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RANKING OPTIMAL SENSOR NODES IN WSN USING SIMPLE ADDITIVE WEIGHTING (SAW) APPROACH

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ABSTRACT
Wireless Sensor Networks (WSNs) are crucial for various applications, and ranking sensor nodes within these networks is a fundamental challenge. The Simple Additive Weighting (SAW) approach, a Multi-Criteria Decision-Making (MCDM) method, offers a systematic solution to this challenge. It considers diverse criteria, including energy, communication range, and processing power, enabling the selection of optimal sensor nodes. Recent research has extended and improved the SAW method in various ways. For instance, fuzzy logic has been applied to address uncertainty in sensor node attributes, dynamic weight adaptation has enhanced adaptability, and entropy weight assignment has improved ranking accuracy. These modifications make the SAW approach even more efficient and practical. The SAW method's theoretical foundation involves creating a pair-wise comparison matrix to assign weights to criteria. The weighted scores are used to construct a decision matrix for sensor nodes, and the final ranking is determined through the weighted sum of these scores. A case study illustrates the practical application of the SAW approach, where sensor A3 is identified as the best choice for a routing operation. This outcome demonstrates the SAW approach's effectiveness in selecting optimal sensor nodes to ensure optimal performance in WSNs.

Keywords: Wireless Sensor Networks (WSNs), ranking sensor nodes, Simple Additive Weighting (SAW), Multi-Criteria Decision-Making (MCDM), optimal sensor nodes

1. INTRODUCTION

Wireless sensor networks (WSNs) are a type of ad hoc network that consists of a large number of sensor nodes that are deployed in a specific area to collect data and transmit it to a sink node. WSNs have a wide range of applications, including environmental monitoring, industrial automation, and healthcare. One of the key challenges in WSNs is to rank the sensor nodes to identify the optimal nodes for performing specific tasks. This is because the sensor nodes have different capabilities and limitations. For example, some sensor nodes may have more energy than others, while others may have a longer communication range. The Simple Additive Weighting (SAW) approach is a multi-criteria decision-making (MCDM) method that can be used to rank the sensor nodes in WSNs. The SAW approach takes into account the different criteria that are important for ranking the sensor nodes, such as energy, communication range, and processing power. WSNs have a wide range of applications, including environmental monitoring (Abbasi and Younis, 2007), industrial automation (Gungor and Hancke, 2009), and healthcare

(Rahmaniet al, 2010).One of the key challenges in WSNs is to rank the sensor nodes to identify the optimal nodes or performing specific tasks (Kumar and Singh, 2015).This is because the sensor nodes have different capabilities and limitations (Singh et al, 2016).The SAW approach is a MCDM method that can be used to rank the sensor nodes in WSNs (Kaur and Kaur, 2016).The SAW approach takes into account the different criteria that are important for ranking the sensor nodes, such as energy, communication range, and processing power (Singh et al, 2017). The SAW approach is a simple and effective method for ranking sensor nodes in WSNs. It takes into account the different criteria that are important for ranking the sensor nodes, such as energy, communication range, and processing power. The SAW approach has been shown to be effective in a variety of WSN applications.

2. REVIEW OF RELATED WORKS

The SAW approach has been widely used for ranking sensor nodes in WSNs in recent years. A number of researchers have proposed improved versions of the SAW approach to address the specific challenges of WSNs. Some recent related works on ranking optimal sensor nodes in WSN using the SAW approach are hereby reviewed. Al-Shammari and Hussain (2021) used fuzzy logic to handle the uncertainty associated with the sensor node attributes. It was shown to be more effective than the traditional SAW approach in terms of energy consumption and network lifetime. Singh and Kumar (2021) used an approach that assigned different weights to the sensor node attributes based on their importance in the specific application. This made the ranking process more accurate and efficient. Sharma S. and Kumar N. (2022) used an approach that combined the SAW and TOPSIS methods to rank the sensor nodes. It was shown to be more effective than the individual SAW and TOPSIS methods in terms of accuracy and robustness. In Kumar and Saini (2022), their approach adapted the weights of the sensor node attributes dynamically based on the current network conditions. This made the ranking process more adaptive and efficient. Zhang et al, (2022) applied an approach which used entropy weight to assign weights to the sensor node attributes. Entropy weight is a measure of the uncertainty associated with an attribute. The higher the entropy weight of an attribute, the more important it is in the ranking process. This approach was shown to be more effective than the traditional SAW approach in terms of ranking accuracy and robustness and also more energy-efficient and capable of extending the network lifetime. Liet al, (2022) used an approach which focused on ranking the sensor nodes in a way that minimizes energy consumption during data collection. It took into account the energy consumption of the sensor nodes, the distance between the sensor nodes and the sink node, and the quality of the data collected. The approach was more energy-efficient than the traditional SAW approach, while still maintaining a high level of ranking accuracy. Khan et al., (2022) focused on ranking the sensor nodes in a way that maximizes the reliability of data transmission. It took into account the communication range of the sensor nodes, the packet loss rate, and the bandwidth available. The approach was more reliable than the traditional SAW approach in terms of data transmission, while still maintaining a high level of ranking accuracy. Kumar et al, (2022) focused on ranking the sensor nodes in a way that extends the network lifetime. It takes into account the energy consumption of the sensor nodes, the communication range of the sensor nodes, and the number of hops between the sensor nodes and the sink node. The approach was capable of extending the network lifetime more effectively than the traditional SAW approach.

3. THEORY OF SIMPLE ADDITIVE WEIGHTING (SAW) APPROACH

Simple additive weighting (SAW), often known as weighted linear combination or scoring systems, is an easy-to-use and popular multi-attribute decision-making technique. The methodology is built on the weighted average. An assessment score is generated for each alternative by summing the findings for all criteria and multiplying the scaled value given to each alternative for that attribute by the weights of relative importance directly assigned by the decision maker. This method has the advantage of keeping the relative order of magnitude of the standardized scores by proportionately linearly transforming the raw data (Alireza et al. 2010). The steps that make up the SAW process are as follows:

Step One

1. Using the Saaty's pairwise comparison 1–9 scale presented in table 1, construct a pair-wise comparison matrix (n x n) for criterion with respect to objective. It is utilized, in other words, to compare each criterion to each other criterion, one at a time. The total number of pairwise comparisons (PwC) can be calculated using the straightforward formula

$$PwC = \frac{n(n-1)}{2} \quad (1)$$

where n is the total number of possibilities. Thus, if there are 20 possibilities, using equation (1) the PwC would be evaluated as follows:

$PwC = \frac{20x(19)}{2} = \frac{380}{2}$ 190 pairs. Table 1 outlines the criteria for achieving Saaty's 1-9 Scale of Pairwise Comparisons.

Table1: Saaty's 1-9 Scale of Pairwise Comparisons (Source: Alireza et al. 2010)

Intensity of importance	Definition	Explanation
1	Equal Importance	The goal is equally benefited by the two activities.
2	Weak or Slight	
3	Moderate Importance	One activity is marginally preferred over another by experience and judgment.
4	Moderate Plus	
5	Strong Importance	One activity is greatly preferred over another by experience and judgment.
6	Strong Plus	
7	Very Strong	Strongly favoring one activity over another
8	Very, very Strong	
9	Extreme Importance	The strongest potential order of affirmation can be found in the data supporting one activity over another.

2. It will be decided which of the two criteria is most crucial for each comparison and then give it a score to indicate how much more crucial it is.

3. Each component of the comparison matrix should be calculated using its column total, and the priority vector should be determined using the row averages (Choo and Wedley, 2004).
4. By multiplying the pairwise comparison matrix and priority vector, the weighted sum matrix is obtained.
5. Each priority vector element is divided by its corresponding weighted sum matrix element.
6. This value's average is then calculated to find λ_{max}.
7. The Consistency Index (CI) is calculated as follows: $CI = \frac{\lambda \max - n}{n-1}$ (2)

   Where n is the size of the matrix.
8. The following formula is used to determine the consistency ratio (CR):

   $CR = \frac{CI}{RI}$ (3)
9. By comparing the consistency ratio (CR) of the CI with the relevant value in Table 2, it is possible to evaluate the consistency of judgment. If the CR is less than 0.10, it is acceptable.

If there are more, the judgment matrix is flawed. Judgments should be examined and strengthened in order to achieve a consistent matrix.

Table 3: Average Random Consistency (RI) (Source:Alireza et al. 2010)

Cont. Table 3: Average Random Consistency (RI)

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

Step Two

Create a decision matrix (m n) with m sensors and n criteria. Make a decision matrix that is normalized for positive criteria:

$n_{ij} = \frac{r_{ij}}{r^*_j}$, i = 1,…, m; and j = 1,…, n. (4)

For negative criteria, it becomes

$n_{ij} = \frac{r_j^{min}}{r_{ij}}$, i = 1,…, m and j = 1, …, n. (5).

r_j^* is the minimum number of r in the r column of j.

Step Three

Finally, evaluate the value of each alternative, denoted as A_i, using the following formula

$A_i = \sum wj.Xij$ (6)

Where x_{ij} denotes the value for the score of the ith alternative with regard to the jth criteria, and w_j denotes the weighted criteria (Asgharpour, 2008). The steps given in the foregoing are generalized for use when carrying out the SAW method.

Multi-attribute decision-making strategies most frequently employ the SAW model which is also known as Scoring Method (SM). To do this, the weight of the criteria must be multiplied by the normalized value of the criteria for the alternatives. The best option with the highest score is then chosen as the preferred option (Janic and Reggiani, 2002). The SAW method's analytical framework for N alternatives and M attributes can be summed up as follows:

$S_i = \sum_{j=1}^{M} Wjrij \qquad i = 1,2, \ldots, N$ (7)

Where s_i is the total score of the ith alternative;

rij is the normalized rating of the ith alternative for the jth criterion which: r_{ij}=

$\frac{xij}{maxi\, xij}$ for the benefit; $r_{ij} = \frac{1/xij}{maxi^{1}/xij}$ for the cost criterion signifying a component for the normalized matrix; x_{ij} is an element of the decision matrix, representing the original value of the *j*th criterion of the *i*th alternative; w_j is the importance (weight) of the *j*th criterion; N and M are the number of alternatives and criteria, respectively. The essential idea of finding a weighted sum of the performance on each alternative for each attribute constitutes the nucleus of the simple additive weighting method. Simple Additive Weighting approach recommends concluding a settlement in the multi-process decision-making system. The decision maker just selects the alternative that has the greatest number of good characteristics, according to the simple additive rule. By introducing the weighted average utilizing the arithmetic mean, SAW uses a weighted linear combination or scoring system. The product of the scaled value for an attribute assigned to each alternative and the respective weights results in an assessment score for each alternative. The relative order of magnitude of the standardized scores stays constant because SAW is acknowledged as a proportional linear modification of the raw data. Getting a weighted sum of performance ratings for each alternative across all qualities is the main goal of the SAW approach (Kim et al. 2019).

4. METHODOLOGY

The three sensors identified as A1, A2 and A3 are the alternative sensors with several attributes ascribed to them. To achieve this objective, the Simple Additive Weighting (SAW) technique which is the preferred technique was used. The process of this ranking, which draws much inference from the theory of the technique used, already discussed extensively in chapter two, is presented in the following discuss. The MADM process was performed using three stages:

1. Preparation of the situation components.
2. Analysis.
3. Information synthesis.

For the purpose of this identification, three sensors were used and identified as Sensor A1, Sensor A2 and Sensor A3.

Three steps were applied in the SAW method as follows:

a. Specifying the criteria to be used as a reference for making decision.

b. The suitability of each alternative is determined by the rating on each criterion.

c. Decision is taken based on the outcome of the criteria matrix after which normalization of matrix R depending on the equation adjusted for the attribute type takes effect.

Table 4: Empirical data 2

A1	Sensing power
A2	Communication range
A3	Packet loss

- ❖ **A1 Sensing power**

Table 5: Sensing power, category and value

Sensing power	Category	Value
0.5w – 3.5w	Good	50%
3.6w – 5.5w	Better	75%
5.6w – 8w	Best	98%

- ❖ **A2 Communication range**

Table 6: Communication range, category and value

Communication range	Category	Value
1m – 45m	Good	50%
46m – 75m	Better	75%
76m – 100m	Best	98%

- ❖ **A3 Packet loss**

Table 7: Packet loss, category and value

Packet loss (kb/s)	Category	Value
76 – 100	Good	50%
46 – 75	Better	75%
1 – 45	Best	98%

- ❖ **To find the best sensor that will sense a target fast among all the sensors.**

Table 8: Identification for the best sensor

Name	Sensing ability	Routing value
Sensor 1	Good	80kb/s
Sensor 2	Better	100
Sensor3	Best	250
Sensing time	**Sensing power**	**Sensing range covered**
5s	5w	45m
3s	3.5w	75m
2s	2w	100m

Any one that loses 5% in the routing value to get packet loss is bad.

- ➢ **To determine the weight of the criteria**

Table 9: Determination of weight of the criteria

	Criteria	Weight	Numerical value
C1	Routing value	Better	0.75
C2	Sensing time	Best	0.98
C3	Sensing power	Good	0.5
C4	Sensing rang covered	Best	0.98

Table obtained by the weight value with the data is presented in the form shown in equation (8):

W = [0.75, 0.98, 0.5, 0.98] (8)

Then, using Simple Additive Weighting (SAW) method, the following procedure was adopted.

- ❖ **First determine the name of the sensors as an alternative**

Table 10: Determination of the Name of the Sensor as an Alternative

Name	Alternative
Sensor1	A1
Sensor2	A2
Sensor3	A3

Since the alternative is determined, make the rating the suitability of each alternative on each criterion.

Table 11: Rating the Suitable of each Alternative on each criterion.

	C1	C2	C3	C4
A1	0.75	0.75	0.5	0.75
A2	0.5	0.75	0.5	0.75
A3	0.75	0.5	1	1

From the table above the decision matrix obtained is as follows:

0.75 0.75 0.5 0.75
X = 0.5 0.75 0.5
0.75 (3.4)
0.75 0.5
1 1

To normalize the matrix X into matrix R take the weights of the criteria W and multiple by the matrix X. Meanwhile the calculation of matrix R requires the classification criteria of value added benefit or cost

Table 12: Classification criteria of value added benefits or costs

Criteria	Benefits	Cost
C1 Routing value	Available	Not Available
C2 Sensing time	Available	Not Available
C3 Sensing power	Available	Not Available
C4 Sensing rang covered	Available	Not Available

Computation of Ranking and Results

In compliance with the criterion by which all the criteria are included in the benefits, the calculation to normalize the matrix X becomes as follows:

$R_{11} = \frac{0.75}{\text{Max}(0.75,0.5,0.75)} = \frac{0.75}{0.75} = 1$

$R_{21} = \frac{0.5}{\text{Max}(0.75,0.5,0.75)} = \frac{0.5}{0.75} = 0.67$

$R_{31} = \frac{0.75}{\text{Max}(0.75,0.5,0.75)} = \frac{0.75}{0.75} = 1$

$R_{12} = \frac{0.75}{\text{Max}(0.75,0.5,0.75)} = \frac{0.75}{0.75} = 1$

$R_{22} = \frac{0.75}{\text{Max}(0.75,0.5,0.75)} = \frac{0.75}{0.75} = 1$

$R_{32} = \frac{0.5}{\text{Max}(0.75,0.5,0.75)} = \frac{0.5}{0.75} = 0.67$

$R_{13} = \frac{0.5}{\text{Max}(0.5,0.5,1)} = \frac{0.5}{1} = 0.5$

$R_{23} = \frac{0.5}{\text{Max}(0.5,0.5,1)} = \frac{0.5}{1} = 0.5$

$R_{33} = \frac{1}{\text{Max}(0.5,0.5,1)} = \frac{1}{1} = 1$

$R_{14} = \frac{0.75}{\text{Max}(0.75,0.75,\ 1)} = \frac{0.75}{1} = 0.75$

$R_{24} = \frac{0.75}{\text{Max}(0.75,0.75,1)} = \frac{0.75}{1} = 0.75$

$R_{34} = \frac{1}{\text{Max}(0.75,0.75,1)} = \frac{1}{1} = 1$

The matrix obtained from the computation becomes

$$R = \begin{bmatrix} 1 & 1 & 0.5 & 0.75 \\ 0.67 & 1 & 0.5 & 0.75 \\ 1 & 0.67 & 1 & 1 \end{bmatrix}$$

Furthermore, the ranking process is done by the sum of the normalized R matrix multiplication with the weight vector. The ranking result in the Table 13. To find the best sensor. Best sensor = ∑weight x R

W = [0.75, 0.98, 0.5, 0.98]

A1 = [(0.75 x 1) + (0.98 x 1) + (0.5 x 0.5) + (0.98 x 0.75)]

A1 = [0.75 + 0.98 + 0.25 + 0.735]

A1 = 2.715

A2 = [(0.75x0.67)+ (0.98x 1) + (0.5x0.5) + (0.98x0.75)]

A2 = [0.5025 + 0.98 + 0.25 + 0.735]

A2 = 2.4675

A3= [(0.75x1)+ (0.98x0.67) + (0.5x 1) + (0.98x 1)]

A3= [0.75+0.6566+ 0.5+0.98]

A3= 2.8866

Table 13: Ranking result

Alternative	Value	Ranking
A1	2.715	2
A2	2.4675	3
A3	2.8866	1

The best sensor among the sensors is sensor A3. From the results of the computation exercise in the ranking process, sensor with the highest value is A3 thereby presenting it as the best sensor for use in the present routing operation in the network to ensure optimal operational performance.

5. CONCLUSION

In conclusion, the Simple Additive Weighting (SAW) approach is a powerful method for ranking sensor nodes in Wireless Sensor Networks (WSNs). It provides a systematic way to evaluate and select the most suitable sensor nodes based on multiple criteria, such as sensing power, communication range, and packet loss. The SAW method is effective in handling complex decision-making processes and has been further improved by recent research, incorporating techniques like fuzzy logic, dynamic weight adaptation, and entropy weight assignment. By assigning appropriate weights to criteria and normalizing the decision matrix, SAW enables decision-makers to determine the optimal sensor nodes for specific tasks. The case study presented in this paper demonstrates the practical application of the SAW approach, where sensor A3 was identified as the best choice for a routing operation, ensuring optimal performance. In essence, the SAW approach offers a valuable framework for enhancing the efficiency and effectiveness of WSNs by facilitating the selection of sensor nodes that align with the specific requirements of various applications. Its simplicity and effectiveness make it a valuable tool for network designers and decision-makers in the field of wireless sensor networks.

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