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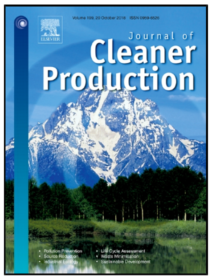

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Finding the optimal combination of power plants alternatives: a multi response Taguchi-neural network using TOPSIS and fuzzy best-worst method

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Abstract

With increasing growth of electricity consumption in developed and developing countries, the necessity of constructing and developing of power plants is inevitable. There are two main resources for electricity generation includes fossil and renewable energies which have some different characteristics such as manufacturing technology, environmental issues, accessibility and etc. In developing plans, it is important to consider and address the policy makers' indicators such as environmental, social, economic and technical criteria. In this paper, an integrated multi response Taguchi-neural network-fuzzy best-worst method (FBWM) -TOPSIS approach is applied to find an optimal level of five different power plants including: gas, steam, combined cycle, wind and hydroelectric. Taguchi method is used to design combinations and calculate some of the signal to noise (S/N) ratios. Then, neural network is applied to estimate the rest of S/N ratios. Finally, FBWM and TOPSIS methods are used for weighing sub-indicators and selecting the best combination, respectively. To illustrate the usefulness of the proposed approach, a case study on the development of power plants in Iran is considered and the results are discussed. According to the results, in general, small size power plants for fossil resources are preferable. In contrast, medium and larger size power plants for renewable resources are preferable.

Keywords: Power plants, Eco-efficiency, Taguchi method, Neural network, Fuzzy best worst method, TOPSIS

1. Introduction

With the growth in economic prosperity, population and energy consumption rate in developed and developing countries, energy demand for consumption in industrial, transportation, services and household sectors has grown significantly in recent years. Increase of energy demands cause new challenges and concerns for policy makers in

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generating and supplying energy. Due to the existence of some limitations in using fossil resources such as environmental concerns and climate changes, policy makers are seeking renewable resources (Ruhl et al. 2012). In addition to the energy production costs, more criteria such as reliability, technology, social and political issues are important in future energy generation and supply.

In Iran, demand for energy is increasing. Worn-out technology and low price of fossil energies have intensified the consumption of energy. The main and important use of energy resources are in electricity generation sector. In fact, the most important part of electricity industry is power generation in power plants. The shortages in generation capacity of the country's power plants have irreparable impacts on the economic, political and social structure of the society. Therefore, the issue of electricity power supply has become a strategic issue and finding the best combination of power plants plays a major role in countries energy managements. In this regard, several researchers have evaluated and also ranked power generation alternatives in many studies using multi criteria decision making (MCDM) techniques, since it is clear that choosing the best alternative is a decision making problem (Kothari et al. 2010). In literature, several MCDM techniques such as, VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Katal and Fazelpour, 2017), Multi-Objective Optimization on the basis of Ratio Analysis (MULTIMOORA) (Streimikiene et al, 2012), fuzzy TOPSIS (Çolak and Kaya, 2017), Analytic Hierarchy Process (AHP) (Amer and Daim, 2011, Emrouznejad and Marra, 2017), Decision-Making Trial and Evaluation Laboratory Model (DEMATEL) (Büyüközkan and Güleryüz, 2016) and etc have been used to choose the optimal energy alternatives. Each energy resource has specific characteristics such as manufacturing technology, environmental issues, technical characteristics, availability, geographical distribution and etc. It is clear that the variety in the generation of electricity is very crucial and countries tend to construct different types of power plants for security in electricity generation simultaneously. Hence, in this research, a novel approach is proposed to find an optimal combination of various power plants (fossil and renewable) for electricity power generation. In fact, by considering the current and future country's program, as well as the advantages and disadvantages of each option, the main question in this article is that, what is the optimal combination of future power generation alternatives in a region respect to the environmental, economic, social and technical aspects. Policy makers are expecting that by selecting best combination of power plant alternatives, some important and critical evaluating sub-indicators values get closer to their optimal values and show less variety near their optimal solutions.

In this paper, an innovative integrated multi response Taguchi method, neural network, FBWM and TOPSIS are used to find the optimal combination of power plants. Briefly, respect to the factors and the number of their levels, Taguchi orthogonal arrays are used to design combinations and S/N ratios of designed combinations are calculated. The aim of Taguchi's method is to determine the best level of alternatives in order to minimize the variability of the solutions in the near of optimal solution. Then, the neural network is used to estimate all of S/N ratios for responses (criteria). Finally, a hybrid FBWM- TOPSIS is applied to find out the optimal combination of power plants in Gilan province of Iran.

The rest of the article is as follows: In the second section, a brief review of literature is provided. The proposed methodology of this paper is presented in section 3. In section 4, the case study is introduced. Section 5 presents the results of the paper. Moreover, sensitivity analysis is performed in section 5. The recommendations for policy makers are suggested in section 6. Finally, in section 7 the conclusion is summarized and direction for future research is given.

2. Literature review

There are several studies for finding the best combination of power plants. In the literature, multiple criteria decision making (MCDM) techniques are widely used methods to evaluate energy resource alternatives. MCDM techniques provide systematic solutions to the problems that involving multiple and even conflicting criteria (Wu et al. 2018). Basically, two major issues should be considered in energy resource evaluation problem using MCDM technique including selection of an appropriate set of evaluation criteria and evaluation methodology. Regarding to the selection of evaluating methodology, various methods may lead to different results (Mardani et al., 2016). Various MCDM methods have been used in literature to evaluate different types of power plants. San Cristóbal (2011) evaluated the alternatives of power generation in Spain using AHP and VIKOR methods. The study showed that among different renewable energy projects, the best option for Spain is biomass energy. Atmaca and Basar (2012) determined the suitability of six kinds of natural gas, wind, geothermal, hydroelectric, coal/lignite and nuclear power plants using analytic network process (ANP). Chatzimouratidis and Pilavachi (2012) applied PROMATHEE technique to evaluate 10 fossil and renewable alternatives considering 12 evaluation criteria and 13 various scenarios. Zhang et al. (2015) presented an improved fuzzy MCDM methodology to evaluate clean electricity alternatives in Jiangsu province, China. In their study, photovoltaic energy was the best option, and wind, biomass and nuclear power plants were in the next positions. By using AHP and additive ratio assessment (ARAS) methods, Štreimikienė et al. (2016) studied the Lithuanian electricity generation options and eventually concluded that nuclear power development was essential for power generation and the biomass power plant was the second choice for power generation. Also, several studies have investigated power plants evaluation in Iran (Arabi, 2014, 2016 and 2017).

Regarding to the selection of evaluation criteria, various evaluation criteria may satisfy the preferences of different stakeholders (Zhang et al., 2015). Therefore, evaluation criteria selection plays a major role in energy resources decision-makings. Evaluation criteria used in literature are mostly associated to environmental, economical, technical and social aspects (Lee and Chang, 2018). For instance, Wu et al. (2018) applied five criteria of capital cost, operation & maintenance cost, electricity cost, pay-back period, and potential market as economical criterion, two criteria of land requirement and impact on ecosystem as environmental criterion, three criteria of employment, public acceptance and social benefits as social criterion and finally maturity, reliability, efficiency and resource availability as technical criterion to evaluate five types of hydropower, solar thermal, wind, solar PV and biomass power plants in China. Also, Lee and Chang (2018) used 10 criteria of investment cost, O&M cost, electric cost as economic indicator, three criteria of efficiency, capacity factor and technical maturity as technical criterion, two criteria of GHG emission and land use as environmental indicator and two criteria of job creation and social acceptance as social indicator to evaluate five types of renewable energy resources. Table (1) demonstrates the methods and criteria used in literature to evaluate energy resource alternatives.

----------------------[Table 1 about here] ---------------------

As it can be seen, in previous researches only priorities of different types of power plants have been determined. However in the case of this study, it is assumed that there are different levels for five types of power plants. As a result, each combination of different levels of considered power plants may have different impact on evaluation criteria. Indeed policy makers in order to put power generation in more secure position tend to establish various types (renewable and fossil) of power plants, but in different levels. In order to find the best and optimal combination of power plants levels, an integrated multi response Taguchi, neural network (NN), and hybrid FBWM-TOPSIS approach has been used.

Taguchi method is one of the most powerful statistical methods of quality improvement. The aim of Taguchi's method is to determine the best level of factors in order to minimize the variability of the solutions in the near of optimal solution (Alizadeh and Yousefi, 2018). Indeed, it aims to improve the parameters setting to reduce deviation and variability in response indexes. Multi responses is an extension to the conventional single response Taguchi method which can deal with real world problems by considering several responses of manufacturers and customers, simultaneously and has mostly applied in literatures to find the best combination of industrial and manufacturing tools. For instance, Li et al., (2016) applied Taguchi method to find the best combination of cutting parameters with the objectives of energy efficiency and processing time. Sarikaya and Güllü (2015) applied Taguchi method to optimize machining parameters under minimum quantity lubrication cooling/lubrication condition. In Taguchi method, optimizing one response may deteriorate other responses, hence, engineering judgment is needed to determine the optimal levels of all factors. In addition, in the situations in that evaluation criteria are involved with features of 'the larger/more is better', 'the nominal is the best' and 'the smaller/less is better' Taguchi method is applicable. Also Taguchi method provides common values of signal to noise (S/N) ratios which makes the evaluations and comparisons more meaningful and easy. However, by increasing the number of factors and their levels, the Taguchi method can lead to a huge number of alternatives. Considering all S/N ratios may lead to huge number of ratios may cause a lot of time and cost. Hence, only some of the S/N ratios are calculated, and the rest of the S/N ratios are estimated by the NN. NN method is able to estimate, classify, optimize and recognize some specific patterns in data. The capabilities of the NN and application in complex and nonlinear problems, make this method preferable to the regression method and many researchers have used NN in literatures. In summary, the NN method has been used in management (Kasiviswanathan et al., 2016), economics (Kordanuli et al., 2017), manufacturing (Conde et al., 2018), agriculture (Espinoza et al., 2016), banking (Kwon and Lee, 2015), pharmacy (Vasilakos et al., 2016), energy (Zeng et al., 2017), efficiency evaluations (Emrouznejad and Shale, 2009) and etc.

After designing the options by Taguchi method and calculating S/N ratios by NN, in the last phase of the proposed integrated approach, this paper employs a hybrid FBWM and TOPSIS approach for finding the best combination of power plants. BWM is one of the latest MCDM techniques which was introduced by Rezaei (2015). The basis of this technique is to weigh the criteria by pairwise comparing such as AHP with two obvious advantages, less pairwise comparison and higher consistency ratio. Flexibility and simplicity of BWM led to use of this method in several researches. Shojaei et al. (2017) used an integrated approach of Taguchi loss function, VIKOR and BWM to evaluate Iranian airports. Ahmed et al. (2017) applied BWM to determine the most important factors affecting the sustainable supply of gas. They found that two most important factors are economic and political factors. In Ren et al. (2017), BWM method was used to weight the sustainable technology alternatives for urban sewage sludge. Also, Gupta and Barua (2016) determined the best enablers among the 30 micro and intermediate economies alternatives by applying the BWM technique.

In real world problems, human qualitative judgments are usually associated with ambiguity and intangibility of uncertain and vague information (Guo and Zhao, 2017). Moreover due to the dynamic nature of energy markets, power plants features and continues changes in stakeholder's preferences, considering crisp values for decision makers' judgments makes the evaluations unrealistic. In order to deal with the inherent ambiguity and uncertainty in human thinking, knowledge limitations of human being and to encounter the dynamic changes in stakeholder's preferences, fuzzy numbers in reference pairwise comparison of BWM is applied which generates more convincing and realistic weights than conventional BWM. After obtaining weights of criteria by FBWM, TOPSIS method has been applied for final ranking. TOPSIS is an MCDM technique which aims to seek optimal solution by identifying both positive ideal solution (PIS) as well as negative ideal solution (NIS). TOPSIS simultaneously considers the distances to both PIS and NIS, and a preference order is ranked according to their relative closeness, and a combination of these two distance measures (Akbaş and Bilgen, 2017; Karahalios, 2017). Indeed, TOPSIS ranks and evaluates alternatives according to the distance measures. A simple computation process which can be programmed in a spreadsheet, a scalar value that accounts for both the best and worst alternatives simultaneously, moderate mathematical calculations, ability to rank all alternatives by providing different scores and providing more realistic and accurate results than other MCDM techniques led this approach applicable in many MCDM studies including energy resource selection (Shih et al., 2007, Akkaya et al. 2015). For instance Štreimikienė et al. (2012) applied TOPSIS and MULTIMOORA to assess electricity production technologies. Çolak and Kaya (2017) applied a fuzzy MCDM approach including fuzzy AHP and TOPSIS in order to prioritize renewable energy resources in Turkey.

The proposed hybrid MCDM approach in the last phase of integrated approach of this study enables policy makers to make a reasonable judgment. The hybrid FBWM-TOPSIS has two main advantages in comparison with other MCDM approaches: First, the capability of taking into accounts both experts' opinion and data in an integrated technique which leads to a more precise and reliable result. Second, there is no need to assign exact numerical values to decision makes reference comparisons which generates the weights more robust and steady in dealing with the ambiguity and uncertainty. The main contribution of this study is the application of the quality control tool (Taguchi method) to determine the best combination of power plants alternatives which has never encountered in any research before. This novel application could led to apply the Taguchi method in other fields such as determining the best combinations of health centers. Besides, by using Taguchi method's S/N ratios, applying criteria with different features of 'the larger/more is better', 'the nominal is the best' and 'the smaller/less is better' is possible. Also the hybrid MCDM technique used in this study led to incorporate both policy makers' preferences and data in decision making process which makes the results more reliable and meaningful. Additionally, the vagueness in the DMs preferences is considered in the decision making process.

3. Methodology

In this paper, an integrated multi-response Taguchi, NN, FBWM and TOPSIS approach is presented to find optimum combination of power plants in Gilan province. The proposed approach is shown in Figure 1. Initially, respect to the factors and the number of their levels, an appropriate Taguchi orthogonal array is designed. Orthogonal arrays represent the minimum required combinations (experiments) to observe power plants effect on responses, then, S/N ratios of designed combination are calculated for measuring the effects of factor levels on responses. In addition, in order to obtain the factor levels effects on responses, calculated S/N ratios are used to train and test back propagation NN for estimating all S/N ratios. For sake of simplicity and applicability of data, estimated S/N ratios are normalized. Meanwhile, fuzzy weights of responses are obtained based on the experts' preferences. Finally, normalized S/N ratios and fuzzy weights of responses are applied in a TOPSIS model to find out the optimal combination of power plants.

---------------------- [Figure 1 about here] ----------------------

3.1. Taguchi method

The Taguchi experimental design method was introduced in 1960 by Professor Taguchi. In this statistical method, the purpose of designing experiments is to determine the optimal combination of factor levels with the least number of experiments and thus significantly reduce the time and cost of performing the required experiments. In the experimental design method, input variables are systematically shifted to observe and identify the effects of shifts on the output parameters of the process. According to the levels and selected orthogonal arrays, the input variables are shifted during experiments to achieve optimal conditions. Due to the number of factors and their levels, different orthogonal arrays can be used in Taguchi method. In orthogonal arrays, the columns which indicate input factors and the rows which present minimum experiments should be performed to achieve the optimal combination. In this method, for the quantification of variations, a signal-to-noise ratio is used, and the experimental conditions with the highest signal-to-noise ratio are selected as optimal conditions. Based on the quality characteristics to be optimized, different *S/N* ratios can be chosen: nominal-the-best, larger-the-better, and smaller-the-better which are formulated as follows, respectively:

$$S/N = 10\log(\frac{\overline{y}^2}{s^2}) \qquad \text{(Nominal the best response)} \qquad (1)$$

$$S/N = -10\log(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}) \qquad \text{(Larger the better response)} \qquad (2)$$

$$S/N = -10\log(\frac{1}{n}\sum_{i=1}^{n}y_i^2) \qquad \text{(Smaller the better response)} \qquad (3)$$

Where y_i is the *i*th observed value of the response and *n* is the number of observations in a trial. The S/N ratio represents the effect of control factor levels on response value. Since the high value of S/N ratio corresponds to the response's better performance, hence, the optimal levels of the parameters are obtained from the combinations with the highest S/N ratios.

3.2. Neural network

An artificial neural network is inspired by the human neural network and tried to formulate the relationship between input and output data. The NN consists of a set of neurons and nodes that the neurons carry out the task of processing information and the processed information is transmitted as a weight in a relationship between neurons. The NN can be trained by adjusting the weight between these neurons. The aim of training the NN is to predict the output values. Based on the type of training, NNs are divided into two supervised and non-supervisor algorithms. In the supervised training algorithm, weights are continuously adjusting, so that the gap between the predicted value and the actual value is negligible. Among the training algorithms, back propagation neural networks (BPNN) are the most widely used one for prediction outputs. The BPNN consists of three input layers, hidden layer and output layer. In Figure (2) a schematic diagram of a BPNN is presented.

--------------------- [Figure 2 about here] ----------------------

The weights in the BPNN are determined through the Delta learning algorithm. Consider the equation (4):

$$Ep = \frac{1}{2}\sum_{p=1}^{p}\sum_{k=1}^{k}(d_{pk} - O_{pk})^2 \tag{4}$$

where *Ep* is a learning error function for all network parameters and weights. d_{pk} and O_{pk} are desired output and calculated output for the k^{th} neuron, respectively. *K* shows number of artificial NN neurons and *p* shows number of samples. In BPNN algorithm, in order to minimize the difference between actual and output data (training error), the weight of connection in NN is adjusted during the training process .To adjust the weights of NN with BPNN algorithm, data are re-processed from output layer to hidden layer. The weight in BPNN algorithm is determined in a relationship based on delta learning rule as follows:

$$\Delta w_{ij} = -\mu \frac{\partial E_p}{\partial w_{ij}} Out_j \tag{5}$$

$$w_{ij}^{new} = w_{ij}^{old} + \Delta w_{ij} \tag{6}$$

Out_j is the output of j^{th} neuron and μ is the training or convergence rate of NN that is fixed value between 0 and 1.

3.3. Fuzzy best worst method (FBWM)

BWM is the latest MCDM technique introduced by Rezaei (2015). The basis of this technique is to weigh the criteria by pairwise comparison. In BWM, by determining preference of the best criterion over other criteria and preference of all criteria on worst criterion by assigning a scale between 1 to 9, the weights of criteria will be specify. Guo and Zhao (2017) expressed “the human qualitative judgments (such as the 1–9 scale-based pairwise comparisons by decision-makers in BWM) usually hold the characteristics of ambiguity and intangibility, and the information of criteria in real world have the drawbacks of vague and uncertain”. So, they designed FBWM for modeling the ambiguity and intangibility in human judgments. The steps of FBWM method is as follows (Guo and Zhao, 2017):

1) Determine a set of criteria as $\{c_1, c_2, ..., c_n\}$

2) Determine the best and the worst criterion by an expert or an experts team

3) Implement fuzzy reference comparison for the best criterion. The fuzzy preferences of best criterion over all criteria are determined using linguistic terms and transformation rules are shown in Table (2). The fuzzy best-to-others vector is as $\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, ..., \tilde{a}_{Bn})$ where $\tilde{a}_{Bj}$ represents the fuzzy preference of the best criterion B over criterion j , $j = 1 , 2 , \cdots, n$. Note that $\tilde{a}_{BB} = (1,1,1)$

---------------------- [Table 2 about here] ----------------------

4) Implement fuzzy reference comparison for the worst criterion. The fuzzy preferences of all criteria over worst criterion are determined using linguistic terms and transformation rules shown in Table (2). The fuzzy others-to-worst vector is as $\tilde{A}_W = (\tilde{a}_{1w}, \tilde{a}_{2w}, ..., \tilde{a}_{nw})$ where $\tilde{a}_{jW}$ represents the fuzzy preference of the criterion *j, j=1,…,n* over the worst criterion *w*. Note that $\tilde{a}_{WW} = (1,1,1)$

5) Find the optimal weights $(\overline{w}_1^*, \overline{w}_2^*, ..., \overline{w}_n^*)$

If the fuzzy preferences are $\tilde{a}_{Bj}$ and $\tilde{a}_{jW}$, the goal is to find the optimal weights which minimize the absolute maximum difference of the $\left| \overline{w}_B / \overline{w}_j - \tilde{a}_{Bj} \right|$ and $\left| \overline{w}_j / \overline{w}_W - \tilde{a}_{jW} \right|$. Considering $\overline{w}_j$, $\overline{w}_W$ and $\overline{w}_B$ as triangular fuzzy numbers, we use $\overline{w}_j = (l_j^w, m_j^w, u_j^w)$ to present the fuzzy weight of criterion j. Also by assuming sum of weights equal to one and non-negativity constraints, the FBWM model expresses as follows (Guo and Zhao, 2017):

$$\begin{aligned}
&\min \max_j \left\{ \left| \overline{w}_B \big/ \overline{w}_j - \tilde{a}_{Bj} \right|, \left| \overline{w}_j \big/ \overline{w}_W - \tilde{a}_{jW} \right| \right\} \\
&s.t: \\
&\sum_{j=1}^{n} R(\overline{w}_j) = 1, \\
&l_j^w \le m^w{}_j \le u_j^w \qquad for\ all\ j \\
&l_j^w \ge 0, \qquad for\ all\ j
\end{aligned} \tag{7}$$

The model (7) can be re-written as follows:

$$\begin{aligned}
&\min \tilde{\xi} \\
&s.t: \\
&\left| \overline{w}_B \big/ \overline{w}_j - \tilde{a}_{Bj} \right| \le \tilde{\xi}, \quad for\ all\ j \\
&\left| \overline{w}_j \big/ \overline{w}_W - \tilde{a}_{jW} \right| \le \tilde{\xi}, \quad for\ all\ j \\
&\sum_{j=1}^{n} R(\overline{w}_j) = 1, \\
&l_j^w \le m^w{}_j \le u_j^w \qquad for\ all\ j \\
&l_j^w \ge 0, \qquad for\ all\ j
\end{aligned} \tag{8}$$

Where $\overline{\xi} = (l^{\xi}, m^{\xi}, u^{\xi})$. By considering $l^{\xi} \le m^{\xi} \le u^{\xi}$ and supposing $\tilde{\xi}^* = (k^*, k^*, k^*), k^* \le l^{\xi}$, the model (8) is transferred as follows:

$$\begin{aligned}
&\min \tilde{\xi} \\
&s.t: \\
&\left| \frac{(l_B^w, m_B^w, u_B^w)}{(l_j^w, m_j^w, u_j^w)} - (l_{Bj}, m_{Bj}, u_{Bj}) \right| \le (k^*, k^*, k^*) \\
&\left| \frac{(l_j^w, m_j^w, u_j^w)}{(l_W^w, m_W^w, u_W^w)} - (l_{jW}, m_{jW}, u_{jW}) \right| \le (k^*, k^*, k^*) \\
&\sum_{j=1}^{n} R(\overline{w}_j) = 1, \\
&l_j^w \le m^w{}_j \le u_j^w \qquad for\ all\ j \\
&l_j^w \ge 0, \qquad for\ all\ j
\end{aligned} \tag{9}$$

By solving model (9), the optimal fuzzy weights will be determine. After obtaining fuzzy weights, we use the graded mean integration representation (GMIR) to transform fuzzy weight of criterion to crisp weights. The GMIR formula is as follow:

$$R(\tilde{a}_i) = \frac{l_i + 4m_i + u_i}{6} \quad (10)$$

In the last stage, it is needed to calculate the consistency ratio. Consistency ratio is employed to check how consistent a fuzzy comparison is. There is full consistency in fuzzy pairwise comparison vector while $\overline{a}_{Bj} \times \overline{a}_{jW} = \overline{a}_{BW}$. In case which $\overline{a}_{Bj} \times \overline{a}_{jW} \neq \overline{a}_{BW}$ inconsistency occurs. Inconsistency will reach to its maximum value $\tilde{\xi}$ when both $\overline{a}_{Bj}$ and $\overline{a}_{jW}$ are equal to $\overline{a}_{BW}$ .Considering the occurrence of the greatest inequality, according to the equality relation, according to the equality relation $\overline{w}_B / \overline{w}_j \times \overline{w}_j / \overline{w}_W = \overline{w}_B / \overline{w}_W$ equation (11) obtained as follows (Gou and Zhao, 2017):

$$(\tilde{a}_{BW} - \tilde{\xi}) \times (\tilde{a}_{BW} - \tilde{\xi}) = (\tilde{a}_{BW} + \tilde{\xi}) \quad (11)$$

Equation (11) can be rewritten as follows:

$$\tilde{\xi}^2 - (1 + 2\tilde{a}_{BW})\tilde{\xi} + (\tilde{a}_{BW}^2 - \tilde{a}_{BW}) = 0 \quad (12)$$

Where $\overline{\xi} = (l^{\xi}, m^{\xi}, u^{\xi})$ and $\overline{a}_{BW} = (l_{BW}, m_{BW}, u_{BW})$. For $\overline{a}_{BW} = (l_{BW}, m_{BW}, u_{BW})$ the maximum fuzzy value cannot exceed 9/2. By using upper bound of u_{BW} in consistency index calculation, all the data affiliated to triangular fuzzy numbers $\overline{a}_{BW}$ can use this consistency index , meanwhile $\overline{\xi}$ is represented a crisp value of ξ. By this considerations, in order to calculate the consistency ratio in FBWM we need to measure equation (13) for all u_{BW}.

$$\xi^2 - (1 + 2u_{BW})\xi + (u^2_{BW} - u_{BW}) = 0 \quad (13)$$

Where $u_{BW} = 1, 3/2, 5/2, 7/2 \, and \, 9/2$ respectively (For more details see Guo and Zhao, 2017).

3.4. TOPSIS

TOPSIS was introduced by Hwang and Yoon (1981). TOPSIS is an MCDM technique which aims to seek optimal solution by identifying both positive ideal solution (PIS) as well as negative ideal solution (NIS). TOPSIS simultaneously considers the distances to both PIS and NIS, and a preference order is ranked according to their relative closeness, and a combination of these two distance measures (Chauhan et al., 2017). Indeed TOPSIS ranks and evaluates alternatives according to the distance measures. A simple computation process which can be programmed in a spreadsheet, a scalar value that accounts for both the best and worst alternatives simultaneously, moderate mathematical calculations, ability to rank all alternatives by providing different scores and providing more realistic and accurate results than other MCDM techniques led this approach applicable in many MCDM studies including energy resource selection. The steps of TOPSIS are as follows:

Step 1: Form the decision matrix A_{ij} consist of m alternatives and n criterion

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}$$

Step2: Normalize the decision matrix through the equation (14):

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^{\ 2}}} \tag{14}$$

Step 3: Obtain the weighted normalized matrix V_i by multiplying weights of criteria in normalized matrix

$$V_{ij} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \dots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \dots & w_n r_{2n} \\ \vdots & \dots & \ddots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \dots & w_n r_{mn} \end{bmatrix}$$

Step 4: Determine PIS A^* and NIS A^- as follow:

$$A^* = \{\langle \max(v_{ij} \mid i = 1,2,\dots,m) \mid j \in J_- \rangle, \langle \min(v_{ij} \mid i = 1,2,\dots,m) \mid j \in J_+ \rangle\} = \{v_1^*, v_2^*, \dots, v_n^*\},$$

$$A^- = \{\langle \min(v_{ij} \mid i = 1,2,\dots,m) \mid j \in J_- \rangle, \langle \max(v_{ij} \mid i = 1,2,\dots,m) \mid j \in J_+ \rangle\} = \{v_1^-, v_2^-, \dots, v_n^-\},$$

Where,

$$J_+ = \{j = 1,2,\dots,n \mid j \ \textit{associated with positive criteria}\}$$

$$J_- = \{j = 1,2,\dots,n \mid j \ \textit{associated with negative criteria}\}$$

Step 5: Calculate the distance of alternatives from PIS and NIS using equations (15) and (16), respectively:

$$S_i^* = \sqrt{\sum_{j=1}^{m}(v_{ij} - v_j^*)^2} \tag{15}$$

$$S_i^- = \sqrt{\sum_{j=1}^{m}(v_{ij} - v_j^-)^2} \tag{16}$$

Step 6: Calculate the relative closeness to the ideal solution using expression (17):

$$C_i^* = \frac{s_i^-}{s_i^- + s_i^*} \tag{17}$$

Step 7: rank the alternatives based on the C_i^* values from highest value to lowest value.

3.5. The proposed approach

Development a set of various power generation alternatives is very important for developing countries such Iran. In order to find out the optimal combination of power plants, this paper utilized an integrated approach with the following steps:

Step 1) Select a proper orthogonal array respect to the number of factors and their levels. For designing experiments, Taguchi proposed 18 main orthogonal arrays. In this step, if the suitable arrays do not exist among 18 proposed main arrays, the closest suitable array will be selected after measuring the degree of freedom which can be calculated using the following equation.

$$DF = \{\sum_{i,j}[(numbers\ of\ \ factor\,(i)\ \text{with (j) level)*(j-1)}]\}+1 \tag{18}$$

Step 2) In this step according to the responses quality characteristics such as ‘the nominal is the best’, ‘the larger is the better’ and ‘the smaller is the better’, the S/N ratios will be calculated using (1), (2) or (3). S/N ratios quantify the effect of shifting factors on responses parameters, and it should be noted that higher values of S/N ratios are desired.

Step 3) Design a BPNN to estimate all S/N ratios. After calculating S/N ratios of designed orthogonal arrays, a BPNN is designed to obtain all S/N ratios. In the BPNN, the factors are considered as input layer and responses are considered as the output layer. The number of hidden layers is also between 1 and 3, which is usually found with trial and error. The accuracy of estimated data is measured using mean square error (MSE). The network with lower MSE is optimal to estimate data.

Step 4) Normalize the S/N ratios. After estimating all S/N ratios, in order to deal with different scales and to simplify the calculations, the S/N ratios will be normalized using the following formula:

$$Z_{ij} = \frac{X_{ij} - \min\left\{X_{ij}, i = 1, 2, .., m\right\}}{\max\left\{X_{ij}, i = 1, 2, .., m\right\} - \min\left\{X_{ij}, i = 1, 2, .., m\right\}}, \quad for \;\; j = 1, 2, ..., n \tag{19}$$

Where X_{ij} is the *j*th response of *i*th trial, and Z_{ij} is the normalized value of S/N ratios.

Step 5) Calculate the responses' weights using the FBWM method. The weights of responses are considered in the TOPSIS. In this step, the best and the worst criteria are determined by the experts based on their policy. Also, policy makers determine a preference linguistic terms of the best criteria over all criteria and all criteria over the worst criterion. After obtaining weights using FBWM, the consistency index shows whether obtained weights have high consistency or not. It should be noted that the values close to zero are desirable for consistency ratio.

Step 6) In this step the score of all alternatives are calculated using TOPSIS method. In fact, this step is to find the score of alternatives. It is obvious that the alternative with the highest score is the optimal solution. The proposed approach is also shown in Figure (1).

4. An application in Power Industry

According to Iran's power industry annual statistics, in 2015, Iran constructed 11 new power plants and the nominal power capacity of Iran reached 74103 Megawatt which shows 1.3% growth compared with the last years (http://amar.tavanir.org.ir). In Iran, electricity demand is mostly based on fossil fuels and the 93% of installed capacity of power plant in Iran is dedicated to gas, combined cycle and steam power plants. To produce the electricity in Iran, about 58424 million cubic meters of gas, 6083 million liters of gasoil and 6946 million liters of oil fuel have been burned in 2015 (http://amar.tavanir.org.ir). It seems that in last decade the criteria of accessibility to the energy and capital costs are widely considered as important sub-indicators. Also, environment, fossil resource constraints and socio-political issues have been considered less important. Iran in terms of different sources of energy is one of the richest countries in the world. It has extensive oil and gas fossil resources in addition to a high renewable energy potential such as wind, geothermal, solar and etc.

In Iran, the existence of suitable sun shining in most areas and in most seasons, existence of ups and downs on the river's route, having high potential wind areas and geothermal energy production capabilities have provided a suitable opportunity to expansion and use of new and clean energies. By considering tangible engineering capabilities in constructing hydroelectric power plants, the utilization of hydroelectricity has become a priority in the construction of new power plants. Meanwhile, the use of wind and geothermal energy as well as thermal energy from solar energy is almost economic. However, solar and photovoltaic power plants will not be economical for the next few years, but the development of researches and technology for their construction is strongly important due to the enormous potential of solar energy in Iran. In Iran, 7% of nominal electricity capacity is generated from renewable sources of hydro, wind, solar and nuclear electricity which is equal to 12910 MW, but according to the Ministry of Energy, it is predicted that on the horizon of 2020, renewable energy generation capacity will increase up to 5000 MW (http://amar.tavanir.org.ir).

There are some potential provinces for developing of new power plants in Iran. Among them, Gilan province has always been the first opt of authorities. Gilan province has some advantages such as existence of about 50 permanent rivers, locating in the boundaries of only two different north and south air streams of Alborz Mountain range and high intensity sun shining in the southern areas of province near 7 month of year. Therefore, investors tend to invest on developing power generation units especially renewable ones. At the moment, six power plants, three fossil fuels and three renewable energy plants are producing a total of 2816 MW of electricity in Gilan (http://amar.tavanir.org.ir). According to the country development plan for the Gilan province, 700 to 1000 MW of electricity power should be added to current capacity of supplying the province and in the case of surplus, electricity will be transferred to the neighboring provinces. Policy makers tend to use five types of gas, wind, hydroelectric, combined cycle and steam power plants to produce this volume of energy. Table (3) shows five alternatives and their production levels. According to the Table (3) for each power plant three levels (Small, Medium and Large) have been assigned.

---------------------- [Table 3 about here] ----------------------

4.1. Evaluating criteria

Establishing proper criteria plays an important role in reflecting the stakeholder's preferences and the potential to rank alternatives. . In this section, four main categories of, environmental, economic, social and technical indicators are considered to evaluate alternatives. Moreover sub-indicators associated to categories based on the availability of data specific to the region and considering major stakeholder's perspective are identified. In the other words, among several evaluation criteria used in the literature, policy makers opted some of them which are the interest of all major stakeholders, however due to the data limitation just six of them have been employed. Data are provided using (http://amar.tavanir.org.ir), (http://isn.moe.gov.ir/getattachment) and (https://www.eia.gov). In this study, six sub-indicators of power generation, capital costs, operation and maintenance (O&M) costs, job, greenhouse gas emission and prime cost of electricity are considered for selecting the best combination of power plants. Table (4) presents four indicators, six sub-indicators, scales and the values of sub-indicators for each power plant It should be noted that, sub-indicators have different scales, however by using the Taguchi method they will be converted to a common value. Moreover, in normalizing step criteria will be scale less. Sub-indicators definitions are as follow:

Environmental indicator

Greenhouse emission: Greenhouse gases consist of NO_X, CO_2, SO_2, SO_3, CO and CH which contributes to greenhouse effect and global warming by absorbing infrared radiations. Greenhouse effects on environment and global warming are very important. So, greenhouse emission is considered as a critical criterion in this research. Different fossil power plants respect to their size and types of the consumption fuel have different greenhouse gases emission and renewable power plants release no greenhouse gases to the environment. Although studies have shown renewable energy such as wind power plants still emit GHG to the environment, but due to the low and negligible amount of their release, it is not considered in the study evaluations. The amount of greenhouse releases to the atmosphere per KWH for each fossil power plant is presented in Table (4).

Economic indicators

Capital costs: Capital costs include all the costs of purchasing land, constructing buildings and the costs of turbines purchasing and installation. The capital costs depend on the capacity and type of power plant, but it is usually higher in renewable rather than fossil power plants.

Operation and Maintenance costs: Costs of energy production operations, manpower costs, fixing and maintenance costs of facilities are form the operation and maintenance (O&M) costs. Due to the high cost of fossil fuels, the O&M costs of fossil units are greater than renewable power plants.

Prime price: Prime price is the proxy of final price of power generation. Amount of power generation, capital costs and maintenance costs are influencing the prime price. Generally, with the increase in power generation, prime price get reduced, since some fixed price can be compensate by generating more electricity. The values of prime price in Rials per KW electricity for different power plants are presented in Table (4).

Social indicator

Job: The manpower required to set up and operate the power plants is called the amount of job created. In developing countries, creating jobs also has impact on social acceptability. Obviously, larger power plants create more jobs than smaller ones. Created jobs are associated to the all processes of maintaining and operating power plants. The amount of jobs created per 1 Gigabyte hour for different power plants are presented in Table (4).

Technical indicator

Power generation: The index of power generating capacity measures the average amount of electricity generated per year. It happens rarely that a power plant generates the power in full capacity. In fossil power plants, fixing and maintenance time and, in the case of renewable plants, climatic conditions are the most important factors affecting power generation process. Power generation is the multiplying of efficiency to the possible time to generate electricity in a year and it is expresses in MWH. The efficiency values for each power plant are presented in Table (4).

---------------------- [Table 4 about here] ----------------------

In summary, in this paper, six criteria of power generation, greenhouse emission, prime price, capital costs, operation and maintenance costs and job considered as responses. Then, by using experts' preferences in FBWM model, the weights of criteria are determined. Finally, the effect on alternatives on the response sub-indicators will be measured using S/N ratio and the scores obtained from implementing FBWM-TOPSIS will determine optimal combination of power plants.

5. Results and Discussion

In this section, the proposed approach is implemented for finding the best combination of power plants' alternatives in Gilan province. The steps are as follows:

Step1: After specifying feasible power plants and their level, an appropriate orthogonal array will be selected. In this paper, five types of power plant are considered as factors. Each power plant has three levels which are shown in Table (3). Calculating the degree of freedom shows that at least 11 experiments are needed to observe the factors effect on responses. Eventually, an orthogonal L_{27} array is calculated. It means that 27 different combinations are required to observe each combination effects on responses. Table (5) represents 27 combinations of designed array.

--------------------- [Table 5 about here] ---------------------

Step 2: According to the criteria characteristics, in this step, S/N ratios of 27 designed combinations will be calculated. Responses of power generation and job are "larger the better" characteristics and greenhouse gas emission, prime price, capital costs and O&M costs are the "smaller the better" characteristics. S/N ratios will be calculated for larger the better and smaller the better characteristics using equations (2) and (3), respectively. The results of calculated S/N ratios are shown in Table (5). As presented in the Table (5), responses which satisfy characteristic feature more have higher S/N ratio values. For example, in the first row of Table (5) which related to $A_1B_1C_1D_1E_1$ combination, capital costs, O&M costs and greenhouse gas emission responses which have "smaller the better" characteristic have higher S/N ratio values rather than other combinations. Since $A_1B_1C_1D_1E_1$ need less capital costs, O&M costs and/or produces less greenhouse gases. However, in prime price index which also has "smaller the better" characteristic, $A_1B_1C_1D_1E_1$ has poor performance in term of S/N ratio. In responses with "larger the better" characteristics such as job and power generation, $A_1B_1C_1D_1E_1$ obtain the minimum S/N ratios since make low job and/or generate less electricity power among all combinations. Also, the calculated S/N ratios are the inputs of next step. Training of BPNN will be done using calculated S/N ratios.

Step 3: After calculating S/N ratios of designed orthogonal array, calculated S/N ratios are applied to train BPNN. After training NN, In order to obtain more consistent and real results, all of S/N ratios are estimated. So, we re-evaluated S/N ratios for all combination including designed orthogonal array combinations. Then, estimated data are applied in evaluations. For sake of simplicity, the designed BPNN is run for each response, separately. In designed BPNN, number of neurons in input layer is adjusted to number of factors, five, and number of neuron in output layer is set to each responses. Also, number of hidden layers and neurons in hidden layers are obtained by trial and error. Actually, to prevent of too much trial and error setting for each index and to achieve best evaluation, different structures are designed to estimate prime price S/N ratios. Since prime price S/N ratios are too close to each other, hence, they are very sensitive to the NN results. Therefore, we tried to design the best structure of NN for estimating the prime price data and applied designed structure for estimating of other results. Properties of designed BPNN are presented in Table (6). Estimated S/N ratios are provided in Table (7). As can be seen, MSE values are very low and acceptable which means that estimated values are almost accurate.

--------------------- [Tables 6 and 7 about here] ---------------------

Step 4: In this step, estimated S/N ratios in later step are normalized using (19). Normalized data are scale less and presented in Table (8). Equation (19) assigns 1 to highest S/N ratio value and 0 to lowest one for each index. As mentioned before, estimated values are applied in evaluation. So, as shown in the Table (8), for example, although $A_1B_1C_1D_1E_1$ indicates the highest S/N ratio in capital cost sub-indicator of Table (4), but due to the normalizing estimated S/N ratios, does not take the value of 1 in Table (8). Also, since in this step, the data are normalized, hence, it is not necessary to normalize data in second step of the TOPSIS method.

---------------------- [Table 8 about here] ----------------------

Step 5: In this step, the weights of criteria are determined. This step is including five sub-steps that have explained in the methodology. According to the FBWM steps, first, the best and the worst criteria should be determined. In order to determine the best and the worst criteria, an expert team of power plant industry gathered and incorporated team preferences in decision making. According to the expert team opinions, power generation and job criteria are considered as the best and worst criteria, respectively. Then, linguistic preference of best criterion over all criteria and preference of all criteria over worst criterion are determined using fuzzy numbers. The linguistic terms for fuzzy preferences of the best criterion over all the criteria and all criteria over worst criterion have been shown in Table (9). It should be noted that linguistic terms are assigned based on expert team opinion, too. Table (10) presents the final weights of each response. Power generation has the highest weight among responses and then, capital costs and greenhouse emissions have second and third importance, respectively. The consistency ratio is 0.0558 which is very close to zero. Therefore, it can be concluded that the FBWM model presents high comparison consistency.

---------------------- [Tables 9 and 10 about here] ----------------------

Step 6: In this step, TOPSIS method is applied to identify and obtain the best combination of power plants. In fact, by using the obtained weights from FBWM and estimated data, TOPSIS method measures the scores of all alternatives. Higher score represent the optimal combination among all combinations. A summary of TOPSIS model results are shown in Table (11). Based on the scores calculated, the combination of $A_1B_3C_1D_2E_1$ is the optimal combination. The score of $A_1B_3C_1D_2E_1$ is 0.5983. This combination is related to 80 MW gas, 200 MW steam, 300 MW combined cycle, 130 MW wind and 200 MW hydroelectric power plants.

---------------------- [Tables 11 about here] ----------------------

The optimal solution is consistent with reality of Gilan. Gas power plants due to the fast operating capability are considered as subsidiary power generation alternatives. But due to short life and low efficiency defects, they cannot be considered as strategic alternatives. Regarding to the steam power plants features such as less greenhouse gas emission, longer life and higher efficiency than gas power plants, they are suitable for Gilan province. In the case of combined cycle power plants, larger power plants require higher investment, generate higher greenhouse gases and are not suitable for the geographic conditions of the province with dispersed population. But the flexibility of the combined cycle power plants in extensibility has made it possible to take steps to develop these types of power plants if needed. Creating large dams for power generation requires special areas and consideration for under-watering valuable land in the area. In addition to that, the time period of constructing large dames is not consistent with Sixth Developing Plan; so smaller type of hydroelectric power plants is desirable. And eventually, the best option for power generation is wind power, which the government is serious about increasing the use of this type of power plant. But this is possible by reducing the cost of building and installing wind turbines and connecting with the world's wind industry.

In proposed approach and in the BWM process, the weights of criteria are obtained by incorporating pairwise comparison and incorporating fuzziness of the decision making process. By taking into the account of the obtained weights in TOPSIS method the optimal solution of this paper is meaningful and reliable. In fact, the optimal solution $A_1B_3C_1D_2E_1$ has closest distance from ideal solution and farthest distance from negative ideal solution. We believe that the precision of the proposed decision-making technique is increased by including decision maker’s preferences and data simultaneously.

5.1. Sensitivity analysis

In this section a sensitivity analysis is performed in two scenarios. In the first scenario, the linguistic preferences of policy makers have been changed to observe the impact of criteria weights on decision-making. Moreover in the second scenario, SAW (Simple Additive Weighting) method is used instead of TOPSIS to observe the impact of using different MCDM methods on final rankings. In the following, the results of applying each scenario has been discussed in summary.

In the first scenario, the preferences of policy makers have been changed. Hence, greenhouse gas emission and job sub-indicators considered as the best and the worst criteria respectively. Also new linguistic preference of best criterion over all criteria and preference of all criteria over worst criterion are determined using fuzzy numbers which are presented in the Table (12).

---------------------- [Tables 12 about here] ----------------------

At last, new obtained weights are incorporated into the TOPSIS method to observe the impact the weights in decision making process. According to the first scenario results, $A_1B_2C_1D_2E_2$ with the score of 0.6983 is ranked the first followed by $A_1B_1C_1D_3E_2$ with the score of 0.6941. This combination relates to the 80 MW gas, 160 MW steam, 300 MW combined cycle, 130 MW wind and 240 MW hydroelectric power plants respectively. With the increase in the weight of greenhouse gas emission criteria, smaller size of fossil power plants and larger or medium size of renewable power plants are desirable to establish.

In the second scenario, scores have just been calculated by using FBWM-SAW method. According to the second scenario, combination of $A_1B_2C_1D_2E_2$ with the score of 0.71 is ranked first. In other words, in the case that we consider subjectivity of policy makers in alternatives evaluations more, 80 MW gas, 160 MW steam, 300 MW combined cycle, 130 MW wind and 240 MW hydroelectric power plants are desirable.

6. Recommendations for policy remarks

It is clear that three sub-indicators of power generation, job and prime cost have large value for the big power plants. So, these sub-indicators have positive impacts on selecting the large size power plants in the optimal combination. In contrast, the other three sub-indicators capital costs, O&M costs and greenhouse emission encourage the smaller power plants to be considered as an optimal one. For example, in optimal combination, the high power generation of combined cycle in larger units is neutralized with the greenhouse gas emission and high capital costs. In fact, smaller units of combined cycle are closer to the ideal solution and they are suitable alternatives. So the smaller unit of combined cycle has been preferred. In the case of renewable energy, since greenhouse gas emissions criterion has less important in the decision making process, power generation and capital costs criteria have the most effect in decision making process.

The results show that the combination of $A_1B_2C_3D_2B_2$ has the lowest score among all combinations. This combination is related to 80 MW gas, 160 MW steam, 380 MW combined cycle, 130 MW wind and 240 MW hydroelectric power plants. As mentioned before, larger unit of combined cycle is not preferable. Also, due to the advantages of larger wind power plants in generating low price power and creating job, smaller size of wind power plants are not suitable for constructing in Gilan. Since the capacity levels of gas power plants are close to each other (80, 100 and 120 MW), so, the type of gas power plant is not more important in selection the best combination.

The last step of the proposed approach can be recalculated using other MCDM techniques such data envelopment analysis (Emrouznejad and Yang 2018), principal component analysis and so on. However, proposed hybrid FWBM-TOPSIS method by taking into account of expert opinion in weighting enable policy makers to make a precise decision. Also, in this flexible method, we can change the input information and investigate the system responses. For instance, we can test other capacity levels of power plants or change the important factors and study the optimal combination.

7. Summary and Conclusion

Considering the increasing energy consumption in Iran, it is important to select an optimal combination of power plants for qualitative and quantitative development of electricity supply. Due to the existence of limitation and environmental pollution of fossil fuels, authorities tend to construct and develop renewable power plants alongside the existing power plants. However, some of the weaknesses of renewable power plants such as high capital costs, and low security in the generation of sustainable energy, have been caused that the authorities do not have a strategic view at these plants and consider a combination of fossil and renewable power plants for development. In this paper, an integrated framework of the multi-response Taguchi, NN and the hybrid FBWM-TOPSIS methods was used to select the optimal combination of power plants in Gilan province. This study considered three types of fossil gas, combined cycle and steam power plants along with two types of conventional renewable wind and hydroelectric power plants. Also, six sub-indicators power generation, job, prime price, capital costs, greenhouse gas emissions and O&M costs were considered for choosing the best combination of power plants in Gilan. The results indicate the combination of $A_1B_3C_1D_2E_1$ with the score of 0.5983 as the optimal combination. This combination is related to 80 MW gas, 200 MW steam, 300 MW combined cycle, 130 MW wind and 200 MW hydroelectric power plants. The novelty of this study is integration of these individual methods to find an optimal combination of power plants. The multi response Taguchi, which was originally introduced for off-line quality control improvement, has not applied for selecting the best combination of power plants. For future studies, final phase of the proposed approach can be implemented by other MCDM techniques such as PCA, VIKOR, DEA and etc. Also, due to the existence uncertainty in NN results, our framework can be extended by using some uncertain approaches such as fuzzy or stochastic fields.

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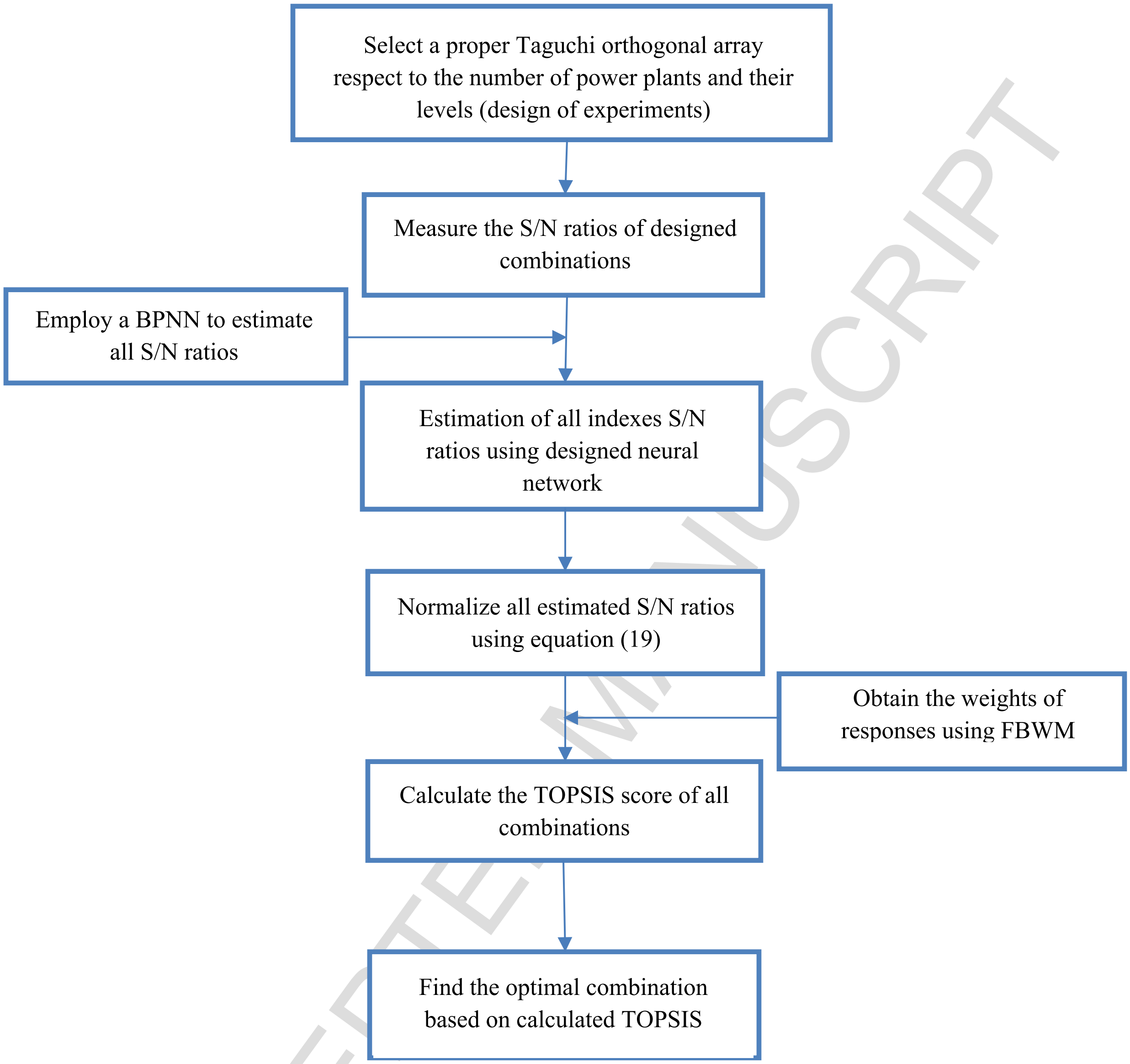

Figure 1. Proposed framework to select optimal combination

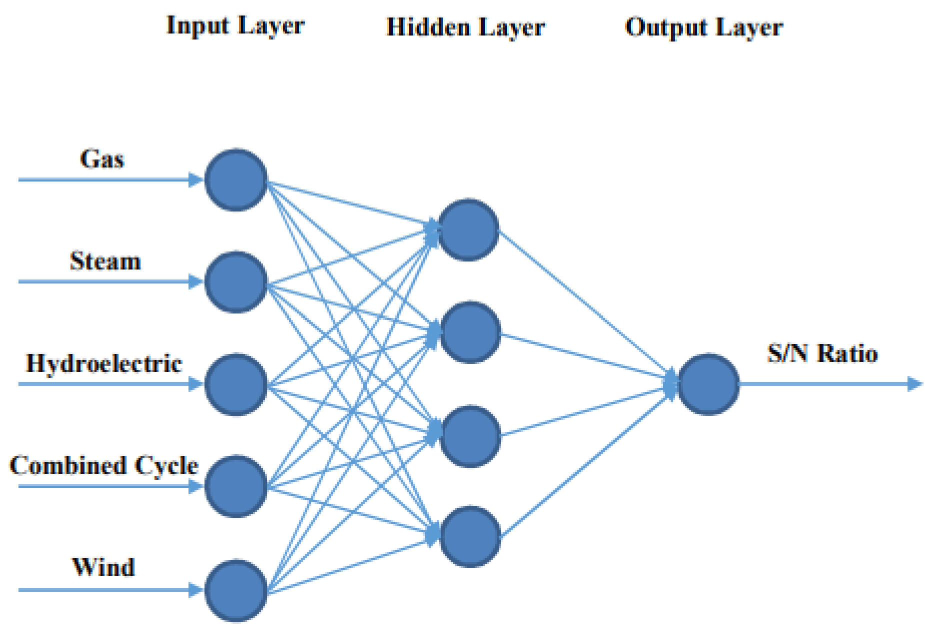

Figure 2. BPNN with one hidden layer

Table 1: Summary of the literature review of power plants selection

Author	Methods	Environmental Factors	Economic Factors	Social Factors	Technical Factors	Power Plants Type
Lee and Chang (2018)	Weighted Sum Method, TOPSIS VIKOR ELECTRE	Land use GHG emission	Investment cost O&M Cost Electric cost	Social acceptance Job	Efficiency Capacity factor Technical maturity	Hydroelectric Solar PV Wind Biomass Geothermal
Wu et al. (2018)	Cumulative Prospect theory Fuzzy set theory	Land use Impact on ecosystem	Capital cost O&M Cost Electric cost Payback period Potential market	Social acceptance Job Social benefit	maturity reliability efficiency resource reserve	hydroelectric Solar PV Wind Biomass Solar thermal power
Katal and Fazelpour (2018)	VIKOR	Land use CO2 Emission	Cost of generation		Efficiency Power generation	Gas Combined heat and power Hydroelectric wind
Amer and Daim (2011)	AHP	Land use Stress on eco-system Emission	Capital cost O & M cost Electricity cost R&D Cost	Social acceptance Job Social benefit	Maturity Reliability Efficiency Availability Resource available	Wind Solar PV Solar thermal power Biomass
Çolak and Kaya (2017)	Fuzzy AHP Fuzzy TOPSIS	Land use GHG emission Environmental damage Need of waste disposal Other environmental effects	Service period Payback period Availability of fund Contribution to economy Affordability levelised energy cost		Maturity Reliability Efficiency Production capacity Installed capacity	hydroelectric Solar Wind Biomass Geothermal Hydrogen Wave
Kobak and Dagdeviren (2014)	ANP	Land use Ecological damages Global effects	Economic value O&M cost Implementation cost Investment cost	Human well-being Job creation Social resistance	Immaturity Technical feasibility Reliability Security	Wind Biomass Geothermal Solar Hydroelectric
Štreimikienė, et al. (2016)	AHP ARAS	Contribution to the energy balance Effects on climate change Treatment of waste compliance with condition	Economic efficiency Production cost Technology completiveness Value of technology	Influence on social welfare Influence on development Public acceptance	Reliability Technology's innovativeness Technology's rated capacity	Nuclear Hydroelectric Wind Geothermal Biomass Gas
Zhang et al. (2015)	Fuzzy measure Shapely value	Land use CO2 emissions	Investment cost Economic sustainability	Job	Technology readiness level Safety	Solar PV Wind Biomass Nuclear
Chatzimouratidis and Pilvaci (2012)	PROMETHEE	Land use GHG emission Radioactivity Ecosystem equilibrum Particulate matter		Job Social acceptance	Reserves to production ratio	Hydroelectric Wind Geothermal Biomass Gas Oil Coal Combined cycle Nuclear
This study	Multi response Taguchi neural network Fuzzy BWM TOPSIS	GHG Emission	Capital cost O&M Cost Prime price	Job	Power generation	Gas Steam Combined cycle Wind Hydroelectric

Table 2. Transformation rules of linguistic variables of decision-makers

Linguistic Terms	Abbreviation	Membership function
Equally importance	(EI)	(1,1,1)
Weakly important	(WI)	(2/3,1,3/2)
Fairly Important	(FI)	(3/2,2,5/2)
Very important	(VI)	(5/2,3,7/2)
Absolutely important	(AI)	(7/2,4,9/2)

Table 3. Considered parameters and levels

Power plants types	**Level (MW)**		
	1	***2***	***3***
Gas, A	80	100	120
Steam, B	120	160	200
Combined cycle, C	300	340	380
Wind, D	100	130	160
Hydroelectric, E	200	240	280

Table 4. Indicators, sub-indicators and their values for different power plants

Indicator	Sub-indicator	Scale	Power plant type				
			Gas	Steam	Combined Cycle	Wind	Hydroelectric
Environmental	Greenhouse emission	gr/KWH	852.403	814.821	472.322	0	0
Economical	Capital costs	U.S. Dollar/KWH	450	1040	800	2020	2150
	O&M costs	U.S. Dollar/KW	25	40	30	50	55
	Prime price	IRR*/KW	348	357	321	467	384
Social	Jobs	Man/GBH	0.108	0.114	0.103	0.314	0.251
Technical	Power generated	Yearly Efficiency	0.166**	0.197	0.382	0.321	0.215

***Iranian Rials**

****Power generating for 80 MW gas power plant type= 80*24*365*0.166=116332.8 MWH**

Table 5. S/N ratios for L27 orthogonal array

L27 Taguchi orthogonal array					S/N ratios					
Gas	Steam	Combined cycle	Wind	Hydro electric	Capital Costs	O&M	Job	Prime Price	Power generation	Greenhouse gas emission
1	1	1	1	1	-168.9286	-138.776	50.15712	-13.5272	124.6294	-117.4486
1	1	1	1	2	-169.4850	-139.237	50.65509	-13.5192	125.0051	-117.4486
1	1	1	1	3	-170.0078	-139.674	51.12605	-13.5156	125.3653	-117.4486
1	2	2	2	1	-170.0868	-139.948	51.36403	-13.4408	127.1298	-118.7657
1	2	2	2	2	-170.5756	-140.352	51.79899	-13.432	127.4131	-118.7657
1	2	2	2	3	-171.0383	-140.738	52.21320	-13.428	127.6874	-118.7657
1	3	3	3	1	-171.1085	-140.981	52.42353	-13.4073	128.1637	-119.9091
1	3	3	3	2	-171.5444	-141.341	52.80963	-13.3981	129.4669	-119.9091
1	3	3	3	3	-171.9595	-141.686	53.17930	-13.3939	129.6842	-119.9091
2	1	2	3	1	-170.4268	-140.163	51.86572	-13.4426	127.2979	-117.8706
2	1	2	3	2	-170.8973	-140.558	52.27684	-13.4338	127.5759	-117.8706
2	1	2	3	3	-171.3437	-140.935	52.66937	-13.4298	127.8452	-117.8706
2	2	3	1	1	-169.9294	-140.001	51.12605	-13.4785	127.4251	-119.1296
2	2	3	1	2	-170.4269	-140.402	51.57278	-13.4701	127.6991	-119.1296
2	2	3	1	3	-170.8974	-140.786	51.99766	-13.4662	127.9646	-119.1296
2	3	1	2	1	-170.0176	-139.896	51.29332	-13.3904	126.9921	-118.4549
2	3	1	2	2	-170.5102	-140.302	51.73175	-13.3811	127.2799	-118.4549
2	3	1	2	3	-170.9763	-140.690	52.14910	-13.3768	127.5584	-118.4549
3	1	3	2	1	-170.2755	-140.214	51.6185	-13.4544	127.5876	-119.2692
3	1	3	2	2	-170.7541	-140.606	52.0412	-13.4458	127.8566	-119.2692
3	1	3	2	3	-171.2077	-140.981	52.44428	-13.4418	128.1175	-119.2692
3	2	1	3	1	-170.3603	-140.112	51.79899	-13.4372	127.1629	-118.6058
3	2	1	3	2	-170.8343	-140.508	52.21320	-13.4283	127.4451	-118.6058
3	2	1	3	3	-171.2838	-140.888	52.60856	-13.4243	127.7185	-118.6058
3	3	2	1	1	-169.8590	-139.948	51.07766	-13.4654	127.292	-119.7691
3	3	2	1	2	-170.3604	-140.352	51.52683	-13.4569	127.5702	-119.7691
3	3	2	1	3	-170.8344	-140.738	51.95390	-13.453	127.8397	-119.7691

Table 6. Properties of designed BPNN

Responses	Structure	MSE (Training)	MSE (Test)
Prime price	5-4-1	2.87E-05	3.84E-06
O&M		6.95E-07	7.10E-04
Power generation		2.96E-05	6.83E-05
Greenhouse gas emission		9.85E-09	3.87E-10
Capital costs		3.67E-06	4.21E-07
Job		1.50E-02	5.9E-04

Table 7. Estimated S/N ratios

L27 Taguchi orthogonal array					Estimated S/N ratios					
Gas	Steam	Combined cycle	Wind	Hydroelectric	Capital Costs	O&M	Job	Prime Price	Power generation	Greenhouse gas emission
1	1	1	1	1	-168.928	-138.776	50.1617	-13.5248	124.6295	-117.4486
1	1	1	1	2	-169.485	-139.237	50.6568	-13.5208	125.0053	-117.4486
1	1	1	1	3	-170.007	-139.727	51.6416	-13.5138	125.3653	-117.4486
1	2	2	2	1	-170.087	-139.949	51.3400	-13.4401	127.1133	-118.7657
1	2	2	2	2	-170.577	-140.352	51.7744	-13.4276	127.4104	-118.7657
1	2	2	2	3	-171.038	-140.738	52.2398	-13.4250	127.6893	-118.7657
1	3	3	3	1	-171.108	-140.980	52.4056	-13.4073	128.1637	-119.9091
1	3	3	3	2	-171.545	-141.34	52.8570	-13.3973	129.4642	-119.9091
1	3	3	3	3	-171.960	-141.686	53.0636	-13.3926	129.6840	-119.9091
2	1	2	3	1	-170.422	-140.163	51.7472	-13.4410	127.2925	-117.8706
2	1	2	3	2	-170.898	-140.558	52.2387	-13.4385	127.5677	-117.8706
2	1	2	3	3	-171.344	-140.934	52.6686	-13.4284	127.8461	-117.8706
2	2	3	1	1	-169.930	-140.000	51.1308	-13.4801	127.4260	-119.1296
2	2	3	1	2	-170.426	-140.402	51.6037	-13.4744	127.6998	-119.1296
2	2	3	1	3	-170.896	-140.787	52.0663	-13.4687	127.9636	-119.1296
2	3	1	2	1	-170.018	-139.895	51.2735	-13.3929	126.9931	-118.4549
2	3	1	2	2	-170.514	-140.302	51.6897	-13.3828	127.2835	-118.4549
2	3	1	2	3	-170.977	-140.690	52.1622	-13.3783	127.5557	-118.4549
3	1	3	2	1	-170.277	-140.215	51.7046	-13.4520	127.5867	-119.2692
3	1	3	2	2	-170.755	-140.608	52.1482	-13.4463	127.8561	-119.2692
3	1	3	2	3	-171.208	-140.981	52.4493	-13.4396	128.1171	-119.2692
3	2	1	3	1	-170.362	-140.113	51.6697	-13.4356	127.1783	-118.6057
3	2	1	3	2	-170.840	-140.510	52.1620	-13.4308	127.4432	-118.6057
3	2	1	3	3	-171.284	-140.887	52.6117	-13.4234	127.7186	-118.6057
3	3	2	1	1	-169.859	-139.948	51.0562	-13.4523	127.2864	-119.7694
3	3	2	1	2	-170.362	-140.352	51.5219	-13.4423	127.5693	-119.7694
3	3	2	1	3	-170.835	-140.738	52.0029	-13.4404	127.8416	-119.7694

Table 8. Normalized S/N ratios

L27 Taguchi orthogonal array					Normalized S/N ratios					
Gas	Steam	Combined cycle	Wind	Hydroelectric	Capital Costs	O&M	Job	Prime Price	Power generation	Greenhouse gas emission
1	1	1	1	1	0.9999970	1	0	0.003975	0.000308	1
1	1	1	1	2	0.8166100	0.844116	0.170613	0.030642	0.074354	1
1	1	1	1	3	0.6441113	0.678063	0.509976	0.077837	0.145578	1
1	2	2	2	1	0.6178111	0.602990	0.406039	0.575031	0.491408	0.4647053
1	2	2	2	2	0.4561226	0.466495	0.555741	0.658972	0.550181	0.4647054
1	2	2	2	3	0.3039193	0.335810	0.716141	0.676745	0.605348	0.4647054
1	3	3	3	1	0.2809600	0.253763	0.773255	0.795772	0.69922	1.22597E-07
1	3	3	3	2	0.1366917	0.131882	0.92882	0.863257	0.956516	1.22598E-07
1	3	3	3	3	0	0.617811	0.60299	0.406039	0.575031	0.4914082
2	1	2	3	1	0.5071772	0.530531	0.546373	0.568985	0.526856	0.8284850
2	1	2	3	2	0.3501959	0.396873	0.715738	0.585874	0.581297	0.8284850
2	1	2	3	3	0.2031446	0.269386	0.863899	0.653708	0.636383	0.8284850
2	2	3	1	1	0.669700	0.585693	0.33395	0.304867	0.55326	0.3168158
2	2	3	1	2	0.5061004	0.449568	0.496915	0.343718	0.607436	0.3168158
2	2	3	1	3	0.3508661	0.319407	0.65635	0.382007	0.659616	0.3168158
2	3	1	2	1	0.6406221	0.621138	0.383129	0.893237	0.467625	0.5910048
2	3	1	2	2	0.4769068	0.483479	0.526549	0.961217	0.525076	0.5910048
2	3	1	2	3	0.3242819	0.352011	0.689369	0.991929	0.578936	0.5910048
3	1	3	2	1	0.5551361	0.512920	0.531688	0.494977	0.585055	0.2600670
3	1	3	2	2	0.3973192	0.379772	0.68456	0.532958	0.63836	0.2600670
3	1	3	2	3	0.2479967	0.253412	0.788312	0.578097	0.689989	0.2600670
3	2	1	3	1	0.5271229	0.547574	0.51965	0.605085	0.504258	0.5297139
3	2	1	3	2	0.3695255	0.413002	0.689314	0.637567	0.556663	0.5297139
3	2	1	3	3	0.2228717	0.285383	0.844279	0.687334	0.611159	0.5297140
3	3	2	1	1	0.6929814	0.603243	0.308241	0.49271	0.525644	0.0568003
3	3	2	1	2	0.5270097	0.466596	0.468735	0.560346	0.581608	0.0568003
3	3	2	1	3	0.3710931	0.335990	0.634496	0.572769	0.635488	0.0568003

Table 9. The linguistic terms for experts team fuzzy preferences of the best criterion over all the criteria and all criteria over worst criterion

Criteria	Prime price	O&M cost	Power generation	Greenhouse emission	Capital costs	Job
Best criterion (Power generation)	FI	VI	EI	WI	WI	AI
Worst criterion (Job)	WI	WI	AI	FI	VI	EI

Table 10. The weights of responses

Criteria	Weight
Power generation	0.2896
Capital cost	0.2079
O&M cost	0.0882
Prime price	0.1331
Greenhouse gas emission	0.1993
Job	0.0818

Table 11. TOPSIS scores of some alternatives

Alternatives Number	Combination					Score	Alternatives Number	Combination					Score
1	1	1	1	1	1	0.4780	**127**	2	2	3	1	1	0.5029
3	1	1	1	1	3	0.4673	**130**	2	2	3	2	1	0.4596
5	1	1	1	2	2	0.5135	**133**	2	2	3	3	1	0.4478
12	1	1	2	1	3	0.4725	**137**	2	3	1	1	2	0.5680
15	1	1	2	2	3	0.4862	**142**	2	3	1	3	1	0.4652
18	1	1	2	3	3	0.5766	**146**	2	3	2	1	2	0.4308
22	1	1	3	2	1	0.4715	**150**	2	3	2	2	3	0.5082
26	1	1	3	3	2	0.4498	**155**	2	3	3	1	2	0.4354
29	1	2	1	1	2	0.5000	**160**	2	3	3	3	1	0.4597
31	1	2	1	2	1	0.5384	**163**	3	1	1	1	1	0.4784
35	1	2	1	3	2	0.5818	**169**	3	1	1	3	1	0.5447
37	1	2	2	1	1	0.4868	**171**	3	1	1	3	3	0.5182
40	1	2	2	2	1	0.5221	**175**	3	1	2	2	1	0.5297
45	1	2	2	3	3	0.5102	**179**	3	1	2	3	2	0.5529
50	1	2	3	2	2	0.4226	**182**	3	1	3	1	2	0.5829
54	1	2	3	3	3	0.5158	**186**	3	1	3	2	3	0.4868
58	1	3	1	2	1	0.5983	**188**	3	1	3	3	2	0.4417
63	1	3	1	3	3	0.5233	**194**	3	2	1	2	2	0.5760
67	1	3	2	2	2	0.4684	**197**	3	2	1	3	2	0.5161
71	1	3	2	3	2	0.4871	**200**	3	2	2	1	2	0.5509
76	1	3	3	2	1	0.4716	**204**	3	2	2	2	3	0.4992
80	1	3	3	3	2	0.5263	**206**	3	2	2	3	1	0.4266
82	2	1	1	1	1	0.4778	**209**	3	2	3	1	2	0.5019
88	2	1	1	3	1	0.5447	**213**	3	2	3	2	3	0.5100
93	2	1	2	1	3	0.4734	**217**	3	3	1	1	1	0.5193
97	2	1	2	3	1	0.5822	**222**	3	3	1	2	3	0.5215
105	2	1	3	2	3	0.4592	**226**	3	3	2	1	1	0.4675
110	2	2	1	1	2	0.4930	**234**	3	3	2	3	3	0.5093
113	2	2	1	2	2	0.5814	**237**	3	3	3	1	3	0.4961
117	2	2	1	3	3	0.5446	**241**	3	3	3	3	1	0.4553
121	2	2	2	2	2	0.5061	**243**	3	3	3	3	3	0.5123

Table 12. The linguistic terms for experts team fuzzy preferences in sensitivity analysis

Criteria	Prime price	O&M cost	Power generation	Greenhouse emission	Capital costs	Job
Best criterion (Greenhouse emission)	FI	VI	WI	EI	FI	AI
Worst criterion (Job)	FI	WI	VI	AI	VI	EI