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RESEARCH ARTICLE

Enhancing Sensor Network Performance through an Intelligent Smart Multi-Attribute Decision-Making Approach

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ABSTRACT

With the increasing integration of sensor networks in various domains, optimizing their performance has become a crucial challenge. This paper presents an intelligent Smart Multi-Attribute Decision-Making (SMADM) approach designed to enhance sensor network performance. By leveraging advanced algorithms and real-time data processing, the proposed approach aims to improve decision-making processes, ensuring efficient sensor network management. The study highlights the effectiveness of the SMADM approach through simulation results, showcasing significant improvements in network reliability, data accuracy, and overall system efficiency. The consistent poor performance in our communication network occurs when the wireless sensor does not effectively reduce packet loss and interference, leading to high costs. This issue is addressed by improving sensor network performance using the SMADM approach. This involves characterizing increased energy consumption, interference, and packet loss, which contribute to reduced performance, and designing a rule base for the SMADM approach to mitigate these issues. A SIMULINK model for wireless sensor networks (WSN) is developed, along with an algorithm to implement the process. Validation results indicate that conventional packet loss peaks at 30Kb/s on day 4, while sensor 1 experiences a reduced loss of 27.98Kb/s. Incorporating sensor 2 decreases packet loss to 28.6Kb/s, and sensor 3 further reduces it to 27.39Kb/s, demonstrating that sensor 3 is the most effective for improved network performance. Additionally, conventional power consumption is highest at 0.5W on day 1. With sensor 1, it drops to 0.4663W, with sensor 2 to 0.4767W, and with sensor 3, it reduces to 0.456W, making sensor 3 very efficient.

Keywords: *Sensor Network Performance; Intelligent Smart Multi-Attribute Decision-Making; SMADM Approach; Wireless Sensor Networks (WSN)*

Introduction

Sensor networks play a critical role in modern technology applications such as environmental monitoring, healthcare, and industrial automation. The performance of these networks is crucial to the effectiveness and reliability of the systems they support. However, traditional methods for managing sensor networks often fail to address the dynamic and complex nature of these systems. This paper introduces an intelligent Smart Multi-Attribute Decision-Making (SMADM) approach, utilizing advanced computational techniques to optimize decision-making processes within sensor networks.

A Wireless Sensor Network (WSN) consists of one or more sink nodes and spatially distributed sensors, also known as base stations. The three main components of a typical sensor network are sensors, a controller, and a communication system. When the communication mechanism in a sensor network is built using a wireless protocol, the networks are referred to as Wireless Sensor Networks, or WSNs. These sensors generate data and continuously monitor physical factors such as temperature, vibration, and motion, as well as other environmental conditions like sound, pressure, and pollutants. A sensor node can function both as a data router and a data originator simultaneously (Ullo & Sinha, 2020). Additionally, sensors can cooperatively transmit their data through the network to a designated sink where the data is needed and applied. A wireless sensor network comprises a large number of small sensor nodes densely positioned either within or close to the phenomenon being sensed. These nodes include components for sensing, data processing, and communication. The exact positions of sensor nodes do not need to be predetermined. Each sensor node acts as a relay station between other nodes and the central data collection point, facilitating long-distance data transmission. Various factors can affect radio signal propagation, impacting their quality and causing deterioration. These effects are even more pronounced in WSNs, which often use low-power radios. Consequently, radio connectivity in WSNs is frequently erratic, with variable quality over time and space, and connectivity is often asymmetric (Srinivasan et al., 2010).

Extent of Past Related Works

Sensor Networks and Their Applications

Sensor networks are composed of spatially distributed autonomous sensors that monitor and record environmental conditions. These networks have been utilized across various fields, including environmental monitoring, healthcare, and industrial automation. In environmental monitoring, sensor networks have facilitated real-time data collection and analysis (Akyildiz et al., 2002). Healthcare applications have leveraged these networks for patient monitoring and remote diagnostics, enhancing the quality and accessibility of medical services (Alemdar & Ersoy, 2010). In the realm of industrial automation, sensor networks have contributed to optimizing processes and improving operational efficiency (Gungor & Hancke, 2009).

Challenges in Sensor Network Management

Managing sensor networks effectively involves tackling numerous challenges, such as ensuring energy efficiency, maintaining data accuracy, enhancing network reliability, and achieving scalability. Traditional management methods often fall short when adapting to the dynamic conditions and high-dimensional data inherent in sensor networks (Yick et al., 2008). Recent research highlights the importance of developing adaptive strategies to address these issues (Yick et al., 2008; Liu et al., 2011; Zhang et al., 2012). Additionally, advancements in machine learning and artificial intelligence have shown promise in improving sensor network management by providing more robust and flexible solutions (Chen et al., 2014; Xu et al., 2016). The cause of the network not withstanding stress has arisen as a result of not having free communication network caused by high bit error rate, interference and congestion (Amana, et al. ,2021).

Multi-Attribute Decision-Making in Sensor Networks

Multi-Attribute Decision-Making (MADM) techniques offer a structured approach to decision-making in environments characterized by multiple conflicting criteria. These techniques have been applied to various aspects of sensor network management, such as optimizing node deployment and enhancing data fusion processes. For instance, the Analytic Hierarchy Process (AHP) has been used to prioritize and select optimal sensor locations, improving network coverage and efficiency (Saaty, 1980; Gholami et al., 2013). Similarly, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has been employed to enhance data fusion, ensuring the reliability and accuracy of the collected information (Hwang & Yoon, 1981; Khedo et al., 2010). Recent studies also explore integrating MADM techniques with other computational methods to further refine decision-making processes in sensor networks (Zavadskas et al., 2014; Kabir et al., 2014).

Implementation

Implementing the decision-making models in simulation environments is crucial for evaluating their effectiveness. These simulations help in understanding the practical implications of theoretical models and identifying areas for improvement. By leveraging advanced simulation tools, researchers can test various scenarios and optimize sensor network performance (Alippi et al., 2009; Guo et al., 2013). This approach ensures that the developed models are robust, scalable, and capable of addressing the complex challenges inherent in managing sensor networks. To secure link margins without diversity, more transmitted power is required to prevent against deep channel fades. As a result, at the user terminal, diversity at the base can be exchanged for lower power consumption and longer battery life (Ngang, et al,2022). In the study conducted by (Bakare, 2021), he affirmed that fuzzy controller is an effective means of regulating system frequency; when combined alongside other control devices would yield good results; hence being used for complementary functions with Artificial neural network (ANN) our design would be effective and efficient.

Methodology

SMADM Approach

The proposed SMADM approach integrates advanced MADM techniques with real-time data processing capabilities to enhance sensor network performance. The approach involves the following steps:

Data Collection: Gathering real-time data from sensor nodes.

Attribute Identification: Identifying relevant attributes affecting network performance, such as energy consumption, data accuracy, and node reliability.

Decision-Making Model:

Simulation Setup

The simulation environment is designed to mimic real-world conditions of sensor networks. Various performance metrics, such as energy efficiency, data accuracy, and network reliability, are used to evaluate the SMADM approach. The simulation results are compared with traditional methods to demonstrate the improvements achieved.

Characterizing Data for Performance of Wireless Sensor Networks

The first step was to characterize and establish increased energy consumption, interference and packet loss responsible for reduced performance of wireless sensor networks.

Table 1: Characterized data for Performance of Wireless Sensor Networks

TIME (DAYS)	*Data transmitted*	*Data RECEIVED*	*Power consumption (w)*	*Time of identifying a target(s)*	*Identification range(M)*
1	200	180	0.5	5	50
2	180	160	1	2	56
3	200	175	1.5	7	72
4	200	170	2.5	7	72
5	190	180	4.7	7	72
6	180	165	7.3	5	56
7	200	185	8	2	29

Applying formula to find packet loss
Packet loss = data transmitted – data received
To find day 1 packet loss
Day 1 Packet loss = data transmitted - data received
Day 1 Packet loss =200 – 180
Day 1 Packet loss = 20
To find day 2 packet loss
Day 2 Packet loss =180 -160
Day 2 Packet loss = 20
To find day 3 packet loss
Day 3 Packet loss =200 -175
Day 3 Packet loss =25
To find day 4 packet loss
Day 4 Packet loss =200 -170
Day 4 Packet loss = 30
To find day 5 packet loss
Day 5 Packet loss =190 -180
Day 5 Packet loss = 10
To find day 6 packet loss
Day 6 Packet loss =180 - 165
Day 6 Packet loss =15
To find day 7 packet loss
Day 7 Packet loss =200-185
Day 7 Packet loss =15

Table 2: Data for Sensor Coverage

A1	*Sensing power*
A2	Communication range
A3	Packet loss

A1 Sensing Power

Table 3: Sensing Power Range of Sensors

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 4: Communication Range

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

A4 Packet Loss

Table 4: Packet Loss

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

Finding the Best Sensor that will Sense a Target Fast among all the Sensors

Table 5: Comparison of the Three Sensors

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

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

Determining the Weight of the Criteria

Table 6: Weight Sensors Determinant

	criteria	*Weight*	*numerical value*
C1	Routing value	Better	0.75
C2	Sensing time	Best	0.98
C3	Sensing power	Good	0.5
C4	Sensing range covered	Best	0.98

Table obtained by the weight value with the data

W = [0.75, 0.98, 0.5, 0.98]

Then, using simple additive weighting method (SAW).

First determine the name of the sensors as an alternative

Table 7: Determinant of the Weight of the Sensors 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 8: For the Rating the Suitability 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

$$X = \begin{pmatrix} 0.75 & 0.75 & 0.5 & 0.75 \\ 0.5 & 0.75 & 0.5 & 0.75 \\ 0.75 & 0.5 & 1 & 1 \end{pmatrix}$$

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

In compliance with the criteria by which all the criteria included in the benefit, the calculation to normalize the matrix X becomes

$$R11 = \frac{0.75}{+\text{Max}\,(0.75, 0.5, 0.75)} = \frac{0.75}{0.75} = 1$$

$$R21 = \frac{.5}{\text{Max}\,(0.75, 0.5, 0.75)} = \frac{0.5}{0.75} = 0.67$$

$$R31 = \frac{0.75}{\text{Max}(0.75, 0.5, 0.75)} = \frac{0.75}{0.75} = 1$$

$$R12 = \frac{0.75}{\text{Max}\,(0.75, 0.5, 0.75)} = \frac{0.75}{0.5} = 1.5$$

$$R22 = \frac{0.5}{\text{Max}(0.75, 0.5, 0.75)} = \frac{0.5}{0.5} = 1$$

$$R32 = \frac{0.75}{\text{Max}(0.75, 0.5, 0.75)} = \frac{0.75}{0.5} = 1.5$$

$$R13 = \frac{0.75}{\text{Max}(0.75, 0.5, 0.75)} = \frac{0.75}{0.75} = 1$$

$$R23 = \frac{0.5}{\text{Max}(0.75, 0.5, 0.75)} = \frac{0.5}{0.75} = 0.67$$

$$R33 = \frac{0.75}{\text{Max}(0.75, 0.5, 0.75)} = \frac{0.75}{0.75} = 1$$

$$R14 = \frac{0.75}{\text{Max}(0.75, 0.75, 0.5)} = \frac{0.75}{0.5} = 1.5$$

$$R24 = \frac{0.75}{\text{Max}(0.75, 0.75, 0.5)} = \frac{0.75}{0.5} = 1.5$$

$$R34 = \frac{0.5}{\text{Max}\,(0.75, 0.75, 0.5)} = \frac{0.5}{0.5} = 1$$

$$R15 = \frac{0.75}{\text{Max}\,(0.75, 0.75, 0.5)} = \frac{0.75}{0.75} = 1$$

$$R25 = \frac{0.75}{\text{Max}\,(0.75, 0.75, 0.5)} = \frac{0.75}{0.75} = 1$$

$$R35 = \underline{0.5} = \underline{0.5} = 0.67$$

Max (0.75, 0.75, 0.5) 0.75

$$R16 = \frac{0.75}{\text{Max}\,(0.75, 0.75, 0.5)} = \frac{0.75}{0.75} = 1$$

$$R26 = \frac{0.75}{\text{Max}\,(0.75, 0.75, 0.5)} = \frac{0.75}{0.75} = 1$$

$$R36 = \frac{0.5}{\text{Max}\,(0.75, 0.75, 0.5)} = \frac{0.5}{0.75} = 0.67$$

$$R17 = \frac{0.5}{\text{Max}\,(0.5, 0.5, 1)} = \frac{0.5}{1} = 0.5$$

$$R27 = \frac{0.5}{\text{Max}\,(0.5, 0.5, 1)} = \frac{0.5}{1} = 0.5$$

$$R37 = \frac{1}{\text{Max}\,(0.5, 0.5, 1)} = \frac{1}{1} = 1$$

$$R18 = \frac{0.5}{\text{Max}\,(0.5, 0.5, 1)} = \frac{0.5}{0.5} = 1$$

$$R28 = \frac{0.5}{\text{Max}\,(0.5, 0.5, 1)} = \frac{0.5}{0.5} = 1$$

$$R38 = \frac{1}{\text{Max}\,(0.5, 0.5, 1)} = \frac{1}{0.5} = 2$$

$$R19 = \frac{0.5}{\text{Max}\,(0.5, 0.5, 1)} = \frac{0.5}{0.5} = 1$$

$$R29 = \frac{0.5}{\text{Max}\,(0.5, 0.5, 1)} = \frac{0.5}{0.5} = 1$$

$$R39 = \frac{1}{\text{Max}\,(0.5, 0.5, 1)} = \frac{1}{0.5} = 2$$

$$R20 = \frac{0.75}{\text{Max}\,(0.75, 0.75, 1)} = \frac{0.75}{1} = 0.75$$

$$R30 = \frac{0.75}{\text{Max}\,(0.75, 0.75, 1)} = \frac{0.75}{1} = 0.75$$

$$R40 = \frac{1}{\text{Max}\,(0.75, 0.75, 1)} = \frac{1}{1} = 1$$

$$R21 = \frac{0.75}{\text{Max}\,(0.75, 0.75, 1)} = \frac{0.75}{0.75} = 1$$

$$R31 = \frac{0.75}{\text{Max}\,(0.75, 0.75, 1)} = \frac{0.75}{0.75} = 1$$

$$R41 = \frac{1}{\text{Max}\,(0.75, 0.75, 1)} = \frac{1}{0.75} = 1.3$$

$$R22 = \frac{0.75}{\text{Max}\,(0.75, 0.75, 1)} = \frac{0.75}{0.75} = 1$$

$$R32 = \frac{0.75}{\text{Max}\,(0.75, 0.75, 1)} = \frac{0.75}{0.75} = 1$$

$$R42 = \frac{1}{\text{Max}\,(0.75, 0.75, 1)} = \frac{1}{0.75} = 1.3$$

The matrix obtained from the computation becomes

$$R = \begin{pmatrix} 1 & 1.5 & 1 & 1.5 & 1 & 1 & 0.5 & 1 & 1 & 0.75 & 1 & 1 \\ 0.67 & 1 & 0.67 & 1.5 & 1 & 1 & 0.5 & 1 & 1 & 0.75 & 1 & 1 \\ 1 & 1.5 & 1 & 1 & 0.67 & .67 & 1 & 2 & 2 & 1 & 1.3 & 1.3 \end{pmatrix}$$

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 1.5)+(0.5 x 1) +(0.98x1.5)+(0.75x1)+(0.98x1)+(0.5x0.5)+(0.98x1)+(0.75x1)+(0.98x0.75)+(0.5x1)+(0.98x1)]

A1= [0.75+1.47+0.5+1.47+0.75+0.98+0.25+0.98+0.75+0.735+0.5+0.98]

A1= 10.115

A2= [(0.75x0.67)+(0.98x1)+(0.5x0.67)+(0.98x1.5)+(0.75x1)+(0.98x1)+(0.5x 0.5) + (0.98 x 1)+(0.75x 1)+(0.98x0.75)+(0.5x 1)+(0.98x1)]

A2= [0.5025+0.98+0.335+1.47+0.75+0.98+0.25+0.98+0.75+0.735+0.5+0.98]

A2 = 9.2125

A3= [(0.75x1)+(0.98x1.5)+(0.5x1)+(0.98x1)+(0.75x0.67)+(0.98x0.67)+(0.5x 1)+ (0.98x2)+(0.75x2)+(0.98x1)+(0.5x1.3)+(0.98x1.3)]

A3= [0.75+1.47+0.5+0.98+0.5025+0.6566+0.5+1.96+1.5+0.98+0.65+1.274]

A3=11.7231

Table 9: Ranking Result of the Three Sensors

Alternative	*Value*	*Ranking*
A1	10.115	2
A2	9.2125	3
A3	11.7231	1

The best sensor among the sensors is sensor A3

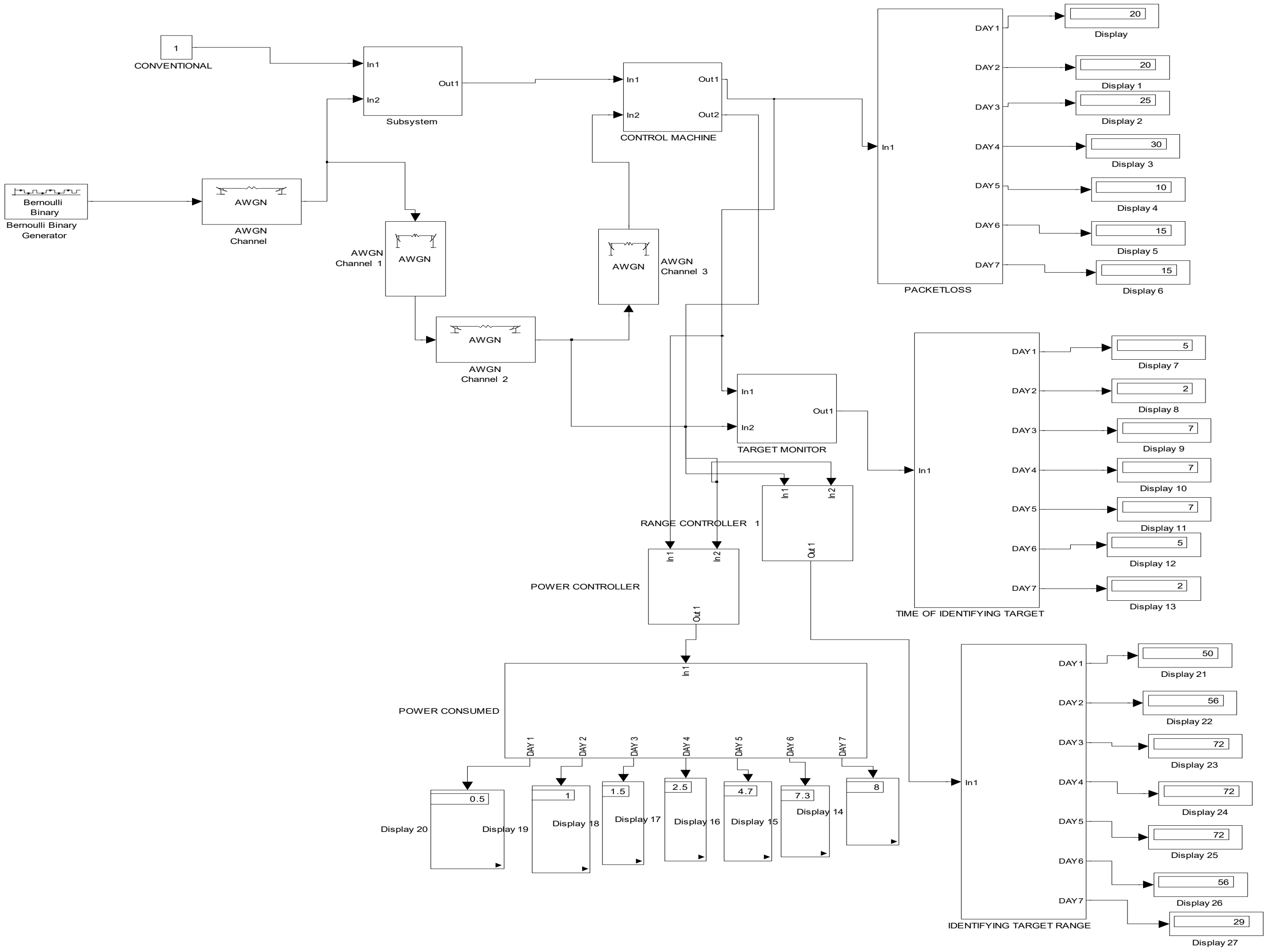
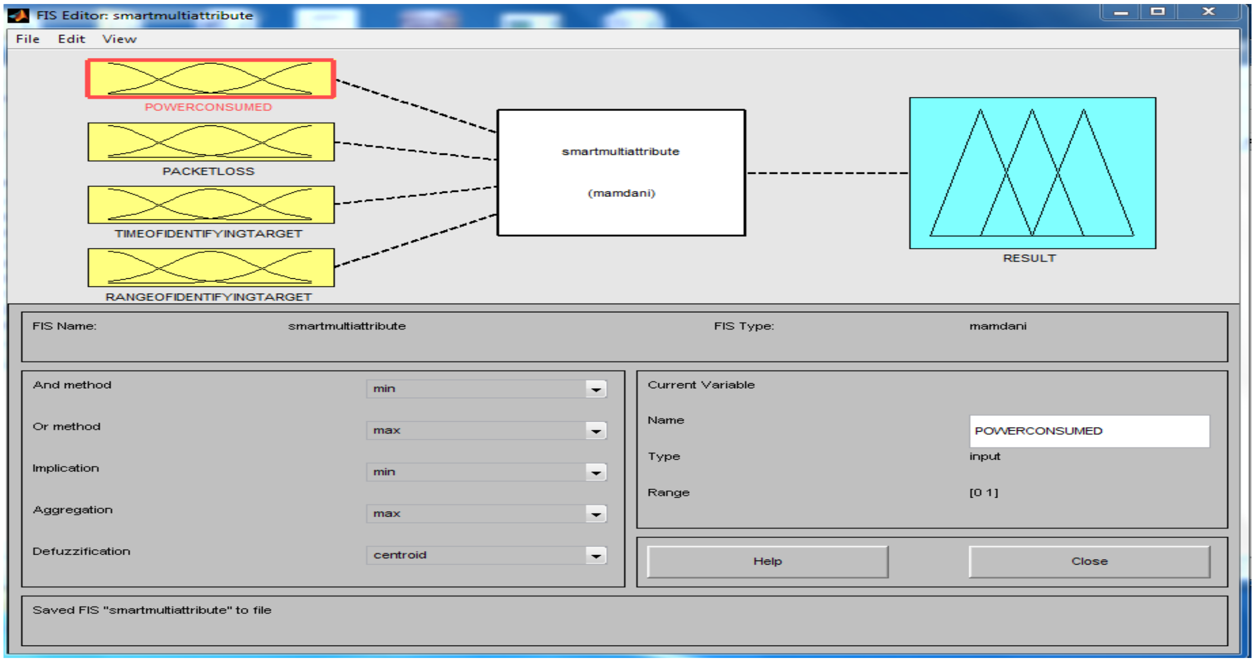


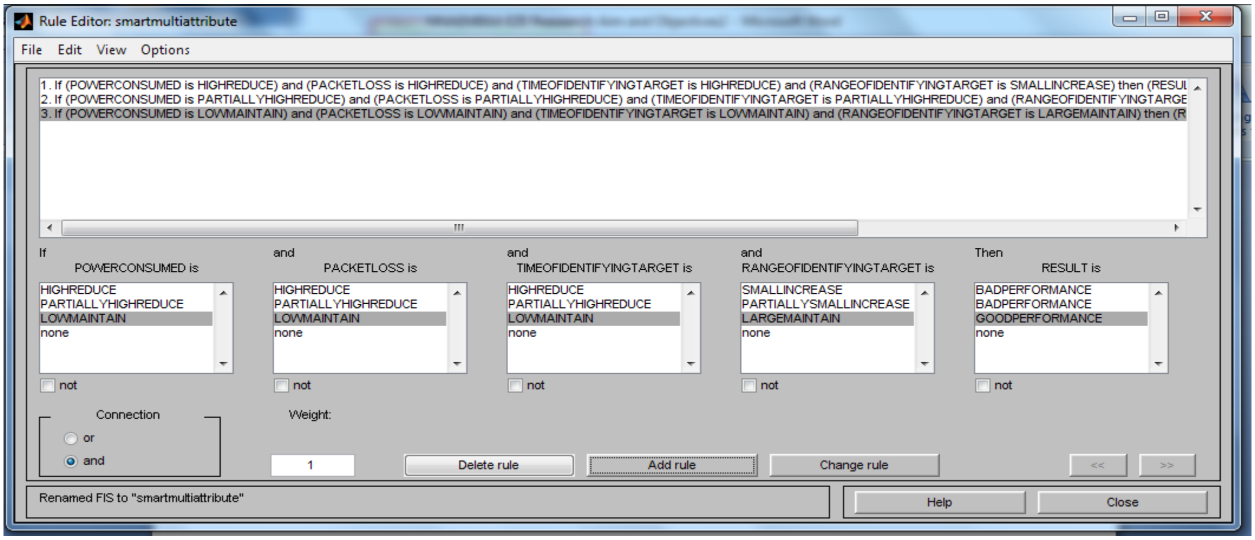
Fig 1: Conventional SIMULINK model for Improving the Performance of Sensor Networks



FIS Name: smartmultiattribute
FIS Type: mamdani
And method: min
Or method: max
Implication: min
Aggregation: max
Defuzzification: centroid
Current Variable
Name: POWERCONSUMED
Type: input
Range: [0 1]

Saved FIS "smartmultiattribute" to file

Fig 2: Designed Fuzzy Inference System for a Smart Multi-Attribute Decision Making (MADM) for Reducing Energy Consumption, Interference and Packet Loss thereby Improving the Performance of Wireless Sensor Networks



1. If (POWERCONSUMED is HIGHREDUCE) and (PACKETLOSS is HIGHREDUCE) and (TIMEOFIDENTIFYINGTARGET is HIGHREDUCE) and (RANGEOFIDENTIFYINGTARGET is SMALLINCREASE) then (RESUL
2. If (POWERCONSUMED is PARTIALLYHIGHREDUCE) and (PACKETLOSS is PARTIALLYHIGHREDUCE) and (TIMEOFIDENTIFYINGTARGET is PARTIALLYHIGHREDUCE) and (RANGEOFIDENTIFYINGTARGE
3. If (POWERCONSUMED is LOWMAINTAIN) and (PACKETLOSS is LOWMAINTAIN) and (TIMEOFIDENTIFYINGTARGET is LOWMAINTAIN) and (RANGEOFIDENTIFYINGTARGET is LARGEMAINTAIN) then (R

Renamed FIS to "smartmultiattribute"

Fig 3: Designed rule base for a smart multi-attribute decision making (MADM) for reducing energy consumption, interference and packet loss thereby improving the performance of wireless sensor networks

Table 10: Showing Comprehensive Details of the Rules

1	IF POWER CONSUMED IS HIGH REDUCE	AND PACKET LOSS IS HIGH REDUCE	AND TIME OF IDENTIFYING TARGET IS HIGH REDUCE	AND RANGE OF IDENTIFYING TARGET IS SMALL INCREASE	THEN RESULT IS BAD PERFORMANCE
2	IF POWER CONSUMED IS PARTIALLY HIGH REDUCE	AND PACKET LOSS IS PARTIALLY HIGH REDUCE	AND TIME OF IDENTIFYING TARGET IS PARTIALLY HIGH REDUCE	AND RANGE OF IDENTIFYING TARGET IS PARTIALLY SMALL INCREASE	THEN RESULT IS BAD PERFORMANCE
3	IF POWER CONSUMED IS LOW MAINTAIN	AND PACKET LOSS IS LOW MAINTAIN	AND TIME OF IDENTIFYING TARGET IS LOW MAINTAIN	AND RANGE OF IDENTIFYING TARGET IS LARGE MAINTAIN	THEN RESULT IS GOOD PERFORMANCE

Designing a SIMULINK model for Wireless Sensor Network (WSN)

Developing an algorithm that will implement the process, the first is to:

1. Characterize conventional wireless sensor.
2. Identify the high packet loss in the process.
3. Identify the large power consumed in the process.
4. Identify increase in the target identification time.
5. Identify decrease in the range of target identification.
6. Design a conventional model for smart multi-attribute decision making approach and incorporate 2, 3, 4 and 5.
7. Design a rule base for a smart multi-attribute decision making (MADM) for reducing energy consumption, interference and packet loss thereby improving the performance of wireless sensor networks.
8. Design a SIMULINK model for wireless sensor network (WSN).
9. Integrate 7 and 8.
10. Integrate 9 and 6.
11. Did packet loss reduced?
12. If yes, go to 23
13. If No, go to 10
14. Did power consumed reduced?
15. If yes, go to 23
16. If No, go to 10
17. Did identification time reduced?
18. If yes, go to 23
19. If No, go to 10
20. Did target range increased?
21. 21 If yes, go to 23
22. If No, go to 10.
23. Improved performance of wireless sensor networks. Smart multi-attribute decision making approach.
24. Stop.
25. End.

To design a SIMULINK model for intelligent based smart multi-attribute decision making approach

To develop an integrated model for a wireless sensor network based multi-attribute decision making (MADM) and simulate to generate results for analysis.

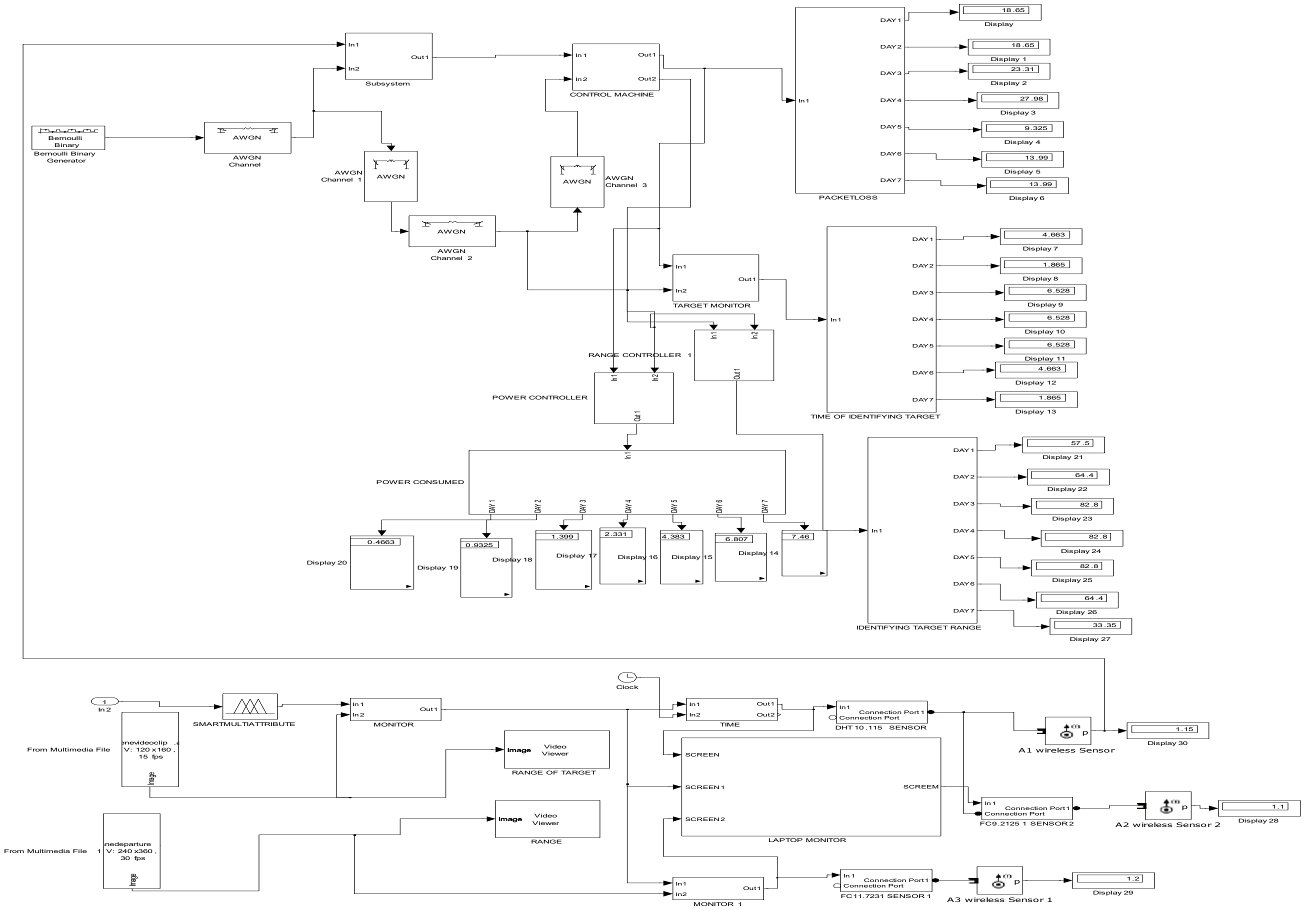


Fig 4: Conventional SIMULINK Model for Improving the Performance of Sensor Networks Integrated with Intelligent Based Smart Multi-attribute Decision making Approach of Sensor 1

The results obtained are as shown in figures 9 and 10.

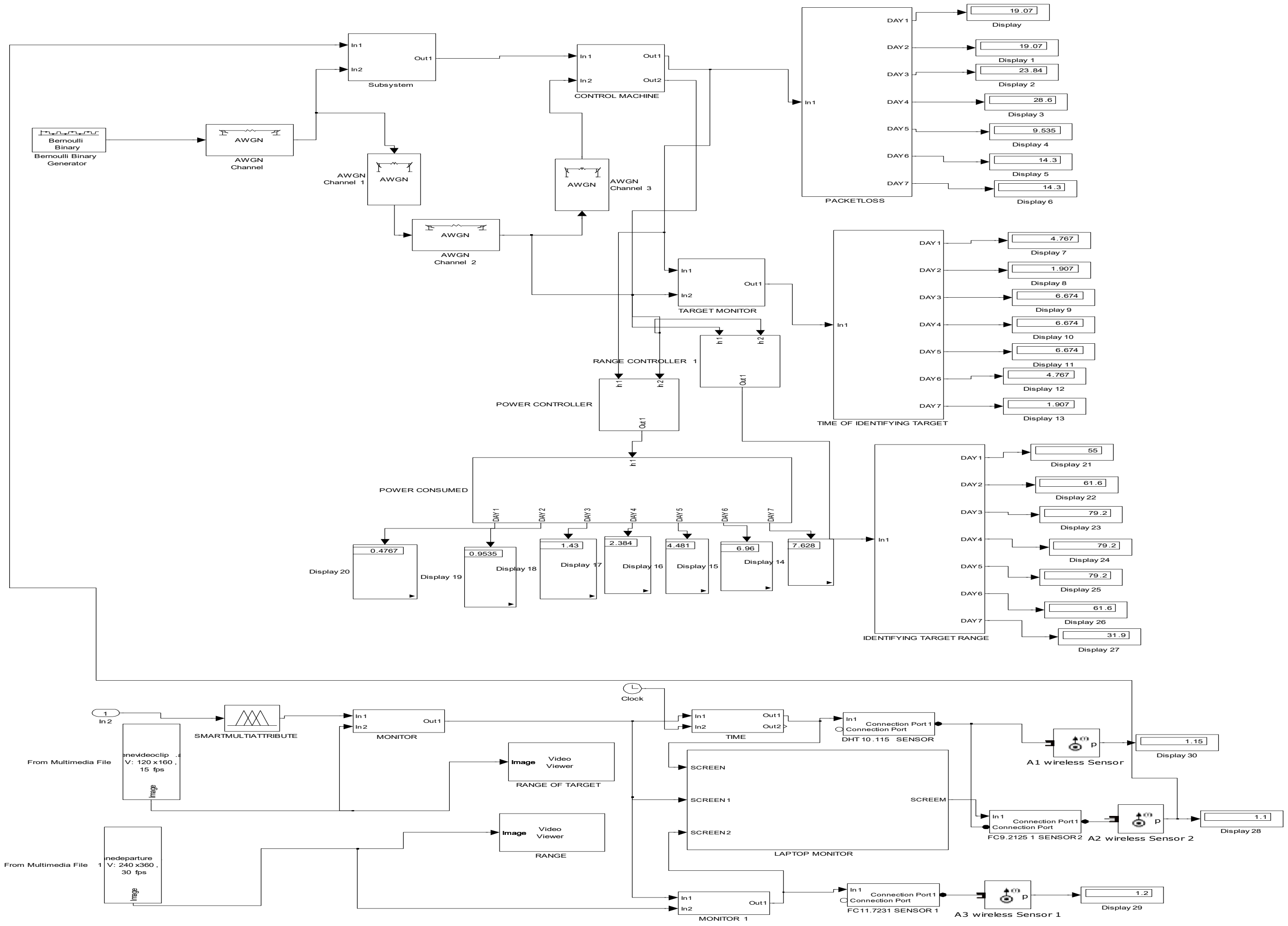


Fig 5: Conventional SIMULINK model for improving the performance of sensor networks integrated with intelligent based smart multi-attribute decision making approach of sensor 2

The results obtained are as shown in figures 9 and 10.

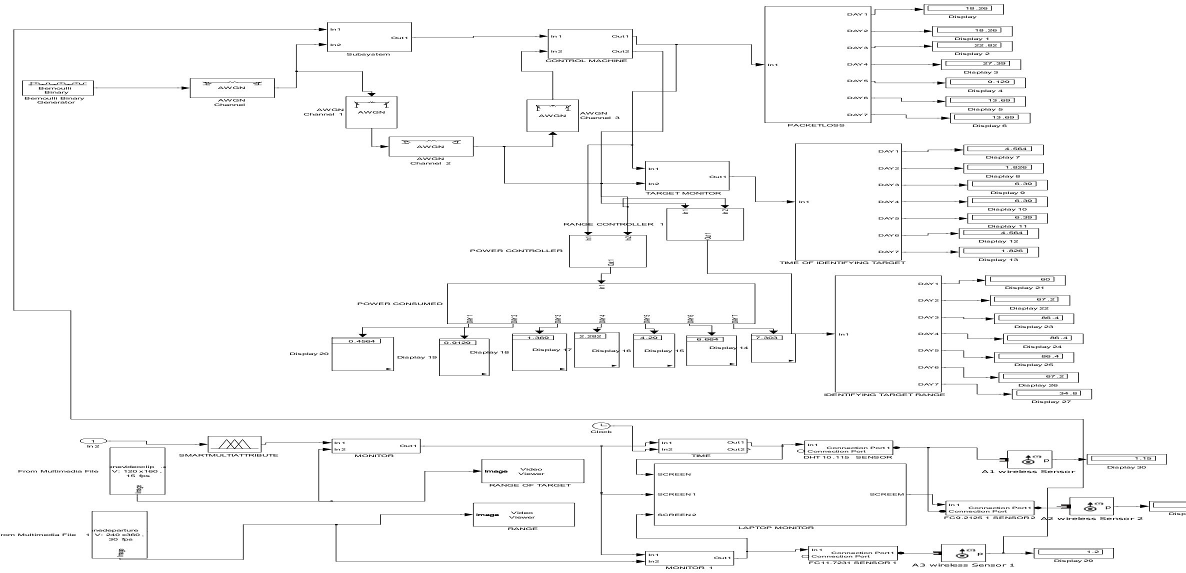


Fig 6: Conventional SIMULINK model for improving the performance of sensor networks integrated with intelligent based smart multi-attribute decision making approach of sensor 3

The results obtained are as shown in figures 9 and 10.

To validate and justify the research technique by computing percentage of improvement in wireless sensor network with and without multi-attribute decision making (MADM).

Conventional day 1 packet loss =20kb

Wireless sensor day 1 packet loss =18.26kb

% improvement packet loss reduction when wireless sensor is incorporated in the system =

$$\frac{\text{Conventional day 1 packet loss - Wireless sensor day 1 packet loss}}{\text{Conventional day 1 packet loss}} \times \frac{100\%}{1}$$

% improvement packet loss reduction when wireless sensor is incorporated in the system = $\frac{20kb - 18.26kb}{20Kb} \times \frac{100\%}{1}$

% improvement packet loss reduction in day 1 when wireless sensor is incorporated in the system = 8.7%

To find percentage improvement packet loss reduction in day 2 when wireless sensor is incorporated in the system

Conventional day 2 packet loss =20kb

Wireless sensor day 2 packet loss =18.26kb

% improvement packet loss reduction in day 2 when wireless sensor is incorporated in the system = 8.7%

To find percentage improvement packet loss reduction in day 3 when wireless sensor is incorporated in the system

Conventional day 3 packet loss =25kb

Wireless sensor day 3 packet loss =22.82kb

% improvement packet loss reduction day 3 when wireless sensor is incorporated in the system =

$$\frac{25kb - 22.82kb}{25Kb} \times \frac{100\%}{1}$$

% improvement packet loss reduction day 3 when wireless sensor is incorporated in the system = 8.72%

To find percentage improvement packet loss reduction in day 4 when wireless sensor is incorporated in the system

Conventional day 4 packet loss = 30kb

Wireless sensor day 4 packet loss = 27.39kb

% improvement packet loss reduction day 4 when wireless sensor is incorporated in the system =

$$\frac{30kb – 27.39kb}{30Kb} \times \frac{100\%}{1}$$

% improvement packet loss reduction day 4 when wireless sensor is incorporated in the system = 8.7%

To find percentage improvement packet loss reduction in day 6 when wireless sensor is incorporated in the system

Conventional day 6 packet loss = 15kb

Wireless sensor day 6 packet loss = 13.69kb

% improvement packet loss reduction day 6 when wireless sensor is incorporated in the system =

$$\frac{15kb - 13.69kb}{15Kb} \times \frac{100\%}{1}$$

% improvement packet loss reduction day 6 when wireless sensor is incorporated in the system = 8.73%

To find percentage improvement packet loss reduction in day 7 when wireless sensor is incorporated in the system

Conventional day 6 packet loss =15kb

Wireless sensor day 6 packet loss = 13.69kb

% improvement packet loss reduction day 7 when wireless sensor is incorporated in the system = 8.73%

To find percentage improvement power consumed reduction in day 1 when wireless sensor is incorporated in the system

Conventional day 1 power consumed =0.5w

Wireless sensor day 1 power consumed = 0.47w

% improvement power consumed reduction in day 1 when wireless sensor is incorporated in the system

% improvement power consumed reduction day 1 when wireless sensor is incorporated in the system =

$$\frac{0.5w - 0.47w}{0.5w} \times \frac{100\%}{1}$$

% improvement power consumed reduction day 1 when wireless sensor is incorporated in the system = 6%

To find percentage improvement power consumed reduction in day 2 when wireless sensor is incorporated in the system

Conventional day 2 power consumed =1w

Wireless sensor day 2 power consumed = 0.913w

% improvement power consumed reduction day 2 when wireless sensor is incorporated in the system =

$$\frac{1w - 0.913w}{1w} \times \frac{100\%}{1}$$

% improvement power consumed reduction day 2 when wireless sensor is incorporated in the system = 8.7%

To find percentage improvement power consumed reduction in day 4 when wireless sensor is incorporated in the system

Conventional day 3 power consumed = 1.5w

Wireless sensor day 3 power consumed = 1.37w

% improvement power consumed reduction day 3 when wireless sensor is incorporated in the system =

$$\frac{1.5w - 1.37w}{1.5w} \times \frac{100\%}{1}$$

% improvement power consumed reduction day 3 when wireless sensor is incorporated in the system = 8.7%

To find percentage improvement power consumed reduction in day 4 when wireless sensor is incorporated in the system

Conventional day 4 power consumed =2.5w

Wireless sensor day 4 power consumed =2.28 w

% improvement power consumed reduction day 4 when wireless sensor is incorporated in the system =

$$\frac{2.5w - 2.28w}{2.5w} \times \frac{100\%}{1}$$

% improvement power consumed reduction day 4 when wireless sensor is incorporated in the system =8.8%

To find percentage improvement power consumed reduction in day 5 when wireless sensor is incorporated in the system

Conventional day 5 power consumed = 4.7w

Wireless sensor day 5 power consumed = 4.29w

% improvement power consumed reduction day 5 when wireless sensor is incorporated in the system =

$$\frac{w - 4.29w}{4.7w} \times \frac{100\%}{1}$$

% improvement power consumed reduction day 5 when wireless sensor is incorporated in the system = 8.72%

% improvement power consumed reduction day 7 when wireless sensor is incorporated in the system =

$$\frac{8w - 7.3w}{8w} \times \frac{100\%}{1}$$

% improvement power consumed reduction day 7 when wireless sensor is incorporated in the system =8.75%

Results and Discussion

The following are the results obtained using the Intelligent Smart Multi-Attribute Decision-Making Approach in the course of the study:

The study demonstrates the effectiveness of the Smart Multi-Attribute Decision Making (SMADM) approach through simulation results, highlighting significant improvements in network reliability, data accuracy, and overall system efficiency. The research focuses on addressing issues such as increased energy consumption, interference, and packet loss, which traditionally reduce performance. To mitigate these issues, a rule base for the SMADM approach was developed and implemented using a SIMULINK model for wireless sensor networks (WSN).

Figure 1 illustrates the conventional SIMULINK model aimed at enhancing sensor network performance. Figure 2 introduces the designed fuzzy inference system for SMADM, which targets reducing energy consumption, interference, and packet loss, thereby boosting the overall performance of WSNs. This model outputs data on power consumption, packet loss, target identification time, and target identification range. Figure 3 details the rule base for SMADM, designed to optimize these parameters. The comprehensive rules are provided in Table 10.

Figures 4, 5, and 6 display the integration of the intelligent SMADM approach with conventional SIMULINK models for different sensor configurations (sensor 1, sensor 2, and sensor 3). The results, as shown in Figures 9 and 10, offer a comparative analysis of packet loss and power consumption across these configurations. Figure 7 presents the comparison of packet loss for conventional and SMADM-enhanced sensors, while Figure 8 compares power consumption.

Notably, the results indicate that sensor 3 achieved the lowest power consumption, reducing it to 0.456W on day 1, compared to 0.5W for the conventional approach. Sensor 1 and sensor 2 also showed improvements, consuming 0.4663W and 0.4767W, respectively. These findings underscore the potential of the SMADM approach to significantly enhance energy efficiency, reduce costs, and improve the overall performance of wireless sensor networks. The intelligent incorporation of SMADM not only addresses key performance issues but also demonstrates a viable pathway for optimizing WSN operations in practical applications.

Table 11: Comparison of conventional, sensor1, sensor2 and sensor3 packet loss in smart multi-attribute decision making Approach

Time (DAY)	*Conventional packet loss*	*Sensor1 packet loss in smart multi-attribute decision making Approach(Kb/s)*	*Sensor2 packet loss in smart multi-attribute decision making Approach(Kb/s)*	*Sensor3 packet loss in smart multi-attribute decision making Approach(Kb/s)*
1	20	18.65	19.07	18.26
2	20	18.65	19.07	18.26
3	25	23.31	23.84	22.82
4	30	27.98	28.6	27.39
5	10	9.325	9.535	9.129
6	15	13.99	14.3	13.69
7	15	13.99	14.3	13

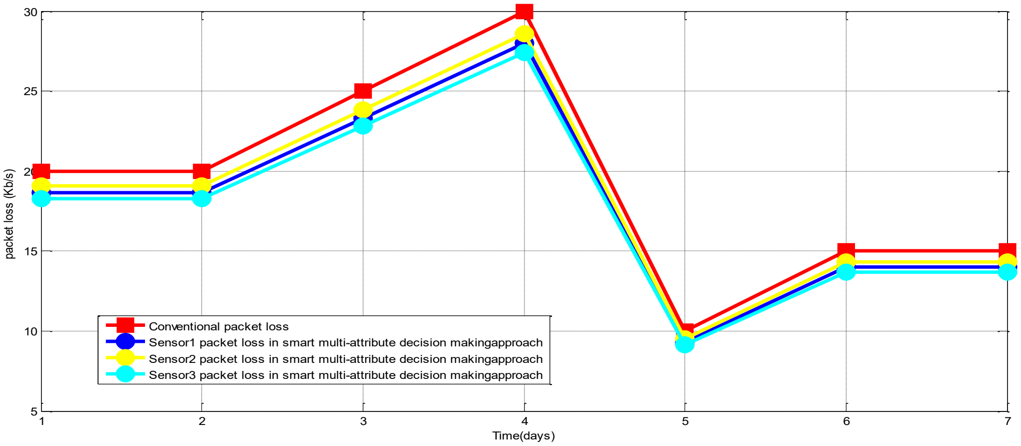


Fig 7: Comparison of conventional, sensor1, sensor2 and sensor3 packet loss in smart multi-attribute decision making Approach

The highest conventional packet loss is 30Kb/s and it occurred in day 4 while that of sensor 1 the same day is 27.98Kb/s. On the other hand, when wireless sensor 2 is incorporated in the system the packet loss observed is 28.6Kb/s and when sensor 3 is injected into the system the packet loss drastically reduced to27.39Kb/s. With these results obtained it shows that sensor 3 is the best sensor among all the sensors for improved network performance.

Table 12: Comparison of Conventional, Sensor1, Sensor2 and Sensor3 Power Consumption in Smart Multi-Attribute Decision Making Approach

Time (DAY)	*Conventional Power consumption(w)*	*Sensor1 Power consumption in smart multi-attribute decision making Approach(W)*	*Sensor2 Power consumption in smart multi-attribute decision making Approach(W)*	*Sensor3 Power consumption in smart multi-attribute decision making Approach(W)*
1	0.5	0.4663	0.4767	0.4564
2	1	0.9325	0.9535	0.9129
3	1.5	1.399	1.43	1.369
4	2.5	2.331	2.384	2.282
5	4.7	4.383	4.481	4.29
6	7.3	6.807	6.96	6.664
7	8	7.46	7.628	7.303

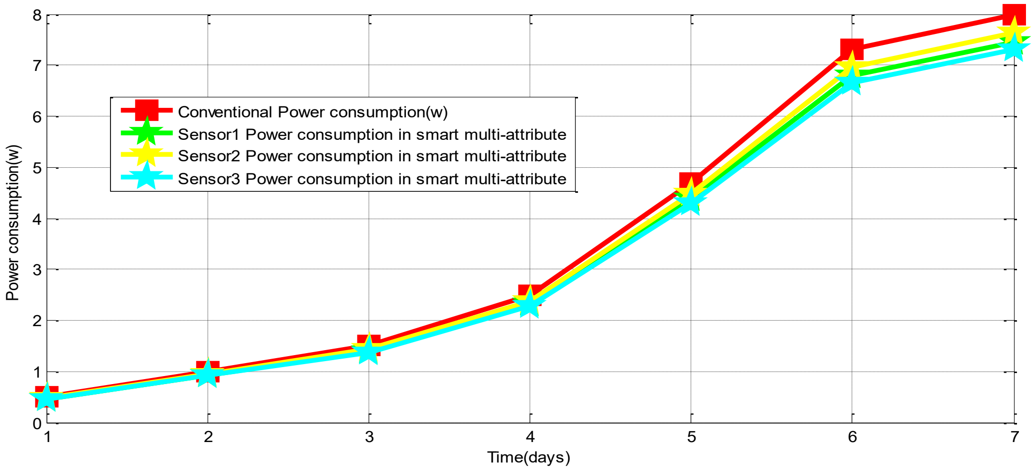


Fig. 8: comparison of conventional, sensor1, sensor2 and sensor3 Power consumption in smart multi-attribute decision making Approach

Conclusion

The persistent underperformance of sensor networks in communication systems has significantly impacted network efficiency and cost-effectiveness. High packet loss and elevated power consumption are primary causes of this issue. To address this, an intelligent multi-attribute decision-making (MADM) approach has been introduced to improve sensor network performance.

The process involves:

1. Identifying and characterizing increased energy consumption, interference, and packet loss in wireless sensor networks.
2. Designing a rule-based MADM system to mitigate these issues and enhance network performance.
3. Creating a SIMULINK model for wireless sensor networks (WSNs).
4. Developing an algorithm to implement the MADM process.
5. Validating the model and results.

The validation results indicated that the highest conventional packet loss was 30 Kb/s on day 4, while sensor 1 had a packet loss of 27.98 Kb/s on the same day. With sensor 2, the packet loss reduced to 28.6 Kb/s, and with sensor 3, it further decreased to 27.39 Kb/s. Thus, sensor 3 demonstrated the best performance in reducing packet loss.

Additionally, conventional power consumption was 0.5W on day 1. With sensor 1, it was 0.4663W, sensor 2 had 0.4767W, and sensor 3 showed the lowest power consumption at 0.456W. These results indicate that sensor 3 is the most efficient in both improving network performance and reducing power consumption, making it the most cost-effective option.

Designing a rule base for an intelligent MADM system can significantly reduce energy consumption, interference, and packet loss, thereby enhancing the overall performance of wireless sensor networks.

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