JJMIE

Volume 5, Number 5, Oct. 2011
ISSN 1995-6665
Pages 451 - 459

Jordan Journal of Mechanical and Industrial Engineering

Selection of Temperature Measuring Sensors Using the Analytic Hierarchy Process

T. Al-Hawari*[,a], S. Al-Bo'ol[a], A. Momani[a]

[a]*Industrial Engineering Department, Jordan University of Science and Technology, Irbid 22110, Jordan*

Abstract

This study presents an analytic hierarchy process (AHP) method to objectively select the best temperature sensor from among different alternative sensors in a certain industrial application. The underlying decision method based on AHP methodology, ranks temperature sensors with different features with a score resulting from the synthesis of relative preferences of each alternative with respect to the others at different levels considering independent evaluation criteria and sub-criteria. At each level, relative preferences of each candidate alternative with respect to the upper immediate level are calculated from pair-wise comparisons among the candidate alternative sensors with respect to a selected application. Pair-wise comparison matrices are compiled based on views of experts in this field. Seven alternative sensors were considered: the thermocouple, the thermister, the resistance temperature detector (RTD), the bimetallic strip thermometer, the mercury-in-glass thermometer, the optical disappearing filament pyrometer, and the liquid crystal display semi conductor thermometer (LCD). Three industrial applications were also considered: Automotives, Chemical Processes, and Heating, Ventilating and Air Conditioning. A case study is conducted which involves selecting the best sensor for an automotive catalytic converter. The thermocouple is found to be the most preferred sensor for this application with the largest score of 0.37849, the second ranked sensor is the RTD with a score of 0.34589, and the least preferred sensor is the thermister with a score of 0.27560. To test the robustness of the proposed work, a sensitivity analysis was conducted in which variations in the relative preferences of the alternative sensors against sub-criteria and criteria were employed.

Keywords: Analytic Hierarchy Process; Temperature; Sensor

1. Introduction

Nowadays, we live in a highly competitive industrial environment that imposes stringent measures on product quality and uniformity. This calls for the employment of efficient and accurate process operations with a complete set of automated measurement sensors and control technologies. In this sense, process sensors are the devices that measure process variables, of which temperature in many cases is of high importance and indicative of process progress. The resulting data is used to control and monitor the process, and to take corrective actions if needed [1]. Additionally, process measurement enables better understanding of the process input and output variables and the various relationships that tie up these variables, which is a preliminary step for process improvement and optimization. The final result is reflected on cost minimization and profit maximization which is the final pursuit of an industrial company.

Temperature sensors selection and alternative sensors preferences are mostly based on subjective views and opinions of decision makers or experts in the sensors field. These views remain personal and subjective and may lead to erroneous judgments of the best sensor for a certain industrial application. These judgments vary from one expert to another and are not based on a systematic approach of the evaluation process. On the other hand, the selection of the best sensor based on AHP, is a systematic way for the evaluation process. It is based on breaking down the decision problem of selecting the best sensor into smaller parts that represent the hierarchical structure levels and their components. These levels range from the lowest level, which is in this case the different alternatives that are to be assessed, to the top most level, which is the final goal; the selection of the best temperature sensor. In between the lowest and the top most levels, lie two levels representing the evaluative criteria and sub-criteria pertaining to sensors selection norms applied in industry. Starting from the lowest level, each alternative sensor is assessed against other alternatives with respect to each sub-criterion in the immediate subsequent level by means of pair-wise comparisons among the different alternatives. Each sub-criterion in the subsequent level is then pair-wise compared against other sub-criteria with respect to parent criterion in the third level; the criteria level. After that, each criterion in the third level is assessed against other criteria with respect to the top most level of the decision hierarchy; the final goal of choosing the best sensor. Finally, the different weights obtained for the different alternatives in the first level are aggregated and lumped together with weights obtained for the criteria and sub-criteria in the third and second levels to come up with overall final scores for different sensors against the overall problem objective. These overall scores are indicative of

* Corresponding author. e-mail: tarek321@hotmail.com

the relative preferences of the sensors against the overall goal. The best sensor with the largest score corresponds to the best (most preferred) sensor and the smallest score corresponds to the worst (least preferred) sensor, and values in between correspond to intermediate preferences.

2. Literature Review

Previous literature indicates the massive use of AHP methodology as a multi-criteria decision making tool in selecting from among nominated alternatives in many industrial fields. However the literature survey has not revealed any research conducted specifically on the selection of temperature sensors using AHP method, and here comes to the fore the importance of this study. Vaidya and Kumar [2] conducted research that overviewed different applications of the AHP method. In their paper, they referred to a total of 150 application papers such as; selection, evaluation, benefit-cost analysis, resource allocation, decision making, forecasting, medicine, QFD, social, political, manufacturing, engineering, education, industry, government, and others. Yurdakul [3] applied AHP as a strategic decision-making tool to justify machine tool, namely machining centers, selection. Analytic Network Process (ANP) method was also used in the same paper to account for calculation of the weights of the criteria due to interdependencies and interrelationships that exist among them. Pi-Fang et al [4] presented an AHP method for objectively selecting medical waste disposal firms in Taiwan based on the results of interviews with experts in the field. In their study, appropriate criteria weights based on AHP were selected to assess the effectiveness of medical waste disposal firms. The proposed AHP-based method offered a more efficient and precise means of selecting medical waste firms than subjective assessment methods, thus reducing the potential risks for hospitals. Che-Wei et al [5] studied and developed a manufacturing quality yield model for forecasting 12 in. silicon wafer slicing machine based on AHP framework. In their work, exponentially weighted moving average (EWMA) control charts were used to demonstrate and verify the feasibility and effectiveness of the proposed AHP-based algorithm. Okada, et al [6] applied AHP to irrigation project improvement. In their study, the work was divided into two parts. In the first part, a questionnaire survey was distributed among irrigation professionals to determine the most important evaluation factors in evaluating an irrigation project. The survey was then processed by the AHP method and local weights of evaluation factors were obtained. In the second part, these local weights were statistically analyzed and modeled by probability density functions. Results indicated that professionals give the first priority to water delivery services and that they consider the irrigation infrastructure of primary canals more important than that for secondary canals. Papalexandrou et al [7] applied AHP method for assessing liquid bio-fuels which are derived from agricultural crops and are a major feasible crude oil substitute in the European Union. Muralidhar et al [8] presented an improved methodology for information systems project selection using AHP. Bevilacqua and Braglia [9] applied AHP for selecting the best maintenance strategy for an important Italian oil refinery. Five possible alternatives were considered: preventive, predictive, condition-based, corrective and opportunistic maintenance.

Despite the fact that, the literature survey reveals a wide array of AHP applications, the survey does not reveal its use in evaluating temperature sensors selection. Research on temperature sensors was primarily concerned in proposing new temperature sensors fabrications that satisfy certain special demands and requirements. Vavra et al [10] proposed the use of Fe/Cr magnetoresisitive sensors at temperatures below 2 K in the MilliKelvin temperature range. Hoa et al [11] studied electrical resistance drift of molybdenum disilicide (MoSi2) thin film temperature sensors to study their thermo-resistance characteristics. Bianchi et al [12] discussed the properties, characteristics, applications and sensing principles of most of present-day integrated smart temperature sensors. A CMOS process-compatible temperature sensor developed for low-cost high-volume integrated Microsystems for a wide range of fields (such as automotive, oil prospecting, and biomedical applications) was also described. Han & Kim [13] developed a diode temperature sensor array (DTSA) for measuring the temperature distribution on a small surface with high resolution. The DTSA consisted of an array of 32x32 diodes (1024) for temperature detection in an 8mmx8mm surface area and was fabricated using the very large scale integration (VLSI) technique.

In the next section, the paper gives a brief introduction of the AHP method and the evaluative criteria used in selecting the best temperature sensor. A case study is then presented and the results are discussed. Sensitivity analysis is presented in the following section. The final section provides some concluding remarks.

3. AHP Method Theoretical Background

The analytic hierarchy process is a multi-criteria decision-making tool mostly used when a decision maker is faced with a problem involving multiple objectives and criteria. The method, which was developed by Thomas Saaty [14], has been widely applied to different decision making problems. AHP’s widespread use may be considered as an evidence of the method's power and reliability among decision makers in dealing with different problems [15]. Typically, the decision maker will have an objective or multiple objectives that must be fulfilled and a group of candidate alternatives that are to be assessed. The alternatives, criteria, sub-criteria, and the objective are linked in a hierarchal structure and each forms a hierarchal level. Each component at a particular level is relatively pair-wise compared with its sister components with respect to the immediate upper level and weights of all components are determined and aggregated for upper levels. The final outcome of the method is a score for each alternative representing its relative preference towards the objective.

4. Method Application

Once the decision maker has identified the objective of the problem, the alternatives, the criteria and sub-criteria governing the comparison process, then the application of AHP becomes easy and can be described in terms of the following steps:

Step 1: The decision hierarchy is setup. The decision hierarchy will be made up of the objective level, the criteria level, the sub-criteria level, and finally the alternatives level.

Table 1 shows the list of criteria and sub-criteria within each criterion that will be used as a basis for the comparison between the alternative sensors. There are four criteria: Static, Dynamic, Environmental, and Others. Static criterion refers to those characteristics that are inherent in the structure of the sensor such as the maximum and minimum operating temperatures for which the sensor is rated. This criterion comprises 11 sub-criteria represented by the symbols: CS1, CS2... CS11. Dynamic criterion refers to dynamic behavior of the sensor and mainly has to do with the sensor's response time which is the time needed for the sensor to reach 63.2% of its steady state response following a step change in input temperature. This criterion comprises 3 sub-criteria represented by the symbols: CS12, CS13, and CS14. Environmental criterion refers, on the other hand, to the medium characteristics that the sensor is to be used in and the degree of suitability of a sensor in a certain medium, it comprises 5 sub-criteria represented by the symbols: CS15… CS19. Finally, Others criterion refers to miscellaneous sub-criteria defining the sensor's behavior, it consists of 4 sub criteria such as the cost sub-criterion.

Table 1: Criteria and sub-criteria factors used as basis for comparison between alternative sensors.

Criteria	**Sub-Criteria**
Static Criteria (C1)	Maximum Operating Temperature (CS1)
	Minimum Operating Temperature (CS2)
	Temperature Curve (CS3)
	Maximum Sensitivity Region (CS4)
	Self-Heating Issues (CS5)
	Long Term Stability and Accuracy (CS6)
	Typical Temperature Coefficient (CS7)
	Extension Wires (CS8)
	Long Wire runs from Sensor (CS9)
	Measurement Parameter (CS10)
	Temperature Measurement (CS11)
Dynamic Characteristics (C2)	Stimulation Electronics required (CS12)
	Typical Output Levels per Degree Celsius (CS13)
	Typical Fast Thermal Time Constant (CS14)
Environmental Parameters (C3)	Typical Small Size (CS15)
	Noise Immunity (CS16)
	Fragility-Durability Characteristics (CS17)
	High Thermal Gradient Environment (CS18)
	Corrosion Resistance (CS19)
Other Criteria (or Simply Others) (C4)	Point or Area Measurement (CS20)
	Manufacturing Variances (CS21)
	NIST Standards (CS22)
	Cost (CS23)

The best temperature sensor can then be selected and evaluated based on four evaluation criteria, twenty three evaluation sub-criteria. Figure 1 shows the hierarchal structure for the temperature sensor selection problem for three alternative sensors.

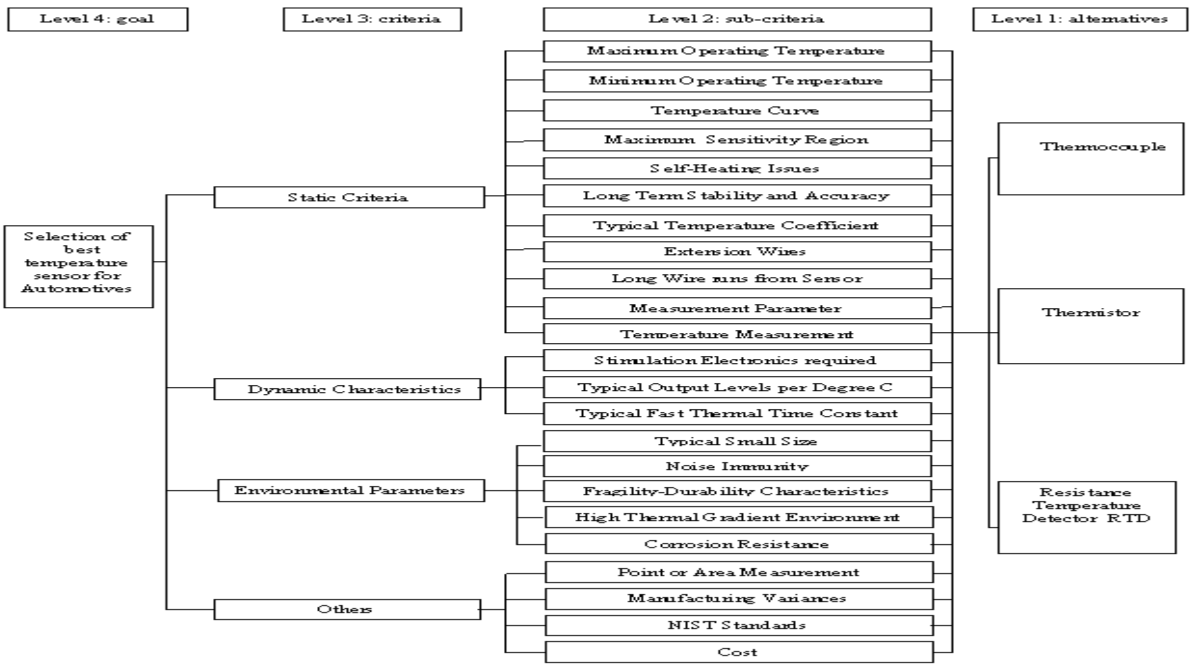

Figure 1: hierarchal structure for the temperature sensor selection problem.

Step 2: Pair-wise comparisons of the alternatives, sub-criteria, and criteria is performed. This is done to determine the weights of the different criteria and sub-criteria and also to determine how well the alternatives score on each sub-criterion and criterion. Values of relative importance (weights) throughout the whole hierarchy were taken from views of experts in the field of sensors. These values were collected and their averages were used. The weights of the different components in the hierarchal structure are aggregated throughout the whole hierarchy starting from the alternatives level through sub-criteria and criteria levels up to the objective level. Starting from the alternatives level, the relative importance of one alternative over the others with respect to the same sub-criterion in the decision hierarchy can be determined using Saaty's scale [16] shown in Table 2. According to Saaty, the relative weight of alternative i compared to alternative j with respect to the same sub-criterion can be obtained from a 9-point scale and assigned to the (i , j)th position of the pair-wise comparison matrix or judgment matrix.

Table 2: The pair-wise comparison scale.

Intensity of importance	Definition
1	Equally important
3	Weakly more important
5	Strongly more important
7	Very strongly more important
9	Extremely more important
2,4,6,8	Intermediate values between two adjacent judgments

In a more general form, let *A1, A2… An* be a set of n pairwise comparison matrices between criteria, sub-criteria and alternatives. Each matrix is composed of numerical weights that represent the evaluative judgments of experts of one component with respect to the others. The comparison of any two components such as criteria Ci and Cj is made using the question of the type: Of the two criteria which is more important and by how much. Saaty's scale is used to transform verbal judgments of the relative preference of one component to the other into numerical values representing the elements (aij) of the comparison matrices. The elements aij are governed by the following rules:

$$a_{ii} = 1, \forall i, a_{ij} > 0, a_{ji} = \frac{1}{a_{ij}}, \forall i, j \tag{1}$$

In the current study, comparison matrices were constructed for seven alternative sensors: the thermocouple, the thermister, the resistance temperature detector (RTD), the bimetallic strip thermometer, the mercury-in-glass thermometer, the optical disappearing filament pyrometer, and the liquid crystal display semi conductor thermometer (LCD). These matrices were constructed for 23 sub-criteria, and 4 criteria, for three different applications: Automotives, Chemical Processes, and HVAC. The matrices were compiled from the average values collected from different experts in the field of sensors. The outcomes of this step are 3 sets, one per application, of 23 matrices of the dimensions 7x7 representing relative preferences of the seven alternatives against each sub-criterion. In addition to, 3 sets of 4 matrices of the dimensions 11x11, 3x3, 5x5, and 4x4 representing relative weights of the Static, Dynamic, Environmental, and Others sub-criteria towards their respective parents criteria, as well as, 3 sets of 4x4 matrices representing the criteria relative weights against the overall goal.

These sets of matrices are ideally capable of dealing with the selection of up to seven sensors simultaneously. However, depending on the restrictions that pertain to the industrial application in terms of temperature range, resolution, and response time the total number of candidate sensors can be reduced. The work proposed permits the extraction of the required entries from the matrices of each application depending on the number of alternatives considered.

Step 3: The comparison matrices are transformed into weights corresponding to the different components, i.e., criteria, sub-criteria and alternatives. The consistency in a decision maker's evaluations is then checked in terms of the consistency index CI and consistency ratio CR. Consider the following equation:

$$AW^T = \Delta W^T \tag{2}$$

Where A represents a pairwise comparison matrix, W is an unknown n-dimensional weight vector of each component and Δ is an unknown number. Saaty proposed a way to compute Δ and W by approximating Δ with Δmax which represents the largest number for which a non trivial solution W exits for equation 2. This is only true, if the decision maker's judgments are consistent in which case Δmax would be close to n. The consistency of the decision maker's judgments is measured by computing CI which is defined as:

$$CI = \frac{\Delta_{\max} - n}{n - 1} \tag{3}$$

CR is defined in terms of CI and random index RI as:

$$CR = \frac{CI}{RI} \tag{4}$$

Values of RI for the appropriate values of n are found in literature [16]. A simple method described in [16] can be used to approximate Δ max, W, CI and CR. The consistency of the decision maker is considered acceptable if CR is less than 0.1.

Step 4: the component weights are aggregated to obtain scores for the different alternatives towards the final objective and a decision is made.

Step 5: Sensitivity analysis is performed to examine the robustness of the selected alternative to changes in the judgments made by the decision maker. It can show the extent of change that can be made to the criteria or sub-criteria weights before the preferred alternative changes in favor of another alternative.

5. Case Study: Automotive Catalytic Converter

A case study is presented here to describe the AHP sensor selection procedure. AHP is applied to the selection of the best temperature sensor from among three alternatives: the thermocouple, the thermister, and the RTD in an automotive catalytic converter application. A catalytic converter is a device which chemically converts harmful exhaust gases, produced by the internal combustion engine as by-products of the fuel combustion process, into harmless carbon dioxide, water vapor, and nitrogen gas. The Automotive catalytic converter operates in the temperature range of 500 to 750 ^{0}C (773 - 1023 K). The resolution of industrial sensors employed practically for this application is 1% of the temperature range, i.e. (5-7.5) ^{0}C. The response time is 5-10 seconds. The relative weights that are related to these three sensors are extracted out of the automotives set of comparison matrices. The AHP method is then applied to find the best sensor.

6. Results

Selected judgment matrices are shown in Table 3, representing relative weights of the three sensor alternatives case study against selected sub-criteria, relative weights of selected sub-criteria against their respective parent criterion, and relative weights of the four criteria against the overall goal. It is shown that the best scoring sensor against the Time Constant sub-criterion is the thermocouple with a weight of 0.62323. This makes sense because the thermocouple is the fastest sensor among all three sensors while the RTD is the slowest one. The thermister, on the other hand, has moderate response time. The value of *CR* is 0.01578 < 0.1 indicating consistent decision maker's comparisons. It can also be seen that the best scoring sensor against the Long Term Stability and Accuracy sub-criterion is the RTD with a weight of 0.63933. This can be explained based on the fact that, the RTD is the most accurate while the thermocouple is the least accurate of the three sensors. The thermister, on the other hand, retains moderate levels of accuracy. The value of *CR* 0.04663 is within acceptable limits.

Table 4 summarizes the three alternatives' weights with respect to the 23 sub-criteria, the 4 criteria weights with respect to the goal, the synthesis (aggregate) weight of the 23 sub-criteria towards the final goal, and the score of each alternative against each criterion. Table 4 shows that the most important criterion in the selection of a temperature sensor in this case is the Static criterion with an overall score towards the goal of 0.53637. Static criterion pertains to those static qualities that are inherent in the sensor architecture and that relate to the basic technical characteristics which makeup a sensor. On the other hand, the score of the Environmental criterion is 0.22045, suggesting less importance. These weights match well with the view of experts who state that the choice of any temperature sensor is dictated by the technical qualities that the sensor has to meet on the first scale, and on the environmental considerations, or alternatively, the medium characteristics that the sensor will be placed in on the second scale. The Dynamic and Others criteria were the least important.

Values of the consistency index (CI) and the consistency ratio (CR) are listed in Table 5 for the matrices of the different components in the hierarchal structure. As can be seen these values are all within acceptable limits indicating consistency in decision maker's judgments.

Table 6 shows the final scores for the three temperature sensors for the case study, the thermocouple is the most preferred sensor with the largest score of 0.37849, the second ranked sensor is the RTD with a score of 0.34589, and the least preferred sensor is the thermister with a score of 0.27560. These results can be matched generally with views of experts in the field. The thermocouple is the simplest to install, the least expensive, the smallest in size, the most durable and reliable, the fastest, the least electronic circuits demanding. It retains reasonable accuracy and is good in many low accuracy applications, as is the case in the automotive catalytic converter, and does not experience any self heating. It is a point measurement sensor with well-established traceable NIST standards. The second best choice, the RTD, retains many of the good qualities that the thermocouple has, but it suffers from serious drawbacks such as: fragility, high cost, relatively slow response time, very low to low self heating issues, large size, and because it is an area measurement sensor it suffers from effects of high thermal gradients. Needless to say, the thermister comes last because of the many drawbacks it shares with the RTD in addition to the high level of self heating issues, and its non-standardized technical data owing to a larger amount of uncertainty in its measurements, and the manufacturing variances that accompany its use.

Table 3: Selected matrices representing relative weights of the three sensor alternatives against selected sub-criteria, relative weights of Environmental sub-criteria towards Environmental criterion, and relative weights of criteria towards the final goal for the case study in the automotive catalytic converter application.

Maximum Op.Temp. Jugement Matrix (CS1):							
	Thermocouple	Thermister	RTD		Thermocouple	Thermister	RTD
Thermocouple	1	3	1	Alternatives Weight Vector =	0.42857	0.14284	0.42857
Thermister	0.3333	1	0.3333	Consistency Index =	0		
RTD	1	3	1	Consistency Ratio =	0		
Long Term Stability and Accuracy Judgment Matrix (CS6):							
	Thermocouple	Thermister	RTD		Thermocouple	Thermister	RTD
Thermocouple	1	0.25	0.1667	Alternatives Weight Vector =	0.08695	0.27371	0.63933
Thermister	4	1	0.3333	Consistency Index =	0.02704		
RTD	6	3	1	Consistency Ratio =	0.04663		
Typical Fast Thermal Time Constant Judgment Matrix (CS14):							
	Thermocouple	Thermister	RTD		Thermocouple	Thermister	RTD
Thermocouple	1	3	4	Alternatives Weight Vector =	0.62322	0.23948	0.13728
Thermister	0.3333	1	2	Consistency Index =	0.00915		
RTD	0.25	0.5	1	Consistency Ratio =	0.01578		
Cost Judgment Matrix (CS23):							
	Thermocouple	Thermister	RTD		Thermocouple	Thermister	RTD
Thermocouple	1	1	6	Alternatives Weight Vector =	0.46153	0.46153	0.07693
Thermister	1	1	6	Consistency Index =	0		
RTD	0.1667	0.1667	1	Consistency Ratio =	0		
Criteria Matrix:							
	Static	Dynamic	Environ.	Others			
Static	1	4	3	4			
Dynamic	0.25	1	0.5	1			
Environ.	0.3333	2	1	2			
Others	0.25	1	0.5	1			
	Static	Dynamic	Environ.	Others			
Criteria Weight Vector =	0.53636	0.12159	0.22045	0.12159			
Consistency Index =	0.00686						
Consistency Ratio =	0.00762						
Environnemental Sub-Criteria Jugement Matrix:							
	CS15	CS16	CS17	CS18	CS19		
CS15	1	3	0.3333	4	0.25		
CS16	0.3333	1	0.25	3	0.2		
CS17	3	4	1	5	0.5		
CS18	0.25	0.3333	0.2	1	0.1667		
CS19	4	5	2	6	1		
Sensor Ranks							
0.37849							
0.2756							
0.34589							

Table 4: Weights of alternatives, sub-criteria, criteria and synthesis values for sub-criteria and the alternatives for the three sensors case study.

Criteria	**Weights of Criteria**	**Sub-criteria**	**Weights of Sub-criteria**	**Synthesis Value**	**Thermocouple**	**Thermister**	**RTD**
C1	0.53637	CS1	0.22119	0.11863	0.42858	0.14283	0.42858
		CS2	0.22119	0.11863	0.5	0.25	0.25
		CS3	0.05379	0.02885	0.25099	0.09602	0.65299
		CS4	0.09836	0.05275	0.06225	0.70131	0.23644
		CS5	0.09777	0.05244	0.65715	0.06825	0.2746
		CS6	0.1504	0.08067	0.086955	0.27371	0.63933
		CS7	0.05233	0.02806	0.09602	0.65299	0.25099
		CS8	0.03038	0.01629	0.07693	0.46154	0.46154
		CS9	0.01983	0.01063	0.19999	0.6	0.19999
		CS10	0.01452	0.00778	0.62322	0.13729	0.23948
		CS11	0.03355	0.01799	0.09642	0.28422	0.619360.619 0.61936
		Score of each alternative against first criterion			0.17481	0.15043	0.20743
C2	0.12159	CS12	0.16019	0.01947	0.62322	0.13728	0.23948
		CS13	0.10093	0.01227	0.46153	0.07693	0.46153
		CS14	0.73887	0.08983	0.62322	0.23948	0.13728
		Score of each alternative against second criterion			0.07378	0.02513	0.02268
C3	0.22045	CS15	0.15164	0.03342	0.53896	0.29726	0.16378
		CS16	0.08645	0.01905	0.09339	0.68529	0.22132
		CS17	0.28264	0.0623	0.65299	0.09602	0.25099
		CS18	0.04767	0.0105	0.68064	0.20141	0.11794
		CS19	0.43157	0.09513	0.08696	0.27371	0.63933
		Score of each alternative against third criterion			0.07557	0.05767	0.0872
C4	0.12159	CS20	0.1575	0.01915	0.53896	0.29726	0.16378
		CS21	0.07747	0.00941	0.09602	0.25099	0.65299
		CS22	0.22913	0.02786	0.44444	0.11111	0.44444
		CS23	0.53589	0.06519	0.46153	0.46153	0.07693
		Score of each alternative against fourth criterion			0.05369	0.04123	0.02667

Table 5: Consistency ratio and consistency index values for the three sensor alternatives, the criteria and sub-criteria matrices for the three sensors automotive case study.

Criteria	Sub-Criteria	CI	CR
Static Criterion	Maximum Operating Temperature	0	0
CI = 0.08281	Minimum Operating Temperature	0	0
CR= 0.05208	Temperature Curve	0.00918	0.01583
	Sensitivity	0.03622	0.06225
	Self-Heating Issues	0.02218	0.03824
	Long Term Stability and Accuracy	0.02705	0.04663
	Typical Temperature Coefficient	0.00918	0.01583
	Extension Wires	0	0
	Long Wire runs from Sensor	0	0
	Measurement Parameter	0.00915	0.01578
	Temperature Measurement	0.04333	0.07471
Dynamic Characteristics	Stimulation Electronics required	0.00915	0.01578
CI = 0.02722	Existence of Maximum Sensitivity Region	0	0
CR = 0.04694	Typical Fast Thermal Time Constant	0.00915	0.01578
Environmental Parameters	Typical Small Size	0.00459	0.00791
CI = 0.06346	Noise Immunity	0.0271	0.0271
CR = 0.05666	Fragility-Durability Characteristics	0.00918	0.01583
	High Thermal Gradient Environment	0.01235	0.02129
	Corrosion Resistance	0.02705	0.04663
Others	Point or Area Measurement	0.00459	0.00791
CI = 0.03752	Manufacturing Variances	0.00918	0.01583
CR = 0.04169	Standards exist	0	0
	Cost	0	0
	The four-criteria matrix:	CI = 0.00687	CR = 0.00763

Table 6: The software final results: the three sensors scores.

Sensor	**Score**	**Rank**
Thermocouple	0.37849	1
Thermister	0.2756	3
RTD	0.34589	2

7. Sensitivity Analysis

This section tackles the sensitivity analysis applied to the case study. Sensitivity analysis for any system of input and output dependent variables refers to intended variations in the input variables of the system for the purpose of monitoring changes in the output dependent variables. In any system, sensitivity analysis gives deeper understanding of the relationships that govern the system and allows for developing and optimizing the system and avoiding critical conditions which make the system unpredictable. In this paper five variations were made and the results studied: variations in the relative weights of an alternative with respect to the others in the 23 matrices, variations in the relative weight of the criteria and also in the sub-criteria, variation in the application, and variations in the number of alternatives that fit the case study application.

7.1. Case 1: Alternative Weights Variation:

In this section the relative weight of the RTD will be increased by 1 relative weight unit on Saaty's scale. This means adding 1 to each entry in all the 23 matrices where the RTD appears and the new scores of the alternatives are monitored and discussed. Table 7 shows the new scores of the alternative sensors for the case study.

It can be clearly seen that increasing the relative weights of the RTD alternative resulted in the dominance of the RTD over the thermocouple, i.e. the thermocouple was the most preferred sensor choice before the increase while the RTD became the most preferred after the increase was employed to the system. This reveals and confirms the challenging decision situation when the differences between the scores of alternatives obtained by AHP are small, in which case the decision maker cannot easily distinguish the preference of one alternative to the others, rather, the closely-scoring alternatives have almost the same preference.

Table 7: Case 1 Sensitivity Analysis results.

Sensor	**Old Score**	**New score**	**New Rank**
Thermocouple	0.37849	0.35457	2
Thermister	0.2756	0.24957	3
RTD	0.34589	0.39585	1

7.2. 2 Case 2: Sub-criterion Relative Weights Variation:

In this case of sensitivity analysis the variation will be made to the Long Term Stability and Accuracy sub-criterion inside the Static criterion and the scores monitored. The relative weights of this sub-criterion among the 11 Static sub-criteria will be increased by a factor of 1 on Saaty's scale while the Static criterion overall score would remain unchanged to ensure that the change in the results is due to this sub-criterion effect. The procedure is merely to increase the whole values of the sixth row of the 11x11 Static sub-criteria matrix by one and the corresponding necessary changes in the reciprocals. The new scores of the three alternatives are shown in Table 8.

It can be clearly seen that although increasing the relative weights of the Long Term Stability and Accuracy sub-criterion by a factor of 1 has decreased the final score of the thermocouple alternative and has increased the final score of the RTD alternative, it did not change the preferences (ranks) of the three alternatives and that the thermocouple remained the most preferred.

Table 8: Case 2 Sensitivity Analysis results.

Sensor	**Old Score**	**New score**	**New Rank**
Thermocouple	0.37849	0.37016	1
Thermister	0.2756	0.27616	3
RTD	0.34589	0.35368	2

7.3. Case 3: Dynamic Criterion Relative Weights Variation:

In this case, the relative weight of the Dynamic criterion is increased by a factor of 1 relative importance on Saaty's scale while the remaining criteria weights are kept unchanged. The results for this case are shown in Table 9.

It can be clearly seen that increasing the Dynamic criterion relative weight by a factor of 1 has increased the thermocouple final score and decreased the thermister and the RTD final scores, this is because the thermocouple scores the best on the response time sub-criterion. This change also made the preference of the thermocouple to the RTD more distinct. The thermocouple final score increased from 0.37849 to 0.39531 and the RTD score decreased from 0.34589 to 0.33446. The difference between the two alternatives before the change was 0.04403 has increased to 0.06085 giving more weight to the thermocouple's preference.

Table 9: Case 3 Sensitivity Analysis results.

Sensor	**Old Score**	**New score**	**New Rank**
Thermocouple	0.37849	0.39531	1
Thermister	0.2756	0.27022	3
RTD	0.34589	0.33446	2

7.4. Case 4: Changing the Application:

AHP is used in this case, to select from among the three sensors used in the case study based on the three different sets of matrices compiled for the three different applications: Automotives, Chemical Processes, and HVAC. The variations in the final scores of the alternatives are monitored. Table 10 shows the score of the three sensors against each application.

Results confirm the view of experts that not only does an alternative temperature sensor selection depend on its inherent characteristics but also it depends on the specific application and the peculiar environment (medium) the sensor is to be put in. The table also reveals the increased suitability of the RTD and the decreased suitability of the thermocouple to the HVAC application. The final score of the RTD in the HVAC application is very close to the thermocouple's score, suggesting that they are almost equally preferred in the HVAC application.

Table 10: Case 4 Sensitivity Analysis results.

Sensor	**Automotives**	**Chemical Processes**	**HVAC**
Thermocouple	0.37849	0.38179	0.35968
Thermister	0.2756	0.26806	0.2867
RTD	0.34589	0.35013	0.35362

7.5. Case 5: Increasing Number of Sensors:

In this case, the results are monitored upon introducing a new viable alternative sensor. In other words, scores for the three sensors case study are compared to those obtained when the pyrometer for example, is introduced. The scores for the four sensors are shown in Table 11. The pyrometer came in third place with a score of 0.25697. This score is comparable to that of the thermocouple and the RTD. The thermister on the other hand, remained the least preferred. All the original sensors' scores have decreased, but the decrease experienced by the thermocouple was the largest, about 29 %, this indicates that the introduction of the pyrometer was at the expense of the thermocouple to a larger degree than it was to the thermister and the RTD which both experienced a decrease in their final score of about 24 %.

Table 11: Case 5 Sensitivity Analysis results.

Sensor	Old Score	New score	% decrease (score)	New Rank
Thermocouple	0.37849	0.2691	29	1
Thermister	0.2756	0.20988	24	4
RTD	0.34589	0.26403	24	2
Pyrometer	-	0.25697	-	3

8. Conclusions

The paper shows how the AHP method enhances the evaluation process of selecting the best temperature sensor. This is because AHP relies on the breakdown of the decision problem into smaller components which are easily assessed and compared. The study also highlights the evaluative criteria and sub-criteria that relate to the selection of temperature sensors. The criteria with the highest weights through the hierarchy can be regarded as being the most important and critical in the evaluation process and can be lumped together in a bundle and may be used in a screening stage as a quick assessment measure. The ability of the AHP method to handle qualitative (verbal) as well as quantitative judgments is also shown. These judgments are transformed into measurable quantitative final scores for the purpose of ranking alternatives. These scores not only rank candidate alternative sensors, but also give a quantitative measure of the degree of dominance of one alternative over the others. This dominance or preference was further tested by means of sensitivity analysis to investigate to what degree the best alternative sensor remains dominant.

The results showed the robustness of the proposed work to the variations carried out in all cases of the sensitivity analysis except for the first case. The analysis shows that when the final scores are very close to each other, they can be regarded as equally preferred. If further distinction is needed, the experts' judgments should be reviewed or more experts can be consulted. Additionally, new criteria or sub-criteria can be introduced to further increase the distinction between alternatives. Finally, the application in which the sensor is to be used can be further investigated and weights can be adjusted accordingly.

References

[1] D.M. Scott. Industrial Process Sensors. Boca Raton, Florida: CRC Press Taylor & Francis Group; 2008

[2] O.S. Vaidya, S. Kumar, “Analytic hierarchy process: An overview of applications”. European Journal of Operational Research, Vol. 169, No. 1, 2006, 1-29.

[3] M. Yurdakul, “AHP as a strategic decision-making tool to justify machine tool selection”. Journal of Materials Processing Technology, Vol. 146, No. 3, 2004, 365-376.

[4] P-F. Hsu, C-R. Wu, Y-T. Li, “Selection of infectious medical waste disposal firms by using the analytic hierarchy process and sensitivity analysis”. Waste Management, Vol. 28, No. 8, 2008, 1386-1394.

[5] C-W. Chang, C-R. Wu, C-T. Lin, H-C. Chen, “An Application of AHP and sensitivity analysis for selecting the best slicing machine”. Computers and Industrial Engineering, Vol. 52, No. 2, 2007, 296-307.

[6] H. Okada, S.W. Styles, M.E. Grismer, “Application of the Analytic Hierarchy Process to irrigation project improvement. Part II. How professionals evaluate an irrigation project for its improvement”. Agricultural Water Management, Vol. 95, No. 3, 2008, 205-210.

[7] M.A. Papalexandrou, P.A. Pilavachi, and A.I. Chatzimouratidis, “Evaluation of liquid bio-fuels using the Analytic Hierarchy Process”. Process Safety and Environmental Protection, Vol. 86, No. 5, 2008, 360-374.

[8] K. Muralidhar, R. Santhanam, R.L. Wilson, “Using the analytic hierarchy process for information system project selection”. Information and Management, Vol. 18, No. 2, 1990, 87-95.

[9] N. Bevilacqua, M. Braglia, “The analytic hierarchy process applied to maintenance strategy selection”. Reliability Engineering & System Safety, Vol. 70, No. 1, 2000, 71-83.

[10] I.Vavra, J. Bydzovsky, K. Flachbart, J. Tejada, L. Kopera, E. Kovacova, K. Temst, Y. Bruynseraede, “Fe/Cr sensor for the MilliKelvin temperature range”. Sensors and Actuators A: Physical, Vol. 91, No. 1, 2001, 177-179.

[11] C.H. Ho , Y.H.C. Cha, S. Prakash, G. Potwin, H.J. Doerr, C.V. Deshpandey, R.F. Bunshah, & M. Zeller, “Electrical resistance drift of molybdenum silicide thin film temperature sensors”. Thin Solid Films, Vol. 260, No. 2, 1995, 232-238.

[12] R.A Bianchi, F. Vinci Dos Santos, J.M. Karam, B. Courtois, F. Pressecq, S. Sifflet, “CMOS-compatible smart temperature sensors”. Microelectronics Journal, Vol. 29, No. 9, 1998, 627-636.

[13] I.Y. Han, S.J. Kim, “Diode temperature sensor array for measuring micro-scale surface temperatures with high resolution”. Sensors and Actuators A: Physical, Vol. 141, No. 1, 2008, 52-58.

[14] T.L. Saaty. The Analytic Hierarchy Process. New York: McGraw Hill; 1980.

[15] P. Goodwin, G. Wright. Decision Analysis for Management Judgment. 2nd ed., West Sussex, England: John Wiley & Sons Ltd; 2000.

[16] W.L. Winston. Operations Research. Applications and Algorithms, 3rd ed., Belmont, California: Wadsworth Publishing Company Inc; 1994.