recommended to launch a unit for the evaluation and supervision of the permanent implementation of GLS projects.

In future researches, incorporating economic indicators such as net present value (NPV) and initial capital cost could be considered in the ANFIS model. A combinatorial model of DEA and goal programming for considering efficiency

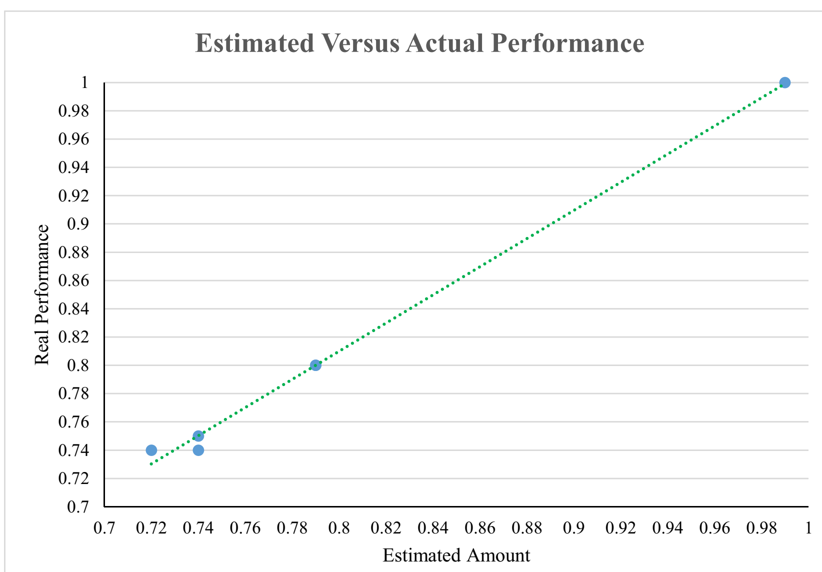


Fig. 11 Comparison between the estimated and actual performance of GLS projects (group #2)

alongside other GLS project goals such as benefit and sustainability development concepts, with incorporating risk management criteria could be studied in future researches.

Author contribution O. Qanadi Taghizadeh: conceptualization, methodology, and software

MJ Ershadi: data curation and writing - original draft preparation

SM Hadji Molana: visualization and investigation

Data availability Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Declaration

Ethics approval and consent to participate "Not applicable"

Consent for publication "Not applicable"

Competing interests The authors declare no competing interests.

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