Selection of a Real Time Intelligent Sensor Using MCDM Methods

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Abstract: One of the most difficult issues in structural engineering is structural damage detection, observation and structural resistance in earthquake conditions. In this regard, the need for style and construction of sensible systems with structural type, combinatory and behavioural adaption capability with environmental conditions in recent decades has been increased. This paper aims to identify the right sensor which can be used for damage detection in structures. This is done by identifying the frequently used sensors and evaluating them using multiple selection criteria and developing a decision making methodology to select the best sensor to be used in structural health monitoring.

Keywords: Structural health monitoring, Smart sensors, Damage detection, Civil Infrastructure.

Introduction: Mankind rely mostly on civil infrastructure upon which many nations have huge investments. Improper functioning of these structures had caused humongous economic loss and led to numerous deaths. Civil infrastructure is, thus, vital to keep the economy running, whereas the infrastructure itself is an important asset to be managed. To manage it properly, its life span and condition need to be assessed. In line with this and additional scenario of existing infrastructures, application of sensible structures like structural health monitoring system, appears to be reasonable. As a result, these systems will cut back repair prices of maintenance and casualties caused by structural injury. Smart structures and systems utilization are mainly used for Structural Health Monitoring. Structural Health Monitoring (SHM)[6] methods quantify structural response and aim to effectively sight, locate, and assess damage created by severe loading and by progressive environmental deterioration. Structural response reflects the structural condition and the excitation force.

From the SHM point of view, smart systems are advantageous to identify structural response both in time and place. The information which is generated from a structure by use of sensors can be huge as large number of sensors are present. These smart sensors allow significant data compression at the node level by extracting solely the data necessary for the task at hand, therefore reducing the amount of information to be transferred through wireless communication. When several sensors are placed, wireless communication seems to be attractive. Moreover, these smart sensors provides the likelihood of autonomous structural health monitoring, with reduced user interaction. Sensors communicate with each other through the RF link to share measured information. The information will be utilised to decide structural soundness.

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In this study, in addition to the use of sensors in structural health monitoring certain other aspects are also looked into. In this, first performance methodology is evaluated and the obtained results are analysed. In the next step effective indices of sensors are derived and appraisement process is done. Finally it is concluded with the results associated with Analytical Hierarchy Process (AHP)[1] and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)[5]. The main scope of the present work is to identify a suitable intelligent sensor. To do this Multi Criteria Decision Making methodology [1] is adopted.

Objective of the study:

The main aim of this study is to develop a real time intelligent sensor selection system and the selected sensor should be using an approach capable of assisting in structural health monitoring.

The objectives of the study are as follow:

i. To identify the preferences needed in selection of sensors used for health monitoring of bridges.

ii. To establish sensor selection criteria to be used in selection of sensors used in bridge health monitoring in particular.

iii. To develop a decision making methodology that is capable of dealing with uncertainty and producing a decision that reflects the needs for health monitoring of bridges / structures.

Study Methodology:

In this study the first and foremost thing which is done is identifying the types of sensors used for Structural Health Monitoring system by thorough literature review. After identifying the types of sensors, the next step is to select a sensor which is best for use in regular monitoring of large structures. This will be done by using Analytical Hierarchy Process (AHP)[1] and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)[5].

The following sensors are considered for doing this research.

i. Optical fibre sensors

ii. Piezoelectric sensors
iii. Magnetostrictive sensors
iv. Self-diagnosing fibre reinforced composites

Analytical Hierarchy Process (AHP): AHP methodology developed by Saaty[9] is aimed towards determining the relative importance of a set of criteria describing varied activities in a decision making problem. It helps the decision maker choose the best decision that most closely fits their understanding of the problem. AHP is widely applied in varied decision making issues like conflict resolution, technological issues and economic / management issues [1]. The AHP methodology relies on 3 steps: 1st, the structure of the model; second, the comparative analysis of the alternatives and also the criteria; third, synthesis of the priorities.

The first step that is structure of the model an advanced decision drawback is structured as a hierarchy. This method breaks down an advanced construction drawback into the hierarchy of objectives, criteria and alternatives. In the next step, the comparisons of the alternatives and criteria are done. Pair wise comparison is adopted within the comparison of alternatives and criteria. A 9 purpose Saaty's scale is adopted for pair wise comparison of these elements. The nine point Saaty's scale is shown in the Table 1.

Table 1 Nine-point intensity of importance scale and its description

Definition	Intensity of Importance
Equally Important	1
Moderately more Important	3
Strongly more Important	5
Very strongly more Important	7
Extremely more Important	9
Intermediate Values	2,4,6,8

In the table 1 classifications of the points on the scale are given briefly which forms the base for the respondents to give responses in pair wise comparisons of entities.

Let $C=\{C_j\ ,\ j=1,2,3,\ldots\ldots..n\}$be the set of criteria. The result of the pair wise comparison on n criteria can be summarized in an (n x n) evaluation matrix A in which every element a_{ij} (i, j=1,2,3,…..n) is the quotient of weights of criteria as shown below:

$$\mathbf{A} = \begin{vmatrix} a11 & \ldots & a1n \\ \ldots & \ldots & \ldots \\ an1 & \ldots & ann \end{vmatrix},\ a_{ij}=1,\ a_{ji} = 1/\ a_{ij}\ ,\ a_{ij} \neq 0$$

In the final step, the mathematical process begins to normalize and find the relative weights of each matrix. The relative weights are given by the right eigenvector (w) corresponding to the largest Eigen value (λ_{max}), as below:

$$Aw = \lambda_{max}w$$

$$(A - \lambda_{max}\ I)\ w = 0 \qquad \text{Equation 1}$$

If pair wise comparisons are completely consistent, the matrix A has rank 1 and $\lambda_{max} = n$. Here the weights can be obtained by normalizing any of the rows or columns of A. The standard of the output of the AHP is strictly associated with the consistency of the pair wise comparison judgements. The consistency is derived by the relation between the entries of A: $a_{ij}\ x\ a_{jk} = a_{ik}$.

The consistency index (CI) is

$$CI = \frac{(\lambda\max - n)}{(n-1)} \qquad \text{Equation 2}$$

Random consistency Index (RI) is obtained from the below Table 2.

Table 2 Average Random Consistency (RI)

Size of the matrix	1	2	3	4	5	6	7	8	9	10
Random Consistency	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The final consistency ratio (CR), by which we can conclude whether the evaluations are necessarily consistent, is calculated as the ratio of the CI to the random index (RI), as specified below:

CR=CI/RI……………………………….. Equation 3.3

Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS):

TOPSIS [5] methodology was developed by Hwang and Yoon (in 1981) for finding a Multi Criteria Decision Making (MCDM) [1] solution. This methodology relies on the idea that the chosen alternative must have shortest geometric distance from the best answer and therefore the farthest from the negative ideal answer. The best answer may be a theoretical answer for which all attributes values correspond to the most attribute values within the information comprising the satisfying answer that all attribute values correspond to the minimum attribute values within the information.

TOPSIS so offers an answer that's not solely nearest to the hypothetically best, that is also the farthest from the hypothetically worst. The strategy is extremely helpful for finding real world issues associated it provides an optimum answer or the alternative's ranking. TOPSIS methodology relies on the idea that *m x n* decision-making matrix D includes m-alternatives and n-criteria which the attributes expressed by linguistic terms are estimated. It's additionally assumed that the advantages of every individual criterion were determined and that relative criteria weights w_i have additionally been outlined.

If *m* alternatives and *n* criteria are taken evaluation to choose the best alternative *a* out of the alternative group, considering all criteria simultaneously

$$A= [a_1, a_2, a_3,\ldots\ldots a_m]$$

Each alternative a_i; $i = 1,2,3,\ldots\ldots,m$ is described by attribute values *fj* ; $j = 1,2,3,\ldots\ldots,n$ marked as follows : x_{ij} ; $i = 1,2,\ldots\ldots,m$; $j = 1,2,\ldots\ldots,n$. Criteria fj is also of profit (profit) or expenditure (price) sort. Profit criteria implies that larger worth of attribute is opted than lesser attribute worth (" max"), whereas cost criteria means that lesser attribute worth is opted than larger worth of attribute ("min"). The above is illustrated with the subsequent matrix D.

$$\begin{array}{c} \\ a_1 \\ \vdots \\ a_m \\ \\ \end{array} \begin{array}{c} \begin{array}{ccc} f_1 & \cdots & f_n \end{array} \\ \begin{bmatrix} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & \end{bmatrix} \\ \begin{pmatrix} max \\ min \end{pmatrix} \cdots \begin{pmatrix} max \\ min \end{pmatrix} \end{array}$$

The entities of the matrix D are real numbers (not negative) or linguistic expressions from the given cluster of expressions. Linguistic attributes have to be measured to be quantified among previously determined and agreed value scale. Interval scale represents the acceptable tool to be used while executing quantification of qualitative attributes. The foremost normally used ordinal scale is one to nine, since the extremes of attributes for the factors being analysed are usually unknown. The table 3 below shows about how to translate qualitative attributes to quantitative attributes.

Table 3 Translating the Qualitative attributes into Quantitative attributes.

Qualitative Estimation	Bad	Good	Average	Very Good	Excellent
Quantitative Estimation	1	3	5	7	9

In order to resolve the matter, it's necessary to normalise the attribute values, i.e. to perform the "unification" or "make the attributes non-dimensional", which implies that the attribute values would be set among 0-1 interval.

After the normalized decision-making matrix R (=$[r_{ij}]$) is created, it's necessary to determine the coefficients of relative criteria importance w_j; j =1,2,.....,n – that are being normalized, which ends up within the following :

$$\sum_{j=1}^{n} Wj = 1 \qquad \text{Equation 4}$$

Relative importance of criteria represents a major a part of multi – criteria task setup, since it ensures the relation between criteria that aren't of constant worth. Relative importance of criteria depends on subjective estimation of the DM (Decision Maker) and has a significant influence on the ultimate result. Multiplication of every normalized matrix's component r_{ij} with the assigned weight constant w_j ends up in weighted normalized decision-making matrix V.

$$V_{ij} = w_j \times r_{ij} \ ; \ i=1,2,3,\ldots\ldots.m \ ; \ j= 1,2,3,\ldots\ldots\ldots n \qquad \text{Equation 5}$$

TOPSIS methodology determines the similarity or closeness to ideal answer. Therefore, it introduces the factors in which each different A_i is represented by a degree within the n-dimensional criteria and coordinates of these points are attribute values of decision-making matrix V. Next step is decisive of ideal and anti-ideal points and finding the alternative with the nearest geometer distance from the anti-ideal point. Figure 1 represents the example of two dimensional criteria during which each different Ai possesses the product coordinates that are up to normalized values of the assigned attributes and normalized weight coefficients, coordinates of ideal purpose A^+ and anti-ideal purpose A^-, as well as the geometric different distances from the ideal and anti-ideal point.

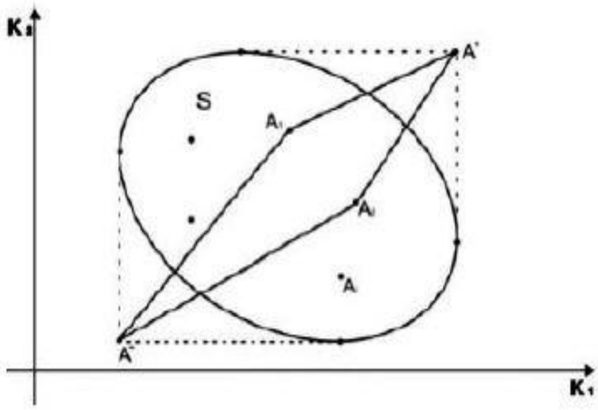

Figure 1 Two Dimensional criteria space

The step-by-step procedure for TOPSIS methodology is as follows:

Step-1: By using vector normalization, the normalized decision matrix is to be calculated. The normalized value of R_{ij} is given by

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} (j = 1,2,3, \ldots \ldots . n) \quad \text{Equation 6}$$

Step-2: The weighted normalized decision matrix is to be calculated. This value V_{ij} is calculated as the product of normalized matrix elements and normalized weight co-efficients *Wj* ; such that

$$\sum_{f=1}^{n} Wj = 1 \text{ , j=1,2,3,} \quad \text{Equation 7}$$

Whereas the elements of the modified decision making matrix are $V_{ij} = W_j \times r_{ij}$

Step-3: Now in this step the ideal and anti-ideal points in n-dimensional criteria space should be determined, such that ideal point is as shown below:

$A^+ = \{(\max_i V_{ij} , j \in J),(\min_i V_{ij} , j \in J')\}$

$A^+ = \{V_1^+, V_2^+, \ldots\ldots V_m^+\}$- Ideal alternative coordinates

$A^- = \{(\min_i V_{ij} , j \in J),(\min_i V_{ij} , j \in J')\}$

$A^- = \{V_1^-, V_2^-, \ldots\ldots V_m^-\}$- Anti Ideal alternative coordinates

Step-4: Now the geometric distance Si^+ of each alternative a_i , from the ideal point and Si^- of each alternative a_i from the anti-ideal point are to be calculated.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_j^+)^2}, i = 1,2,3, \ldots \ldots . m$$

Equation 8

Geometric distance of the i^n alternative from the ideal point.

$$S_i^- = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_j^-)^2}, i = 1,2,3, \ldots \ldots . m$$

Equation 9

Geometric distance of the i^n alternative from the anti-ideal point.

Step-5: The relative similarity of the alternatives is to be calculated from the ideal and anti-ideal points in the following manner:

$$C_i = \frac{S_i^-}{(S_i^+ + S_i^-)}; 0 < C_i \leq 1; i = 1,2,3, \ldots \ldots \ldots , n \quad \text{Equation 10}$$

Here C_i denotes the index value which lies between 0 and 1. Greater the index value, better the performance of the alternative. It can also be called as composite or overall performance score of alternative A_i. If C_i = 1 then $a_i = A^+$ and if C_i = 0, then $a_i = A^-$. Therefore, the conclusion is that *ai* is closer to *A+* if the C_i is closer to value 1.

Step-6: Now the preference order is to be ranked. To rank these alternatives using relative similarity, alternatives are to be arranged in decreasing order of index of value, C_i which indicates the most and least preferred feasible solutions.

Data Collection and Analysis:

Obtaining precise data is probably the foremost and vital part of the research method. Data is obtained in many ways, in several settings-field or laboratory and from totally different sources-primary or secondary. There are wide range of methods to collect data. Some of them are interview, questionnaire survey, observation, unassertive ways, documents and historical knowledge. The use of acceptable data collection technique greatly enhances the strength of information and, therefore, the worth of the analysis. Firstly, interviews were conducted to try and filter criteria which do not fit in the selected decision criteria. Based on this information a questionnaire was prepared.

In this study, a structured survey may be a pre developed written set of queries, comparisons to that respondent record their answers, typically among rather closely outlined alternatives. An initial list of ten criteria were recognized which are related to this topic and to spot that of these criteria which would be important for the study, respondents were consulted to elicit their opinions on the connectedness of those criteria in assessing the capabilities of sensors. Based on the inputs given by the respondents, five out of the ten criteria were selected and included in the questionnaire. Relative Ranking Index (RRI) was used to select these criteria using a six-point Likert's scale.

As per Likert's scale, six different rankings were given. The rankings are shown in the table below.

Table 4 Six-point Likert's Scale

Rank	Importance
0	Irrelevant (IR)
1	Very Low Important (VLI)
2	Low Important (LI)
3	Medium Important (MI)
4	Important (I)
5	Very Important (VI)

Ten different criteria are taken for evaluation. They are listed in the table below.

Table 5 Criteria Taken for Survey

Code	Description of Criteria
X1	Performance Damage Detection
X2	Performance Speed
X3	Mode of Output
X4	Localization of Sensor Technology
X5	Performance Cost
X6	Temperature Flexibility
X7	Communication Range Adjustment
X8	Electricity Consumption
X9	Maintenance
X10	Resistance of Weather Effects

RRI Analysis:

This technique is used to compare important levels of entities and values of Likert's scale which represent the level of importance of variables given by the respondents which later needs to be converted as Relative Ranking Index which has a value of one or zero.

RRI will be calculated using the following formula:

$$RRI = \frac{1}{n \times N}\sum_{i=1}^{n}\binom{n}{k} l_i\, x_i \qquad \text{Equation 11}$$

Where, RRI refers to Relative Ranking Index
n- Maximum value in Likert's scale
N-Total no. of responses
i- 1,2,3,………n
l_i = Likert scale ($l1$ is the least important and ln is the most important)
x_i = the frequency of the i^th response.

Upon fixing the criteria, the questionnaire forms are distributed and their responses based on Likert's scale were collected. The details of the survey results are shown below.

Table 6 Survey results obtained from Respondents.

li =	0	1	2	3	4	5	Σ(*li* * *xi*)	RRI	No. of respondents
	IR	VLS	LS	MS	S	VS			
X1	0	0	0	3	6	11	88	0.880	20
X2	0	0	0	4	8	8	84	0.840	20
X3	0	0	4	4	9	3	73	0.730	20
X4	0	0	0	3	8	9	86	0.860	20
X5	0	0	0	3	11	6	83	0.830	20
X6	0	0	2	8	6	4	72	0.720	20
X7	0	0	3	5	8	4	73	0.730	20
X8	0	0	0	7	8	5	78	0.780	20
X9	0	0	0	5	9	6	81	0.810	20
X10	0	0	1	6	9	4	76	0.760	20

Code	Description of Criteria	RRI Values
X1	Performance Damage Detection	0.880
X4	Possibility Localization Of Sensor Technology	0.860
X2	Performance Speed	0.840
X5	Performance Cost	0.830
X9	Maintenance	0.810

Table 7 Sensor selection criteria (RRI > 0.800)

Based on the survey results and ranking given using RRI, the criteria which have RRI values more than 0.80 are considered for selecting the sensors. The below table shows the criteria having RRI value more than 0.80.

Application of MCDM methods to Sensor Selection and Results:

After identifying the criteria for selecting a smart sensor, another survey form was prepared to collect the responses on the performance of sensors. After collecting the responses, evaluation was done using both Analytical Hierarchy Process (AHP) and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) to select the best optimal sensor.

Evaluation using Analytical Hierarchy Process Model:

Here the AHP method is used to validate and select the intelligent sensor technology. The data collected is converted into matrices and checked for consistency using MATLAB. The eigen values and thus consistency rations are determined using a mathematical model. The overall rankings of the sensors are shown in the table below.

Table 8: Shows the overall priority of all Sensors and their individual ranking

Importance Co-efficient	Criteria	Scores from Expert's Opinion

		Optical Fibre Sensor	Piezoelectric Sensors	Magnetostrictive Sensors	Self-Diagnosing Fibre Reinforced Composites
Performance Damage Detection	0.4083	0.4996	0.2382	0.1003	0.1619
Performance Damage Detection x average obtained score		0.2093	0.0972	0.0409	0.0661
Possibility of Localization of Sensor Technology	0.3174	0.6034	0.2061	0.0974	0.0931
Possibility of Localization of Sensor Technology x average obtained score		0.1915	0.0654	0.0309	0.0295
Performance Speed	0.1311	0.5778	0.1964	0.1091	0.1167
Performance Speed x average obtained score		0.0757	0.0257	0.0143	0.0152
Performance Costs	0.0918	0.5647	0.2332	0.1339	0.0682
Performance Costs x average obtained score		0.0518	0.0214	0.0122	0.0062
Maintenance	0.0523	0.5591	0.2666	0.1088	0.0655
Maintenance x average obtained score		0.0292	0.0139	0.0056	0.0034
Final score of Real Time Intelligent Sensors		0.5521	0.2236	0.1039	0.1204
Ranking		**1**	**2**	**4**	**3**

Based on the above calculations, sensor A1 is selected as the optimal.

Evaluation using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) Model:

Here the data collected through questionnaire survey is normalised and further ideal alternative values are found out in terms of geometric distances from which the solution is found. The overall priorities of the sensors and their ranks are listed in the table below.

Table 9: Overall Priorities of Sensors

Criteria	Ci	Rank
A1	0.815	1
A2	0.217	4
A3	0.353	3
A4	0.504	2

From the above table it can be observed that sensor A1 is ranked first and it is selected as the best.

Conclusions:

This study is carried out to find the best sensor technology to use in Structural Health Monitoring using Multi Criteria Decision Making methods. The conclusions from this study are:

1. These methods can be used to assess and identify Real Time Intelligent Sensor.
2. Out of all the criteria which are selected, Performance Damage Detection, Performance Speed, Maintenance, Performance Cost and Localization of Sensor Technology are the indices chosen in the same order.
3. These five criterial were scrutinized using RRI analysis. The criteria which had RRI>0.80 have been selected.
4. From the AHP method, sensor A1 i.e., Optical Fibre sensor was ranked 1.
5. From the TOPSIS method, also sensor A1 is ranked 1.
6. Thus from both the MCDM methods it is concluded that Optical Fibre Sensors are the optimal sensors which can be used for Structural Health Monitoring.

Scope of future work:

Though this study attempted to identify the best sensor using a couple of MCDM methods, the work can be extended by doing the same with other MCDM methods and validating this sensor technology based on field studies using these sensors. Also the long term sensing ability of the Optical Fibre sensors due to weathering and aging can be studied.

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