Engineered Science
DOI: https://dx.doi.org/10.30919/es882

A Novel TOPSIS Linear Programming Model Based on the Taguchi Method for Solving the Multi-Response Optimization Problems: A Case Study of a Fish Scale Scraping Machine

Anucha Sriburum, Narong Wichapa,* and Wanrop Khanthirat

Abstract

Multi-response optimization (MRO) is a statistical technique that can improve the performance of machines by considering multiple responses simultaneously. By optimizing machine parameters, manufacturers can increase productivity, reduce expenses, and improve product quality. There are many different methods for solving MRO problems, but the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) is one of the most used. Hence, this paper presents a novel TOPSIS linear programming model based on the Taguchi method for solving the MRO of a fish scale scraping machine in order to improve fish scaling removal efficiency while reducing fish damage. The experiments were initially designed using the Taguchi experimental design. The proposed TOPSIS model was then used to convert the MRO problem into a single objective optimization problem. Finally, the Taguchi method based on the results of the TOPSIS model was developed, and the optimal combination of parameters (speed = 50 rpm, time = 180 seconds, and capacity = 30 kg) was determined. Compared with the initial parameters, the fish damage decreases by 23.95%, and the fish scaling removal efficiency increases by 29.74%. In addition, it is believed that the TOPSIS linear programming model can be extended to solve other MRO problems.

Keywords: TOPSIS; Taguchi method; fish scale scraping machine; multi-response optimization problem; Java carp.
Received: 05 January 2023; Revised: 04 April 2023; Accepted: 05 May 2023.
Article type: Research article.

1. Introduction

Thailand has an abundance of natural freshwater food sources. There are approximately 25 major freshwater basins and 254 sub-basins. These freshwater sources include main rivers, tributary rivers, reservoirs, canals, creeks and marshes, as well as manmade water sources for use in agriculture and fisheries, totaling approximately 511,361 square kilometers. Most of the people who live near the water sources are engaged in agriculture and fishing at the same time. Some groups make a career in fishing as their main occupation and generate income for their families. According to the survey results for freshwater fish caught in 2020, there were 112,727.31 tons of catch, accounting for 96.47 percent of the total aquatic animals, with a total value of 6,754.98 million baht, representing 90.50 percent of the total aquatic animals' value. Carp were caught the most at 19,384.86 tons, accounting for 16.59 percent of the total aquatic animals with a value of 946.06 million baht, or 12.68 percent of the total aquatic animals. Tilapia followed, with a catch of 15,647.26 tons, accounting for 13.39 percent of the total aquatic animals with a value of 878.90 million baht, or 11.78 percent of the total aquatic animals' value. The third place went to white-tailed fish with a catch of 11,231.23 tons, accounting for 9.61 percent of the total aquatic animals valued at 477.28 million baht and representing 6.39 percent of the total aquatic animal value.[1,2] Kalasin Province has a large earthen dam, Lam Pao Dam, which serves as a reservoir for agriculture, fisheries and water supply, and is a famous tourist attraction for the province. Lam Pao Dam is a source of water that generates income for local farmers. Most of the population is engaged in agriculture, and fishing is the main occupation that generates income for the community. The occupation that generates high income for the community is the production of fish products such as dried fish, sour fish and fermented fish. For processing dried fish products and pickled

Department of Industrial Engineering, Faculty of Engineering and Industrial Technology, Kalasin University, Kalasin 46000, Thailand.
**Email:* narong.wi@ksu.ac.th (N. Wichapa)

fish, raw materials from carp and white fish from Lam Pao Dam are used. From the data survey, it was found that the demand for products such as dried fish and pickled fish was very high in both the domestic and international markets. However, the production process of processed fish is not enough to meet the needs of consumers. This is due to the production process of processed fish, both dried fish and pickled fish, in which there are steps that require slow production times, have a high labor cost and insufficient hygiene. In addition, entrepreneurs still lack the knowledge of tools to assist in production. In the process of processing dried fish and pickled fish, there will be the same main production steps: (1) prepare fresh fish bought from fishermen in the area; (2) remove fish scales by manual labor; (3) wash the fish; (4) remove the head and (5) ferment the fish. Finally, the fish will be further processed into dried fish or pickled fish. Based on interviews and gathering information from entrepreneurs in the case study area, Kalasin province, it was found that the fish scale removal process was the bottleneck for the dried fish and pickled production processes. It will take approximately 4 workers and 8 hours to complete this process. According to the data survey, the income from the distribution of processed fish products is quite high. In addition, market demand tends to increase annually. However, the capacity of each entrepreneur is insufficient to meet the rising customer demand. Due to the arduous and time-consuming nature of fish processing, a substantial amount of labor is required. Hence, the research team has developed a fish scale scraping machine to improve the processing of dried fish and pickled fish by increasing capacity, reducing labor costs and enhancing production convenience. From preliminary experiments on the proposed machine, the following significant flaws were discovered: low fish scale removal efficiency and high fish damage because the relevant parameters of the proposed machine were not properly configured or inappropriate. This is one of the Multi-Response Optimization (MRO) problems in which there are many factors involved and many responses that must be optimized simultaneously.

Multi-response optimization (MRO), sometimes referred to as multi-objective optimization or Pareto optimization, is the practice of simultaneously optimizing numerous objectives. It is utilized when there are competing objectives, such as cost reduction, quality enhancement, and cycle time reduction. There are numerous methods for addressing multi-objective optimization problems. However, the meta-heuristic algorithm is one that is widely used for solving the optimization problems with a large size (Np-hard problems).[3-9] The purpose of multi-response optimization is to identify the optimal input parameters that simultaneously optimize all of the objectives. This requires the creation of a Pareto front, a graph that illustrates the trade-off between the various objectives. The Pareto front represents the collection of optimal solutions for all objectives.[10] The MRO has a wide range of potential applications and industries, including the engineering and industrial sectors, the financial sector and the healthcare sector. When the numerous factors are taken into consideration during the decision-making process, it can assist companies in producing decisions that are better informed. Due to the intricacy of the MRO problem, this problem is difficult to solve because of the complexity of finding a single optimal solution that satisfies all objectives, but it can provide significant insight into the real-world difficulties that these solutions address. In MRO problems, Multi-Attribute Decision Making (MADM), one of the Multi-Criteria Decision Making (MCDM) methods, can be used to assist the decision maker in locating the optimal solution. The decision-maker must initially identify the criteria and assign weights to them based on their relative importance. The decision-maker is then able to evaluate the alternatives based on the criteria and rank them according to their total score. The final step is for the decision-maker to select the optimal option based on the rankings. MADM techniques such as Grey Relational Grade (GRG),[11,12] Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS),[13,14] Data Envelopment Analysis Ranking Approach (DEAR),[15,16] the Multimoora method[17] and Data Envelopment Analysis (DEA)[18,19] can be used to determine optimal parameters for MRO problems.

The Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), proposed by Hwang and Yoon,[20] is a relative evaluation method that employs a weighted linear combination of criteria to determine the best or most preferred alternative. It is based on the concept of the "ideal solution," which is the combination of criteria that meets the decision-objectives maker's most effectively. The main advantages of TOPSIS are as follows:[21-27] (1) This method considers all the criteria and alternatives, providing a holistic approach to decision-making; (2) The TOPSIS method is relatively easy to implement and understand. Its simplicity makes it a popular choice for decision-makers; (3) The method can be applied to a wide range of decision-making problems across industries, making it a versatile approach; (4) The TOPSIS method provides a clear ranking of alternatives, enabling decision-makers to make informed decisions by choosing the best alternative based on the given criteria, and the method is an objective approach to decision-making, as it involves a systematic and balanced evaluation of alternatives based on the given criteria; (5) its simplicity has helped it gain popularity. In addition, TOPSIS is one of the most prevalent MADM techniques for solving multi-response optimization problems. For example, Manivannan and Kumar[28] presented a TOPSIS-based multi-response optimization of micro-EDM process parameters on AISI 304 steel. A design of experiments (DOE) with five levels for each process parameter was utilized to perform the optimization. The results of this study provide useful information for optimizing the micro-EDM process parameters for AISI 304 steel. Sharma *et al*.[29] presented a multi-response optimization technique for friction stir welding (FSW) process parameters for dissimilar material joining of Al6101 to pure copper using the TOPSIS method based on standard deviation. The process parameter optimization resulted in enhanced mechanical properties, including increased ultimate tensile strength, yield strength and ductility. This indicates that the TOPSIS method based on standard deviation can be used effectively to optimize the process parameters in order to improve the mechanical properties. Singh *et al*.[30] presented a multi-response optimization process for producing micro-holes in CFRP composites utilizing the TOPSIS method. The results of the optimization process demonstrate that the optimal parameters produced micro-holes of higher quality and size than the factorial design parameters. Ananthakumar *et al*.[31] demonstrated the use of Response Surface Methodology (RSM) and TOPSIS to optimize multi-response characteristics in plasma arc cutting of Monel 400™. The optimization procedure yielded satisfactory results in terms of increased cutting speed, decreased surface roughness, kerf width and electrode wear.

The Taguchi method is a qualitative tool that effectively improves manufacturing processes. The objective of the Taguchi method is to determine the optimal parameters of the manufacturing process by designing an orthogonal array experimental plan and reducing the number of experiments to be sufficient for the specified conditions. The signal-to-noise ratio (S/N) can be used to determine optimal parameters, and it can be divided into 3 categories: the larger the better, the smaller the better, and the more targeted the better. In addition, due to the advantages of this method, it has been used in various fields.[32-34] There are several approaches[35-39] based on the combination of the Taguchi method and other MADM methods for solving multi-response optimization problems. However, TOPSIS and Taguchi methods are two commonly used methods for solving multi-response optimization problems. The primary benefit of the Taguchi method is its capacity to minimize product costs and optimize product performance. The design of experiments is used to identify and reduce the sources of variation in a product's manufacturing process. This assists in enhancing product quality and decreasing product costs. In addition, it assists in identifying the most influential factors that contribute to product performance. As it focuses on optimizing the process rather than the product, the Taguchi method also facilitates the efficient use of resources.[40-42] In addition, the primary advantage of TOPSIS is that it is a straightforward and simple decision-making technique that can be easily applied to a wide variety of decision-making problems. It is especially helpful when multiple criteria must be considered in making a decision. In addition, it provides a comprehensive method for comparing and assessing alternatives by considering the positive and negative aspects of each alternative. It is a systematic approach that does not require complex calculations or assumptions about the preferences of decision makers.[38,43-45]

In this study, both fish scale removal efficiency and fish damage were considered for determining the optimal parameters of speed, time, and capacity for the proposed machine. The two responses were assessed by entrepreneurs or decision-makers using five rating scales. Developing a suitable evaluation method for determining optimal parameters is one way to maximize the efficiency of the proposed machine. Besides, this is to increase the competitiveness and income of fish processing entrepreneurs through the application of engineering knowledge and innovation to the enhancement of production. The type of fish used for the dried fish and pickled fish is Java carp, as shown in Fig. 1.

Fig. 1 Raw materials for processing dried fish and pickled fish.

Based on the above reasons and the literature review in Section 2, the main contributions of this research are as follows:

1. In the context of TOPSIS, Euclidean distance is used to determine the similarity between each alternative and the ideal solution. Instead of measuring the Euclidean distance between two points, the proposed method would calculate the Manhattan distance. Based on the original TOPSIS method, we formulated a novel TOPSIS linear programming model to convert the two responses into a single output for each run. The TOPSIS linear programming model can be used to obtain reliable results and is easier-to-use in solving MRO problems because the computational steps are fewer than the traditional TOPSIS method.

2. Based on the CC_i scores, we used the Taguchi method to determine the optimal parameters of the proposed fish scale scraping machine for maximizing the efficiency of the proposed machine. This will be extremely valuable for studies in this field in nearly every nation, particularly in countries with a high number of freshwater fish producers.

The rest of this paper is as follows: The next section presents a literature review. Section 3 then introduces the proposed method for determining the optimal parameters of the fish scale scraping machine that is based on the concepts of the data envelopment analysis-Taguchi method. In Section 4, a case study is tested. Finally, Section 5 presents the conclusions.

2. The original TOPSIS

Hwang and Yoon were the first to propose the TOPSIS.[20] This method is based on the idea that the selected alternative (appropriate alternative) should be the closest to the positive ideal solution and the farthest from the negative ideal solution. The positive ideal solution maximizes the beneficial criteria while minimizing the adverse criteria, whereas the negative ideal solution maximizes the adverse criteria while minimizing the beneficial criteria. The steps involved in calculating the relative closeness to the ideal solution values based on the original TOPSIS are as follows.

Step 1: Generate decision matrix

This step entails the creation of a matrix format. Each row of this matrix corresponds to an alternative, while each column corresponds to an attribute. The decision matrix (P) can be expressed as follows:

$$P = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_m \end{array} \\ \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nm} \end{bmatrix} \end{array}. \quad (1)$$

Here, A_i (i = 1, 2,…, n) represents the candidate alternatives, C_j (j = 1,2,…, m) represents the criteria relating to alternative performance, and p_{ij} is the performance of candidate alternative i with respect to criterion j.

Step 2: Calculate the normalized decision matrix

The normalized decision matrix (Q matrix) can be represented as:

$$Q = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_m \end{array} \\ \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1m} \\ q_{21} & q_{22} & \cdots & q_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ q_{n1} & q_{n2} & \cdots & q_{nm} \end{bmatrix} \end{array}. \quad (2)$$

Here, q_{ij} represents the normalized performance of alternative i with respect to criterion j, $q_{ij} = \frac{p_{ij}}{\sqrt{\sum_{i=1}^{n} p_{ij}^2}}$.

Step 3: Calculate the weighted normalized decision matrix

The weighted normalized decision matrix can be defined as:

$$V = w_j q_{ij} \quad (3)$$

Here, $\sum_{j=1}^{m} w_j = 1$.

Step 4: Determine the ideal (best) and negative ideal (worst) solutions in this step.

The ideal and negative ideal solution can be expressed as:

(1) The ideal solution:

$$A^+ = \{(max\, v_{ij} / j \in J), (min\, v_{ij} / j \in J')\}, i = 1,2,\dots,n,$$
$$= \{v_1^+, v_2^+, \dots, v_n^+\}. \quad (4)$$

(2) The Anti-ideal solution:

$$A^- = \{(min\, v_{ij} / j \in J), (max\, v_{ij} / j \in J')\}, i = 1,2,\dots,n,$$
$$= \{v_1^-, v_2^-, \dots, v_n^-\}. \quad (5)$$

Here,

J = {j =1, 2,…, m}: Associated with the beneficial attributes,

J' = {j =1, 2,…, m}: Associated with the non-beneficial adverse attributes.

Step 5: Calculate the separation measures (distance from ideal solutions)

The separation of each alternative from the ideal solution is given by n dimensional Euclidean distance from the following equations:

$$S_i^+ = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^+)^2}, i = 1,2,\dots,n. \quad (6)$$

$$S_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^-)^2}, i = 1,2,\dots,n. \quad (7)$$

Step 6: Calculate the relative closeness to the ideal solutions

The relative closeness coefficient i can be defined as

$$CC_i = \frac{S_i^-}{S_i^- + S_i^+}, i = 1,2,\dots,n. \quad (8)$$

A larger relative closeness coefficient is a better alternative.

3. Proposed method

This experiment consisted of the following steps: (1) Prepare the raw materials (Java carp); (2) Determine relevant factors and levels of each factor; (3) Apply the Taguchi method for experimental design and (4) Determine the optimal parameters for the fish scale scraping machine using a novel TOPSIS linear programming based on the Taguchi method. The framework of this paper is shown in Fig. 2.

3.1 Material preparation

The raw materials used in the production of processed fish are Java carp (see Fig. 1) obtained from the area of the case study, Kalasin Province.

3.2 Determining relevant factors of the proposed fish scale scraping machine

Three relevant factors were determined: speed (rpm), time (seconds) and capacity (kg). The speed refers to the rotational speed of the fish scale scraping machine. The capacity refers to the amount of Java carp put into the tank each time, and the time refers to the time it takes to operate the fish scale scraping machine. In this paper, each factor has three levels, as shown in Table 1.

Table 1. The relevant factors for the fish scale scraping machine.

Factors	Level		
	1	2	3
Speed (rpm)	50	60	70
Time (seconds)	180	240	300
Capacity (kg)	20	25	30

3.3 Taguchi experimental design

In this research, there are three related factors, and each factor has three levels (see details in Table 1). The L9 orthogonal array design was selected based on the Taguchi method, called Taguchi-L9 experimental design. From the preliminary experiment, two relevant responses were identified: fish damage (R_1) (smaller is better) and fish scale-removal efficiency (R_2) (larger is better).

3.4 Determining the optimal parameters for the fish scale scraping machine using a novel TOPSIS linear programming model based on the Taguchi method

This section offers a novel TOPSIS linear programming model based upon the ideas of the original TOPSIS for ranking alternatives. The proposed model is described as follows.

3.4.1 The novel TOPSIS linear programming model

After obtaining the results of fish damage (R_1) and fish scale-removal efficiency (R_2), the TOPSIS linear programming model is used to convert the two responses into a single output. Based on the concepts of the original TOPSIS method, the normalized performance of each run with respect to each criterion must be evaluated first using Step (2) of the original TOPSIS method. Using Equation (2), the normalized decision matrix (Q matrix) can be obtained. In the Q matrix, a set of runs can be viewed as a set of alternatives. The set of responses can be viewed as a set of criteria. A set of criteria can be divided into two categories: (1) beneficial criteria and (2) cost criteria. These relevant datasets can be utilized to develop the TOPSIS linear programming model. In the context of TOPSIS, Euclidean distance is used to determine the similarity between each alternative and the ideal solution. The ideal solution is defined as the one that maximizes the benefits of all criteria and minimizes the costs of all criteria. Instead of measuring the Euclidean distance between two points, the proposed method would calculate the Manhattan distance. Definitions of indices, parameters, objective functions, and constraints are shown as follows.

Assume that each alternative i (i = 1,2,..., n) with a set of cost criteria j^c (x_{ij^c}, j^c = 1,.2,...,m) produces a set of beneficial criteria j^b (y_{ij^b}, j^b = 1,2,...,s). Let u_{j^b} and v_{j^c} be the weights of benefit and cost criteria, respectively. The determination of the u_{j^b} and v_{j^c} is based on the opinion of decision makers. The η_i and ρ_i variables are the optimal weights of the summation of the distances from the negative ideal solutions to alternative i and the summation of distances from the positive ideal solutions to alternative I, respectively. Let $x_{j^c}^n$ and $x_{j^c}^p$ be the negative ideal and ideal values of each cost criterion j^c, $x_{j^c}^n = max\{x_{ij^c}\}, \forall j^c$ and $x_{j^c}^p = min\{x_{ij^c}\}, \forall j^c, j^c = 1,2,\ldots,m$. . Let $y_{j^b}^n$ and $y_{j^b}^p$ be the negative ideal and positive ideal values of each beneficial criterion j^b, $y_{j^b}^n = min\{y_{ij^b}\}, \forall j$ and $y_{j^b}^p = max\{y_{ij^b}\}, \forall j^b, j^b = 1,2,\ldots,s$. The relative closeness coefficient score (CC_i) for a set of alternatives i ($1 \le i \le n$) can be defined as:

$$\mathrm{CC}_i = \frac{\eta_i\left(\sum_{j^c=1}^{m} v_{j^c}\left(x_{j^c}^n - x_{ij^c}\right) + \sum_{j^b=1}^{s} u_{j^b}\left(y_{ij^b} - y_{j^b}^n\right)\right)}{\eta_i\left(\sum_{j^c=1}^{m} v_{j^c}\left(x_{j^c}^n - x_{ij^c}\right) + \sum_{j^b=1}^{s} u_{j^b}\left(y_{ij^b} - y_{j^b}^n\right)\right) + \rho_i\left(\sum_{j^b=1}^{s} v_{j^c}\left(x_{ij^c} - x_{j^c}^p\right) + \sum_{j^b=1}^{s} u_{j^b}\left(y_{j^b}^p - y_{ij^b}\right)\right)}, \forall i = 1,2,\ldots,n$$

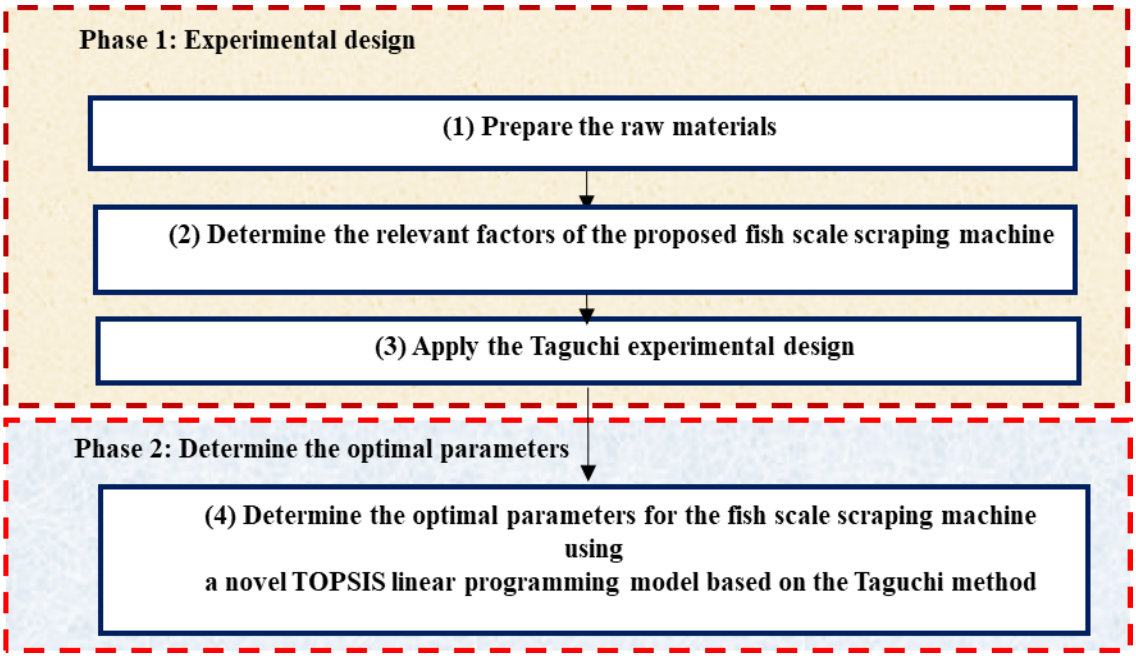

Fig. 2 The framework of this paper.

$$u_{j^b}, v_{j^c} \geq 0, j^c = 1,2,\ldots,m; j^b = 1,2,\ldots,s$$

$$\eta_i, \rho_i \geq 0, i = 1,2,\ldots,n \qquad (9)$$

To achieve the optimal solutions of CC$_i$ values (maximum relative closeness coefficient), the maximum value of CC$_i$ (the η_i and ρ_i variables must be maximum values) can be formulated as

$$\mathrm{CC}_i = max\left(\frac{\eta_i\left(\sum_{j^c=1}^{m} v_{j^c}\left(x_{j^c}^n - x_{ij^c}\right) + \sum_{j^b=1}^{s} u_{j^b}\left(y_{ij^b} - y_{j^b}^n\right)\right)}{\eta_i\left(\sum_{j^c=1}^{m} v_{j^c}\left(x_{j^c}^n - x_{ij^c}\right) + \sum_{j^b=1}^{s} u_{j^b}\left(y_{ij^b} - y_{j^b}^n\right)\right) + \rho_i\left(\sum_{j^b=1}^{s} v_{j^c}\left(x_{ij^c} - x_{j^c}^p\right) + \sum_{j^b=1}^{s} u_{j^b}\left(y_{j^b}^p - y_{ij^b}\right)\right)}\right), \forall i = 1,2,\ldots,n$$

$$u_{j^b}, v_{j^c} \geq 0, j^c = 1,2,\ldots,m; j^b = 1,2,\ldots,s$$

$$\eta_i, \rho_i \geq 0, i = 1,2,\ldots,n \qquad (10)$$

The above model is a nonlinear programming model. Hence, the above model can be converted to model (11).

$$\mathrm{CC}_i = max\, \eta_i\left(\sum_{j^c=1}^{m} v_{j^c}(x_{j^c}^n - x_{ij^c}) + \sum_{j^b=1}^{s} u_{j^b}(y_{ij^b} - y_{j^b}^n)\right), \forall i = 1,2,\ldots,n$$

$$\eta_i\left(\sum_{j^c=1}^{m} v_{j^c}(x_{j^c}^n - x_{ij^c}) + \sum_{j^b=1}^{s} u_{j^b}(y_{ij^b} - y_{j^b}^n)\right) + \rho_i\left(\sum_{j^b=1}^{s} v_{j^c}(x_{ij^c} - x_{j^c}^p) + \sum_{j^b=1}^{s} u_{j^b}(y_{j^b}^p - y_{ij^b})\right) = 1, \forall i = 1,2,\ldots,n$$

$$u_{j^b}, v_{j^c} \geq 0, j^c = 1,2,\ldots,m; j^b = 1,2,\ldots,s$$

$$\eta_i, \rho_i \geq 0, i = 1,2,\ldots,n \qquad (11)$$

The objective function of the proposed TOPSIS linear programming model is to be maximized; the CC$_i$, η_i and ρ_i can be achieved using model (11). After obtaining the CC$_i$, a set of alternatives can be ranked by preference in descending order of the CC$_i$ value. The larger the CC$_i$ value, the better the alternative's ranking.

3.4.2 Taguchi method based on the TOPSIS linear programming model for optimizing the relative closeness coefficient

In this section, the Taguchi method based on the results obtained from the TOPSIS linear programming model is developed for optimizing the parameters of the fish scale scraping machine. After obtaining the CC$_i$ scores of each run, the Taguchi method will be used to analyze the experimental results of the fish scale scraping machine using Minitab statistical software. The fish damage and the fish scale-removal efficiency will be analyzed using the S/N Ratio values. The fish damage response is calculated (smaller is better) using Equation (12). The fish scale-removal efficiency response is calculated (larger is better) using Equation (13).

$$S/N = -10\,log \sum_{i=1}^{n} \frac{y^2}{n} \quad (12)$$

$$S/N = -10\,log \sum_{i=1}^{n} \frac{y^{-2}}{n} \quad (13)$$

where y and n are the response and number of replications, respectively.

In this paper, the CC_i response, obtained by the proposed TOPSIS linear programming model, is calculated (larger is better) using Equation (13). Using Minitab statistical software for solving this problem, the optimal parameters of the proposed machine can be obtained.

3.5. Validation using confirmation experiment

In order to verify the reliability and generalizability of the results, confirmation experiments are a crucial validation technique. This section compares the ideal parameters predicted by the proposed method to their original values for confirmation purposes. Taguchi, in reference to Jeyapaul *et al.*,[46,47] advocated a confirmation experiment as a handy way for validating the model with the optimal amounts of the specified parameters. If the confirmation result is comparable to the response predicted by the main effects model, the additive model is deemed viable. Thus, the model may be applied to accurately estimate the response for any combination of component values inside the experimental zone. The optimum condition is calculated using Equation (14) to obtain the expected mean ($\hat{\mu}$) at the optimal parameters.

$$\hat{\mu} = \gamma_a + \sum_{i=1}^{n\Sigma_a}(\gamma_i^{max} \quad (14)$$

If γ_a is the grand average, γ_i^{max} is the optimal mean value of the i^{th} parameter, and n is the number of controllable factors that significantly impact quality.

4. Results

After the experimental design in Section 3, this section is to analyze the experimental results in the following order.

4.1 The results of the experiment with the Taguchi method

In this research, there are three relevant factors used in the experiment, and each factor has three levels. Therefore, in order to reduce costs and shorten the trial period, we applied the Taguchi method in the experiment to determine the optimal parameters of the fish scale scraping machine. The Taguchi-L9 experimental design was used for the case study. Speed (S), time (T) and capacity (C), have been considered as the three relevant factors; each factor has three levels. In each run, the fish damage response (R_1) and the fish scale-removal efficiency response (R_2) were evaluated by 15 entrepreneurs using a five-level rating scale, as shown in Table 2 and Table 3, respectively.

Table 2. The five-level rating scale for the fish damage response.

Score	Meaning
1	Not damaged
2	Slightly damaged
3	Medium
4	Very damaged
5	Most damaged

Table 3. The five-level rating scale for the fish scale-removal efficiency response.

Score	Meaning
1	Inefficient
2	Less efficient
3	Medium
4	Very efficient
5	Most efficient

The averages of the fish damage and fish scale removal efficiency responses were then calculated by 15 entrepreneurs. For example, in Experiment No. 1, the decision makers provided the rating scores for the fish scale removal efficiency (R_1) as follows: 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 2, 1, 2, and 1, whose mean is 1.200. Details of other experimental results are shown in Table 4.

Table 4. The experimental results based on the Taguchi-L9 experimental design for the case study.

Exp. No.	Experimental parameters			Responses	
	Speed (rpm)	Time (second)	Capacity (kg)	R_1	R_2
1	50	180	20	1.200	3.800
2	50	240	25	1.467	4.400
3	50	300	30	2.000	3.800
4	60	180	25	1.467	4.933
5	60	240	30	1.733	4.733
6	60	300	20	3.000	3.800
7	70	180	30	1.533	4.533
8	70	240	20	3.000	3.933
9	70	300	25	3.800	4.000

After experimenting according to the Taguchi-L9 experimental design, the data set in Table 4 was used to calculate the signal-to-noise ratio (S/N Ratio) of the fish damage response (R_1) using Minitab. The experimental results of the S/N Ratio for the R_1 response are shown in Fig. 3.

Figure 3 shows that the main effects for the signal-to-noise ratio of the R_1, a speed of 70 rpm, a time of 300 seconds, and a capacity of 20 kg, are the optimal parameters for the R_1. As depicted in Fig. 4, for calculating the S/N Ratio for the R_2, set the format to “larger is better”.

Fig. 3 The signal-to-noise ratio (S/N Ratio) of the fish damage response (R_1).

Figure 4 shows that the main effects for the signal-to-noise ratio of the R_2, a speed of 60 rpm, a time of 180 seconds, and a capacity of 25 kg, are the optimal parameters for the R_2. Analysis of Variance (ANOVA) for the R_1 and R_2 are shown in Table 5 and Table 6, respectively.

Table 5. The Analysis of Variance for the fish damage response (R_1).

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Speed	2	2.26074	1.13037	24.61	0.039
Time	2	3.54667	1.77333	38.61	0.025
Capacity	2	0.67852	0.33926	7.39	0.119
Error	2	0.09185	0.04593		
Total	8	6.57778			
Model Summary		R^2 = 98.60	R^2 (adj) = 94.41		

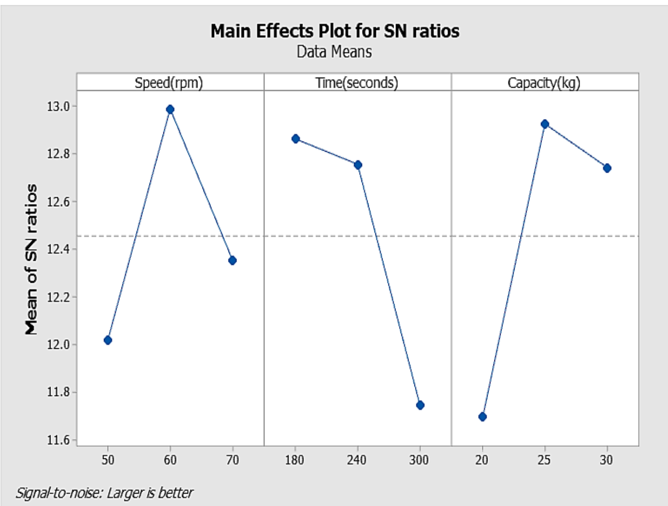

Fig. 4 The signal-to-noise ratio (S/N Ratio) of the fish scale removal efficiency response (R_2).

Table 6. The Analysis of Variance for the fish scale removal efficiency response (R_2).

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Speed	2	0.37432	0.18716	54.14	0.018
Time	2	0.5521	0.276049	79.86	0.012
Capacity	2	0.62914	0.314568	91	0.011
Error	2	0.00691	0.003457		
Total	8	1.56247			
Model Summary		R^2 = 99.56	R^2 (adj) = 98.23		

As seen in Tables 5 and 6, the R_1 and R_2 results obtained from the relevant variables were analyzed using ANOVA. Speed (S), time (T), and capacity (C) were found to have a significant effect on the fish damage response and the fish scale removal efficiency response; P-values < 0.05. The fish damage response is defined as "smaller is better," while the fish scale removal efficiency response is defined as "larger is better." This is one of those multi-objective optimization problems in which it is difficult to determine the optimal parameters because the two responses have opposing viewpoints. Hence, the proposed TOPSIS linear programming model based on the Taguchi method was utilized for solving this problem. The TOPSIS linear programming model was used to combine the two responses into the CC_i scores for each run. Finally, the Taguchi method was used to optimize the parameters for the fish scale scraping machine. The calculation steps of the proposed method are shown in the next section.

Table 7. The experimental results based on the Taguchi-L9 experimental design for the case study.

Exp. No.	Responses(P matrix)		Normalized decision matrix (Q matrix)	
	R_1	R_2	X_1	Y_1
1	1.200	3.800	0.17405	0.29907
2	1.467	4.400	0.21272	0.34629
3	2.000	3.800	0.29008	0.29907
4	1.467	4.933	0.21272	0.38827
5	1.733	4.733	0.25140	0.37253
6	3.000	3.800	0.43511	0.29907
7	1.533	4.533	0.22239	0.35678
8	3.000	3.933	0.43511	0.30956
9	3.800	4.000	0.55114	0.31481

4.2 Determining the optimal parameters using the TOPSIS linear programming model based on the Taguchi method

After obtaining the results of fish damage response (R_1) and fish scale removal efficiency response (R_2), the two data sets for the two responses were normalized using Equation (2). As a result, the normalized decision matrix (Q matrix) was obtained. Details of the Q matrix are shown in Table 7.

In the Q matrix, let R_1 and R_2 be X_1 (smaller is better) and Y_1 (larger is better) respectively. Then x_1^n,x_1^p,y_1^n,y_1^p are defined as

$x_1^n = \max\{x_{11}, x_{21}, x_{31}, x_{41}, x_{51}, x_{61}, x_{71}, x_{81}, x_{91}\}$

$= \max\begin{Bmatrix} 0.17405, 0.21272, 0.29008, 0.21272, 0.25140, \\ 0.43511, 0.22239, 0.435111, 0.55114 \end{Bmatrix}$

$= 0.55114$,

$x_1^p = \min\{x_{11}, x_{21}, x_{31}, x_{41}, x_{51}, x_{61}, x_{71}, x_{81}, x_{91}\}$

$= \min\begin{Bmatrix} 0.17405, 0.21272, 0.29008, 0.21272, 0.25140, \\ 0.43511, 0.22239, 0.435111, 0.55114 \end{Bmatrix}$

$= 0.17405$,

$y_1^n = \min\{y_{11}, y_{21}, y_{31}, y_{41}, y_{51}, y_{61}, y_{71}, y_{81}, y_{91}\}$

$= \min\{0.29907, 0.34629, 0.29907, 0.38827, 0.37253, 0.29907, 0.35678, 0.30956, 0.31481\}$

$= 0.29907$,

$y_1^p = \max\{y_{11}, y_{21}, y_{31}, y_{41}, y_{51}, y_{61}, y_{71}, y_{81}, y_{91}\}$

$= \max\{0.29907, 0.34629, 0.29907, 0.38827, 0.37253, 0.29907, 0.35678, 0.30956, 0.31481\}$

$= 0.38827$,

After that, based on the concepts of the proposed TOPSIS linear programming model, the results of the two responses were taken into model (10), setting v_1 =0.5 and u_1 =0.5. As a result, the values of CC_i were calculated. For example, to obtain the value of CC_1, the relevant data listed in Table 8 were taken into model (11):

Objective:

$$CC_1 = max\Big(\eta_1\big(0.5(0.5511 - 0.17405) + 0.5(0.29907 - 0.29907)\big)\Big).$$

Subject to:

$$\eta_1\big(0.5(0.5511 - 0.17405) + 0.5(0.29907 - 0.29907)\big) + \rho_1\big(0.5(0.17405 - 0.17405) + 0.5(0.38827 - 0.29907)\big) = 1;$$

$$\eta_1\big(0.5(0.5511 - 0.17405) + 0.5(0.29907 - 0.29907)\big) \leq \eta_1\big(0.5(0.5511 - 0.17405) + 0.5(0.29907 - 0.29907)\big) + \rho_1\big(0.5(0.17405 - 0.17405) + 0.5(0.38827 - 0.29907)\big);$$

$$\eta_1 \geq 0; \rho_1 \geq 0; \eta_1 = \rho_1.$$

In this paper, this linear programming model of CC_1 was solved using the LINGO software. As a result, CC_1 is 0.8087. Table 8 provides information on each CC_i value.

Details of the CC_i are shown in the last column of Table 8. After obtaining the CC_i scores, Taguchi's larger-is-better criterion is used to determine the optimal parametric condition for the CC_i. The main effects of the S/N Ratio are shown in Table 9 and Fig. 5.

Table 8. The experimental results for the fish scale scraping machine (R_2).

Experiment No.	Experimental parameters	X_1 (R_1)	Y_1 (R_2)	CC_i
1	$S_1 T_1 C_1$	1.200	3.800	0.8087
2	$S_1 T_2 C_2$	1.467	4.400	0.8270
3	$S_1 T_3 C_3$	2.000	3.800	0.5599
4	$S_2 T_1 C_2$	1.467	4.933	0.9171
5	$S_2 T_2 C_3$	1.733	4.733	0.8004
6	$S_2 T_3 C_1$	3.000	3.800	0.2488
7	$S_3 T_1 C_3$	1.533	4.533	0.8288
8	$S_3 T_2 C_1$	3.000	3.933	0.2713
9	$S_3 T_3 C_2$	3.800	4.000	0.0338

Table 9. The main effects for S/N Ratios of the CC_i response.

Level	Speed	Time	Capacity
1	-2.84*	-1.41*	-8.42
2	-4.92	-4.97	-10.61
3	-14.13	-15.52	-2.87*
Delta	11.29	14.11	7.74
Rank	2	1	3

According to Table 9, a greater delta value indicates that process parameters exert a greater impact on the multi-response performance indicator. Thus, the delta statistics in Table 9 reveal that the CC response is primarily affected by time, followed by speed and capacity. Further, speed, capacity and time significantly affect performance metrics due to their roles in determining the fish damage response and the fish scale removal efficiency response throughout the fish production process.

Figure 5 shows that desirable values of S/N ratios of the CC_i response are achieved at the first level of speed (50 rpm), the first level of time (180 seconds), and the third level of capacity (30 kg). The results of S/N ratios in Table 9 also specify the same levels for the variables. In addition, Analysis of Variance (ANOVA) for the CC_i response are shown in Table 10.

Table 10. The Analysis of Variance for the CC_i response.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Speed	2	0.20807	0.104037	17.98	0.053
Time	2	0.49746	0.248729	42.99	0.023
Capacity	2	0.12339	0.061695	10.66	0.086
Error	2	0.01157	0.005786		
Total	8	0.84049			
Model Summary		R^2 = 98.62	R^2 (adj) = 94.49		

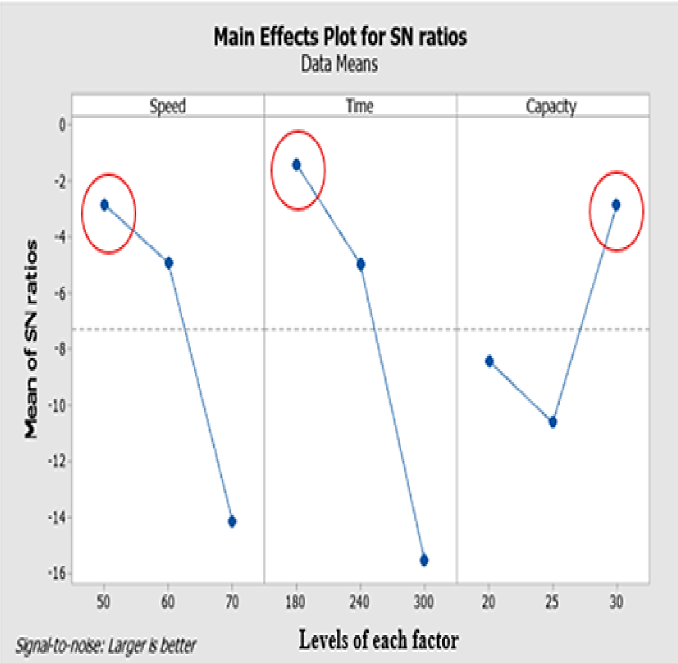

Fig. 5 The main effect plot for S/N Ratios of the CC_i response.

4.3 Validation using confirmation experiment

In this section, a confirmation test was performed using the optimal parameters calculated using the proposed method compared to the original parameters. Table 11 shows the main effects for means of the CC_i response.

Table 11. The main effects for means of the CC_i response.

Level	Speed	Time	Capacity
1	0.7319	0.8515	0.4430
2	0.6554	0.6329	0.5926
3	0.378	0.2808	0.7297
Delta	0.3539	0.5707	0.2867
Rank	2	1	3

The predicted CC_i can be calculated using Equation (14),

$$\gamma_a = (0.7319 + 0.8515 + 0.443 + 0.6554 + 0.6329 + 0.5926 + 0.378 + 0.2808 + 0.7297)/9 = 0.5884,$$

$$\gamma_1^{max} = 0.7319, \gamma_2^{max} = 0.8515, \quad \gamma_3^{max} = 0.7297$$

$$\hat{\mu} = 0.5884 + (0.7319 - 0.5884) + (0.8515 - 0.5884) + (0.7297 - 0.5884) = 1.1363$$

Table 12 shows that the optimal parameters obtained from the proposed method can improve the fish damage response by 23.95% and the fish scale removal efficiency by 29.74%.

After testing the fish scale scraping machine with the optimal parameters, Figure 6 depicts the characteristics of the scaled fish obtained by the proposed machine.

Finally, the proposed method was compared with the original TOPSIS[48] and Grey Relational Analysis (GRA).[47] The comparison results are shown in Table 13.

Fig. 6 The characteristics of the scaled fish obtained by the proposed machine.

After that, Spearman's rank correlation test was used to evaluate the correlation coefficients (r_s) for the proposed method, the r_s value for the proposed method and original TOPSIS is obtained as r_s = 0.983 (sig. = 0.000) . Besides, the r_s value for the proposed method and GRA is obtained as r_s = 0.900 (sig. = 0.000). The proposed method is highly correlated with the original TOPSIS and the GRA. This means that the proposed method is more consistent with the original TOPSIS and the GRA. Lastly, the optimal parameters for the proposed method and the original TOPSIS, based on the Taguchi method, are the same. Consequently, the proposed method can be utilized to handle the multi-response optimization problem in this case study in an effective and trustworthy manner. In addition, other multi-response optimization problems from the existing literature were employed to validate the proposed method. The validation's details are as follows:

Table 12. Confirmation experiment.

Response	Original parameters	Optimal parameters		Improvement	
		Prediction	Experiment	Prediction	Experiment
Level	$S_1T_3C_3$	$S_1T_1C_3$	$S_1T_1C_3$		
CC	0.5599	1.1363	-	75.617%	-
R_1	2.00	-	1.270	-	23.95%
R_2	3.80	-	4.933	-	29.74%

Table 13. The comparison results for the proposed method, the original TOPSIS and grey relational analysis.

Experiment No.	Experimental parameters	GRA	TOPSIS	Proposed
		GRG (rank)	CC (rank)	CC (rank)
1	$S_1 T_1 C_1$	0.66667(5)	0.8087 (4)	0.8087 (4)
2	$S_1 T_2 C_2$	0.67247(4)	0.8569 (2)	0.8270 (3)
3	$S_1 T_3 C_3$	0.47619(6)	0.6408 (6)	0.5599 (6)
4	$S_2 T_1 C_2$	0.91489(1)	0.9005 (1)	0.9171 (1)
5	$S_2 T_2 C_3$	0.72411(2)	0.7963 (5)	0.8004 (5)
6	$S_2 T_3 C_1$	0.37634(8)	0.2961 (8)	0.2488 (8)
7	$S_3 T_1 C_3$	0.69106(3)	0.8526 (3)	0.8288 (2)
8	$S_3 T_2 C_1$	0.39053(7)	0.2994 (7)	0.2713 (7)
9	$S_3 T_3 C_2$	0.35556(9)	0.0394 (9)	0.0338 (9)

Problem 1: Parida and Routara[49] proposed the original TOPSIS approach for the multi-response optimization of process parameters in the turning of Glass Fiber Reinforced Polymer (GFRP). The objectives of this research were to examine the impacts of cutting speed (v), feed rate (f) and depth of cut (d) on the surface roughness (Ra) and material removal rate (MRR). Details of the data set are shown in Table 14.

After obtaining the Q matrix, let R_a response and MRR response be X_1 (smaller is better) and Y_1 (larger is better) respectively. Based on the same calculation steps of the proposed TOPSIS linear programming model, set $x_1^n = 0.5080, x_1^p = 0.2082, y_1^n = 0.1115, y_1^p = 0.4863$ v_1 =0.5 and u_1 =0.5. After that, the results of the two responses were taken into model (11). As a result, the values of CC_i were obtained. Table 15 provides a comparison of the results for the proposed method and the original TOPSIS.

From Table 15, it can be seen that the proposed method tends to be highly consistent with the original TOPSIS. After that, Spearman's rank correlation test was used to evaluate the

Table 14. The experimental results based on the Taguchi-L9 experimental design for this problem.

Exp. No.	Experimental parameters			Responses (P matrix)		Normalized decision matrix (Q matrix)	
	v (rpm)	f (mm/rev)	d (mm)	Ra	MRR	X_1	Y_1
1	200	0.03	0.5	2.60	319.49	0.27064	0.11154
2	200	0.04	1.0	2.80	625.82	0.29146	0.21848
3	200	0.05	1.5	2.00	913.26	0.20819	0.31882
4	300	0.03	1.0	2.50	971.28	0.26024	0.33908
5	300	0.04	1.5	2.80	1155.08	0.29146	0.40324
6	300	0.05	0.5	3.40	493.13	0.35392	0.17215
7	400	0.03	1.5	3.52	1392.92	0.36641	0.48628
8	400	0.04	0.5	4.88	974.42	0.50798	0.34018
9	400	0.05	1.0	3.44	1211.15	0.35808	0.42282

Table 15. Comparison of results for the proposed method and the original TOPSIS.

Exp. No.	Experimental parameters			CC_i	
	v (rpm)	f (mm/rev)	d (mm)	TOPSIS (rank)	Proposed (rank)
1	200	0.03	0.5	0.3845 (8)	0.3519 (7)
2	200	0.04	1.0	0.4627 (6)	0.4795 (6)
3	200	0.05	1.5	0.6852 (3)	0.7518 (3)
4	300	0.03	1.0	0.6830 (4)	0.7046 (4)
5	300	0.04	1.5	0.7555 (1)	0.7534 (2)
6	300	0.05	0.5	0.3235 (9)	0.3183 (9)
7	400	0.03	1.5	0.7169 (2)	0.7654 (1)
8	400	0.04	0.5	0.4067 (7)	0.3390 (8)
9	400	0.05	1.0	0.6797 (5)	0.6837 (5)

r_s value for the proposed method, the r_s value for the proposed method and original TOPSIS is obtained as r_s = 0.967 (sig. =0.000) . This means that the proposed method is highly correlated with the original TOPSIS. Lastly, the optimal parameters for the proposed method and the original TOPSIS, based on the Taguchi method, are the same.

Problem 2: Kamalizadeh *et al*.[50] proposed the original TOPSIS approach for the multi-response optimization of process parameters in the milling of Titanium-based metal matrix composites (Ti-MMCs). The objective of this research was to examine the impacts of the initial cutting speed (v_1), secondary cutting speed (v_2), and feed rate (f) on the surface roughness (R_a) and tool wear rates (V_b). Details of the data set for this problem are shown in Table 16.

After obtaining the Q matrix, let R_a response and V_b response be X_1 (smaller is better) and Y_1 (larger is better) respectively. Based on the same calculation steps of the proposed TOPSIS linear programming model, set $x_1^n = 0.31589$, $x_1^p = 0.07722$, $y_1^n = 0.29935$, $y_1^p = 0.07541$ v_1 =0.5 and u_1 =0.5. After that, the results of the two responses were taken into model (11). As a result, the values of CC_i were obtained. Table 17 provides a comparison of the results for the proposed method and the original TOPSIS.

After obtaining the CC_i scores, the r_s value for the proposed method and original TOPSIS is obtained as r_s = 0.9996 (sig. =0.000). This means that the proposed method is highly correlated with the original TOPSIS.

5. Conclusion

Multi-response optimization (MRO) is a statistical technique for maximizing numerous response variables within a single experiment or study. MRO seeks input variables that optimize or minimize multiple responses. MRO is utilized in engineering, manufacturing and pharmaceutical research to improve a variety of performance factors. MRO enables researchers to identify the optimal input variables for a variety of criteria. MRO is rigorous and methodical, and usually uses computer algorithms to investigate numerous possible options.

Table 16. The L27 full factorial experimental design for this problem.

Exp. No.	Experimental parameters			Responses (P matrix)		Normalized decision matrix (Q matrix)	
	v_1 (m/min)	v_2 (m/min)	f (mm/rev)	R_a	V_b	X_1	Y_1
1	40	40	0.10	1.907	220.2	0.14394	0.22024
2	40	40	0.15	1.999	232.2	0.15089	0.23224
3	40	40	0.20	1.776	194.2	0.13405	0.19423
4	40	60	0.10	1.684	179.0	0.12711	0.17903
5	40	60	0.15	1.902	138.0	0.14356	0.13802
6	40	60	0.20	1.769	159.0	0.13353	0.15903
7	40	80	0.10	3.685	296.3	0.27815	0.29635
8	40	80	0.15	4.185	228.6	0.31589	0.22864
9	40	80	0.20	3.983	283.6	0.30064	0.28365
10	60	40	0.10	1.284	114.5	0.09692	0.11452
11	60	40	0.15	1.257	123.5	0.09488	0.12352
12	60	40	0.20	1.517	153.0	0.11450	0.15303
13	60	60	0.10	2.514	204.5	0.18976	0.20453
14	60	60	0.15	2.884	162.0	0.21769	0.16203
15	60	60	0.20	2.194	151.7	0.16560	0.15173
16	60	80	0.10	3.687	299.3	0.27830	0.29935
17	60	80	0.15	3.318	271.2	0.25045	0.27125
18	60	80	0.20	3.447	243.5	0.26018	0.24354
19	80	40	0.10	1.683	166.3	0.12703	0.16633
20	80	40	0.15	1.483	150.4	0.11194	0.15043
21	80	40	0.20	1.565	119.2	0.11813	0.11922
22	80	60	0.10	1.023	95.4	0.07722	0.09542
23	80	60	0.15	1.028	75.4	0.07759	0.07541
24	80	60	0.20	1.083	81.3	0.08175	0.08131
25	80	80	0.10	3.43	187.5	0.25890	0.18753
26	80	80	0.15	3.381	189.4	0.25520	0.18943
27	80	80	0.20	3.574	201.3	0.26977	0.20133

Table 17. Comparison of results for the proposed method and the original TOPSIS.

Exp. No.	Experimental parameters			CC_i	
	v_1 (m/min)	v_2 (m/min)	f (mm/rev)	TOPSIS (rank)	Proposed (rank)
1	40	40	0.10	0.5427 (15)	0.5427 (15)
2	40	40	0.15	0.5069 (16)	0.5017 (17)
3	40	40	0.20	0.6146 (14)	0.6203 (14)
4	40	60	0.10	0.6606 (12)	0.6682 (12)
5	40	60	0.15	0.7213 (9)	0.7212 (9)
6	40	60	0.20	0.6954 (10)	0.6975 (10)
7	40	80	0.10	0.1125 (25)	0.0881 (25)
8	40	80	0.15	0.1996 (24)	0.1529 (24)
9	40	80	0.20	0.0669 (27)	0.0669 (27)
10	60	40	0.10	0.8674 (4)	0.8729 (4)
11	60	40	0.15	0.8464 (5)	0.8578 (5)
12	60	40	0.20	0.7430 (8)	0.7516 (8)
13	60	60	0.10	0.4795 (18)	0.4776 (18)
14	60	60	0.15	0.5057 (17)	0.5091 (16)
15	60	60	0.20	0.6434 (13)	0.6440 (13)
16	60	80	0.10	0.1110 (26)	0.0813 (26)
17	60	80	0.15	0.2141 (23)	0.2022 (23)
18	60	80	0.20	0.2409 (22)	0.2411 (22)
19	80	40	0.10	0.6902 (11)	0.6958 (11)
20	80	40	0.15	0.7534 (7)	0.7628 (7)
21	80	40	0.20	0.8169 (6)	0.8169 (6)
22	80	60	0.10	0.9401 (3)	0.9568 (3)
23	80	60	0.15	0.9988 (1)	0.9992 (1)
24	80	60	0.20	0.9773 (2)	0.9775 (2)
25	80	80	0.10	0.3702 (20)	0.3649 (20)
26	80	80	0.15	0.3727 (19)	0.3688 (19)
27	80	80	0.20	0.3201 (21)	0.3116 (21)

The optimal input variables satisfy performance objectives across multiple response variables, hence addressing complex optimization issues. Although there are many different multi-criteria decision-making (MCDM) methods for solving multi-response optimization problems, the TOPSIS technique is one of the most commonly used. For this reason, it would be wise to experiment with a new technique based on TOPSIS ideas that yield reliable and easier-to-use results in solving these problems. This research provides a novel TOPSIS linear programming approach based on the Taguchi method for addressing the MRO of a fish scale scraping machine to increase fish scale removal efficiency while minimizing fish damage. The initial experiment design was based on the Taguchi experimental design. The two responses were then combined into a single output using the TOPSIS linear programming model. The optimal combination of parameters (speed = 50 rpm, time = 180 seconds, and capacity = 30 kg) was determined. Compared with the initial parameters, the fish damage decreases by 23.95%, and the fish scaling removal efficiency increases by 29.74%. In addition, the proposed method is effective and reliable compared to the original TOPSIS method. Therefore, the proposed method can be used to determine the optimal parameters for this case study.

In conclusion, the TOPSIS linear programming model can be used as a multi-criteria decision-making method that can be applied in various fields, such as engineering, manufacturing and economics studies. However, there is still much room for improvement and further development in the future. One potential direction for future work is to enhance the efficiency and accuracy of the TOPSIS linear programming model by incorporating the other DOE methods for solving the MRO problems. Moreover, the integration of the TOPSIS linear programming model with other decision-making methods, such as Analytic Hierarchy Process (AHP) and Decision-Making Trial and Evaluation Laboratory (DEMATEL), could further improve the decision-making process. In addition, the integration of the TOPSIS linear programming model with response surface methodology could enable the optimization of multiple responses simultaneously, while also accounting for the interactions between factors. In this paper, the TOPSIS linear programming model assumes that all criteria are precise and certain. However, in many real-world MRO problems, responses may be imprecise. Future research could extend the TOPSIS linear programming model to tackle uncertainty and imprecision, for example by using fuzzy logic.

Acknowledgements
This work was supported by the National Research Council of Thailand (No. N71A650921). Finally, the authors would like to thank the reviewers for their valuable comments and recommendations which enabled the improvement of the quality of this paper.

Conflict of Interest
There is no conflict of interest.

Supporting Information
Applicable.

References
[1] "The World Bank," THAILAND ENVIRONMENT MONITOR Integrated Water Resources Management: A Way Forward, 2011, Available: https://documents1.worldbank.org/curated/en/367151468303847751/pdf/633680ESW0P1080RM00June020110Final0.pdf.
[2] T. Jutagate, C. Grudpan and A. Suvarnaraksha, in Aquatic Biodiversity Conservation and Ecosystem Services, Nakano, S.-i., Yahara, T., and Nakashizuka, T., Eds. Springer Singapore, Singapore, 2016, 31-39, doi: 10.1007/978-981-10-0780-4_3.
[3] A. Goli, A.-M. Golmohammadi, J.-L. Verdegay, Two-echelon electric vehicle routing problem with a developed moth-flame meta-heuristic algorithm, *Operations Management Research*, 2022, **15**, 891-912, doi: 10.1007/s12063-022-00298-0.
[4] Efficient multi-objective meta-heuristic algorithms for energy-aware non-permutation flow-shop scheduling problem, *Expert Systems with Applications*, 2023, **213**, 119077, doi: 10.1016/j.eswa.2022.119077.
[5] Alireza, Goli, Hybrid artificial intelligence and robust optimization for a multi-objective product portfolio problem Case study: the dairy products industry, *Computers & Industrial Engineering*, 2019, **137**, 106090, doi: 10.1016/j.cie.2019.106090.
[6] A. Goli, T. Keshavarz, Just-in-time scheduling in identical parallel machine sequence-dependent group scheduling problem, *Journal of Industrial and Management Optimization*, 2022, **18**, 3807, doi: 10.3934/jimo.2021124.
[7] M. Alinaghian, A. Goli, Location, allocation and routing of temporary health centers in rural areas in crisis, solved by improved harmony search algorithm, *International Journal of Computational Intelligence Systems*, 2017, **10**, 894, doi: 10.2991/ijcis.2017.10.1.60.
[8] A. Goli, H. Khademi-Zare, R. Tavakkoli-Moghaddam, A. Sadeghieh, M. Sasanian, R. Malekalipour Kordestanizadeh, An integrated approach based on artificial intelligence and novel meta-heuristic algorithms to predict demand for dairy products: a case study, *Network: Computation in Neural Systems*, 2021, **32**, 1-35, doi: 10.1080/0954898x.2020.1849841.
[9] A. Goli, A. Ala, S. Mirjalili, A robust possibilistic programming framework for designing an organ transplant supply chain under uncertainty, *Annals of Operations Research*, 2022, 1-38, doi: 10.1007/s10479-022-04829-7.
[10] I. Vinogradova, Multi-attribute decision-making methods as a part of mathematical optimization, *Mathematics*, 2019, **7**, 915, doi: 10.3390/math7100915.
[11] P. Achuthamenon Sylajakumari, R. Ramakrishnasamy, G. Palaniappan, Taguchi grey relational analysis for multi-response optimization of wear in Co-continuous composite, *Materials*, 2018, **11**, 1743, doi: 10.3390/ma11091743.
[12] T, Muthuramalingam, Application of Taguchi-grey multi responses optimization on process parameters in electro erosion, *Measurement*, 2014, **58**, 495-502, doi: 10.1016/j.measurement.2014.09.029.
[13] N. Yuvaraj, M. Pradeep Kumar, Multiresponse optimization of abrasive water jet cutting process parameters using TOPSIS approach, *Materials and Manufacturing Processes*, 2015, **30**, 882-889, doi: 10.1080/10426914.2014.994763.
[14] T.-L. Su, H.-W. Chen, C.-F. Lu, Systematic optimization for the evaluation of the microinjection molding parameters of light guide plate with TOPSIS-based Taguchi method, *Advances in Polymer Technology*, 2010, **29**, 54-63, doi: 10.1002/adv.20181.
[15] G. B. Kamath, K. Subramaniam, S. Devesh, V. Chavan, N. Mohan, R. Bhat, H. T. Wijerathne, Multi-response optimization of milling process parameters for aluminium-titanium diboride metal matrix composite machining using taguchi- data envelopment analysis ranking approach, *Engineered Science*, 2022, **12**, 271-277, doi: 10.30919/es8d680.
[16] H.-C. Liao, Y.-K. Chen, Optimizing multi-response problem in the Taguchi method by DEA based ranking method, *International Journal of Quality & Reliability Management*, 2002, **19**, 825-837, doi: 10.1108/02656710210434766.
[17] A. Goli, H. Mohammadi, Developing a sustainable operational management system using hybrid Shapley value and Multimoora method: case study petrochemical supply chain, *Environment, Development and Sustainability*, 2022, **24**, 10540-10569, doi: 10.1007/s10668-021-01844-9.
[18] C.-W. Tsai, L.-I. Tong and C.-H. Wang, Optimization of multiple responses using data envelopment analysis and response surface methodology, *Journal of Applied Science and Engineering*, 2010, **13**, 197-203, doi: 10.6180/jase.2010.13.2.10.
[19] A. Al-Refaie, M. D. Al-Tahat, Solving the multi-response problem in Taguchi method by benevolent formulation in DEA, *Journal of Intelligent Manufacturing*, 2011, **22**, 505-521, doi: 10.1007/s10845-009-0312-8.
[20] C.-L. Hwang, K. Yoon, Methods for multiple attribute decision making. Multiple Attribute Decision Making. Berlin, Heidelberg: Springer Berlin Heidelberg, 1981, 58-191, doi:

10.1007/978-3-642-48318-9_3.
[21] C.-H. Chang, J.-J. Lin, J.-H. Lin, M.-C. Chiang, Domestic open-end equity mutual fund performance evaluation using extended TOPSIS method with different distance approaches, *Expert Systems with Applications*, 2010, **37**, 4642-4649, doi: 10.1016/j.eswa.2009.12.044.
[22] M. Behzadian, S. K. Otaghsara, M. Yazdani and J. Ignatius, A state-of-the-art survey of TOPSIS applications, *Expert Systems With Applications*, 2012, **39**, 13051-13069, doi: 10.1016/j.eswa.2012.05.056.
[23] G. Kim, C. S. Park, K. Paul Yoon, Identifying investment opportunities for advanced manufacturing systems with comparative-integrated performance measurement, *International Journal of Production Economics*, 1997, **50**, 23-33, doi: 10.1016/S0925-5273(97)00014-5.
[24] S. H. Zyoud, D. Fuchs-Hanusch, A bibliometric-based survey on AHP and TOPSIS techniques, *Expert Systems With Applications*, 2017, **78**, 158-181, doi: 10.1016/j.eswa.2017.02.016.
[25] B. Dutta, S. D. Dao, L. Martínez, M. Goh, An evolutionary strategic weight manipulation approach for multi-attribute decision making: TOPSIS method, *International Journal of Approximate Reasoning*, 2021, **129**, 64-83, doi: 10.1016/j.ijar.2020.11.004.
[26] S. Singh, V. Agrawal, K. K. Saxena, K. A. Mohammed, Optimization of Manufacturing Processes at Indian Industries Using TOPSIS, *Indian Journal of Engineering and Materials Sciences*, 2023, **30**, 32-44, doi: 10.56042/ijem3s.v1i1.61931.
[27] F. M. Abdullah, A. M. Al-Ahmari, S. Anwar, An integrated fuzzy DEMATEL and fuzzy TOPSIS method for analyzing smart manufacturing technologies, *Processes*, 2023, **11**, 906, doi: 10.3390/pr11030906.
[28] R. Manivannan, M. P. Kumar, Multi-response optimization of Micro-EDM process parameters on AISI304 steel using TOPSIS, *Journal of Mechanical Science and Technology*, 2016, **30**, 137-144, doi: 10.1007/s12206-015-1217-4.
[29] N. Sharma, Z. A. Khan, A. N. Siddiquee, M. A. Wahid, Multi-response optimization of friction stir welding process parameters for dissimilar joining of Al6101 to pure copper using standard deviation based TOPSIS method, *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 2019, **233**, 6473-6482, doi: 10.1177/0954406219858628.
[30] M. Singh, S. Singh, J. K. Arora, P. Antil, A. D. Oza, D. Doru Burduhos-Nergis, D. P. Burduhos-Nergis, Multi response optimization of ECDM process for generating micro holes in CFRP composite using TOPSIS methodology, *Polymers*, 2022, **14**, 5291, doi: 10.3390/polym14235291.
[31] K. Ananthakumar, Measurement and optimization of multi-response characteristics in plasma arc cutting of Monel 400™ using RSM and TOPSIS, *Measurement*, 2019, **135**, 725-737, doi: 10.1016/j.measurement.2018.12.010.
[32] C. A. Başar, A. A. Korkmaz, Y. Önal, T. Utku, Evaluation of optimum carbonization conditions of the blended domestic polymeric waste, biomass and lignite in the presence of catalyst by Taguchi and ANOVA optimization analysis, *Journal of Hazardous Materials Advances*, 2022, **8**, 100164, doi: 10.1016/j.hazadv.2022.100164.
[33] T. Saeheaw, Application of integrated CRITIC and GRA-based Taguchi method for multiple quality characteristics optimization in laser-welded blanks, *Heliyon*, 2022, **8**, e11349, doi: 10.1016/j.heliyon.2022.e11349.
[34] A. I. Ingle, H. D. Shashikala, M. K. Narayanan, M. T. Dubeto, S. Gupta, Optimization and analysis of process parameters of melt quenching technique for multiple performances of rare earth doped Barium borate glass synthesis using Taguchi's design and grey relational approach, *Results in Engineering*, 2023, **17**, 100784, doi: 10.1016/j.rineng.2022.100784.
[35] L.-I. Tong, C.-T. Su, Optimizing multi-response problems in the taguchi method by fuzzy multiple attribute decision making, *Quality and Reliability Engineering International*, 1997, **13**, 25-34, doi: 10.1002/(SICI)1099-1638(199701)13: 125: AID-QRE59>3.0.CO;2-B.
[36] Y. Kuo, T. Yang, G.-W. Huang, The use of a grey-based Taguchi method for optimizing multi-response simulation problems, *Engineering Optimization*, 2008, **40**, 517-528, doi: 10.1080/03052150701857645.
[37] A. Kumar, S. Clement, V. P. Agrawal, Optimum selection and ranking of electroplating system process parameters: Taguchi-MADM approach, *International Journal of Applied Decision Sciences*, 2011, **4**, 341, doi: 10.1504/ijads.2011.043304.
[38] A. Singh, S. Datta, S. S. Mahapatra, Application of TOPSIS in the taguchi method for optimal machining parameter selection, *Journal for Manufacturing Science & Production*, 2011, **11**, 49-60, doi: 10.1515/jmsp.2011.002.
[39] Y. Tansel İç, S. Yıldırım, MOORA-based Taguchi optimisation for improving product or process quality, *International Journal of Production Research*, 2013, **51**, 3321-3341, doi: 10.1080/00207543.2013.774471.
[40] A. Salmasnia ,M. Bastan and A. Moeini, A Robust Intelligent Framework for Multiple Response Statistical Optimization Problems Based on Artificial Neural Network and Taguchi Method, *Journal of Quality and Reliability Engineering*, 2012, 494818, doi: 10.1155/2012/494818.
[41] K.-L. Tsui, An overview of taguchi method and newly developed statistical methods for robust design, *IIE Transactions*, 1992, **24**, 44-57, doi: 10.1080/07408179208964244.
[42] R. S. Rao, C. G. Kumar, R. S. Prakasham, P. J. Hobbs, The Taguchi methodology as a statistical tool for biotechnological applications: a critical appraisal, *Biotechnology Journal*, 2008, **3**, 510-523, doi: 10.1002/biot.200700201.
[43] S, Tripathy, Multi-attribute optimization of machining process parameters in powder mixed electro-discharge machining using TOPSIS and grey relational analysis, *Engineering Science and Technology, an International Journal*, 2016, **19**, 62-70, doi: 10.1016/j.jestch.2015.07.010.
[44] H.-P. Nguyen, V.-D. Pham, N.-V. Ngo, Application of TOPSIS to Taguchi method for multi-characteristic optimization of electrical discharge machining with titanium powder mixed into dielectric fluid, *The International Journal of Advanced*

Manufacturing Technology, 2018, **98**, 1179-1198, doi: 10.1007/s00170-018-2321-2.

[45] A. Khan, K. Maity, Application of MCDM-based TOPSIS method for the selection of optimal process parameter in turning of pure titanium, *Benchmarking: an International Journal*, 2017, **24**, 2009-2021, doi: 10.1108/bij-01-2016-0004.

[46] R. Jeyapaul, P. Shahabudeen, K. Krishnaiah, Simultaneous optimization of multi-response problems in the Taguchi method using genetic algorithm, *The International Journal of Advanced Manufacturing Technology*, 2006, **30**, 870-878, doi: 10.1007/s00170-005-0095-9.

[47] A. N. Haq, P. Marimuthu, R. Jeyapaul, Multi response optimization of machining parameters of drilling Al/SiC metal matrix composite using grey relational analysis in the Taguchi method, *The International Journal of Advanced Manufacturing Technology*, 2008, **37**, 250-255, doi: 10.1007/s00170-007-0981-4.

[48] S. Jozić, D. Bajić, L. Celent, Application of compressed cold air cooling: achieving multiple performance characteristics in end milling process, *Journal of Cleaner Production*, 2015, **100**, 325-332, doi: 10.1016/j.jclepro.2015.03.095.

[49] A. K. Parida, B. C. Routara, Multiresponse optimization of process parameters in turning of GFRP using TOPSIS method, *International Scholarly Research Notices*, 2014, **2014**, 1-10, doi: 10.1155/2014/905828.

[50] S. Kamalizadeh, S. Ali Niknam, M. Balazinski, S. Turenne, The use of TOPSIS method for multi-objective optimization in milling Ti-MMC, *Metals*, 2022, **12**, 1796, doi: 10.3390/met12111796.

