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# A Comparison of Regression and Neural Network Based for Multiple Response Optimization in a Real Case Study of Gasoline Production Process

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## Abstract

Most of existing researches for multi response optimization are based on regression analysis. However, the artificial neural network can be applied for the problem. In this paper, two approaches are proposed by consideration of both methods. In the first approach, regression model of the controllable factors and S/N (signal to noise) ratio of each response has been achieved, and then a fuzzy programming has been applied to find the optimal factors' levels. In the second approach, a tuned Artificial Neural Network (ANN) is used to relate controllable factors and overall exponential desirability function then genetic algorithm (GA) is used to find factors' optimum values. Mentioned approaches have been discussed in a real case study of oil refining industry. Experimental results for the suggested levels confirm efficiency of the both proposed methods; however, the Neural Network based approach seems to be more suitable for our case study.

**Keywords**: Multi-response optimization, Taguchi method, Artificial Neural Network, Genetic Algorithm, Fuzzy programming.

## 1- Introduction

Many processes around us need to be analyzed for their performance improvement. The analyzer is interested in optimizing processes with minimal experiments and the least cost. Taguchi method (Taguchi, 1991) is an important technique in design of experiment and is used in many case

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studies we are dealing with them. Taguchi method can be carried out based on a few periods of time and low number of experiments; also, it is a useful and coincident method for industrial experiments. The Taguchi method of robust parameter design is an offline statistical quality control

technique in which the level of controllable factors or input process parameters are so chosen to nullify the deviation in responses due to uncontrollable or noise factors such as humidity, vibration and environmental temperature (Taguchi, 1991; Podder et al., 2001).

Today's studies in Taguchi method usually have focused on multi response optimization. Recently, Taguchi method has been combined with complementary approaches to solve multi-response problems. Some prior approaches in multi-response optimization with Taguchi method have used weighted SN ratio approach (Gauri and Chakraborty, 2010; Gauri and Pal, 2010). Meta-heuristic algorithms have been applied to calculate weight of each response (Jeypaul et al. 2006), moreover, multi criteria decision-making (MCDM) (Lan, 2009), grey rational analysis (GRA) (Lin and Tarng, 1998) and principal component analysis (PCA) (Tong et al. 2005) have been used to optimize responses. In addition, some researchers have focused on multiple response optimizations by ANN (Chang, 2008; Chang and Chen, 2011). Some of mentioned approaches have been more illustrated in the next section.

In this study, we evaluate two approaches based on regression model and neural network respectively. In the first approach, Combination of Taguchi method, Analytical Hierarchy Process (AHP) technique and fuzzy programming have regarded to evaluate the quality of achieved optimal levels. In this approach, regression model is used to find the relation function between controllable factors and S/N ratio of each response. Then, response weights derived by AHP are used as objectives' coefficients in fuzzy programming. In the second approach, the relation between controllable factors and response variables is trained by a neural network and then optimal factors' levels are determined by Genetic Algorithm considering overall desirability. It is worth to mention that the Taguchi method is used for tuning the ANN parameters.

The rest of this paper is organized as follows: section 2 reviews some of existing works on multiple response problems using Taguchi method and ANN. The details of the proposed methods are expounded in section 3. The proposed approaches have been more illustrated as an application in the Gasoline production process in Section 4. Efficiency of the proposed methods by a confirmation experiment and its analysis has been reported in section 5 and finally, the conclusion remarks are discussed in section 6.

## 2- Literature review

In this section literature review of multi response optimization approaches based on Taguchi method and ANN have been surveyed. Also, the usage of Taguchi method for tuning the parameters of ANN has been considered. In previous works, many studies have been done to optimize single response problems by using Taguchi method (Al-Refaie, 2009; Li et al., 2009). Recently, more studies have tended to multi- response problems. In this regards, weighted SN ratio (WSN) has been used to transform all of SN ratios in each treatment to the unique value for more easily decision (Gauri and Chakraborty, 2010; Gauri and Pal, 2010). Also, meta-heuristic algorithms have been used to attain desirable factors' levels for achieving best responses. Jeypaul et al. (2006) have presented an approach for computing the response weights based on maximization of total weighted S/N ratio which has been considered as GA fitness function. Frequently, gray rational analysis (GRA) in Taguchi method has been reported as an efficient approach to choose the best design factors in multi response problems (Lin and Tarng, 1998). Many researchers have considered this approach for optimizing factors' levels and grey rational optimization is most commonly used in real cases (Manivannan et al., 2011; Al-Refaie, 2010). Since multiple regression models are useful techniques to create the relation between responses and process factors (Montgomery, 2009), Al-Refaie et al. (2009) have presented regression model by using grey rational approach.

Multi attribute decision-making approaches are other methods which have been studied in previous researches, in this regard; TOPSIS (technique for order preference by similarity to ideal solution) have been used to determine the best levels (Lan, 2009). In addition to TOPSIS, They used mean effects for S/N ratios for determining best levels to achieve the turning parameters. Kuo et al. (2010) have used Taguchi method to design the experiment and they have employed hierarchical structure of the AHP technique to establish the positive comparison matrix, for more information see (saaty, 1980; saaty et al., 1989). After consistency verification, global weight calculation, and priority sequencing, the optimal multi-attribute parameter has been obtained.

The main problem which occurs is that when the mean square error (MSE) of the regression model is a high value, the ability of the model to describe the relationship of the response variable and the controllable factors would be poor (Kim et al., 2001). For overcoming this problem ANN can be used as a proper substitute method for response estimation. Some authors have compared response surface and regression models with ANN in model building and the preciseness of ANN has been verified in their results (Erzurumlu & Oktem, 2007; Tsao, 2008; Desai et al., 2008; Namvar-Asl et al., 2008). In other hand, to obtain better performance of ANN, tuning some effective parameters seems necessary. However, a proportion of researches in this area have chosen these parameters by try and error, while there are some methods based on design of experiments to tune effective parameters (Sukthomya & Tannock, 2005; Yum & Kim, 2004; Tortum et al., 2007; Bashiri & Farshbaf Geranmayeh, 2011). In this paper, optimum parameters of ANN are obtained using Taguchi method. For this purpose, at first determining performance criterion of ANN and effective parameters in it is essential. Some of the published works have used ANN in multiple response optimizations. Gutierrez and Lozano (2010) have obtained the most efficient treatment by using ANN and CCR Data Envelopment Analysis (DEA) model. Noorossana et al. (2009) first used radial based function (RBF) neural network to determine the set of effective parameters and by multi-layer perceptron neural network they estimated the relation between determined effective parameters and response variables and finally have obtained optimum treatment by applying desirability function and GA. Chang (2008) proposed an approach using data mining, ANN, desirability function and SA for optimizing a dynamic multi response problem. Chang and Chen (2011) used ANN to approximate relation between controllable factors and responses. They computed optimum values by using the overall desirability function and genetic algorithm. Lin et al. (2012) have compared integration of neural network, desirability function and genetic algorithm to find optimal combination of parameters’ levels against other methods. Results of this paper show that integrated procedure outperforms Taguchi method and traditional approaches. Sibalija et al. (2011) have converted the quality losses of the correlated responses into uncorrelated components using the Principal Component Analysis (PCA) and then the Grey Relational Analysis (GRA) was applied to synthesis components into a synthetic performance measure. They have applied artificial neural network for estimating the relation between controllable factors and a synthetic performance measure and a genetic algorithm for finding the optimum laser drilling parameters. Sibalija and Majstorovic (2012), in a similar approach, have applied PCA, GRA, ANN and Simulated Annealing (SA) to find the optimal combination of parameters in a multiple response problem. Rong et al (2015) have extended a novel approach based on neural network and genetic algorithm. They have improved the quality of weld joint and the effect of the proposed design of experiment has been checked in an actual laser brazing process. Their procedure has been done by Taguchi L-25. Then their input factors have been optimized using the couple of back propagation neural network and Genetic algorithm in an interactive method. Koyee et al. (2014) have proposed a novel five-step approach including pre-process of data (design the experimentations base on Taguchi), different MADM techniques (AHP-TOPSIS), converting the crisp inputs to fuzzy trapezoidal numbers, fuzzy additive weighted method and determination of ranks and post-process the numbers. Beigmoradi et al. (2014) have applied Taguchi method to reduce number of simulations to reach optimum values of parameters in a real case study of optimization of rear end of a simplified car model. In their proposed approach, results of Taguchi have been used to obtain a relation between parameters and objectives employing ANNs. The results of the model have been conducted by the ANN and multi objective Genetic Algorithm methods. Finally, flow around the optimized model has been studied by numerical simulation and results have been reported.

As mentioned above, multi response optimization is a useful tool in wide range of problems. Recent studies on Gasoline production have been had less attention to design of experiments. Rezai et al. (2008) have surveyed four controllable factors which affect on flotation of coal. Authors have considered Gasoline as one of the controllable factors. They have reported Taguchi method as more efficient method compared to factorial design. Attending the literature review shows that investigation of multi response optimization in adding materials to base Gasoline is a novel issue. The summery of papers which is surveyed in the literature has been shown in Table 1.

**Table 1.** The summary of related published works in the literature

| | Taguchi Method | Artificial Neural Network | Regression Model | Complementary solving approach |
|---|---|---|---|---|
| Gauri and Chakraborty (2010)<br>Gauri and Pal (2010) | * | | | WSN |
| Jeypaul et al. (2006) | * | | | GA |
| Manivannan et al. (2011)<br>Al-Refaie, (2010) | * | | | GRA |
| Lan, (2009)<br>Kuo et al. (2010) | * | | | MADM |
| Al- Refaie et al. (2009b) | * | | * | GRA |
| Gutierrez and Lozano (2010) | * | * | | DEA |
| Noorossana et al. (2009) | | * | | Desirability Function & GA |
| Chang and Chen (2011) | * | * | | Desirability Function & GA |
| Chang (2008) | * | * | | Desirability Function & SA |
| Lin et al. (2012) | * | * | | Desirability Function & GA |
| Sibalija et al. (2011) | * | * | | PCA, GRA & GA |
| Sibalija and Majstorovic (2012) | * | * | | PCA, GRA & SA |
| Rong et al (2015) | * | * | | GA& back propagation neural network |
| Koyee et al. (2014) | * | | | Fuzzy MADM |
| Beigmoradi et al. (2014) | * | * | | - |
| Proposed approaches | * | * | * | Fuzzy Programming, Desirability Function & GA |

## 3- Proposed methods

In this section, two approaches are discussed. The first one is based on regression modeling and Fuzzy Programming and the second one is based on ANN and GA.

### 3-1- Regression analysis and fuzzy programming

In this section, the proposed method for optimizing S/N ratio of response based on Taguchi method is presented. This approach contains 3 phases as illustrated in Figure 1.

<table>
<tr><th colspan="2">Phase 1: Experimental Design and calculation of the S/N Ratios</th></tr>
<tr><td>Step 1: S/N ratio calculation</td><td>Step 2: Normalization</td></tr>
<tr><th colspan="2">Phase 2: Responses' weight calculation</th></tr>
<tr><td colspan="2">Step3: Responses' weights calculation using the AHP</td></tr>
<tr><th colspan="2">Phase3: Multi Response Optimization</th></tr>
<tr><td>Step 4: Regression analysis for each response</td><td>Step 5: Optimization of the responses using the Fuzzy programming</td></tr>
</table>

**Figure 1.** Multi response optimization proposed approach based on Fuzzy Programming

**3-1-1- Experimental design and calculation of the S/N Ratios**

**Step1:** S/N ratio calculation

For each experiment, calculate S/N ratio value, $L_{ij}$, at experiment $i$ for response $j$ using an appropriate equation according to kind of responses (e.g. for larger the better (LTB) use

$$L_{ij} = -10\log_{10}\left(\frac{1}{n}\right)\sum_{i=1}^{n}\frac{1}{y_{ij}} \text{ ).} \tag{1}$$

**Step 2:** Normalization

Adopt S/N ratio according to normalizing approach (e.g. for LTB response use appropriate relation)

$$z_{ij} = \frac{L_{ij} - min(L_{ij}, i = 1,2,...,n)}{max(L_{ij}, i = 1,2,...,n) - min(L_{ij}, i = 1,2,...,n)} \text{ ).} \tag{2}$$

**3-1-2- Responses' weight calculation**

In this phase, weight of each response is determined.

**Step 3:** Responses' weights calculation using the AHP

Compute weight of each response by using AHP technique (saaty, 1980; saaty et al., 1989) and notice that inconsistency ratio would be suitable (less than 0.1).

### 3-1-3- Multi response optimization

In this phase, we want to predict each objective function for each response as a regression analysis and optimize the problem based on fuzzy programming as a multi objective decision-making technique.

**Step4:** Regression analysis for each response

Perform a regression analysis to find the relation function between each response and its factors. Notice that *R-sq* and Adjusted *R-sq* should be appropriate for the regression model.

**Step5:** Optimization of the responses using the Fuzzy programming

Fuzzy programming (for more realization see (Zimmerman, 1978; Cheng et al. 2002)) is considers as following steps:

1- Solve each objective function separately and find the other objectives' values by the optimal controllable factors.

2- Construct the payoff matrix.

$Z_i^*$ is the optimum value of *i*th objective function and $Z_{ij}$ is attained by putting the optimal value of variables of $Z_i$ in the *j*th objective function.

3- Define $\mu(Z_j)$ as linear membership function for *j*th objective function according to (3).

$$\mu(z_j)=\begin{cases} 0 & \text{if} \quad Z_j \le U_j - \Delta j \\ \dfrac{Z_j-(U_j-\Delta j)}{\Delta j} & \text{if} \quad U_j-\Delta j \le Z_j \le U_j \\ 1 & \text{if} \quad Z_j \ge U_j \end{cases} \tag{3}$$

Where, $\Delta_j = U_j - L_j$ is acceptable tolerance for each objective function ( $Z_j$ ).

4- Solve the fuzzy programming model as (4)-(6).

$$Max \sum w_i \alpha_i \tag{4}$$

$$\alpha \le \frac{Z_i - L_i}{U_i - L_i} \qquad i=1,2,...,k \tag{5}$$

$$g_i(x_1, x_2, ..., x_n) \substack{\le \\ \ge} b_i \qquad i=1,2,...,k \tag{6}$$

Where $w_i$ is the weight of each *j*th objective determined by AHP. The best factors' levels are obtained from equations (3)-(6).

## 3-2- Artificial neural network

This section contains the proposed approach, which has been illustrated in Figure 2. In the first step, we determine the best number of layers and its neurons, then, by training the neural network, we compute exponential desirability function and finally, Genetic Algorithm is used to find the optimal levels of controllable factors in optimizing the overall desirability function.

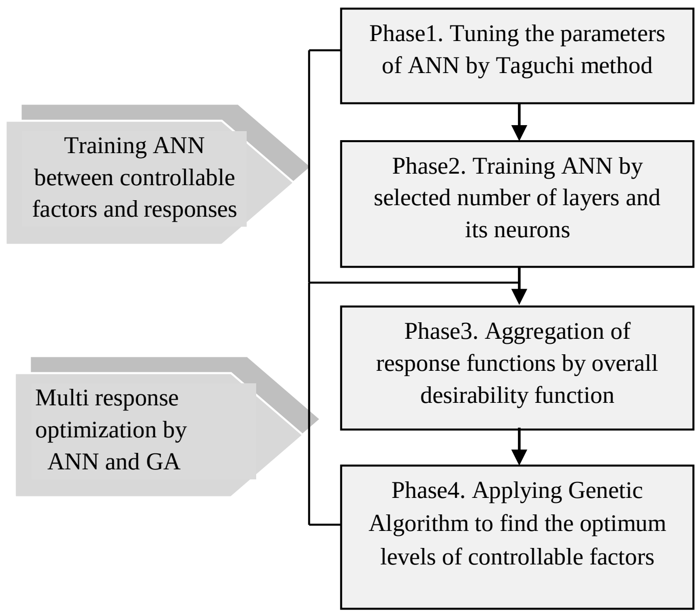


**Figure 2.** The proposed approach of Multi response optimization by ANN and GA

### 3-2-1- Tuning the parameters of ANN

During the training a neural network, some parameters must be defined like the number of hidden layers and the number of neurons in each layer; For this purpose, most of recent researches have selected these parameters randomly or by means of trial and error. Tuned neural network has low error for training the relation between controllable factors and response variables, so we select the best parameters of ANN by Taguchi method. For this purpose, numbers of hidden layer in neural network and number of neurons are considered as effective parameters in performance of ANN and Root Mean Square Error (RMSE) between outputs and targets of the neural network is considered as performance criteria. Note that RMSE is a smaller the better (STB) type performance criterion. Ideal value for RMSE is zero where in ANN structure, trained output values are fitted on target values.

Figure 3 shows the structure of ANN and Table 2 shows the ANN's performance criterion and related effective parameters, which are applied for tuning the parameters of ANN. By analyzing Taguchi, design key levels for each effective parameters in performance of ANN can be computed.

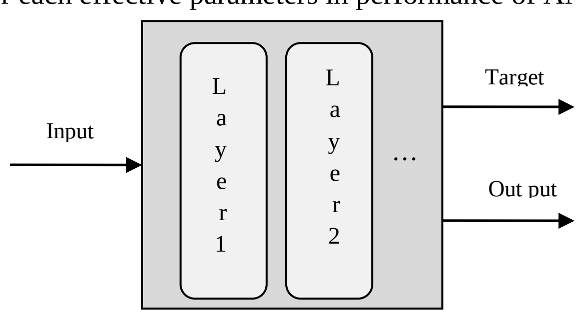

**Figure 3.** Topology of Black Box in ANN

**Table 2.** ANN's performance criterion and related effective parameters

| Effective parameters | Performance criterion |
|---|---|
| The number of neurons in the first and second hidden layer of ANN | RMSE between the outputs and targets of ANN |

### 3-2-2- Training ANN

By obtaining layers status, for predicting the response variables, we need to train the relation between response and its controllable factors. Therefore, one of the existing treatments is selected as test treatment and others are selected for ANN training. If we have more than one response variable, for simplifying, we could train one neural network for each response.

### 3-2-3- Aggregation of responses by overall desirability function

To optimize several responses simultaneously, desirability function technique is represented (Del Castillo et al. 1996). The desirability function transforms value of response to scale free-value and denotes it as $d_i$ for *i*th response. Desirability function's value is between 0 and 1. The more $d_i$ close to one, the more desirable response is (Jeong and Kim, 2009). Derringer and Suich (1980) defined this function for a nominal-the best (NTB) type response.

In this paper, we use exponential desirability function for determining the desirability value of each response variable, separately. The formulas for each type of response (i.e. LTB, STB and NTB) are given in equations (7), (8) and (9).

$$d^{NTB} = \exp\left(-\left|\frac{2\hat{y}_j - \left(y_j^{\max} + y_j^{\min}\right)}{y_j^{\max} - y_j^{\min}}\right|\right) \tag{7}$$

$$d^{LTB} = \exp\left(-\left(\exp\left(-\frac{\hat{y}_j - y_j^{\min}}{y_j^{\min}}\right)\right)\right) \tag{8}$$

$$d^{STB} = \exp\left(-\left(1 + \frac{\hat{y}_j - y_j^{\max}}{y_j^{\max}}\right)\right) \tag{9}$$

Where $y_j^{\min}$ and $y_j^{\max}$ are the lower and upper bounds of the selected response, respectively. $\hat{y}_j$ is approximated value of response which is obtained as output of ANN. But for a final decision, we need to have a total objective function based on each desirebility function. For this porpose, Harrington (1965) proposed a geometric mean in order to aggregate individual desirability functions and approach to overall desirability function *D*. Then the optimal combination set of factors is determined by maximizing *D*. In this study, weighted geometric mean, which is proposed by Derringer (1994), is used according to Equation (10).

$$D = \left(d_1^{W_1} d_2^{W_2} \ldots d_I^{W_I}\right)^{\frac{1}{\sum W_i}} \tag{10}$$

Where $w_i$ is the computed weight of the *i*th response.

### 3-2-4- Applying Genetic Algorithm to find optimum combination of controllable factors

Genetic algorithm has been proved to be a successful method for solving LP and NLP problems inspired by the process of natural selection and genetic evaluation. GA applies mutation, crossover and selecting operators to a population of encoded parameters space. The algorithm searches different areas of the parameters space and guides the solution to the region where there is a high probability of global optimum. For studying more about genetic algorithm see (Ahn, 2006). In proposed method, after establishing overall desirability function according to the desirability of each response, GA is applied for finding the optimum combination set of controllable factors.

## 4- A real case study in gasoline production process

Mentioned approaches have been implemented in a real case study of Isfahan oil refining company and the results have been reported and analyzed in this section. The factors and their levels considered in this study are shown in Table 3. Experiments are conducted with five controllable factors each at two levels. Also we tested 8 treatments with 2 replicates given in Table 4. Rate of octane number (RON), rapid vapor pressure (RVP) and density are considered in this research as interested responses, which are LTB, STB and LTB, respectively.

**Table 3.** Controllable factors and their levels for the case study

| Parameters | Unit | Levels (%) | |
|---|---|---|---|
| | | 1 | 2 |
| Methanol (M) | ml | 3.5 | 5 |
| Ethanol (E) | ml | 5 | 10 |
| Propanol (P) | ml | 3 | 5 |
| Butanol (B) | ml | 3 | 5 |
| Methyl acetate (MA) | ml | 5 | 7.5 |

**Table 4.** *L*8 Orthogonal array for designed experiment and response values for the case study

| Trial No. | M | E | P | B | MA | Responses (2 replicates) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | RVP | | RON | | DENSITY | |
| 1 | 1 | 1 | 1 | 1 | 1 | 64 | 63 | 89 | 88.3 | 0.7507 | 0.7510 |
| 2 | 2 | 2 | 1 | 1 | 1 | 63 | 62.5 | 93.5 | 92.4 | 0.7550 | 0.7553 |
| 3 | 1 | 1 | 2 | 2 | 1 | 62 | 60.5 | 88 | 87.1 | 0.7530 | 0.7535 |
| 4 | 2 | 2 | 2 | 2 | 1 | 61.5 | 60.5 | 94 | 93 | 0.7557 | 0.7561 |
| 5 | 2 | 1 | 2 | 1 | 2 | 63 | 62 | 93.2 | 92.1 | 0.7585 | 0.7590 |
| 6 | 1 | 2 | 2 | 1 | 2 | 62.5 | 61.5 | 91.8 | 91 | 0.7560 | 0.7563 |
| 7 | 2 | 1 | 1 | 2 | 2 | 62 | 61 | 93.5 | 92.4 | 0.7583 | 0.7587 |
| 8 | 1 | 2 | 1 | 2 | 2 | 61 | 59.5 | 91.5 | 90.5 | 0.7566 | 0.7568 |

In the both approaches in the section 4.1 and 4.2, response weights derived from AHP are used. So Table 5 shows the allocated values in comparison matrix (CM) by standpoint of chemical engineering specialist. Also in Table 6, weights of each response and inconsistency ratio (IR) have been reported.

**Table 5.** Comparison matrix for response weights calculation in Analytical Hierarchy Process

| | RON | RVP | DENSITY |
|---|---|---|---|
| RON | 1 | 6 | 9 |

| | | | |
|---|---|---|---|
| RVP | $\frac{1}{6}$ | 1 | 2 |
| DENSITY | $\frac{1}{9}$ | $\frac{1}{2}$ | 1 |

**Table 6.** Calculated weights for each response of the case study

| Response | Weight value |
|---|---|
| RON | 0.779 |
| RVP | 0.143 |
| DENSITY | 0.079 |
| Inconsistency Ratio(IR)=0.01 | |

In the next sections (4.1 and 4.2) multiple response optimization approaches on case study are illustrated.

## 4-1- Multi response Optimization Based on Regression analysis and Fuzzy Programming.

In this approach, the experiments are studied using *L*8 orthogonal array which is presented in Table 4. According to kind of each response, proportionate equation are used to compute SN ratios and their normalized values (e.g. for RON, LTB formula is appropriate in S/N computation). Table 7 shows the SN and normalized SN ratios for each response of each treatment.

**Table 7.** S/N and Normalized S/N ratio values for the Gasoline production process case study

| Trial No. | SN ratios | | | Normalized values of SN ratios | | |
|---|---|---|---|---|---|---|
| | RVP | RON | DENSITY | RVP | RON | DENSITY |
| 1 | -36.0557 | 38.95337 | -2.48894 | 1 | 0.190153 | 0 |
| 2 | -35.9523 | 39.36453 | -2.43934 | 0.77321 | 0.910121 | 0.545607 |
| 3 | -35.7428 | 38.84478 | -2.46122 | 0.31355 | 0 | 0.304899 |
| 4 | -35.7069 | 39.41586 | -2.43071 | 0.23485 | 1 | 0.640448 |
| 5 | -35.9179 | 39.33645 | -2.39803 | 0.69762 | 0.860947 | 1 |
| 6 | -35.8481 | 39.21867 | -2.42784 | 0.54461 | 0.654716 | 0.672047 |
| 7 | -35.7778 | 39.36453 | -2.40089 | 0.39036 | 0.910121 | 0.96852 |
| 8 | -35.5998 | 39.18043 | -2.42153 | 0 | 0.587755 | 0.741521 |

At this stage, the regression analysis result has been reported in Table 8. R-square and adjusted R-square confirm that the additive model is fitted to the experimental data.

**Table 8.** Regression model between the S/N ratio of each response and controllable factors

| Response | Regression relation | R-square value (%) |
|---|---|---|
| RON | 1.97+0.375M+0.0596E+0.0913MA | R-Sq=97.3, R-Sq(adj)=95.2 |
| RVP | 2.28-0.0424E-0.26B-0.0689MA | R-Sq=94,R-Sq(adj)=89.5 |
| Density | -1.59+0.239M+0.189MA | R-Sq=91.3,R-Sq(adj)=87.8 |

In the above regression analysis, 90% of confidence level has been set, so deleted factors have no significant effect in this analysis.
Table 9, shows the pay off matrix for the Gasoline production case study.

**Table 9.** Pay off matrix of the case study

| | RON | RVP | Density | $\left(M^{*}, E^{*}, P^{*}, B^{*}, MA^{*}\right)$ |
|---|---|---|---|---|
| RON | 1.1* | 0.56 | 1 | (5,10,3,3,7.5) |
| RVP | 0.097 | 0.94* | 0.19 | (3.5,5,3,3,5) |
| Density | 0.88 | 0.77 | 1* | (5,5.3,3,7.5) |
| Lower bound | 0.097 | 0.56 | 0.19 | |
| Upper bound | 1.1 | 0.94 | 1 | |

According to equations (1) – (4), the problem is solved by classic optimization software and results are given in table 10.

**Table 10.** Optimum factors levels which are obtained by the proposed approach

| Factor | M | E | P | B | MA |
|---|---|---|---|---|---|
| Selected coded Level | 2 | 2 | 1 | 1 | 2 |
| Uncoded Value | 5 | 10 | 5 | 3 | 7.5 |

As it is obvious in Table 10, $M_2$ $E_2$ $P_1$ $B_1$ $MA_2$ is optimum solution for case study.

## 4-2- Multi response optimization based on ANN

In this approach, the first phase is tuning the parameters of ANN. For this purpose, a Taguchi design based on two controllable factors and one response variable is considered. The first factor is the number of neurons in layer 1 and the second is the number of neurons in layer 2. Notice that if the quality of network with the second layer would be better, we will choose it and its neurons, so, if the number of neurons in layer 2 would be equal to zero, layer 1 is sufficient for ANN structure. Root of mean square errors (RMSE) is most important index for evaluation of the quality of ANN parameters (i.e. the number of layers and its neurons). Hence, RMSE is introduced as the response and we want to find the best level of parameters (controllable factors) with consideration of minimum RMSE (smaller the better response). Table 11 shows the levels at each controllable factor and desirable response variables. Also, Table 12 illustrates treatments contains Taguchi design of experiment, level of controllable factors and RMSE result in each treatment. Since we have three responses in this case study, so we should tune three ANN structure parameters.

**Table 11.** summary of controllable factors and response variable

| Levels of Controllable Factors | | | | | | Performance index for ANN (Response variable) |
|---|---|---|---|---|---|---|
| Controllable factor 1 (Neurons No. in layer 1) | | | Controllable factor 2 (Neurons No. in layer 2) | | | |
| 3 | 8 | 13 | 0 | 3 | 6 | RMSE |

**Table 12.** Orthogonal Arrays for tuning the parameters of ANN

| Trt | Neurons in layer 1 | Neurons in layer 2 | RMSE(RVP) | RMSE(RON) | RMSE(DENSITY) |
|---|---|---|---|---|---|
| 1 | 3 | 0 | 0.72566 | 1.02783 | 0.0014139 |
| 2 | 3 | 3 | 0.99049 | 1.07238 | 0.0019992 |
| 3 | 3 | 6 | 0.94183 | 1.53496 | 0.0011413 |
| 4 | 8 | 0 | 1.45209 | 2.25732 | 0.0023611 |
| 5 | 8 | 3 | 0.71466 | 2.65749 | 0.0014734 |
| 6 | 8 | 6 | 1.13604 | 2.16779 | 0.0021009 |
| 7 | 13 | 0 | 1.74704 | 2.58517 | 0.0038092 |
| 8 | 13 | 3 | 1.54758 | 1.23292 | 0.0024986 |
| 9 | 13 | 6 | 1.65974 | 4.96190 | 0.0061913 |

The result of Taguchi analysis selects two hidden layers for ANN structure with three neurons at each layer. Details of this analysis are given in Table 13. As it is clear in Table 13, the first level is more suitable (maximum mean value) for neuron number in layer one in all networks. Also, the second level is suggested as the best number of neurons in second layer for all three networks.

**Table 13.** Details of analysis for selection of best number of neurons according to Taguchi method

| | Effective parameters in performance of ANN | Mean value of Taguchi method for number of neurons in layer1 | Mean value of Taguchi method for number of neurons in layer2 |
|---|---|---|---|
| ANN parameters for RVP | 1 | 1.1296* | -1.7669 |
| | 2 | -0.4766 | -0.2640* |
| | 3 | -4.3466 | -1.6627 |
| ANN parameters for RON | 1 | -1.522* | -5.187 |
| | 2 | -7.427 | -3.638* |
| | 3 | -7.994 | -8.118 |
| ANN structure for Density | 1 | 56.61* | 52.64 |
| | 2 | 54.24 | 54.22* |
| | 3 | 48.2 | 52.19 |

By considering obtained number of layers and their neuron number, neural network is trained. For this purpose, the first replicate of the experiments (reported in Table 4) is supposed as the test data and its second replicate is considered as validation data. RMSE results for the neural networks are presented in Table 14.

**Table 14.** RMSE results for the training, test and validation data for each network

| Response variable | Train data | Test Data | Validation data |
|---|---|---|---|
| RVP | 0.5590 | 0.3971 | 0.6029 |
| RON | 0.5034 | 0.4228 | 0.6772 |
| Density | 5.37E-04 | 2.39E-05 | 5.24E-04 |

After training the neural network, for applying desirability function, maximum value of RVP (64) and minimum value of RON (87.1) and Density (0.7507) should be considered in equations (6),(7). Moreover, by using GA for exploring new solutions, 57$^{th}$ generated treatment is better than the others. Table 15 shows the best level of controllable factors. Also, the values of predicted responses and desirability function are presented in Table 15.

**Table 15.** Results of multiple response optimization by ANN approach

| the selected controllable factors' value | | | | | Predicted value of each response by ANN | | | Desirability Function | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| M | E | P | B | MA | $\hat{y}_{RVP}$ | $\hat{y}_{RON}$ | $\hat{y}_{Density}$ | $d_{RVP}$ | $d_{RON}$ | $d_{Density}$ | $D_{Total}$ |
| 5 | 8.825 | 5 | 4.52 | 7.5 | 58.9951 | 93.9598 | 0.7613 | 0.3978 | 0.3968 | 0.3731 | 0.3946 |

## 5- Confirmation experiment

After completing the identification of the optimal levels, the confirmation experiment is to be conducted to check the efficiency of the proposed approaches. The real test of achieved values for controllable factors confirmed the optimality of levels, which have been attained. The full information about results of final experiment about two approaches is shown in Table 16. Also, improvement value for treatment which has been calculated based on the proposed approaches has been compared to other treatments which have been tested beforehand (see Table 4). Note that for computing the values of each treatment and comparison between existing treatments and proposed solution, the mean of two replications of existing treatments has been considered.

**Table 16.** Confirmation Experiment For Checking the Efficiency of Proposed Approaches

| Treatments | Response values by real experiments | | | Improvement of the proposed treatment compared with the other experimental data (%) | |
|---|---|---|---|---|---|
| | RVP (STB) | RON (LTB) | DENSITY (LTB) | Regression analysis and Fuzzy Programming | Artificial Neural Network |
| Proposed Treatment based on ANN | 60.08 | 94.07 | 0.7608 | - | - |
| Proposed Treatment based on Fuzzy Programming | 62.5 | 94.3 | 0.7571 | - | - |
| 1 | 63.5 | 88.65 | 0.75085 | 5.255817 | 5.22716 |
| 2 | 62.75 | 92.95 | 0.75515 | 1.208787 | 1.264627 |
| 3 | 61.25 | 87.55 | 0.75325 | 5.754538 | 5.696628 |
| 4 | 61 | 93.5 | 0.7559 | 0.327426 | 1.0989 |
| 5 | 62.5 | 92.65 | 0.75875 | 1.370138 | 1.654189 |
| 6 | 62 | 91.4 | 0.75615 | 2.366266 | 2.597312 |
| 7 | 61.5 | 92.95 | 0.7585 | 0.884313 | 0.991825 |
| 8 | 60.25 | 91 | 0.7567 | 2.295096 | 0.840204 |

Table 16 shows that the proposed treatment obtained by mentioned approaches are better than the others (the reported values are sum of the improvements in the responses at each treatment). For example, this table specifies that according to the experimentation results, improvement of selected treatment in Fuzzy programming approach is 5.75% and 0.33 % better than others in the best and worst case respectively.

Moreover, for comparison of two mentioned approaches based on weight of response variables, comparison of regression analysis and ANN approach is shown in Table 17. According to the results, ANN works better than Fuzzy Programming approach in our Gasoline production case.

**Table 17.** Comparison of two approaches in the Gasoline production case

| | Overall Desirability Function | Total weighted Normalized response values |
|---|---|---|
| Fuzzy Programming | 0.77575 | 0.849488 |
| ANN | 0.779031 | 0.947441 |

## 6- Conclusion and remarks

In this paper, two approaches for multi response optimization were proposed. In the first approach which is based on regression analysis, after computing S/N ratio for each response, its regression model between normalized S/N ratio and controllable factors were achieved. The entire regression models ware considered as fuzzy programming objective function and then, by using AHP weights of response variables, factors' levels were optimized. In the second approach, after tuning the ANN parameters, existing experiments were applied for training the neural network, then, by defining desirability function, controllable factors' optimal value were determined by GA. We implemented two approaches in a case study on adding the additive material to base Gasoline and confirmation experiments showed that both of approaches are efficient. Comparison of two approaches shows that ANN approach is better than regression analysis and fuzzy programming in this case study. Proposed treatment in both approaches saves the economic resulting from decreasing amount of additive material in base Gasoline and increasing the quality of responses especially octane number of Gasoline rather than other treatments.

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