



Research Article

Optimization of strain measurement procedure based on fuzzy quality evaluation and Taguchi experimental design

Mehdi Moayyedean¹ · Javad Farrokhi Derakhshandeh¹ · Sang Heon Lee²

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Abstract

The reliability of the measurement system, accuracy, and precision are significant criteria at any measurement procedure. Strain gage sensors are one of the tools to measure the strain of structures in engineering applications. Different controllable and extraneous parameters will change the accuracy and precision of the strain gauges. As a result, it is valuable to investigate the most significant parameters and the percentage of their contributions affecting the strain measurement. This paper presents the multi-objective optimization in strain gauge measurements to determine the Reliability and Noise indices. The best set of parameters with a high-reliability index (which means low noise index) for strain measurement based on two significant objectives of accuracy and precision are evaluated. The significant parameters, their optimal levels and percentage of contributions are identified according to the Taguchi and Fuzzy Analytic Hierarchy Process (FAHP) with Technique for the Order Performance by its Similarity to the Ideal Solution (TOPSIS) methods. To obtain this evaluation, three levels (L_1 , L_2 , and L_3) of temperature (P_1), the length of wires (P_2), and the point of applied force (P_3) are considered. This configuration leads to L_9 orthogonal array of Taguchi approach based on the number of parameters and their levels. The triangular membership function for the weightiness of accuracy and precision is used via AHP. By using the Taguchi method, the optimum set of parameters are identified as P_1 at L_1 , P_2 at L_2 , and P_3 at L_3 to have a higher reliability index compared to trial 8. By applying the optimum design of experiment, it is found that the reliability index is 95%. The results also show that the highest reliability index is related to trial 8 with 87.65% reliability. Finally, the combination of FAHP and TOPSIS with Taguchi method for multi-objective optimization is introduced and proposed as a practical and useful model to determine the best set of parameters with the highest reliability index in strain measurement.

Keywords Strain measurement · Accuracy · Precision · TOPSIS · Fuzzy · FAHP · Taguchi · Reliability index

1 Introduction

Piezo-resistivity or change in the electrical resistivity can be considered as one of the widely used physical phenomena at different kind of sensory applications. Strain gauges are useful and valuable devices to measure the time-dependent magnitude of deformation and can be associated with determining the stresses of the structure in a wide range of applications [5, 11–13, 19, 21, 23, 34]. To achieve this, a deep knowledge of mechanical engineering

is required for modeling calculation to a constitutive equation for the stress–strain relationship [22, 33]. The basic function of the strain gauge is based on transforming the strain in a certain direction to change its electric resistance [20, 38]. While the strain gauges have been employed for a few decades, still there is little guidance on how to evaluate mechanical properties and the aspects of strain measurement have been covered in brief [22, 31, 33].

There are several uncertainties in measuring the strain of the object, which can be related to the geometry,

✉ Mehdi Moayyedean, mehdi.moayyedean@aum.edu.kw | ¹College of Engineering and Technology, American University of the Middle East, Kuwait City, Kuwait. ²School of Engineering, University of South Australia, Mawson Lakes Campus, Mawson Lakes, SA 5095, Australia.



material, and optical of the test case. Besides, other uncertainties which can be considered in analyzing the system are related to the methods of measurement such as configuration, the number, and distribution of measuring points, the number of sampling, and the operator [8, 40]. Davis [8] conducted an excellent study using different techniques of strain measurement during tensile testing. It was found that the size of the sample, environmental conditions, measurement requirement for accuracy and precision of anticipated strain levels are important factors and can significantly affect the deformation of the structure [8]. Therefore, it was found that a precise optimization method is required to characterize the tensile testing of materials properly.

To have a product with high quality and low-cost, manufacturing companies typically attempt to produce valuable products in a short time to compete with others. For a complex product, the design of the product requires optimization tasks comprising multiple objectives. This optimization can be considered both in numerical simulations and experimental measurements. In computational simulations, for instance, it will take more than 100 h to run one crash simulation for a non-very complicated model [16, 39]. For a two-variable optimization problem, assuming on average 50 iterations are needed by optimization and assuming each iteration needs one crash simulation, the total computation time would be more than 2 months. This type of study is mostly associated with trial and error. Trial and error has been identified as the main methodology in problem solving and has been employed extensively, in particular, in numerical modeling [1, 4, 9, 10, 16]. Therefore, to decrease the number of test case studies, the design of experiments and optimization of measurement are valuable skills, which can be employed to enhance productivity and efficiency.

One of the optimization method, which is implemented for quality evaluation in industry is the Design of Experiment (DOE) and using relevant tools such as Taguchi method, Signal to noise (S/N) ratio and Analysis of Variance (ANOVA) [2, 25, 28]. One of the most advantage of DOE is to find the significant parameters and their optimum level. This assists to find the best quality evaluation of the products. Amer et al. [3] showed that DOE can be considered as a valuable tool in order to define the right parameters and levels in injection moulding with less internal and external defects. The effect of cutting fluid in manufacturing process also can be optimized by DOE. Sarikaya and Güllü [35] found to have a lower rate of tool wear pattern and surface roughness, the most significant parameters and their levels are vegetable based cutting fluid with 180 mL/h fluid flow rate and 30 m/min cutting speed. Besides, the surface roughness was investigated for turning machine and the results indicated that the most

significant parameter was feed rate on the surface roughness [35]. Later, Sarikaya et al. [36] showed that DOE is able to reduce the amount of oil used for machining purposes with an improvement in machinability of material. Also, in drilling process, the most significant parameters affecting the dimensional accuracy is cutting speed for both coated and uncoated tools using DOE [24].

Two conventional methods which determine the practical and possible factors in increasing the quality in different applications are Fuzzy logic and TOPSIS. It was shown that the combination of these methods can be used in injection molding to find the optimum set of parameters and reduce the number of internal and external defects [17, 29]. Consequently, choosing the wrong set of geometrical and process parameters will decrease the mechanical properties of the injected part [26, 27]. The Taguchi method and DOE can be employed and used as tools for single and not for multi-objective problems. To guarantee that different internal and external defects can be controlled appropriately, the fuzzy logic theory can be proposed [6]. It was shown that in injection molding, in order to find the best set of process parameters, the combination of fuzzy and TOPSIS can be employed, which has the high level of moldability for producing the product [7, 29, 30, 32].

There is an extensive investigations which implemented the TOPSIS concept for optimization process. For instance, in micromachining procedure, to have an accurate result, TOPSIS was applied [15]. To determine the effect of different input parameters on the machining accuracies, two types of fluids were employed. Hence, sodium chloride was selected as a fluid with higher material removal rate using TOPSIS [15]. Another application of TOPSIS method is related to the surface performance measurements in electrical discharge machining process. Huo et al. [18] found that magnitude of the current has the most influence on the performance measurement of the process.

The above review intimates that that although the integration of FAHP with TOPSIS and AHP with FTOPSIS are useful methods for quality evaluation at different engineering applications, they are unable to cover all different possibilities to determine the optimum level and the contribution rate of significant controllable factors. To the best of the author's knowledge, there is no published study employing Taguchi with FAHP and TOPSIS in strain measurement to evaluate the optimum parameters of DOE. Consequently, the objective of this paper is to evaluate and determine the most significant parameters affecting the reliability of strain gauges for different industrial applications. This paper investigates and proposed a new approach for the multi-objective optimization method in strain measurement based on two significant objectives comprising accuracy and precision. Thus, a new approach

based on Taguchi with FAHP and TOPSIS for quality evaluation of strain measurement process is developed and introduced. There are controllable and extraneous parameters to evaluate the final quality of any process. One of the main application of Taguchi method is to enhance the control of the parameters. In this paper, three controllable parameters namely the temperature, the length of wire and the point of application are considered. Besides, uncontrollable parameters such as operator which leads to produce noises is noted.

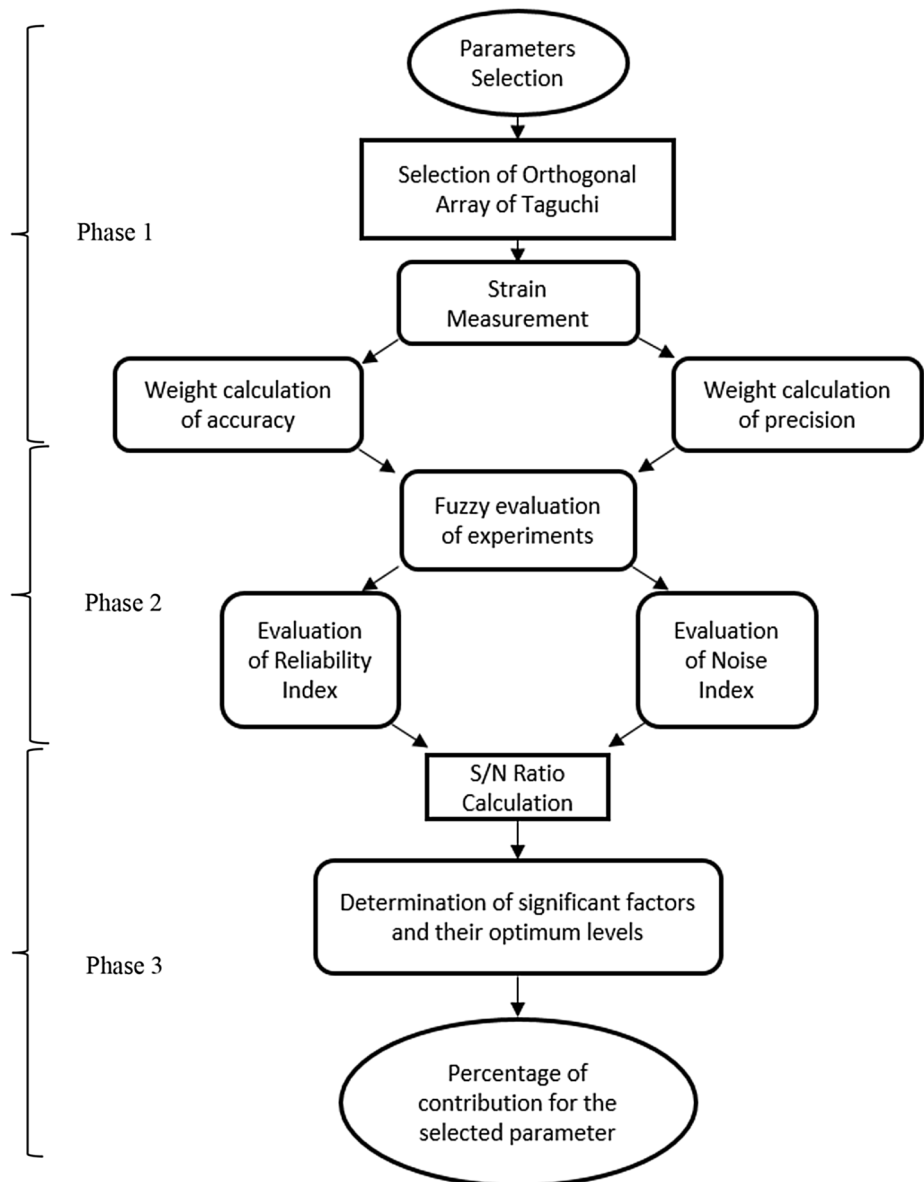
In general, the Taguchi method is applied for a single objective. So, the novelty of the paper is to determine the reliability index in strain measurement based on two objectives (accuracy and precision) via Fuzzy Analytic Hierarchy Process (FAHP) and TOPSIS. Finally, by having

a single objective (Reliability index), Taguchi method is implemented to find the most significant parameters, their optimum levels, and their contribution to find the highest reliability index.

2 Proposed methodology to enhance the quality of measurement

A comprehensive methodology is developed and introduced herein by applying FAHP along with TOPSIS and Taguchi that aims to optimize the multi-objective process in strain measurement. The proposed approach determines the best alternatives with higher reliability, as shown in Fig. 1.

Fig. 1 Flowchart of optimization of strain measurement based on fuzzy approach and the Taguchi method



The objective of this paper is to determine the significant parameters affecting the reliability of strain gauges.

2.1 Problem description

Two common objectives in strain measurement which evaluate the reliability of the measurement procedure are defined as precision and accuracy. These two objectives are significantly related to different controllable parameters. The accuracy of the measurement is the difference between the measured value and the real value. Any deviation of the measured value from the real value is the error within the system [31, 37]. Furthermore, the precision is the closeness of two or more measurement to each other. By employing these two criteria, the reliability of strain measurement is determined.

For rating the seriousness of each criterion, a fuzzy evaluation method is applied. Five different levels are defined, namely $\tilde{\alpha}_1, \tilde{\alpha}_2, \tilde{\alpha}_3, \tilde{\alpha}_4,$ and $\tilde{\alpha}_5$. The seriousness of each criterion is evaluated by applying linguistic terms named as very low, low, medium, high, and very high. For rating the seriousness of precision and accuracy, the triangle membership functions with triplet descriptions are used as shown in Fig. 2 and Table 1, respectively [6, 30].

2.2 Weight calculation of state variables

For weighting the selected parameters, Analytic Hierarchy Process (AHP) is implemented based on the weight profit factor [7].

The vector $S(x_j) = \{s_1(x_j), s_2(x_j), \dots, s_p(x_j)\}$ is given as follow:

$$s_j(x_j) = \begin{cases} \lambda_1 \alpha & x_j = \tilde{\alpha}_1 \\ \alpha & x_j = \tilde{\alpha}_2 \\ 1 & x_j = \tilde{\alpha}_3 \\ \beta & x_j = \tilde{\alpha}_4 \\ \lambda_2 \alpha & x_j = \tilde{\alpha}_5 \end{cases} \quad (1)$$

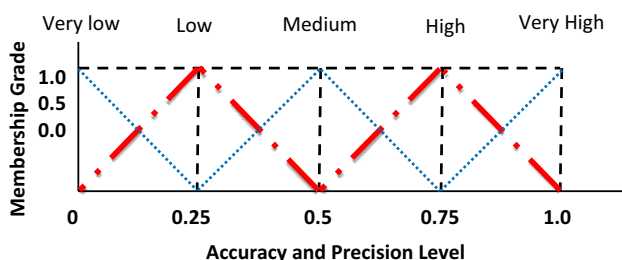


Fig. 2 Triangular membership function for the weightiness of accuracy and precision

Table 1 Triplet description of Linguistic variables for the evaluation of accuracy and precision weightiness associated with Fig. 1

Linguistic variables	Fuzzy rating	Triple description
Very high	a_5	(0.75, 1, 1)
High	a_4	(0.5, 0.75, 1)
Medium	a_3	(0.25, 0.5, 0.75)
Low	a_2	(0, 0.25, 0.5)
Very low	a_1	(0, 0, 0.25)

where $\alpha, \beta,$ and λ are positive, negative, and regulative factors, respectively.

2.3 Variable weight definition and implementation

The initial weights for accuracy and precision are implemented via AHP. The variable weight vector W is the normalized product of constant weight factor w and variable weight state vector s which can be evaluated based on Eq. 2.

$$W_j(x_j) = \frac{w_j s_j(x_j)}{\sum_{k=1}^n w_k s_k(x_j)} \quad (2)$$

2.4 Taguchi orthogonal array

Taguchi is a technique to reduce the number of experiments which create robustness for different industrial applications. Hence, there is a huge reduction of time and cost throughout the manufacturing process [14]. In this paper, the interaction of Taguchi with TOPSIS and FAHP is implemented to investigate the highest reliability index throughout the strain measurement procedure. Selected parameters and their relevant levels are listed and introduced, as shown in Table 2.

Based on the number of parameters and their levels, the L_9 orthogonal array is created as shown in Table 3.

2.5 TOPSIS

In this study, m represent the trial number of experiments number n represent different objectives for quality

Table 2 Three levels of the temperature (P_1), the length of wires (P_2), and the point of applications (P_3)

	P_1 (°C)	P_2 (cm)	P_3 (cm)
Level 1	23	5	1
Level 2	37	10	2
Level 3	50	15	3

Table 3 L_9 orthogonal array of Taguchi

Trial number	P_1	P_2	P_3
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

evaluation. Initial weight calculation is implemented via AH. Then, fuzzy relative matrix based on the seriousness of accuracy and precision is applied and different weight of each criterion is considered by Eqs. 1 and 2. Finally, the varied weighted fuzzy evaluation matrix is based on Eq. 3 as follow:

$$\tilde{V} = [\tilde{v}_{ij}]_{m \times n} \quad i = 1, 2, \dots, m \quad \text{and} \quad j = 1, 2, \dots, n \quad (3)$$

here $\tilde{v}_{ij} = \tilde{r}_{ij} \times W_j = (r_{ij1}W_j, r_{ij2}W_j, r_{ij3}W_j)$.

TOPSIS is applied to rank the order of 9 experiments. Based on the selected fuzzy decision matrix, it is evident that the elements \tilde{v}_{ij} of normalized positive triangle numbers and their range is related to interval [0, 1]. Hence, the definition of fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) is defined as:

$$A^+ = \{\tilde{v}_1^+, \tilde{v}_2^+ \dots \tilde{v}_n^+\} \quad (4)$$

$$A^- = \{\tilde{v}_1^-, \tilde{v}_2^- \dots \tilde{v}_n^-\} \quad (5)$$

where $\tilde{v}_j^+ = (v_j^+, v_j^+, v_j^+)$, $\tilde{v}_j^+ = \max(v_{ij}^+)$, $\tilde{v}_j^- = (v_j^-, v_j^-, v_j^-)$, and $v_j^- = \min(v_{ij}^-)$.

The distance of each alternative or experiment based on the orthogonal array can be calculated by following equations:

$$d_i^+ = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^+), \quad \forall i = 1, 2, \dots, m \quad (6)$$

$$d_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad \forall i = 1, 2, \dots, m \quad (7)$$

where $d(\tilde{v}_{ij}, \tilde{v}_j^\pm) = [1/3((v_{ij1} - v_{j1}^\pm)^2 + (v_{ij2} - v_{j2}^\pm)^2 + (v_{ij3} - v_{j3}^\pm)^2)]^{0.5}$.

Finally, the quality index of "n" alternatives can be calculated as the reliability index (R_i) and noise index (N_i) (Eqs. 8 and 9). The higher reliability index, and lower noise index means that there is less noise within the measurement procedure.

Table 4 Descriptions of the experimental components associated with Fig. 3

Part number	Description	Technical information
1	Load cell	Crow-tail sensor with HX711 amplifier
2	Arduino micro-controller	(ATmega328)
3	Analog to digital convertor	Digital I/O pins 24
4	Intermediate software	Lab view

$$R_i = \frac{d_i^+}{d_i^+ + d_i^-} \quad i = 1, 2, \dots, m. \quad (8)$$

$$N_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad i = 1, 2, \dots, m. \quad (9)$$

2.6 Experimental setup

The experimental components used in strain measurement are described in Table 4, including the technical information for each component.

In the experimental tests, a Crow-tail load cell sensor was employed. The HX711 amplifier was embedded in the kit, with high accuracy of a 24-bit analog-to-digital converter (ADC) as shown in Fig. 3a. The Crow-tail load cell has been designed for a weigh scale and industrial control applications with the accuracy of the mass sensor of 0–5 kg as shown in Fig. 3b. The calibration process for the selected sensor is implemented by applying the same mass (40 g) to guarantee that no noise is produced.

In the experimental tests, a C++ program was provided and embedded in the Arduino controller. The measured data as outputs were collected from the controller by altering the inputs. In the next section, the details of strain measurements are explained.

3 Result and discussion

3.1 Strain measurement

The strain value was evaluated based on the mass, the cross-section area of the square aluminum bar and the module of elasticity employing the following equations:

The total stress was evaluated by Eq. 10:

$$\sigma = \frac{F}{A} = \frac{mg}{A}, \quad (10)$$

where F (N) stands for the applied force, A (m^2) represents the cross-section area of the bar, and m (kg) is the mass. Equation 11 is used to calculate the strain value as follow:

Fig. 3 **a** Crow-tail series sensor with HX711 amplifier, front and back view, **b** Square aluminum beam used in the tests with the attached load cell

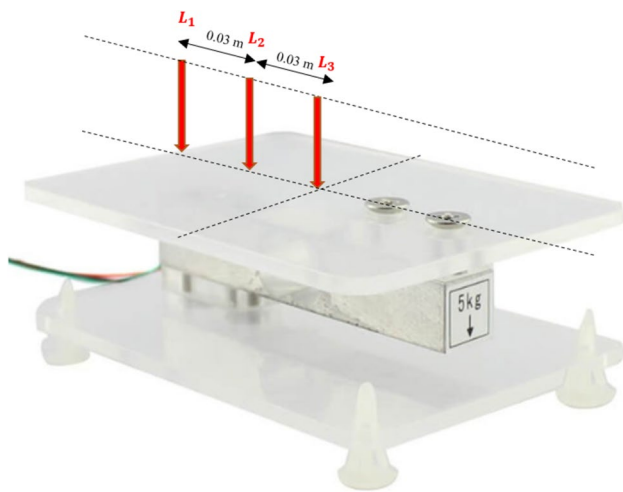
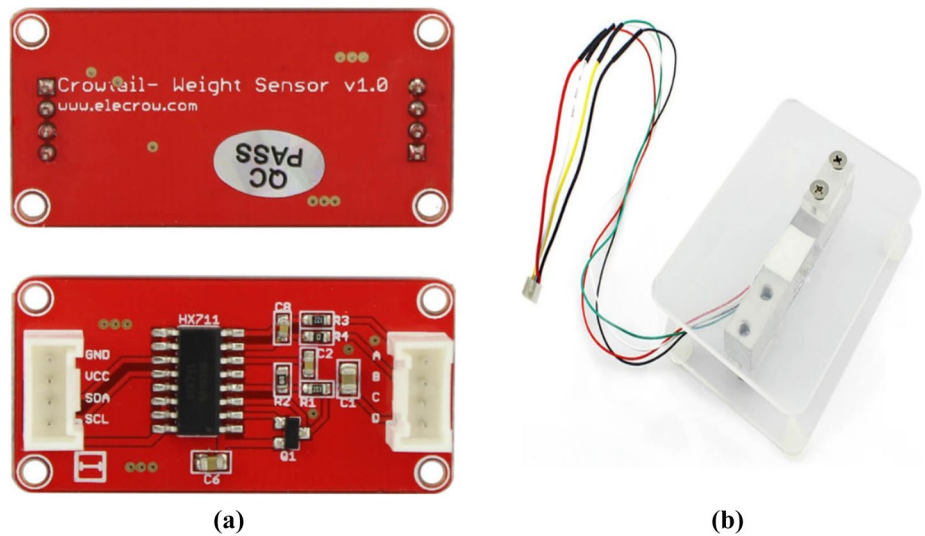


Fig. 4 Point of applied force on the strain gauge (L_1, L_2 , and L_3), including the gaps between the loads

$$s = \frac{\sigma}{E} \tag{11}$$

here s and σ are the strain (unitless) and the stress (N/m^2), respectively. E (N/m^2) represents the module of elasticity of the aluminum. Three points of the applied forces with a gap of 0.03 (m) are considered as shown in Fig. 4. Both the S/N ratio and the analysis of variance were applied to determine the significance and percentage of contribution of each parameter.

Table 5 summarizes the evaluation of outcomes, including the stresses and strains of all experimental tests. The tests were conducted for three measurements known as m_1, m_2 , and m_3 , for the same mass (40 g), which are obtained by Arduino micro-controller. This repetition enhances the accuracy of the strain measurements. The mass was evaluated according to the employed material, which is aluminum ($E_{Al} = 69 \times 10^9 \text{ MPa}$).

Table 5 Strain measurement of the test cases based on the L_9 orthogonal array, using three types of masses

Trial number	m_1 (g)	m_2 (g)	m_3 (g)	Stress 1 (Pa)	Stress 2 (Pa)	Stress 3 (Pa)	Strain 1	Strain 2	Strain 3
1	39.5	39.6	39.5	40.40	40.62	40.40	5.84E-08	5.86E-08	5.84E-08
2	38.9	38.8	38.8	39.09	39.87	39.87	5.76E-08	5.74E-08	5.74E-08
3	38.9	38.9	38.9	39.09	39.09	39.09	5.76E-08	5.76E-08	5.76E-08
4	40.9	40.6	41	41.46	41.81	41.68	6.05E-08	6.01E-08	6.07E-08
5	42.2	42	41.6	43.31	42.87	42.75	6.24E-08	6.22E-08	6.16E-08
6	42	41.7	41.5	42.80	42.22	42.78	6.22E-08	6.17E-08	6.14E-08
7	38	38.3	38.3	38.10	39.785	39.78	5.62E-08	5.67E-08	5.67E-08
8	40	40	40.1	40.50	40.50	40.71	5.92E-08	5.92E-08	5.93E-08
9	39.5	38.8	41.7	40.40	39.87	42.21	5.84E-08	5.74E-08	6.17E-08

Table 6 Calculation of initial weights

	S_1	S_2	Initial weight
Step weight	0.5	0.5	–
Accuracy	1	–	0.5
Precision	–	1	0.5

Table 7 Fuzzy rating of 9 trial numbers based on accuracy and precision

Trial number	Accuracy	Precision
1	$\tilde{\alpha}_2 (0,0.25,0.5)$	$\tilde{\alpha}_2 (0,0.25,0.5)$
2	$\tilde{\alpha}_3 (0.25,0.5,0.75)$	$\tilde{\alpha}_2 (0,0.25,0.5)$
3	$\tilde{\alpha}_3 (0.25,0.5,0.75)$	$\tilde{\alpha}_1 (0, 0, 0.25)$
4	$\tilde{\alpha}_3 (0.25,0.5,0.75)$	$\tilde{\alpha}_3 (0.25,0.5,0.75)$
5	$\tilde{\alpha}_5 (0.75,1,1)$	$\tilde{\alpha}_2 (0,0.25,0.5)$
6	$\tilde{\alpha}_5 (0.75,1,1)$	$\tilde{\alpha}_4 (0.5, 0.75, 1)$
7	$\tilde{\alpha}_5 (0.75,1,1)$	$\tilde{\alpha}_4 (0.5, 0.75, 1)$
8	$\tilde{\alpha}_1 (0, 0, 0.25)$	$\tilde{\alpha}_1 (0, 0, 0.25)$
9	$\tilde{\alpha}_1 (0, 0, 0.25)$	$\tilde{\alpha}_5 (0.75,1,1)$

3.2 Optimization process

The initial weight of each criterion, based on their classifications (Fig. 2), is calculated using AHP, and the results are tabulated in Table 6.

Fuzzy rating for accuracy and precision of nine experiments is implemented. Based on their seriousness, different level of fuzzy rating is considered as triangular fuzzy numbers, and the results are tabulated in Table 7.

Based on the literature, the regulative factors are selected as $\alpha = \beta = 1.25$, $\lambda_1 = \lambda_2 = 1.5$ [7]. The varied weight of each criterion was determined in Table 7 via Eqs. 1 and 2. The reliability index was also evaluated for all trial numbers (Eq. 8) as shown in Table 8. Then, fuzzy evaluation was used to determine the results of nine experiments for accuracy and precision as shown in Table 9 using Eq. 3. It is found

Table 8 Calculation of varied weight based on variable weight profit factor

Trial number	Accuracy			Precision		
	x_j	$s_j(x_j)$	$w_j(x_j)$	x_j	$s_j(x_j)$	$w_j(x_j)$
1	$\tilde{\alpha}_2$	1.25	0.50	$\tilde{\alpha}_2$	1.25	0.50
2	$\tilde{\alpha}_3$	1.00	0.44	$\tilde{\alpha}_2$	1.25	0.56
3	$\tilde{\alpha}_3$	1.00	0.35	$\tilde{\alpha}_1$	1.87	0.65
4	$\tilde{\alpha}_3$	1.00	0.50	$\tilde{\alpha}_3$	1.00	0.50
5	$\tilde{\alpha}_5$	1.87	0.60	$\tilde{\alpha}_2$	1.25	0.40
6	$\tilde{\alpha}_5$	1.87	0.60	$\tilde{\alpha}_4$	1.25	0.40
7	$\tilde{\alpha}_5$	1.87	0.60	$\tilde{\alpha}_4$	1.25	0.40
8	$\tilde{\alpha}_1$	1.00	0.35	$\tilde{\alpha}_1$	1.87	0.65
9	$\tilde{\alpha}_1$	1.87	0.50	$\tilde{\alpha}_5$	1.87	0.50

Table 9 Fuzzy evaluating results of nine experiments for accuracy and precision

Trial number	Accuracy	Precision
1	(0, 0.125, 0.25)	(0, 0.125, 0.25)
2	(0.11, 0.22, 0.33)	(0, 0.14, 0.28)
3	(0.0875, 0.175, 0.2625)	(0, 0, 0.162)
4	(0.125, 0.25, 0.375)	(0.125, 0.25, 0.375)
5	(0.45, 0.6, 0.6)	(0, 0.1, 0.2)
6	(0.45, 0.6, 0.6)	(0.2, 0.3, 0.4)
7	(0.45, 0.6, 0.6)	(0.2, 0.3, 0.4)
8	(0, 0, 0.0875)	(0, 0, 0.162)
9	(0, 0, 0.125)	(0.375, 0.5, 0.5)

Table 10 Reliability and Noise indices of nine experiments based on accuracy and precision

Trial number	d_i^+	d_i^-	$d_i^+ + d_i^-$	R_i	N_i
1	0.8744	0.3227	1.1972	0.7304	0.2695
2	0.7681	0.4183	1.1865	0.6474	0.3525
3	0.8833	0.2828	1.1661	0.7574	0.2425
4	0.6346	0.5400	1.1746	0.5402	0.4597
5	0.4948	0.6836	1.1784	0.4199	0.5800
6	0.3026	0.8654	1.1680	0.2590	0.7409
7	0.3026	0.8654	1.1680	0.2590	0.7409
8	1.0246	0.1443	1.1690	0.8765	0.1234
9	0.6336	0.5342	1.1678	0.5425	0.4574

that trial number 8 has the highest reliability index based on accuracy and precision as shown in Table 10 after all calculations (Fig. 5).

A sample of calculation is performed here for trial test 1, for evaluation of accuracy employing Eq. 3. The result can be evaluated as follow.

Sample of calculation:

$$(0, 0.25, 0.5) \times 0.5 = (0, 0.125, 0.25)$$

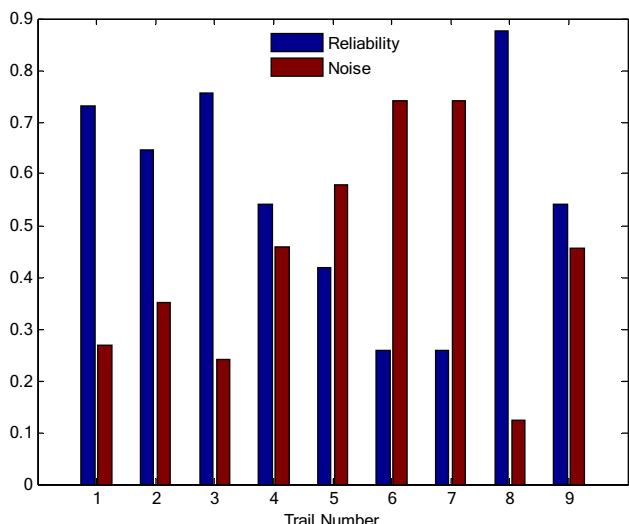


Fig. 5 Comparison of Reliability and Noise indices at 9 levels applying the data of Table 10

Reliability index (R_i) and Noise index (N_i) are calculated for nine experimental tests and shown in Table 10. The maximum reliability index is 0.8765 and the minimum noise index is 0.1234 which are related to experiment number 8. Although, the best set of parameters are P_1 at level 3, P_2 at level 2, and P_3 at level 1. It, the calculation of Signal to Noise ratio will determine the optimum level of individual parameters with higher reliability index and lower noise index. The distance of each alternative or experiment based on the orthogonal array can also be calculated using Eq. 8:

$$d_{Accuracy}^+ = [1/3((0 - 0.6)^2 + (0.125 - 0.6)^2 + (0.25 - 0.6)^2)]^{0.5} = 0.4858$$

$$d_{precision}^+ = [1/3((0.5 - 0)^2 + (0.5 - 0.125)^2 + (0.5 - 0.25)^2)]^{0.5} = 0.3886$$

So the distance of trial 1 is calculated as:

$$d_1^+ = 0.4858 + 0.3886 \cong 0.8744$$

After determining the Reliability and Noise Indexes, the next step is to apply S/N ratios to find the significant parameters and their optimum level in order to find the minimum noise (high accuracy and precision). To reduce the noise, "The smaller the better" is chosen for the Noise index. The calculated results for temperature measurement and S/N ratio have been determined in Table 11. The value for the S/N was calculated based on Eqs. 12 and 13 for each experiment. MSD stands for mean squared deviation.

$$MSD = \frac{1}{N} \sum_{i=1}^n y_i^2 \tag{12}$$

Table 11 S/N ratio for all test cases

Trial number	N_i	MSD	S/N ratio
1	0.2695	0.06	11.70
2	0.3525	0.09	10.45
3	0.2425	0.04	13.97
4	0.4597	0.16	7.95
5	0.5800	0.25	6.02
6	0.7409	0.49	3.09
7	0.7409	0.49	3.09
8	0.1234	0.01	20
9	0.4574	0.16	7.95

Table 12 The response table of S/N ratio

	P_1 : Temperature	P_2 : length of wire	P_3 : point of application
Level 1	12.04	7.58	11.59
Level 2	5.69	12.15	8.79
Level 3	10.35	8.34	7.69
Difference $ \Delta T $	6.35	4.57	3.90

$$S/N = -10 \log(MSD) \tag{13}$$

From the collecting data in Table 11, the average S/N ratio for the response table can be calculated. The responses are summarized in Table 12 to determine the optimal levels of the selected parameters.

The difference between the levels is defined as $|\Delta T|$. The larger value of $|\Delta T|$ demonstrates the significance of the parameter. It is clear that P_1 is the most significant parameter followed by P_3 , and P_2 , respectively. The optimum set of parameters can be evaluated from Table 12 by selecting the highest level of S/N for each parameter. The best results are P_1 at level 1, P_2 at level 2, and P_3 at level 1. This is clearly highlighted in a bar chart as shown in Fig. 6. The results reveal that by setting the temperature at 23 °C, length of wires at 10 cm, and point of application at 1 cm, the highest reliability is achievable with minimum noise. After setting the controllable parameters to their optimal levels, the final result for the selected mass was 40 g.

Once the optimum level of individual parameters was determined, the degrees of freedom, the sum of squares, the variance, F ratio, the pure sum of a square and their contribution are calculated via ANOVA. The individual sum of a square and the total sum of the square are calculated based on Eqs. 14–16:

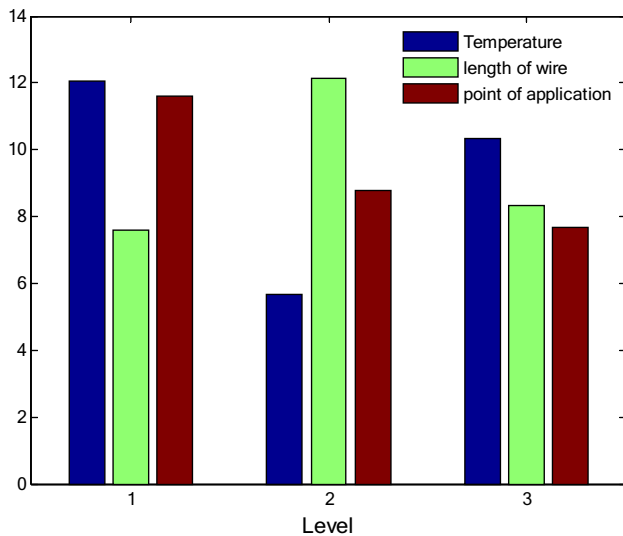


Fig. 6 Comparison of Temperature, the length of wire and the point of application at three levels based on Table 12

$$SS_{P_i} = \sum_{i=1}^{K_A} \left(\frac{A_i^2}{n_{A_i}} \right) - \frac{\left(\sum_{i=1}^N x_i \right)^2}{N}, \tag{14}$$

$$SS_T = \sum_{i=1}^{K_A} x_i^2 - \frac{\left(\sum_{i=1}^N x_i \right)^2}{N}, \tag{15}$$

$$SS_E = \left(SS_T - \sum_{i=1}^{K_A} SS_{P_i} \right), \tag{16}$$

where A_i is the average temperature for each level, n_{A_i} stands for the number of levels, x_i represents the temperature value in each experiment, N is the number of experiments and k_A represents the number of parameters. For the calculation of the degree of freedom of each level (F_i) and the total degree of freedom (F_t) the following equations were used, respectively:

$$F_i = x_i - 1, \tag{17}$$

$$F_t = N - 1. \tag{18}$$

Thus, to determine the error of the degree of freedom, Eq. 19 is applied as follow:

$$F_e = F_t - \sum_{i=1}^{K_A} F_i \tag{19}$$

The variance of the individual parameter (V_{P_i}) and the variance of error (V_e) are calculated as follow:

$$V_{P_i} = \frac{SS_{P_i}}{F_i}, \tag{20}$$

$$V_e = \frac{SS_e}{F_e} \tag{21}$$

Finally, the percentage of contribution of each parameter (P_{P_i}) can be determined by Eq. 22.

$$P_{P_i} = \frac{SS_{P_i}}{SS_T}, \tag{22}$$

$$S_e = S_T - S_{P_1} - S_{P_2} - S_{P_3} \tag{23}$$

By using Eqs. 10–18, the weight or percentage of contribution of each parameter is calculated, as shown in Table 13 which is associated with Fig. 7. The results indicate that the temperature with 67.36% has the highest contribution, followed by the length of wire with 17.15% and the point of application with 15.48%. According to Eqs. 18 and 19, the amount of error for degree of freedom is 2. Also, based on Eq. 23 the error for both sum of square and the percentage of contribution is zero. The

Table 13 Analysis of variance (ANOVA) for the selected parameters

	F	SS	P (%)
P_1 : Temperature	2	0.1398	67.36
P_2 : length of wire	2	0.03561	17.15
P_3 : point of application	2	0.03214	15.48
Error	2	0	0
Total	8	0.2076	100

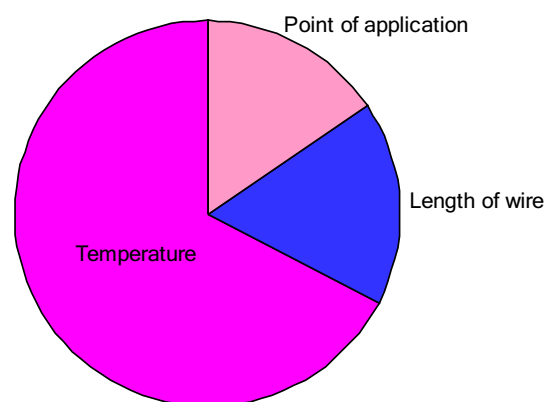


Fig. 7 Pie chart of contribution of Variance (ANOVA) for the three selected parameters, including Temperature, the length of wire and the point of application

combination of Taguchi and TOPSIS was implemented. The determination of an experiment with the highest reliability of strain gauge was considered and experiment number 8 is nominated with the highest reliability index. In addition, the contribution of Taguchi led to the determination of significant parameters and their percentage of contribution affecting the reliability of strain gauges for different applications.

4 Conclusion

Combination of Taguchi and FAHP with TOPSIS offers a well-organized use approach for multi-objective problems. Determining the highest reliability index in strain measurement is the objective of this study. By using the Taguchi method, the significant controllable factors and their optimum levels were identified. Two common concepts in measurement were selected as a different criterion to evaluate the reliability and noise index. The proposed method was applied for three different controllable parameters, namely the temperature, the length of wire, and the point of application. For rating the seriousness of each criterion, a fuzzy evaluation is considered by defining five different levels. TOPSIS was chosen to rank the order of nine experiments. According to the TOPSIS approach, it is found that the highest reliability index is related to trial number 8. The best set of parameters are P_1 at level 3, P_2 at level 2, and P_3 at level 1 with 88% reliability index and 12% noise index. The optimum levels are P_1 at level 1, P_2 at level 2, and P_3 at level 1 and the temperature is the most significant parameters with 67.36% contribution, which alters the accuracy and precision in strain measurement.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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